INTERNATIONAL ECONOMIC REVIEW
Vol. 59, No. 4, November 2018 DOI: 10.1111/iere.1

# TESTING FOR MICRO-EFFICIENCY IN THE HOUSING MARKET*

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Using highly granular transaction-level data for the Norwegian housing market over the period 2002–2014, we investigate whether excessive prices persist or revert in repeat sales. Excessiveness in prices is detected by comparing selling prices to predicted prices implied by a hedonic model, which includes a rich set of attributes. Persistence is rejected and there is substantial reversion in excessive prices. Our results also show little scope for profitable arbitrage by investing in apparently underpriced units. We suggest that excessive prices are related to the stochastic arrival of interested purchasers at public showings, which we show is nonrepeatable.

## 1. INTRODUCTION

House price indices display time persistence. This has led several researchers to conclude that returns contain predictable components. However, evidence based on aggregate indices is only part of the story since the development of an index between two time periods reflects movements in the aggregate, that is, between two scalars that each summarize 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 can 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 sold?

If there is persistence, a high first selling 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 selling 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. The return on his investment will be lower than the market return. Conversely, a buyer who purchased at a price lower than the expected price can reasonably expect to sell at a price that is closer to the expected price. Thus, the absence of persistence and presence of reversion imply that the market punishes overpayments and rewards underpayments. At the same time, if underpayments are rewarded, it could be possible to detect units that are underpriced ex ante and make an ex post gain by investing in these units.

*Manuscript received July 2016; revised January 2018.

[1] This article 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. We thank the editor, Holger Sieg, and three anonymous reviewers for comments that have improved this article. The article 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, Saskia ter Ellen, Solveig Erlandsen, Sigurd Galaasen, Steffen Grønneberg, Joe Gyourko, Mathias Hoffmann, Steinar Holden, Andreas Kostøl, Spencer Norman, Are Oust, Dagfinn Rime, Asbjørn Rødseth, Dag Einar Sommervoll, Bernt Stigum, Kjetil Storesletten, Genaro Succarat, Leif Anders Thorsrud, Paloma Taltavull de La Paz, and Robert Wassmer for stimulating comments and feedback that helped improve this article. Please address correspondence to: André Kallåk Anundsen, Norges Bank Research, Norges Bank, Bankplassen 2, P.O. Box 1179 Sentrum, NO-0107 Oslo, Norway. E-mail: *andre-kallak.anundsen@norgesbank.no*.

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 469,127 transactions of owner-occupier units between 2002 and 2014, we do, however, find that the housing market does not display evidence of micropersistence. To reach this conclusion, we follow units across repeat sales. We detect a clear pattern. When the first selling 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 selling price is higher than the hedonic model's price prediction. Then, the second selling price is also high. This demonstrates that the market 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 time-invariant unit fixed effects. Results are further strengthened when studying a subsample, for which we have information on appraisal prices set by external and independent inspectors. These appraisal prices allow us to control for time-varying attributes of individual units, such as changes in the exterior or interior. Controlling for this, we reject full persistence and find evidence of full reversion in excessive prices. Although our findings suggest excess return predictability, we show that risk-adjusted excess returns from investing in units that are underpriced relative to the hedonic model ex ante cannot be made. This leads to the conclusion that the Norwegian housing market is micro-efficient.

To understand the mechanism generating reversion, we explore bidding-specific factors. For this purpose, we acquired a unique data set on the auction process from 7,915 housing auctions, containing the number of bids, the appraisal price, the selling price, a unit identifier, and the exact transaction date. We find no statistically significant relationship between the number of bids the second time a unit is sold and the number of bids the first time the unit is sold. This suggests that the number of bids is unrelated to the unit and that a high number is nonrepeatable. However, units that receive many bids experience a significant increase in the selling price relative to the common value component. Thus, our results suggest that reversion is related to randomness on the buy side.

Our contribution is threefold. First, we propose a simple framework to test for micropersistence in housing markets. Our framework builds on the persistence idea from macrotests. In contrast to macrotests, our results show little micropersistence. Moreover, we find that it is difficult to beat the market by systematically investing in units that are underpriced relative to the price implied by a hedonic model. Thus, our findings support the notion that the Norwegian housing market is semistrong efficient at the micro level. Second, we bring results from a comprehensive data set. The data allow ultrafine 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, that is, 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 and appraisal prices, in addition to a long list of attributes. Institutionally, Norway is a well-suited country for studying micro- versus macropersistence, since Norwegian households transact houses through speedy and transparent ascending-bid auctions after public showings on one or two preannounced dates. In these auctions, the realtor mediates bids by phone or 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. As a third contribution, we have acquired data on this auction process that allow us to investigate the mechanisms behind reversion in excessive prices.

Our findings suggest that the housing market is an example of what Jung and Shiller (2005) dub "Samuelson's Dictum," which ventures that the stock market is micro-efficient, but macro-inefficient. The underlying idea of the dictum 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 may involve 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 results in this article bear resemblance to Sieg et al. (2002), who construct interjurisdictional house price indices consistent with locational equilibrium theory using hedonic models. They construct several alternative estimates of interjurisdictional price indices for the LA metro area, and these indices are evaluated based on how well they correspond with the implications of locational equilibrium theory. An interesting finding is that relative prices across communities remain intact across specifications. This stable ranking of communities is related to our finding of reversion of excessive prices, which implies a stable ranking of relative house prices over time.

The finding that there is little micropersistence in excessive prices adds nuance to the literature following the seminal article by Case and Shiller (1989), documenting macropersistence in the housing market (Røed Larsen and Weum, 2008; Miles, 2011; Elder and Villupuram, 2012). Macropredictability has been accepted as a key 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 was found by, for example, Caplin and Leahy (2011) and Head et al. (2014).

The finding that the housing market appears to be semistrong efficient at the micro level adds to the literature on micro-efficiency in the housing market. In an early contribution, Linnemann (1986) use data for the single-family housing market in Philadelphia from the Annual Housing Survey with owners' own estimates of the value of their house in 1975 and 1978 to show that undervalued houses experienced greater house price appreciation. However, once transaction costs are taken into account, he shows that no profitable arbitrage can be made. This leads him to the conclusion that the Philadelphia housing market was semistrong efficient. Using a similar methodology for the Vancouver apartment market, Londerville (1998) reaches the same conclusion. In addition to exploring persistence at the macro level, Case and Shiller (1989) test if lagged appreciation in house price indices can predict individual returns. In contrast to the predictability at the index level, they do not find that individual prices are forecastable—a finding that is consistent with the results in this article. In a paper that is related to the Case and Shiller (1989) study, Itô and Hirono (1993) explore weak-form efficiency using data for the Tokyo condominium market. Inspecting individual listings of units with prices and rents, they do find some predictability in excess returns, but are also careful to note that caution should be shown in concluding with market inefficiency given the relatively short sample period. Comparing selling prices and the present value of future rental payments for Swedish co-ops, Hjalmarsson and Hjalmarsson (2009) find that selling prices do not fully reflect increases in the present value of rents. From this, they conclude that the Swedish co-op market is not efficient.

Although several studies have looked into the efficiency of the housing market at the micro level, results point in different directions. An advantage with our analysis is that we have a comprehensive data set of all publicly registered housing transactions that allows us to construct an estimate of the common value component and also to follow the same units in repeat sales. The last point is important, since it allows us to control for unit fixed effects that are not appropriately accounted for by a hedonic model. In addition, we have data on ask prices and appraisal prices that enable us to conduct different robustness exercises and to control for time-varying, unit-specific omitted variables. Finally, we can use auction data to explore the mechanisms generating reversion in excessive prices.

The rest of the article is structured as follows: Section 2 presents our conceptual framework. The data and econometric approach are set out in Section 3. Section 4 shows results from tests for micropersistence in the ratio of sell to predicted prices. In the same section, we test whether ex post arbitrage can be made by exploiting ex ante information. In Section 5, we provide evidence suggesting that the mechanism generating reversion is related to the stochastic arrival rate of interested purchasers at public showings. Several robustness exercises are carried out in Section 6, whereas the final section concludes the article.

## 2. CONCEPTUAL FRAMEWORK

2.1. *Micro- versus Macro-efficiency.* 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 for 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. One interpretation of this 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 straightforward 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 (WTP).

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 follow $t$, there exists a nonzero subjective component that 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) test 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 macrotest of housing markets. However, it has not been fully clarified how the aggregation of nonzero 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.

Our idea centers around a combination of a price discovery process (Andersen et al., 2003) and a search-and-matching process (Nenov et al., 2016) by individual owner-occupiers who compare utility per monetary unit for all potential houses they inspect in their search. They seek bargains and walk away from rip-offs. The marginal buyer discontinues his bidding in auctions in which bids have gone high, but continues his bidding in auctions in which bids still are low. This mechanism induces a tendency in the market to price the common value accurately and thus rank houses in value. At a given point in time, the market value of house A is a multiple of a numeraire house. The market value of house B is another multiple of the numeraire house. A market that incorporates information would tend to revert to this ranking at other points in time and thus produce consistent relative values of house A and house B. This information assimilation, we think, is the cornerstone of a housing market version of the process that leads to the micro-efficiency suggested by Jung and Shiller (2005).

The question is what happens after there has been a deviation, that is, when a house has been sold for a low or high relative price. The answer to that question depends on why it happened in the first place. The deviation could be persistent or the deviation could be nonpersistent. Knowledge about whether there tends to be persistence or reversion could be utilized by profit-seeking market participants. Thus, a plan for studying micro-efficiency involves two steps: First, one needs to find out whether there tends to be persistence or reversion. Second, one investigates how this knowledge may be exploited. For example, if there is reversion, then buyers would be rewarded when they buy at low prices and punished when they buy at a high prices. If there is persistence, buyers could potentially construct profitable schemes if they were able to identify high prices that with a nonzero probability could go even higher (Gyourko et al., 2013).

In Section 5, we present a skeleton model in which we seek to sketch a simple thought process depicting how persistence could result from a search-and-match process. Owner-occupiers search for matches between their own preferences and the attributes of the housing unit. When this search results in a good match, the buyer has a high WTP, and the resulting selling price is high if the buyer competes with other bidders who also have high WTPs. But the arrival rate of bidders is stochastic, so good matches and high prices occur only with a given probability. Two sales of the same house are independent processes, and a high selling price in the first auction does not imply a high selling price in a subsequent sale. Thus, the search-and-match process implies reversion.

However, whether persistence or reversion may be utilized to construct profitable trading strategies on a house-by-house basis in micro is different from persistence in the aggregate. The absolute price level of the numeraire house depends on key macro-economic variables that determine the financing of the purchase, that is, interest rates, income levels, and credit constraints. News about these key variables is incorporated into the price level through the price discovery process. If there is time structure in these variables, they may imply forecastability of the absolute price level of the numeraire. This means that the housing market could be characterized by consistent ranking of relative prices in micro, while at the same time allowing forecastability in absolute levels.

2.2. *Testing for Micropersistence.* To test for persistence in excessive prices at the individual house level, we follow a three-step procedure. The first step is to estimate the common value component of a given housing unit. Our measurement of the common value component mainly relies on hedonic price estimation. Housing is a highly composite good that can vary in size, location, and other amenities. The hedonic model measures implicit partial prices of these attributes, even though they are not traded as separate goods. In the seminal contribution of Rosen (1974), it is shown that the price that clears the market for differentiated products is given by the sum of implicit prices for attributes. In a utility maximizing framework, these implicit prices should reflect the marginal WTP for a small change in a given attribute. A house consists of a bundle of attributes, and the price of the unit is given by the sum of these implicit prices, as represented by the hedonic pricing function:

$$P_{i,t} = f(\boldsymbol{X}_{i,t}), \tag{1}$$

in which $\boldsymbol{X}_{i,t}$ is a vector of attributes that pertain to house $i$ at time $t$. The function $f()$ represents the hedonic pricing function that maps both time-invariant and time-varying attributes of unit $i$ at time $t$ into an equilibrium price, $P_{i,t}$. Although the theory for pricing differentiated goods through implicit prices is well established, theory provides less guidance about the functional form that links the price of a composite good to the different attributes. A common approach is to use a semi-log specification of the following form (see Rosen, 1974; Cropper et al., 1988; Pope, 2008; Kuminioff et al., 2010; von Graevenitz and Panduro, 2015):

$$P_{i,t} = \rho + \boldsymbol{\gamma}' \log(\boldsymbol{X}_{i,t}) + \varepsilon_{i,t}, \tag{2}$$

in which $\varepsilon_{i,t}$ is a zero-mean error term. Estimating (2), one can obtain a predicted price, $\hat{P}_{i,t}$, for each unit $i$ transacted at time $t$ conditional on its attributes. Thus, given the vectors of observable attributes, the hedonic model encompasses the aggregate knowledge of the market. It represents the market expectation, that is, $E_{i,t}(P_{i,t}|\boldsymbol{X}_{i,t}) = \hat{P}_{i,t}$.

Having estimated the market expectation using the hedonic approach, we construct a measure for the ratio of observed selling price to predicted price (SPPP), which is given by $SPPP_{i,t} = \frac{P_{i,t}}{\hat{P}_{i,t}}$. Using SPPP ratios instead of residual deviations makes the analysis more transparent and easier

TABLE 1
OUTCOME SPACE FOR EXCESSIVE PRICES ACROSS TWO TRANSACTIONS

| $E(SPPP_{i,T2i}\|SPPP_{i,T1_i})$ | $SPPP_{i,T1_i} > 1$ | $SPPP_{i,T1_i} = 1$ | $SPPP_{i,T1_i} < 1$ |
|---|---|---|---|
| $> SPPP_{i,T1_i}$ | a) Buy high, sell higher | d) Buy normal, sell higher | g) Buy low, sell higher |
| $= SPPP_{i,T1_i}$ | b) Buy high, sell same | e) Buy normal, sell same | h) Buy low, sell same |
| $< SPPP_{i,T1_i}$ | c) Buy high, sell lower | f) Buy normal, sell lower | i) Buy low, sell lower |

NOTES: The table shows the complete outcome space of expected SPPP ratios in the second transaction for different values of SPPP ratios in the first transaction. SPPP is an abbreviation for selling price divided by predicted price.

to interpret and also joins the literature on selling price–appraisal price ratios (see Bourassa et al., 2006; de Vries et al., 2009; Shi et al., 2009). We measure persistence by following units over time and examining whether a high SPPP in one transaction is repeated in a future transaction. If a high SPPP is nonrepeatable, we say that there is no persistence. Instead, there is reversion. This setup is inspired by Malkiel (2003) in that we evaluate whether the price-index-adjusted common value part of the selling price, not the price-index-adjusted selling price itself, at time $t$ is the best predictor of the selling price at time $t + s$. If excessive prices are not repeatable, there is no time persistence in residuals for a given unit. At time $t$, the expected residual deviation at time $t + s$ is 0.

Third, we estimate an equation of the following form:[2]

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

in which the notations $T1_i$ and $T2_i$ make clear that the dates of the first and second transactions may differ from unit to unit.

Full persistence in excessive prices is implied by $(\alpha, \beta) = (0, 1)$, since $E(SPPP_{i,T2_i}| SPPP_{i,T1_i}; \alpha = 0, \beta = 1) = SPPP_{i,T1_i}$. Thus, under full persistence, $SPPP_{i,T1_i}$ is the best predictor of $SPPP_{i,T2_i}$. This implies that current residual deviations may be exploited to forecast future residual deviations. Full reversion is implied by $(\alpha, \beta) = (1, 0)$, which gives $E(SPPP_{i,T2_i}|SPPP_{i,T1_i}; \alpha = 1, \beta = 0) = 1$. In this case, the best predictor of future prices is simply the price implied by the hedonic model. Interestingly, this may also be exploited in trading strategies.

Deviations from full persistence and full reversion are interesting, since they may imply an expected arbitrage. From (3), we have that $E(SPPP_{i,T2_i}|SPPP_{i,T1_i}) = \alpha + \beta SPPP_{i,T1_i}$. For a given pair of $(\alpha, \beta)$, if $E(SPPP_{i,T2_i}|SPPP_{i,T1_i}) < SPPP_{i,T1_i}$, a loss is expected relative to the market from buying unit $i$ at T1 and reselling at T2. Whenever $E(SPPP_{i,T2_i}|SPPP_{i,T1_i}) > SPPP_{i,T1_i}$, there is, however, an expected gain relative to the market from investing in this unit. If $E(SPPP_{i,T2_i}|SPPP_{i,T1_i}) = SPPP_{i,T1_i}$, the expected return is equal to the market return. Thus, the presence and degrees of persistence and reversion can lead to implementation of trading strategies. Table 1 summarizes the different constellations.

Cases a, d, and g suggest a scope for arbitrage, either by buying above market and selling even more above market (a), buying at market, but selling above market (d), or buying below market and selling above market (g). In all other cases, one would either expect to break even (cases b, e, and h), or incur a loss relative to the market (cases c, f, and i).[3] Finding evidence for case a or d would be consistent with the idea of superstar cities, as suggested by Gyourko et al. (2013). In that case, expectations of future rent appreciations drive up prices today, but even

[2] Note that SPPP is a constructed variable, since the denominator is computed based on results from the estimation of a hedonic model. We have checked if our results are sensitive to this additional uncertainty by sampling from the distributions for the predicted values. None of our results are affected by accounting for this additional uncertainty.

[3] Note that in the special case where $\alpha = 0$, we have that $\beta > 1$ implies that buying below, at, or above the expected price is expected to result in a second selling price that is even higher than the predicted price (cases a, d, and g). Cases b, e, and h are implied by $\beta = 1$ when $\alpha = 0$, whereas cases c, f, and i are implied by $\beta < 1$.

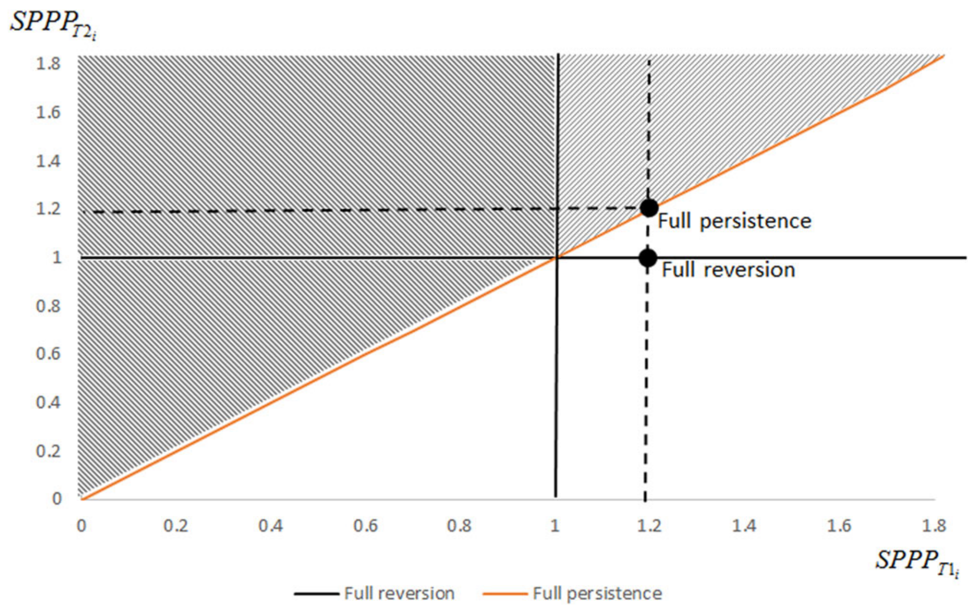


FIGURE 1

PERSISTENCE VERSUS NO PERSISTENCE. SELLING PRICE ON PREDICTED PRICE, FIRST, AND SECOND SALES [COLOR FIGURE CAN BE VIEWED AT WILEYONLINELIBRARY.COM]

more so in the future. Thus, in the presence of superstar cities, it could be the case that houses that are bought at an excessive price today sell at an even more excessive price in the future.

To illustrate in a bit more detail, we shall consider a simple example. A hedonic model has been estimated, and it predicts a selling price of USD 500,000 for a given unit $i$ at time $T1_i$. The observed selling price is USD 600,000. Thus, $SPPP_{i,T1_i} = 600{,}000/500{,}000 = 1.2$ and this outcome would be placed to the right of the solid vertical line at $SPPP_{i,T1_i} = 1$ in Figure 1, as indicated by the dotted vertical line at $SPPP_{i,T1_i} = 1.2$. What is the best predictor of the next selling price of unit $i$? Full persistence means that the SPPP ratio in the next transaction would be expected to be 1.2. Thus, if the house price level increases and the hedonic model predicts USD 600,000 at time $T2_i$, the best predictor for the next selling price of this particular unit would be $1.2 \times$USD 600,000 = USD 720,000. In Figure 1, full persistence is indicated by the black circle where the dotted vertical line at $SPPP_{i,T1_i} = 1.2$ intersects the 45 degree line, which gives $SPPP_{i,T2_i} = 1.2$. We highlight this case by drawing a dotted horizontal line from the level 1.2 on the vertical axis. No persistence means the SPPP ratio in the second transaction is 1, which is shown by the black circle at the intersection of the dotted vertical line at $SPPP_{i,T1_i} = 1.2$ and the solid line at $SPPP_{i,T2_i} = 1$. Under no persistence, the best predictor is USD 600,000, that is, the prediction of the hedonic model.

Figure 1 also highlights that any point below the 45 degree line is associated with a loss relative to the market. Likewise, any point above the 45 degree line is associated with a gain relative to the market, as indicated by the shaded areas. It is clear that full reversion implies that any SPPP ratio above unity in the first transaction is associated with a loss relative to the market. However, full reversion does not rule out that a profit can be made relative to the market by investing in underpriced units.

Our simple framework suggests that the break-even condition for a profitable arbitrage can be calculated by equating the expected SPPP ratio in the second transaction with the SPPP ratio in the first transaction:

$$E(SPPP_{i,T2_i} | SPPP_{i,T1_i}) = SPPP_{i,T1_i}. \tag{4}$$

Using (3) to calculate the left-hand side in (4) and solving out for $SPPP_{i,T1_i}$, we find the ratio of the SPPP in the first transaction that is consistent with an expected return equal to the market return upon the next sale:

$$SPPP_{i,T1_i} = \frac{\alpha}{1-\beta} = \mu, \tag{5}$$

whenever $SPPP_{i,T1_i} < \mu$, a profit in excess of the market return is expected, so one possible investment strategy would be to invest in those units. In the case where $\mu > 1$, the second selling price is expected to be higher than the predicted price when buying below, at, and above (up to $\mu$) the expected price. Again, this finding may be consistent with the idea of superstar cities (Gyourko et al., 2013). When $0 < \mu < 1$, it is not possible to buy higher than the market and expect to resell even higher. However, this situation is consistent with buying low (up to $\mu$) and reselling higher. When $\mu < 0$, no profits can be made from any strategy.

## 3. DATA, INSTITUTIONAL BACKGROUND, AND EMPIRICAL APPROACH

3.1. *The Transaction and Auction Data Sets.* We have acquired data from the firm Eiendomsverdi AS, a private firm that collects data from realtors, official records, and Finn.no (a Norwegian classified advertisement Web site) and combines such data with other information. Eiendomsverdi 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 1, 2002, and February 1, 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, selling price, and appraisal price made by an independent appraiser. Unit data include unique ID, address, GPS coordinates, size, number of rooms, number of bedrooms, floor, and other attributes.

To remove errors, not-arms-length transactions, and invalid entries, we trim the data by truncation at percentile points. We exclude co-ops. To estimate the hedonic model without imputation, we exclude any observation with any missing variable. We are left with 484,243 observations, which we employ in the estimation of the hedonic model, but we truncate on the ratio of SPPP at the 1st and 99th percentiles to delete suspicious outliers. A total of 469,127 observations remain. We observe that 72,707 units are sold exactly twice and 16,877 units are sold exactly three times.

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, the uniqueness of this ID is examined by inspecting latitudes and longitudes using the 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. To ensure that we consider comparable units over time, our study of repeat sales only samples units that have unaltered size. Table 2 summarizes the data.[4]

In general, units that are transacted more times are smaller and cheaper, and apartments are represented more often than detached houses. Units that are transacted often are to a larger extent sold in the capital city of Oslo. To explore the sensitivity of our results to this variation, we check for robustness to estimation in subsamples with detached houses only and apartments only, small versus large units, and different price segments. In addition, we test the robustness of our results to estimation on a subsample excluding Oslo.

To study the role of bidding-specific factors in affecting SPPP ratios, we have collected a unique data set on the auction process from 7,915 housing auctions between 2013 and 2016. The

[4] Values are converted to USD using the average exchange rate between USD and NOK in the period 2002–2014: USD/NOK = 0.158.

TABLE 2
SUMMARY STATISTICS AND CHECKS FOR BALANCE FOR TRANSACTION DATA SET

| | Sold Once | Sold Twice | Sold Three Times | All Transactions |
|---|---|---|---|---|
| Selling price (mean) | 409,396 | 374,901 | 345,213 | 389,184 |
| Predicted price (mean) | 407,526 | 378,808 | 353,511 | 390,546 |
| Square footage (mean) | 1,420 | 1,231 | 1,064 | 1,308 |
| Time on market (mean days) | 42 | 41 | 39 | 41 |
| Percent Oslo | 13 | 18 | 22 | 16 |
| Percent detached | 57 | 40 | 27 | 47 |
| Percent semidetached | 12 | 13 | 13 | 12 |
| Percent row house | 7 | 8 | 9 | 8 |
| Percent apartment | 24 | 39 | 51 | 33 |
| No. of units | 258,658 | 72,707 | 16,877 | 351,713 |
| No. of observations | 258,658 | 145,414 | 50,631 | 469,127 |

NOTES: The table shows summary statistics for our sample of housing transactions. The "sold once" category consists of units that are sold exactly once, "sold twice" are units that are sold exactly twice, and "sold three times" are units that are sold exactly three times. The term "all transactions" indicates all transactions that are included in our data set. This category includes units that are sold exactly once, exactly twice, exactly three times, as well as units sold more than three times. NOK values are converted to USD using the average exchange rate between USD and NOK in period 2002–2014, where USD/NOK = 0.158. The reason why the mean selling price and the mean predicted price do not coincide is because the data are truncated at the 1st and 99th percentile of SPPP after the hedonic model has been estimated.

TABLE 3
SUMMARY STATISTICS FOR AUCTION DATA SET

| | 10th Percentile | Median | Mean | 90th Percentile |
|---|---|---|---|---|
| Number of bidders | 1 | 2 | 2.59 | 5 |
| Number of bids | 2 | 7 | 8.29 | 17 |
| Number of bids/bidder | 1.33 | 3 | 3.22 | 5.5 |
| No. of observations | | 7,915 | | |

NOTES: The table shows summary statistics for our sample of housing auctions. Number of bids per bidder is calculated by taking the number of bids in a given auction and then dividing by the number of bidders in that auction.

data are collected from one of the largest realtor companies in Norway and include information on the number of bids, appraisal prices, actual selling prices, and transaction dates. In addition, the data include a unit identifier, so that we can follow repeat sales of the same unit. Table 3 summarizes the distribution of three key variables in the data set.

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. 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, but it is possible to extend bids prior to the public showing. The auction is arranged as an ascending bid auction in which 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, and addresses).

3.3. *Specification of the Hedonic Model.* To estimate the hedonic model, we use a lin-log specification of the following form (see Rosen, 1974; Cropper et al., 1988; Pope, 2008; Kuminioff et al., 2010; von Graevenitz and Panduro, 2015):[5]

$$P_{i,t} = a + b_1 \log(S_i) + b_2(\log(S_i))^2 + \boldsymbol{c}'\boldsymbol{A}_i + \boldsymbol{d}'\boldsymbol{M}_t + \varepsilon_{i,t}, \tag{6}$$

in which $P_{i,t}$ denotes observed selling price for unit $i$ at time $t$. The size of the unit is denoted by $S_i$, and $\boldsymbol{A}_i$ is a vector of attributes; building type (detached, semidetached, row house, and apartment), a dummy for lot sizes above 10,765 square feet (1,000 m$^2$), and construction period dummies (four periods) to control for different construction eras. There are about 5,000 zip codes in Norway and we include zip code dummies to control for location fixed effects. We also allow size to be priced differently for apartments and for the capital city of Oslo by adding interaction terms. Finally, we include a vector of monthly dummies $\boldsymbol{M}_t$ (146 months).[6] For each sale, we compute a predicted price $\hat{P}_{i,t}$ and calculate the ratio of selling price to 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 Table A.1. We achieve an adjusted $R^2$ of 0.801 in the hedonic model.[7]

3.4. *Omitted Variables and Repeat-Sales Analysis.* As pointed out by, for example, Bajari et al. (2012) and von Graevenitz and Panduro (2015), most hedonic models are plagued by the challenges posed by omitted variables. Omitting unit-specific quality factors (e.g., the view from the property or a newly renovated kitchen) may lead to inconsistent estimates of partial prices, which is of particular concern when trying to estimate WTP functions for a particular attribute—for instance, the effect on house prices of improved air quality (see the discussion in Bajari et al., 2012). These qualities are attributes that are relevant to the home price and that are observed by both sellers and buyers, but not the econometrician. Although our interest is not to study WTP functions, omitted variables may still be of great concern. Omitting unit-specific quality factors may generate the appearance of persistence in excessive prices, since the difference between the selling price and the predicted price for a given unit will be correlated over time when relevant variables are omitted.

Following Bajari et al. (2012), we shall think of the attribute vector $\boldsymbol{X}_{i,t}$ in (1) as consisting of three parts: $\boldsymbol{X}_{1,i}$, which is observable to the econometrician (size, building year, and location), $\boldsymbol{X}_{2,i}$, which measures time-invariant attributes not observable to the econometrician (view, exposure to sun light), and $\boldsymbol{X}_{3i,t}$, which measures time-varying attributes (home improvements, need for new drainage, windows that need to be replaced). The challenge from an empirical point of view is that both $\boldsymbol{X}_{2,i}$ and $\boldsymbol{X}_{3i,t}$ include attributes that are relevant to the common value component of a house, and which are observed by both sellers and buyers, but not the econometrician. We deal with this challenge in three different ways:

[5] Another specification that offers good fit, reduces the influence of outliers, and allows easy computations of index developments is the log-log form. In other papers, it has been shown that index estimates are robust across different functional forms; see, e.g., Sieg et al. (2002), who develop interjurisdictional house price indices for the LA metro area. They opt for the log-log specification for index construction. Similarly, we use the log-log specification in the hedonic time dummy setup to verify macropersistence. However, we employ the lin-log specification when we predict individual house prices since the inversion of the log-log form does not yield an unbiased price predictor due to the nonlinearity of the log-transformation of the dependent variable. We also considered a lin-lin specification, but the lin-log specification has marginally better explanatory power.

[6] In testing different models, we also included number of rooms and number of bedrooms as separate regressors. None of these variables have a significant effect once we control for the size of the unit.

[7] In the hedonic model, we have implicitly assumed that the coefficients for the different attributes are time-invariant. Given that our sample covers a period of 12 years, this may seem like a strong assumption. We have investigated separate hedonic models for each of the years included in our sample to see how results are changed. The overall correlation coefficient between the predicted prices from the two approaches is 0.97. Furthermore, the adjusted $R^2$ from the year-specific models are almost equal across years, and they are close to the adjusted $R^2$ of the model covering the whole period. These results are summarized in Table A.2. We also ran our full analysis using the predicted prices from the year-specific models instead of the predicted prices from the full sample model in calculating SPPP ratios. None of our econometric results are materially affected by this.

1. Exploiting information from a third transaction, including the ask price set by the seller.
2. Estimating a fixed effects model.
3. Looking at a subsample of units containing information on externally set appraisal prices.

3.4.1. *Using information from a third sale or ask price.* Our first way of dealing with omitted variables entails identifying units that are sold exactly three times. For each unit, we compute the ratio of selling price to predicted price for each of the transactions ($SPPP_{i,T1_i}$, $SPPP_{i,T2_i}$, and $SPPP_{i,T3_i}$, with $T1_i < T2_i < T3_i \ \forall\ i$).

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

$$SPPP_{i,T2_i} = \alpha + \beta SPPP_{i,T1_i} + \phi Q_i + u_{T1_i,T2_i}, \quad T2_i > T1_i, \tag{7}$$

in which $Q_i$ is a unit-specific, time-invariant quality indicator not captured by the hedonic model. To deal with the challenge of omitted variables, we use additional information from the third transaction, $SPPP_{i,T3_i}$, as a proxy for $Q_i$. If both the first and the third selling prices are high relative to the predictions of the hedonic model, this is plausibly caused by a time-invariant omitted variable, and it is therefore likely that $SPPP_{i,T2_i}$ is also 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 $SPPP_{i,T2_i}$.

We also use information 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 attributes that are not observable to the econometrician. The first case we consider is when all three $SPPP_{i,T1_i}$, $APPP_{i,T1_i}$, and $APPP_{i,T2_i}$ are high, in which $APPP$ denotes the ask price relative to the predicted price. The natural interpretation is that this occurs when a unit-specific variable is omitted from the hedonic model. Second, we consider the case when $SPPP_{i,T1_i}$ is high, but $APPP_{i,T1_i}$ and $APPP_{i,T2_i}$ are low. This case is likely to be caused by bidder- or bidding-specific factors.

3.4.2. *Fixed effects model.* Our second approach to deal with potential omitted variables is to estimate a fixed-effect, repeated cross section model in which unobserved, permanent unit-specific effects are captured by individual unit intercepts:

$$SPPP_{i,s_i} = \alpha_i + \beta SPPP_{i,t_i} + u_{i,s_i}, \qquad s_i = T2_i,\ T3_i; \qquad t_i = T1_i, T2_i. \tag{8}$$

In this case, we follow units that are sold exactly three times to be able to estimate the unit fixed effects.

3.4.3. *Time-varying unit-specific attributes.* Although the first two approaches deal with time-invariant unit-specific factors, $\boldsymbol{X}_{2,i}$, it may also be important to control for time-varying, unit-specific factors, $\boldsymbol{X}_{3,i,t}$. For this purpose, we exploit information on appraisal prices.

In Norway, it is customary that an external and independent appraiser inspects the home prior to sale.[8] The appraiser thoroughly inspects the unit's exterior and interior and writes a technical report on the general condition of the unit (need for drainage, water pressure, damp problems, age of wet rooms, if and when renovation of different rooms where undertaken). The report also includes information on view, sunlight exposure (balcony facing west versus east), proximity to grocery stores, kindergartens, etc. Based on the inspection, the appraiser sets an appraisal price that is supposed to reflect the technical condition of the unit, together with size, location, etc. When a home is listed for sale, the appraisal price and the technical report are

[8] A description of appraiser activities can be accessed online at, for example, http://www.ntf.no.

freely available to both sellers and buyers. Since the appraiser is independent and since the report is written prior to sale, the appraisal price should not be distorted by strategic pricing or bidding-specific factors. The appraisal price should therefore reflect what the hedonic model misses, namely, both time-invariant attributes and attribute changes that affect the value of the unit but that are not observable to the econometrician, that is, $\boldsymbol{X}_{2,i}$ and $\boldsymbol{X}_{3i,t}$.

Our data set includes appraisal prices for about half of the transactions in our sample (264,386 transactions include information on appraisal prices),[9] and our approach can be described as follows:

1. Regress the appraisal price on the same set of observed attributes as those considered in the hedonic model in (6):

$$P_{i,t}^{Appraisal} = \tilde{a} + \tilde{b}_1 \log(S_i) + \tilde{b}_2 (\log(S_i))^2 + \tilde{\boldsymbol{c}}' \boldsymbol{A}_i + \tilde{\boldsymbol{d}}' \boldsymbol{M}_t + e_{i,t}. \tag{9}$$

2. The estimated residuals from this regression, $\hat{e}_{i,t}$, are proxies for the part of estimated market value set by the inspector that cannot be explained by observable attributes, that is, it as a proxy for $\boldsymbol{X}_{2,i}$ and $\boldsymbol{X}_{3i,t}$
3. Augment the specification of the hedonic model in (6) with $\hat{e}_{i,t}$ to deal with both time-invariant and time-varying attributes that are not directly observable:[10]

$$P_{i,t} = a + b_1 \log(S_i) + b_2 (\log(S_i))^2 + \boldsymbol{c}' \boldsymbol{A}_i + \boldsymbol{d}' \boldsymbol{M}_t + b_3 \hat{e}_{i,t} + \varepsilon_{i,t}. \tag{10}$$

4. Construct SPPP ratios using the predicted prices based on estimating (10) and reestimate the fixed effects model in (8).

Although our full sample covers 16,877 units that are sold exactly three times, we only have the appraisal price for 6,721 units sold exactly three times. This analysis will therefore be carried out on a somewhat smaller sample.

## 4. EMPIRICAL RESULTS ON MICROPERSISTENCE

4.1. *Testing for Persistence in SPPP.* Persistence in deviations from predicted prices 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 translation. Table 4 tabulates results from estimating the baseline specification in (3) using the sample of units for which we have information on exactly two transactions.

The coefficient on $SPPP_{i,T1_i}$ is both statistically significant and economically important. The table also reports $p$-values from standard Wald tests for full persistence, which is implied by $(\alpha, \beta) = (0, 1)$, and full reversion, $(\alpha, \beta) = (1, 0)$. The results from these tests are reported as pval (Full persistence) and pval (Full reversion) in Table 4. We clearly reject full persistence of zero intercept and unit slope. We also reject full reversion. However, as seen in the bottom part of Table 4, in which we input values 0.7, 1.0, and 1.3 for $SPPP_{i,T1_i}$—numbers that are close to the 10th percentile, the median, and the 90th percentile—the main pattern is a reversion to unity.[11] The interpretation of the estimated regression coefficients is clear: When the selling

[9] The subsample of units with appraisal prices are mostly similar to the overall sample in terms of observables (compare Table A.5 with Table 2 in the article). However, the average selling price of units in this sample is a bit higher than the overall sample. Also, Oslo is more heavily represented in this sample.

[10] Note that exactly the same results would be achieved controlling for the appraisal price directly. The only difference is that this would make it harder to distinguish gross and net effects on prices of different attributes. However, the fitted values would be exactly the same.

[11] We rounded the 90th percentile and the 10th percentile to the first decimal that ensured symmetry around 1. Strictly speaking, the 10th percentile is 0.75, whereas the 90th percentile is 1.33. However, to ensure symmetry around 1, we used 0.7 and 1.3 instead of 0.8 and 1.3. Qualitative results are, of course, not affected by this. A histogram of the SPPP distribution is shown in Figure A.1.

TABLE 4

REGRESSING $SPPP_{i,T2_i}$ ON $SPPP_{i,T1_i}(T2_i > T1_i\ \forall\ i)$. UNITS SOLD EXACTLY TWICE. NORWAY, 2002–2014

| Independent Variables | Dependent Variable Is $SPPP_{i,T2_i}$ |
|---|---|
| Intercept | 0.271 (0.004) |
| $SPPP_{i,T1_i}$ | 0.713 (0.004) |
| Break-even if $SPPP_{i,T1_i}$ equals | 0.979 (0.001) |
| pval (Full persistence) | 0.0000 |
| pval (Full reversion) | 0.0000 |
| No. of obsevations | 72,707 |
| Adj. $R^2$ | 0.216 |
| $SPPP_{i,T1_i} \rightarrow SPPP_{i,T2_i}$ | $0.7 \rightarrow 0.903$ (0.001) |
| $SPPP_{i,T1_i} \rightarrow SPPP_{i,T2_i}$ | $1.0 \rightarrow 0.985$ (0.001) |
| $SPPP_{i,T1_i} \rightarrow SPPP_{i,T2_i}$ | $1.3 \rightarrow 1.066$ (0.001) |

NOTES: The table reports results when we regress the second SPPP on the first SPPP for units transacted exactly twice. SPPP is an abbreviation for selling price divided by predicted price. Standard errors robust to heteroskedasticity are reported in parentheses. The break-even condition, which shows the value of the first SPPP yielding a return equal to the market return, is calculated based on the expression in (5) and the standard error reported in parentheses has been calculated using the delta method. A value of first SPPP higher than the number implied by the break-even condition indicates that a loss is incurred relative to the market, whereas a value of SPPP lower than this number indicates a first SPPP for which a potential profit may be made. The terms "pval (Full persistence)" and "pval (Full reversion)" report $p$-values from a standard Wald test for the joint restrictions $(\alpha, \beta) = (0, 1)$ and $(\alpha, \beta) = (1, 0)$, respectively.

price is 30% above the predicted price in the first round, it is associated with a selling price that is 7% higher than the predicted price in the second round, a substantial reversion toward unit SPPP. When the selling price is 30% below the predicted price in the first round, it is associated with a selling price that is 10% lower than the predicted price in the second round, a reversion toward unit SPPP. When the selling price is equal to the predicted price in the first round, it is associated with a selling price that is roughly 1.5% lower than the predicted price in the second round. The break-even condition calculated based on (5) shows that the only possible profit opportunity comes from investing in units that have a first SPPP ratio less than unity.

We take these results as indicative of the market's relative pricing ability consistent with the lack of micropersistence, since price deviations are corrected upon the second sale. However, this parsimonious regression specification does not control for omitted variables.

4.2. *Unit-Specific Factors and the Third Sale.* The results presented above demonstrate a return to unity when $SPPP_{i,T1_i}$ is high. Omitted variables may bias the results. Our first approach in dealing with this entails looking at units that are sold three times, not twice. The third transaction may function as a control for unobserved quality factors, and we use $SPPP_{i,T3_i}$ as a gauge.

Cases 1 and 2 in Table 5 show fitted values of $SPPP_{i,T2_i}$ for two pairs of $(SPPP_{i,T1_i}, SPPP_{i,T3_i})$, that is, (1.3,1.3) and (1.3,1.0). These fitted values are based on estimating the same equation, and detailed results from the underlying equation are reported in the second column of Table 6. Cases 3 and 4 in Table 5 show fitted values of $SPPP_{i,T2_i}$ for two pairs of $(APPP_{i,T1_i}, APPP_{i,T3_i})$, that is, (1.3,1.3) and (1.3,1.0). The fitted values from cases 3 and 4 are based on estimating the same equation, and detailed results from the underlying equation are reported in the third column of Table 6.

Our main findings are twofold: The fitted $SPPP_{i,T2_i}$ is high when the associated high $SPPP_{i,T1_i}$ appears to be caused by unit-specific 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. The same phenomenon occurs when we instead look at APPP ratios. 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 (cases 1 and 3), is associated with a fitted level of $SPPP_{i,T2_i}$ in the range 1.25–1.30. A level of $SPPP_{i,T1_i}$ equal to 1.3, when quality gauges are equal to 1.0 (cases 2 and 4), is associated with a fitted level of $SPPP_{i,T2_i}$ in the range 1.05–1.08.

TABLE 5
FITTED $SPPP_{i,T2_i}$ BASED ON INFORMATION ON THIRD SALE AND ASK PRICES

| Case | Fitted Dependent Variable Is | Interpretation | When Independent Variables Are | | | |
|---|---|---|---|---|---|---|
| | | | $SPPP_{i,T1_i}$ | $SPPP_{i,T3_i}$ | $APPP_{i,T1_i}$ | $APPP_{i,T2_i}$ |
| 1 | $SPPP_{i,T2_i} = 1.250$ (0.003) | unit-specific | 1.3 | 1.3 | | |
| 2 | $SPPP_{i,T2_i} = 1.080$ (0.002) | bidder or bidding | 1.3 | 1.0 | | |
| 3 | $SPPP_{i,T2_i} = 1.302$ (0.001) | unit-specific | 1.3 | | 1.3 | 1.3 |
| 4 | $SPPP_{i,T2_i} = 1.047$ (0.002) | bidder or bidding | 1.3 | | 1.0 | 1.0 |

NOTES: The table reports fitted values of second SPPP for different values of the explanatory variables. The fitted values are obtained from two separate regressions. Cases 1 and 2 are constructed by regressing second SPPP on first and third SPPP, whereas cases 3 and 4 are constructed by regressing second SPPP on first and second APPP. SPPP is an abbreviation for selling price divided by predicted price and APPP is short for appraisal price relative to predicted price. Standard errors robust to heteroskedasticity are reported in parentheses next to the fitted values in the second column. The results of the underlying regression equations are reported in Table 6.

TABLE 6
UNDERLYING MODELS FOR THE CASES 1–4 IN TABLE 4A

| Independent Variable | Dependent Variable Is $SPPP_{i,T_{2i}}$ | |
|---|---|---|
| Intercept | 0.141 (0.009) | 0.053 (0.003) |
| $SPPP_{i,T1_i}$ | 0.287 (0.006) | 0.111 (0.008) |
| $SPPP_{i,T3_i}$ | 0.566 (0.010) | |
| $APPP_{i,T1_i}$ | | −0.087 (0.008) |
| $APPP_{i,T3_i}$ | | 0.936 (0.004) |
| No. of observations | 16,877 | |
| Adj. $R^2$ | 0.570 | 0.906 |

NOTES: The table reports estimation results from the equations used to construct the fitted values for the four different cases considered in Table 5. The results reported in the second column are used to construct the fitted values for cases 1 and 2, whereas the results in the third column are used to construct fitted values for cases 3 and 4. Standard errors robust to heteroskedasticity are reported in parentheses.

4.3. *A Fixed Effects Model.* Using ask prices in the first and the second transactions 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 effects model of the type described by Equation (8). We consider both a model with unit fixed effects only and a model with both time and unit fixed effects.[12] The results of these specifications are reported in Table 7.

We reject both full persistence and full reversion also in this model, but point estimates are closer to suggesting full reversion when controlling for unit fixed effects. There is clear evidence of reversion to unit SPPP, for $SPPP_{i,t_i} = 0.7/1/1.3$, suggesting that, with the exception of very high or very low values of $SPPP_{i,t_i}$, the absence of micropersistence is a robust finding. The break-even condition indicates that potential profits can be made by investing in underpriced units, but not in units that are overpriced.

4.4. *Controlling for Time-Varying Omitted Variables.* To deal with time-varying, unit-specific factors, we first estimate the specification in (9) to strip out observable attributes from the appraisal price. Results are summarized in Table A.3. Then, we augment the hedonic model in (6) with the residual from this regression, that is, the specification in (10). The coefficient on the residual is 0.871, suggesting that the additional value estimated by the assessor is almost fully reflected in the sales price. Detailed results are given in Table A.4. We then construct the SPPP ratio based on this alternative hedonic specification and estimate the fixed effects regression in (8). Results are reported in the third column of Table 8.

[12] Throughout the article, we use the same time fixed effects for all units, independent of their geographical location. We have also investigated whether considering regional time fixed effects has any impact on our findings. Results are similar in that case.

TABLE 7

REGRESSING $SPPP_{i,s_i}$ ON $SPPP_{i,t_i}$ ($s_i > t_i \; \forall \; i$). UNITS SOLD EXACTLY THREE TIMES. CONTROLLING FOR UNIT FIXED EFFECTS. NORWAY, 2002–2014

| Independent Variables | Dependent Variable Is $SPPP_{i,s_i}$ | |
|---|---|---|
| Intercept | 0.853 (0.006) | 0.973 (0.105) |
| $SPPP_{i,t_i}$ | 0.130 (0.006) | 0.111 (0.005) |
| Break-even if $SPPP_{i,T1_i}$ equals | 0.980 (0.000) | 1.024 (0.011) |
| pval (Full persistence) | 0.0000 | 0.0000 |
| pval (Full reversion) | 0.0000 | 0.0000 |
| No. of observations | 33,754 (16,877 units sold three times yields 16,877×2 pairs) | |
| Within $R^2$ | 0.050 | 0.118 |
| Between $R^2$ | 0.544 | 0.381 |
| Overall $R^2$ | 0.375 | 0.281 |
| Time fixed effects | NO | YES |
| Unit fixed effects | YES | YES |
| $SPPP_{i,t_i} = 0.7 \rightarrow SPPP_{i,s_i}$ | 0.944 (0.002) | 0.988 (0.010) |
| $SPPP_{i,t_i} = 1.0 \rightarrow SPPP_{i,s_i}$ | 0.983 (0.000) | 1.021 (0.010) |
| $SPPP_{i,t_i} = 1.3 \rightarrow SPPP_{i,s_i}$ | 1.022 (0.001) | 1.055 (0.010) |

NOTES: 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 ($N = 16{,}877$), and we use both transaction pairs (1,2) and (2,3). SPPP is an abbreviation for selling price relative to predicted price. Standard errors robust to heteroskedasticity are reported in parentheses. The second column reports results when we control for unit fixed effects, whereas both unit and time fixed effects are controlled for in the third column. The break-even condition, which shows the value of the first SPPP yielding a return equal to the market return, is calculated based on the expression in (5), and the standard error reported in parentheses has been calculated using the delta method. A value of first SPPP higher than the number implied by the break-even condition indicates that a loss is incurred relative to the market, whereas a value of SPPP lower than this number indicates a first SPPP for which a potential profit may be made. The terms "pval (Full persistence)" and "pval (Full reversion)" report $p$-values from a standard Wald test for the joint restrictions $(\alpha, \beta) = (0, 1)$ and $(\alpha, \beta) = (1, 0)$, respectively.

It is evident that controlling for time-varying unit-specific factors further strengthens our finding of SPPP reversion. In fact, not only can we reject full persistence, but our results also suggest that the hypothesis of full reversion cannot be rejected. To explore if this result is related to the different sample considered for this analysis, results from using the predicted price from the baseline hedonic model on the sample for which we have data on appraisal prices are reported in the second column. It is clear that our findings are not driven by the different sample, since full reversion is still rejected for the baseline SPPP. The finding of full reversion in SPPP is consistent with being rewarded for underpayment and punished for overpayments—as also evidenced by the break-even condition. Our results therefore suggest little persistence in SPPP ratios over time, and in the next section, we shall explore if profitable arbitrage may be made from investing in units that appear underpriced.

4.5. *Trading Strategy.* Judging by our findings that there is reversion in excessive prices, a possible investment strategy is:

1. Estimate the hedonic model to obtain an estimate of the expected market price of unit $i$ at time $t_i$, $\hat{P}_{i,t_i}$.
2. Invest if the actual price is lower than the expected market price, $P_{i,t_i} < \hat{P}_{i,t_i}$.

To get an estimate of the expected price, we use the predicted market price from the hedonic model accounting for time-varying, unit-specific factors. This lowers the chance of investing in units that appear underpriced due to a misspecified model.

The trading strategy involves the following implementation: At each point in time between 2002 and 2014, the investor purchases all units satisfying the condition that $P_{i,t_i} < \hat{P}_{i,t_i}$. We assume deep pockets and no liquidity constraints, so that the investor can always purchase units that appear underpriced relative to the hedonic model. We also make the simplifying

TABLE 8

REGRESSING $SPPP_{i,s_i}$ ON $SPPP_{i,t_i}$ ($s_i > t_i\ \forall\ i$). UNITS SOLD EXACTLY THREE TIMES. CONTROLLING FOR UNIT FIXED EFFECTS. INCLUDING APPRAISAL PRICE. NORWAY, 2002–2014

| Independent Variables | Dependent Variable Is $SPPP_{i,s_i}$ | |
|---|---|---|
| Intercept | 1.098 (0.176) | 1.132 (0.083) |
| $SPPP_{i,t_i}$ | 0.090 (0.013) | −0.081 (0.052) |
| Break-even if $SPPP_{i,T1_i}$ equals | 1.030 (0.013) | 1.003 (0.003) |
| pval (Full persistence) | 0.0000 | 0.0000 |
| pval (Full reversion) | 0.0000 | 0.1521 |
| No. of observations | 13,446 (6,723 units sold three times yields 6,723×2 pairs) | |
| Within $R^2$ | 0.126 | 0.057 |
| Between $R^2$ | 0.354 | 0.066 |
| Overall $R^2$ | 0.264 | 0.001 |
| Time fixed effects | YES | YES |
| Unit fixed effects | YES | YES |
| Time-varying unit-specific factors | NO | YES |
| $SPPP_{i,t_i} = 0.7 \rightarrow SPPP_{i,s_i}$ | 1.000 (0.012) | 1.028 (0.003) |
| $SPPP_{i,t_i} = 1.0 \rightarrow SPPP_{i,s_i}$ | 1.027 (0.012) | 1.003 (0.003) |
| $SPPP_{i,t_i} = 1.3 \rightarrow SPPP_{i,s_i}$ | 1.054 (0.012) | 0.979 (0.003) |

NOTES: 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 and for which we have data on appraisal prices in all three transaction ($N = 6{,}721$). We use both transaction pairs (1,2) and (2,3). SPPP is an abbreviation for selling price relative to predicted price. Standard errors robust to heteroskedasticity are reported in parentheses. The specification in the second column is based on an SPPP ratio using the predicted price from the baseline hedonic model estimated on the sample for which we have appraisal prices. Detailed results for the underlying specification are reported in the second column of Table A.4. The specification in the third column is based on an SPPP ratio using the predicted price that controls for appraisal prices. Detailed results for the underlying specification are reported in the third column of Table A.4. The break-even condition, which shows the value of the first SPPP yielding a return equal to the market return, is calculated based on the expression in (5), and the standard error reported in parentheses has been calculated using the delta method. A value of the first SPPP higher than the number implied by the break-even condition indicates that a loss is incurred relative to the market, whereas a value of SPPP lower than this number indicates a first SPPP for which a potential profit may be made. The terms "pval (Full persistence)" and "pval (Full reversion)" report $p$-values from a standard Wald test for the joint restrictions $(\alpha, \beta) = (0, 1)$ and $(\alpha, \beta) = (1, 0)$, respectively.

assumption that an investor may enter an auction at the winning bid.[13] The returns on this portfolio are evaluated against the portfolio of all properties to evaluate if the trading strategy is profitable.

Unlike stocks, houses are traded infrequently and have different holding times. To account for this, we follow Londerville (1998) and back out annualized rates of return for all transaction pairs of units sold two or three times. For residential housing unit $i$, the annualized rate of return when the unit was bought at $t_i$ and sold at $s_i$ is given by

$$R_{i,s_i} = \left(\frac{P_{i,s_i}}{P_{i,t_i}}\right)^{1\,(s_i - t_i)} - 1, \quad \text{where } s_i > t_i.$$

For a given housing portfolio, $k$, there are $N_{k,s}$ units that are sold at time $s$. The average annualized return on this portfolio at time $s$ can therefore be calculated as

$$R_{k,s} = \frac{1}{N_{k,s}} \sum_{j=1}^{N_{k,s}} R_{j,s}.$$

[13] In practice, some of these auctions could have continued after the investor made his bid, since the observed winner could have made a counterbid. This would have made the profit opportunities even smaller than in our simple setup.

TABLE 9
EXCESS RETURNS FOR PORTFOLIO OF UNDERVALUED HOUSES VERSUS THE MARKET PORTFOLIO

| | Underpriced Units | | Market Return |
|---|---|---|---|
| $\bar{R}_k$ | 0.054 | | 0.045 |
| $S_k$ | 0.031 | | 0.026 |
| $\hat{\lambda}$ | | 1.162 (0.083) | |
| $\hat{\chi}$ | | 0.002 (0.003) | |
| $R^2$ | | 0.951 | |
| No. of observations | | 33 | |

NOTES: The table reports average excess returns, $\bar{R}_k$, and standard deviations, $S_k$, for the market portfolio and the portfolio of units that at the time of purchase are undervalued relative to the hedonic model. These measures are calculated on the basis of a sample of quarterly excess returns over the period 2005Q1–2014Q1. Excess returns are calculated by subtracting the three-year government bond yield. The table also reports the estimated risk factor ($\hat{\lambda}$) and the intercept ($\hat{\chi}$) from the CAPM model in (11). Standard errors robust to heteroskedasticity are reported in parentheses.

Excess returns on a given portfolio are typically defined in relation to a risk-free reference security:

$$R_{k,s}^{Excess} = R_{k,s} - R_s^F.$$

In our sample, the average holding time for units sold more than once is three years, and we use the three-year government bond yield at the date of purchase as our measure of the risk-free rate, $R_s^F$.[14] The sample period starts in 2005 and ends in 2014, since the risk-free rate is subtracted at the date of purchase.[15] We construct a time series of excess returns for the portfolio of underpriced houses at a quarterly frequency. On average, there are about 825 units sold in each quarter that were purchased at a price below the expected price, that is, that are in our portfolio.

In Table 9, we report average excess returns and their standard deviations over the period 2005Q1–2014Q1 for the overall housing market portfolio and for the portfolio of underpriced houses.[16] The average annualized return on the portfolio of undervalued houses is about 1 percentage point higher than the market return, but the standard deviation is also higher for this portfolio, suggesting that there may be more risk associated with the purchase of houses that appear underpriced relative to the hedonic model.

A way of evaluating whether excess returns can be made is to consider the capital asset pricing model (CAPM) developed by Sharpe (1964) and Linter (1965). In a housing context, the CAPM could be expressed as

$$E(R_{k,s}) = R_{F,s} + \chi_k(R_{M,s} - R_{F,s}),$$

in which $R_{k,s}$ is the return on housing portfolio $k$, $R_{F,s}$ is the risk-free interest rate, $R_{M,s}$ is the return on the market portfolio, and $\chi_k$ is the risk premium for portfolio $k$. CAPM therefore

[14] The distribution of holding times for underpriced units and the market is similar.

[15] Since the first observations in our sample are in 2002, the first returns from which we can subtract the risk-free rate occur in 2005.

[16] For portfolio $k$, average returns are calculated as

$$\bar{R}_k = \frac{1}{33} \sum_{s=2005Q1}^{2014Q1} R_{k,s}^{Excess},$$

and the standard deviation is given by

$$S_k = \sqrt{\frac{1}{32} \sum_{s=2005Q1}^{2014Q1} \left(R_{k,s}^{Excess} - \bar{R}_k\right)^2}.$$

suggests that higher returns can only be made by taking on greater risk than that of the market as a whole ($\chi_k > 1$). A common way of testing for excess returns for a given portfolio is to estimate an equation of the following form:[17]

$$(R_{k,s} - R_{F,s}) = \lambda_k + \chi_k(R_{M,s} - R_{F,s}) + \upsilon_{k,s}, \tag{11}$$

in which $\upsilon_{k,s}$ is an error term, and then test if $\lambda_k = 0 \; \forall \; k$. Thus, a $\lambda_k$ different from 0 can be interpreted as indicating that the market is not efficient (see, e.g., Gibbons et al., 1989).

We estimate (11) using annualized returns on investing in undervalued houses as our measure of $R_{k,s}$, whereas the annualized returns in the overall market are used to measure $R_{M,s}$. As seen in Table 9, our results suggest that there is more risk associated with investing in undervalued houses than in the market as a whole. Once this risk is adjusted for, we find that no excess return can be made from investing in undervalued units. This result would be even further strengthened if transaction and search costs are accounted for.[18] Thus, even though our results provide evidence of some excess return predictability, as implied by the reversion in prices for undervalued units, it does not seem possible to exploit this to achieve a risk-adjusted excess return. This allows us to conclude that the Norwegian housing market is micro-efficient.[19]

## 5. BIDDING-SPECIFIC FACTORS AS AN EXPLANATION OF REVERSION IN EXCESSIVE PRICES

We hypothesize that there will be a random process leading to reversion in SPPP, and we propose that this randomness is related to the bidding process.[20] We also think that this bidding-specific component is nonrepeatable. More specifically, we think that the randomness is related to the stochastic arrival of interested bidders at public showings.

To show how this mechanism could work, we demonstrate by constructing an illustrative skeleton model. Assume that the number of bidders $N$ is a stochastic variable. A bidder $b$ with preferences $F_b$ considers a unit $h$ with attributes $A_h$. He extracts utility from consuming the service streams from these attributes. There are two types of match quality between preferences and attributes, high or low:

$$M_{bh} = \begin{cases} H & \text{if} \quad m(F_b, A_h) \geq \bar{M} \\ L & \text{otherwise,} \end{cases}$$

in which $m(F_b, A_h)$ is a general function mapping preferences and attributes to match quality. A high match quality between bidder $b$ and unit $h$ results in a high willingness to pay, $WTP_{H,}$

[17] In a study of the role of speculation in driving regional differences in housing returns across U.S. Metropolitan Statistical Areas (MSAs), Case et al. (2011) estimate a similar model. They use quarterly percentage changes in MSA-level house price indices from Federal Housing Finance Agency as proxies for MSA-specific house price returns. As a proxy for the market return, they use the quarterly percentage change in the national price index. Their results indicate that the market factor is important in driving MSA returns, a finding that is robust to controlling for other risk factors.

[18] Though the sample of returns is much smaller, we also estimate the same model for a portfolio of units that were undervalued by more than 10%. The risk factor is somewhat larger in that case, but results still suggest that no risk-adjusted excess returns can be made.

[19] Another approach to investigate if risk-adjusted returns can be made is to calculate Sharpe ratios; see Londerville (1998) for an application using data from the Vancouver housing market. The Sharpe ratio measures return per unit of risk. The higher this ratio is, the better the portfolio performance. We find little difference in Sharpe ratios between the two portfolios, corroborating the evidence above. We also formally test if there are statistical differences between Sharpe ratios using the approach suggested by Jobson and Korkie (1981). Results suggest no statistically significant difference in Sharpe ratios.

[20] An alternative explanation may be that sellers randomize prices (Burdett and Judd, 1983). Randomized price setting by different sellers of the same unit at different points in time could generate reversion in SPPP. To shed light on the empirical relevance of randomization versus benchmarking, we calculated the correlation coefficient between the ask price and the externally set appraisal price. This correlation coefficient is 0.994, suggesting that prices are not set randomly, but rather that they are grounded in the common value of the unit. Thus, although it is an interesting theoretical possibility, we find little support for this hypothesis.

and a low match quality implies a willingness to pay of $WTP_L$ that equal two monetary levels, $P_H$ and $P_L$:

$$WTP_{bh} = \begin{cases} WTP_H = P_H, & M_{bh} = H \\ WTP_L = P_L, & \text{otherwise.} \end{cases}$$

The probability of a good match is $\rho$. Since each bidder's arrival is stochastically independent, the probability that one bidder has match quality $M_{bh} = H$ with a unit $h$ when the number of bidders is $N_h = 1$ is $\rho$. Let $N_{H,h}$ be the number of bidders for unit $h$ with high match quality. The probability that $N_{H,h} = n_h$ bidders have high match quality for unit $h$ when $N_h$ bidders arrive at the auction of unit $h$ follows a binomial distribution:

$$\text{Prob}(N_{H,h} = n_h) = \binom{N_h}{n_h} \rho^{n_h} (1-\rho)^{N_h - n_h}.$$

The selling price becomes the high monetary level, $p_h = P_H$, if and only if at least two bidders have a high match quality. Thus, given the arrival of $N_h$ bidders at the auction of unit $h$, the probability of the selling price for unit $h$ to become $P_H$ is

$$\text{Prob}(p_h = P_H) = \sum_{j=2}^{N_h} \binom{N_h}{j} \rho^j (1-\rho)^{N_h - j}.$$

For example, if three bidders arrive, and the probability of a good match is $\rho = 0.3$, the probability of a high selling price is $\text{Prob}(p_h = P_H) = \binom{3}{2}0.3^2 0.7 + \binom{3}{3}0.3^3 = 0.189 + 0.027 = 0.216$. The probability $\text{Prob}(p_h = P_H)$ is increasing in $N_h$ (Stevenson and Young, 2015) and $\rho$. Thus, increases in the number of bidders at the auction of unit $h$ increase the probability of a high selling price.

To investigate whether this skeleton model, or thought scheme, appears to capture essential mechanisms in the bidding rounds and that they help us understand reversion, we exploit the auction data to answer two questions:

1. Are more bids associated with an increase in selling price relative to appraisal price?
2. Is there persistence in the number of bids for a given unit?

TABLE 10
BIDDING-SPECIFIC FACTORS AS AN EXPLANATION OF SPPP REVERSION

| | Dependent Variable: SPVP | | Dependent Variable: No. of Bids | |
|---|---|---|---|---|
| Variable | (I) | (II) | (I) | (II) |
| Constant | 0.955 (0.010) | 0.995 (0.049) | 6.577 (1.308) | 0.550 (4.337) |
| No. of bids | 0.009 (0.001) | 0.009 (0.001) | | |
| No. of bids lagged | | | 0.124 (0.123) | −0.083 (0.168) |
| Year: | | | | |
| 2014 | | 0.011 (0.029) | | |
| 2015 | | 0.002 (0.033) | | 4.470 (4.107) |
| 2016 | | −0.022 (0.037) | | 5.532 (4.543) |
| Unit fixed effects (FE) | YES | YES | NO | NO |
| Month FE | NO | YES | NO | YES |
| $R^2$ | 0.478 | 0.539 | 0.021 | 0.233 |
| No. of observations | 78 | | 39 | |
| No. of units | 39 | | 39 | |

NOTES: The table reports results from regressing the selling price to appraisal price, SPVP, on the number of bids, without and with month FE, and regressing the number of bids on its lagged value, without and with month FE.

To control for unit-specific effects in answering the first question and to study replicability in the second question, we need to confine ourselves to repeat auctions. Among all the auctions in our sample, 78 transactions fulfill the condition of the unit's sale having been facilitated twice by the same realtor company, that is, 39 units are transacted twice through the same realtor.

In Table 10, we summarize the results. In the first two columns, we provide an answer to the first question by regressing the ratio of the selling price to the appraisal price, SPVP, on the number of bids. In the last two columns, we investigate the second question by regressing the number of bids for a given unit the second time it is sold on the number of bids the first time the unit is sold. The table reveals that our answer to the first question is yes, whereas the answer to the second question is no. The affirmative answer to the first question lends support to the idea in the skeleton model that higher bids are associated with more bidders. The negative answer to the second question lends support to the notion in the skeleton model that the arrival rate is stochastic and thus that the number of bidders for a given unit the second time is independent of the number of bidders for the same unit the first time.

## 6. ROBUSTNESS AND SENSITIVITY CHECKS

6.1. *Does Reversion Depend on Sellers' Holding Time?* To investigate if the finding of reversion in excessive prices depends on how long $SPPP_{i,T1_i}$ and $SPPP_{i,T2_i}$ are apart in terms of time, that is, holding time, we reestimate the fixed effects model with an interaction term consisting of the product of the SPPP and the number of days elapsed between the transaction pairs:

$$SPPP_{i,s_i} = \alpha_i + \beta SPPP_{i,t_i} + \nu Holding\ time \times SPPP_{i,t_i} + u_{i,s_i}, \qquad s_i = T2_i, T3_i; \qquad t_i = T1_i, T2_i.$$

Results suggest that adding the holding time has no impact on our results, and the coefficient on the interaction term is estimated to be insignificant. Detailed results are reported in Table A.6.

6.2. *Testing Asymmetries in Reversion.* We also explore possible asymmetries in SPPP reversion. If the reversion only holds for units that are bought below the expected price, it may indicate loss aversion, whereas symmetric reversion is indicative of bidder- or bidding-specific factors. To explore this, we estimate a modified version of Equation (8):

$$\begin{aligned} SPPP_{i,s_i} = {} & \alpha_i + \beta^{Above} I(SPPP_{i,t_i} \geq 1) SPPP_{i,t_i} \\ & + \beta^{Below}(1 - I(SPPP_{i,t_i} \geq 1)) SPPP_{i,t_i} + u_{i,s_i}, \qquad s_i = T2_i,\ T3_i; \qquad t_i = T1_i, T2_i, \end{aligned}$$

in which $I(SPPP_{i,t_i} \geq 1)$ is an indicator variable that is equal to 0 when the initial SPPP is greater than or equal to 1, and equal to 0 otherwise. We interact this indicator variable with the SPPP by constructing a product of the indicator variable and the SPPP. Detailed estimation results are reported in Table A.7. Results suggest that there is reversion both when the first SPPP is lower than 1 and when it is greater than 1. The finding that reversion is symmetric is indicative of bidder- or bidding-specific factors, as we also argue in Section 5.

6.3. *Investigating Compositional Bias.* As we saw from the summary statistics in Table 2, units that are transacted more than once are in general smaller and cheaper. Apartments are represented more often than detached houses, and these units are to a larger extent sold in the capital city of Oslo. We investigate the sensitivity of our results to this potential compositional bias. In particular, we rerun the fixed effects model and the test for excess return for cheap units (below the 25th percentile), normally priced units (between the 25th and 75th percentile), and expensive units (above the 75th percentile). We do a similar robustness test for small-sized, normally sized, and large units. Moreover, we redo all our calculations for segments consisting of apartments only and nonapartments. Finally, we study an Oslo-only sample and a sample for the entire country excluding Oslo. None of our results are sensitive to these segmental analyses, and detailed results are reported in Table A.8. An interesting finding from these results is differences in the risk factor from the CAPM. We find that smaller and cheaper units have a larger risk factor. Also, apartments and units sold in Oslo have a higher risk factor. However, there is little evidence of risk-adjusted excess returns.

6.4. *An Alternative Approach to Testing for Excess Return Predictability.* Using survey data for the Philadelphia housing market for the years 1975 and 1978, Linnemann (1986) tests whether the deviation between a self-assessed selling 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 suggest that there were possibilities for a gross arbitrage, but that once costs were taken into account, the arbitrage opportunity ceased. Our framework for analyzing reversion in SPPP ratios is related to the approach in Linnemann (1986) in the sense that different degrees of persistence are indicative of excess return predictability.

As a complementary analysis, we therefore follow the Linnemann (1986) approach and test if excess returns can be predicted by residual information from the hedonic model. Consistent with our finding of reversion in excessive prices, we find that units that are undervalued relative to the hedonic model experience greater house price appreciation. Details are reported in Table A.9.

## 7. CONCLUDING REMARKS AND POLICY IMPLICATIONS

We document that a housing unit's selling price that deviates from its expected price in one transaction tends to deviate much less in the next transaction. There is little persistence and substantial reversion in price deviations. This is the result of a micropersistence test of the Norwegian housing market. It appears that the housing market is effective at ranking houses by value. When a selling price deviates considerably from the predicted price, this deviation appears to be due to nonrepeatable bidder- or bidding-specific factors, not repeatable unit-specific factors. Since the bidder- or bidding-specific factors are nonrepeatable, they are also nonexploitable 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. However, it is not impossible. It is possible to exploit reversion when buying at low prices and to exploit persistence when buying at high prices. This article therefore complements persistence tests with tests of trading strategies. We show that risk-adjusted excess returns cannot be made on a systematic basis by utilizing structure in individual prices.

This adds nuance to the conventional finding that housing markets are inefficient. Although the conventional finding builds on macrotests of persistence in price indices, our results are based on a microtest of persistence in deviations from a model of single units followed over time and in trading tests. In our framework, selling 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 several sources of information to gauge what constitutes a high or low selling price: the price prediction from a standard hedonic model, the seller's ask price, an appraisal price from an external appraiser, and a third selling price for units sold three times. The former builds on the covariation between attributes and selling prices in the market and the second employs the information possessed by the most knowledgeable agent, the seller.

The workhorse model is a regression of the ratio of SPPP in one transaction on the ratio of SPPP of the same unit in the previous transaction. We then include a battery of auxiliary tools to control for time-variant and time-invariant omitted variables, for example, by estimating fixed effect models.

Our 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 claiming that the housing market is 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. As the housing market prices units well, it is very difficult to buy low and sell high. This leaves less room for arguments supporting regulation. In particular, policymakers in Norway have voiced the opinion that housing auctions need strict monitoring and regulation. This article presents the somewhat sobering counterevidence that housing auctions tend to produce informative and consistent prices that reflect the implicit partial value of attributes.

Banks are also highly dependent on estimating the market value of the houses that are collateralized against the mortgages they have outstanding. This is because it helps them performing stress tests and calculating risk-weighted capital ratios to comply with bank regulation. Since our results imply that a selling price that is higher than the predicted price reverts to the predicted price in the next transaction, the predicted price may be a better gauge of current market value than the selling price for newly transacted houses—especially for those units that sell much above or below the expected price.

Finally, homeownership rates are close to 80% in Norway. Owner-occupiers should be relieved that the market is efficient, since it implies little mispricing and that selling prices reflect publicly available information. In an efficient market, it is easier to make an informed decision on what, for most people, is the largest investment carried out during a life span.

## APPENDIX

### A.1. *Additional Tables and Figures.*

TABLE A.1
HEDONIC MODEL FOR SELLING PRICES. NORWAY, 2002–2014

| Independent Variables | Coefficient |
|---|---|
| Intercept | 18,986,417*** |
| log(Size) | −5,194,631*** |
| $(\log(\text{Size}))^2$ | 681,062*** |
| Detached | 267,808*** |
| Row house | 11,150*** |
| Apartment | −8,072,857*** |
| Apartment × log(Size) | 2,694,922*** |
| Apartment × $(\log(\text{Size}))^2$ | −202,754*** |
| Oslo × log(Size) | −3,857,558*** |
| Oslo × $(\log(\text{Size}))^2$ | 559,220*** |
| Constr. Per. 1950–80 | −45,642*** |
| Constr. Per. 1980–2000 | 232,845*** |
| Constr. Per. 2000–14 | 603,870*** |
| Lot size > 10,764 square feet (1,000 $m^2$) | 58,824*** |
| Zip code FE | YES |
| Time FE | YES |
| No. of observations | 484,243 |
| Adj. $R^2$ | 0.801 |

NOTES: The table shows estimation results for the hedonic model used to construct the predicted price in the SPPP ratios we employ throughout the article. *** indicates significance at the 1% level. Semidetached is the default type for type dummies and the period before 1950 is default for the construction period. Therefore, these dummies are excluded to avoid perfect multicollinearity. Zip code FEs are dummies for the zip code in which the unit is located (there are about 5,000 zip codes in Norway). Finally, Time FEs are 145 dummies for each month in the sample (the first month is excluded).

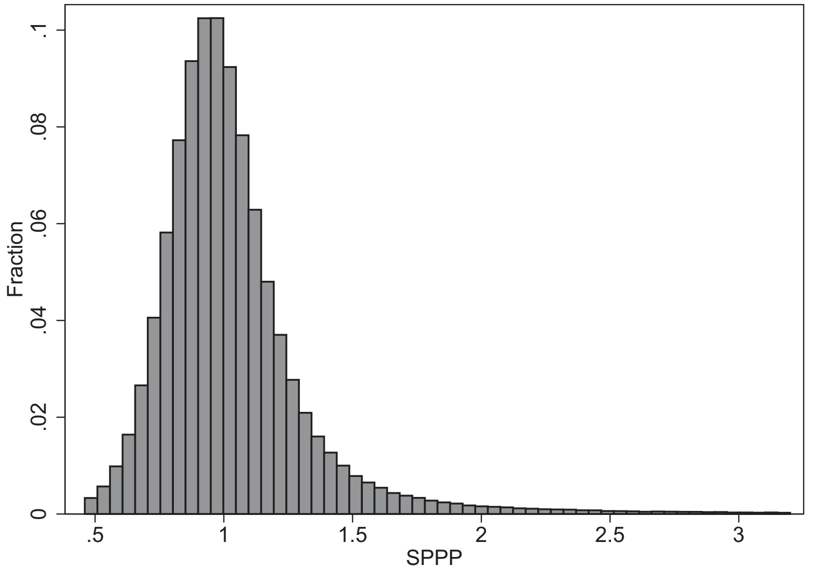


FIGURE A.1

HISTOGRAM OF SPPP RATIOS

TABLE A.2
ESTIMATING HEDONIC MODELS YEAR BY YEAR

| Year | Adj. $R^2$ | Corr (Year-by-Year, Full Sample) |
|---|---|---|
| 2002 | 0.810 | 0.965 |
| 2003 | 0.796 | 0.974 |
| 2004 | 0.808 | 0.978 |
| 2005 | 0.807 | 0.982 |
| 2006 | 0.814 | 0.988 |
| 2007 | 0.815 | 0.990 |
| 2008 | 0.811 | 0.989 |
| 2009 | 0.808 | 0.991 |
| 2010 | 0.815 | 0.991 |
| 2011 | 0.822 | 0.992 |
| 2012 | 0.826 | 0.991 |
| 2013 | 0.833 | 0.990 |
| 2014 | 0.856 | 0.960 |
| All years | 0.801 | 0.972 |

NOTES: The table shows results from estimating the hedonic model year by year, thereby allowing all parameters to change every year. The second column shows adjusted $R^2$ for each of the years in our sample, achieved by estimating the hedonic model year by year. For comparison, the last row shows the adjusted $R^2$ when we estimate the hedonic model on the full sample (see Table A.1. for details). The third column shows the correlation coefficient between the predicted prices from the hedonic model estimated on the full sample and the predicted prices from the hedonic model estimated year by year. These correlation coefficients are shown for each of the years covered by our sample. The final row shows this correlation coefficient for the full sample.

TABLE A.3
HEDONIC MODEL FOR APPRAISAL PRICE. NORWAY, 2002–2014

| Independent Variables | Coefficient |
|---|---|
| Intercept | 23,965,203*** |
| log(Size) | −7,485,583*** |
| $(\log(\text{Size}))^2$ | 931,576*** |
| Detached | 279,297*** |
| Row house | −34,405*** |
| Apartment | −11,145,497*** |
| Apartment × log(Size) | 3,818,672*** |
| Apartment × $(\log(\text{Size}))^2$ | −304,035*** |
| Oslo × log(Size) | −3,619,190*** |
| Oslo × $(\log(\text{Size}))^2$ | 527,628*** |
| Constr. Per. 1950–80 | −59,401*** |
| Constr. Per. 1980–2000 | 221,597*** |
| Constr. Per. 2000–14 | 639,642*** |
| Lot size > 10,764 square feet (1,000 $m^2$) | 40,554*** |
| Zip code FE | YES |
| Time FE | YES |
| No. of observations | 264,386 |
| Adj. $R^2$ | 0.819 |

NOTES: The table shows estimation results for the hedonic model for appraisal prices used to construct the proxies for unobserved time-varying attributes, as explained in Section 3.4.3. *** indicates significance at the 1% level. Semidetached is the default type for type dummies and the period before 1950 is default for the construction period. Therefore, these dummies are excluded to avoid perfect multicollinearity. Zip code FEs are dummies for the zip code in which the unit is located (there are about 5,000 zip codes in Norway). Finally, Time FEs are 145 dummies for each month in the sample (the first month is excluded).

TABLE A.4
HEDONIC MODEL FOR SELLING PRICE. AUGMENTED WITH APPRAISAL PRICE RESIDUAL. NORWAY, 2002–2014

| Independent Variables | Coefficient | Coefficient |
|---|---|---|
| Intercept | 19,013,493*** | 19,013,492*** |
| log(Size) | −5,685,166*** | −5,685,166*** |
| $(\log(\text{Size}))^2$ | 735,758*** | 735,758*** |
| Detached | 274,388*** | 274,388*** |
| Row house | −22,745*** | −22,745*** |
| Apartment | −7,723,193*** | −7,723,192*** |
| Apartment × log(Size) | 2,399,451*** | 2,399,451*** |
| Apartment × $(\log(\text{Size}))^2$ | −160,216*** | −160,216*** |
| Oslo × log(Size) | −3,245,911*** | −3,245,911*** |
| Oslo × $(\log(\text{Size}))^2$ | 483,323*** | 483,323*** |
| Constr. Per. 1950–80 | −57,463*** | −57,463*** |
| Constr. Per. 1980–2000 | 227,102*** | 227,102*** |
| Constr. Per. 2000–14 | 613,090*** | 613,090*** |
| Lot size > 10,764 square feet (1,000 $m^2$) | 48,657*** | 48,657*** |
| Res. from appraisal regression | | 0.871*** |
| Zip code FE | YES | YES |
| Time FE | YES | YES |
| No. of observations | 264,386 | |
| Adj. $R^2$ | 0.823 | 0.965 |

NOTES: The table shows estimation results for the hedonic model augmented with the residuals from regressing appraisal prices on attributes (see Table A.3). The second column shows the baseline hedonic model without the residuals from regressing appraisal prices on attributes when estimated on the sample for which we have information on appraisal prices. Predicted values based on those results are used to construct the SPPP ratios for the results reported in the second column of Table 8. The third column augments the standard specification with the residuals from regressing appraisal prices on attributes. The predicted values from this model are used to construct SPPP ratios controlling for time-varying unit-specific attributes, as detailed in Section 3.4.3. The predicted values based on the results reported in the third column are used to construct the SPPP ratios used to get the results reported in the third column in Table 8. *** indicates significance at the 1% level. Semidetached is the default type for type dummies and the period before 1950 is default for the construction period. Therefore, these dummies are excluded to avoid perfect multicollinearity. Zip code FEs are dummies for the zip code in which the unit is located (there are about 5,000 zip codes in Norway). Finally, Time FEs are 145 dummies for each month in the sample (the first month is excluded).

TABLE A.5

SUMMARY STATISTICS AND CHECKS FOR BALANCE FOR SAMPLE WITH APPRAISAL PRICE

| | Sold Once | Sold Twice | Sold Three Times | All Transactions |
|---|---|---|---|---|
| Selling price (mean) | 432,924 | 401,898 | 368,276 | 416,836 |
| Predicted price from baseline specification (mean) | 432,133 | 406,358 | 378,668 | 418,766 |
| Predicted price controlling for appraisal (mean) | 432,159 | 402,570 | 370,516 | 416,817 |
| Square footage (mean) | 1,398 | 1,184 | 1,008 | 1,294 |
| Time on market (mean days) | 39 | 37 | 36 | 38 |
| Percent Oslo | 20 | 30 | 37 | 25 |
| Percent detached | 54 | 35 | 22 | 45 |
| Percent semidetached | 11 | 11 | 9 | 11 |
| Percent row house | 7 | 8 | 9 | 7 |
| Percent apartment | 28 | 46 | 60 | 37 |
| No. units | 141,629 | 33,185 | 6,723 | 182,679 |
| No. of observations | 141,629 | 66,370 | 20,169 | 232,877 |

NOTES: The table shows summary statistics for our sample of housing transactions for the observations for which we also have data on appraisal prices. The term "sold once" denotes a segment consisting of units that are sold exactly once, "sold twice" are units that are sold exactly twice, whereas "sold three times" are units that are sold exactly three times. The term "all transactions" indicates all transactions that are included in our data set. These transactions include units that are sold exactly once, exactly twice, exactly three times, as well as units sold more than three times. NOK values are converted to USD using the average exchange rate between USD and NOK in the period 2002–2014, where USD/NOK = 0.158. The reason why the mean selling price and the mean predicted price do not coincide is because the data are truncated at the 1st and 99th percentile of SPPP.

TABLE A.6

REGRESSING $SPPP_{i,t_i}$ ON $SPPP_{i,s_i}$ AND $SPPP_{i,s_i} \times \textit{Holding time}$ ($t_i > s_i \ \forall\, i$). UNITS SOLD EXACTLY THREE TIMES. CONTROLLING FOR UNIT FIXED EFFECTS AND INCLUDING APPRAISAL PRICE. NORWAY, 2002–2014

| Independent Variables | Dependent Variable Is $SPPP_{i,t_i}$ |
|---|---|
| Intercept | 1.124 (0.085) |
| $SPPP_{i,s_i}$ | −0.078 (0.054) |
| $SPPP_{i,s_i} \times \textit{Holding time}$ | −0.001 (0.001) |
| No. of observations | 13,446 (6,723 units sold three times yields 6,723×2 pairs) |
| Within $R^2$ | 0.058 |
| Between $R^2$ | 0.068 |
| Overall $R^2$ | 0.001 |
| Time fixed effects | YES |
| Unit fixed effects | YES |

NOTES: The table reports results when we regress SPPP in one transaction on the SPPP in the previous transaction and the interaction between the SPPP in the previous transaction and the number of days elapsed between the transaction pairs. The regression model utilizes units that are sold exactly three times and for which we have data on appraisal prices in all three transaction ($N = 6{,}723$). We use both transaction pairs (1,2) and (2,3). SPPP is an abbreviation for selling price relative to predicted price. Standard errors robust to heteroskedasticity are reported in parentheses. The SPPP ratio uses the predicted price controlling for appraisal prices. Detailed results for the underlying specification are reported in the third column of Table A.4.

TABLE A.7

FIXED EFFECTS REGRESSION WITH ASYMMETRIES

| Independent Variables | Dependent Variable Is $SPPP_{i,s_i}$ |
|---|---|
| Intercept | 1.087 (0.080) |
| $I(SPPP_{i,t_i} > 1)SPPP_{i,t_i}$ | −0.057 (0.045) |
| $(1 - I(SPPP_{i,t_i} > 1))SPPP_{i,t_i}$ | −0.015 (0.049) |
| Break-even if $SPPP_{i,T1_i}$ equals when $SPPP_{i,T1_i} > 1$ | 0.982 (0.002) |
| Break-even if $SPPP_{i,T1_i}$ equals when $SPPP_{i,T1_i} < 1$ | 1.023 (0.002) |
| pval (Full persistence), when $SPPP_{i,T1_i} > 1$ | 0.0000 |
| pval (Full persistence), when $SPPP_{i,T1_i} < 1$ | 0.0000 |
| pval (Full reversion), when $SPPP_{i,T1_i} > 1$ | 0.0887 |
| pval (Full reversion), when $SPPP_{i,T1_i} < 1$ | 0.1262 |
| No. of observations | 13,446 (6,723 units sold three times yields 6,723×2 pairs) |
| Within $R^2$ | 0.108 |
| Between $R^2$ | 0.192 |
| Overall $R^2$ | 0.010 |
| Time fixed effects | YES |
| Unit fixed effects | YES |
| $SPPP_{i,t_i} = 0.7 \rightarrow SPPP_{i,s_i}$ | 1.027 (0.002) |
| $SPPP_{i,t_i} = 1.0 \rightarrow SPPP_{i,s_i}$ | 0.981 (0.002) |
| $SPPP_{i,t_i} = 1.3 \rightarrow SPPP_{i,s_i}$ | 0.964 (0.002) |

NOTES: The table reports results when we regress SPPP in one transaction on the SPPP in the previous transaction, allowing different coefficients depending on whether the previous SPPP was greater than unity or below unity. The regression model utilizes units that are sold exactly three times and for which we have data on appraisal prices in all three transactions ($N = 6{,}723$). We use both transaction pairs (1,2) and (2,3). SPPP is an abbreviation for selling price relative to predicted price. Standard errors robust to heteroskedasticity are reported in parentheses. The SPPP ratio uses the predicted price controlling for appraisal prices. Detailed results for the underlying specification are reported in the third column of Table A.4. The break-even condition, which shows the value of the first SPPP that yields a return equal to the market return, is calculated based on the expression in Equation (5) and the standard error reported in parenthesis has been calculated using the delta method. A value of first SPPP higher than this number indicates that a loss is incurred, whereas a value of SPPP lower than this number indicates a first SPPP for which a potential profit may be made. The terms "pval (Full persistence)" and "pval (Full reversion)" are short notation for reports of $p$-values from a standard Wald test for the joint restrictions $(\alpha, \beta) = (0, 1)$ and $(\alpha, \beta) = (1, 0)$, respectively.

TABLE A.8

RESULTS ACROSS DIFFERENT PRICE, SIZE, TYPE, AND LOCATION SEGMENTS

| Segmentation | Break-Even | pval (Full persistence) | pval (Full reversion) | $\hat{\lambda}$ | $\hat{\chi}$ |
|---|---|---|---|---|---|
| Price: | | | | | |
| Below 25th percentile | 1.005 (0.002) | 0.0000 | 0.0001 | −0.007 (0.011) | 1.686 (0.349) |
| Btw. 25th & 75th percentile | 1.000 (0.004) | 0.0000 | 0.2363 | 0.001 (0.005) | 1.185 (0.130) |
| Above 75th percentile | 1.001 (0.003) | 0.0000 | 0.0379 | −0.004 (0.005) | 0.969 (0.124) |
| Size: | | | | | |
| Below 25th percentile | 1.003 (0.003) | 0.0000 | 0.0000 | −0.022 (0.012) | 1.531 (0.337) |
| Btw. 25th & 75th percentile | 0.998 (0.006) | 0.0000 | 0.2818 | 0.001 (0.004) | 1.252 (0.087) |
| Above 75th percentile | 0.999 (0.004) | 0.0000 | 0.0219 | 0.014 (0.002) | 0.870 (0.058) |
| Type: | | | | | |
| Apartment | 1.000 (0.002) | 0.0000 | 0.0000 | −0.012 (0.009) | 1.433 (0.253) |
| Not apartment | 1.002 (0.004) | 0.0000 | 0.2064 | 0.013 (0.003) | 0.928 (0.093) |
| Location: | | | | | |
| Oslo | 0.987 (0.005) | 0.0000 | 0.0088 | −0.007 (0.009) | 1.480 (0.249) |
| Rest of the country | 1.009 (0.005) | 0.0000 | 0.1309 | 0.005 (0.002) | 0.991 (0.059) |

NOTES: The table reports results for different subsamples. The second column shows the break-even condition, which is the value of the first SPPP that yields a return equal to the market return. It is calculated based on the expression in Equation (5), and the standard error reported in parentheses has been calculated using the delta method. A value of first SPPP higher than this number indicates that a loss is incurred, whereas a value of SPPP lower than this number indicates a first SPPP for which a potential profit may be made. The terms "pval (Full persistence)" and "pval (Full reversion)" are short notation for reports of $p$-values from a standard Wald test for the joint restrictions $(\alpha, \beta) = (0, 1)$ and $(\alpha, \beta) = (1, 0)$, respectively. These measures are calculated utilizing units that are sold exactly three times and for which we have data on appraisal prices in all three transactions ($N = 6{,}723$). We use both transaction pairs (1,2) and (2,3). Detailed results for the underlying specification are reported in the third column of Table A.4. The fourth and fifth columns report the estimated risk factor ($\hat{\lambda}$) and the intercept ($\hat{\chi}$) from the CAPM model in (11). Standard errors robust to heteroskedasticity are reported in parentheses.

TABLE A.9
TEST OF GROSS RETURN PREDICTABILITY

| Independent Variables | Dependent Variable Is $R_{i,s_i}$ |
|---|---|
| Intercept | 0.080 (0.036) |
| $\text{Spread}_t$ | −0.728 (0.095) |
| Years elapsed | 0.087 (0.002) |
| No. of observations | 13,446 (6,723 units sold three times yields 6,723×2 pairs) |
| Within $R^2$ | 0.480 |
| Between $R^2$ | 0.247 |
| Overall $R^2$ | 0.364 |
| Time fixed effects | YES |
| Unit fixed effects | YES |

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

A.2. *Macropersistence.* Following the seminal contributions of Case and Shiller (1989), there is a copious literature that tests the efficiency of housing markets using aggregate macrodata. The standard approach is to consider an equation of the following type:

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

in which we use the notation $\Delta$ as a difference operator and $ph$ is the logarithm of a 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.

In the hedonic model used to construct the aggregate price index, we include the same set of variables[21] as in model I in Table A.1. However, for the purpose of calculating a price index, we took the logarithm of the dependent variable. Thus, the hedonic model used for index construction takes the following form:

$$\log(P_{i,t}) = a + b_1 \log(S_i) + b_2(\log(S_i))^2 + \boldsymbol{c}'\boldsymbol{A}_i + \boldsymbol{d}'\boldsymbol{M}_t + \varepsilon_{i,t}. \tag{A.1}$$

This operation makes the computation of the index very simple, since the index value in a given period is simply given by exponentiating the difference between the coefficient on the dummy for that period and the coefficient on the dummy for the base period. Since the base period is excluded from the model to avoid perfect multicollinearity, this means that the index in a given period is simply the exponentiation of the coefficient on the dummy for that period. Thus, the price index in, for example, 2004m4 is given by $Index_{2004m4} = e^{d_{2004m4}}$, where $d_{2004m4}$ denotes the coefficient for the dummy variable in 2004m4.

Using the constructed index to estimate an AR(24) model for house price growth and testing the joint hypothesis that all of the AR-parameters are equal to 0 (i.e., testing if house prices follow a random walk), we achieve a $p$-value of 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). Although coefficients at some longer lags are negative, the sum of the lags is positive, suggesting little evidence of mean reversion.

[21] We use a smaller spatial grid and city and region dummies instead of zip code dummies.

A.3. *Excess Return Predictability.* Let $\psi$ denote the coefficient obtained by regressing actual return between $t_i$ and $s_i$ ($s_i > t_i$) for unit $i$ on the spread between the selling 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

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

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 differently from the expected price, which is represented by the difference between $P_{i,t_i}$ and $P^*_{i,t_i,}$. The parameter $\psi$ 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:

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

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

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

Letting the price expectation be measured by the price predicted by a hedonic model, $\hat{P}_{i,t_i}$, gives

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

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 $\psi > 0$, that is, 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 $\psi < 0$, that is, 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. Note that the first case is similar to case (a) in the SPPP model (cf. Table 1), whereas the second case is similar to case (g) in the SPPP model.

To get an estimate of $\psi$, we estimate an equation of the following form:

$$R_{i,s_i} = \omega_i + \eta_{t_i} + \eta_{s_i} + \psi\left(\frac{P_{i,t_i} - \hat{P}_{i,t_i}}{\hat{P}_{i,t_i}}\right) + \sigma Holding\ time + \varepsilon_{i,s_i},$$

in which $R_{i,s_i}$ is the actual percentage return on unit $i$ between $t_i$ and $s_i$ and the variable *Holding time* measures the number of days that have elapsed between the two transactions (transformed to years by dividing by 365). The two time dummies, $\eta_{t_i}$ and $\eta_{s_i}$, 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, $\omega_i$, to control for permanently omitted variables that are not captured by the hedonic model.

Consistent with the SPPP model, we find that excess returns can only be made by investing in units that are underpriced relative to the hedonic model. However, as shown in Section 4.5, risk-adjusted returns are insignificant.

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