Erling Røed Larsen and Steffen Weum

Home, Sweet Home or Is It -- Always? Testing the Efficiency of the Norwegian Housing Market


Abstract: The question of whether the housing market is efficient or not is posed by an increasing number of economists, policymakers, current homeowners and prospective homebuyers. This article tests the efficiency hypothesis on the Norwegian housing market in its capital, Oslo. We employ the Case-Shiller time-persistence-test on a repeated-sales model of house price index and returns to housing. Our data cover the period 1991-2002 and consist of 55,961 sales of housing objects from the OBOS register; of which we use 20,752 transactions of same-object-repeated-sales. We explain how the uniqueness of the data set makes it well suited for our purpose, and demonstrate that the repeated-sales house price index contains inertia and time-persistence. In addition, we investigate how the price history of returns; which consist of capital gains, dividends, and interest payments; can be exploited to predict future returns. Thus, both house price index and returns contain forecastable elements, so we reject the null hypothesis of martingale processes, a finding that is indicative of Case-Shiller inefficiency. This discovery is supplemented with an exploration of the standard trading and timing rules by examinations of intra-market and inter-market returns. We show that the housing market consistently yield higher return at lower risk than does the stock market, which is inconsistent with inter-market efficiency.

Key Words: efficient market hypothesis, excess returns, house prices, housing market, martingale process, risk, time persistency, trading rules

JEL Classification: C22, C43, D12, E37, G14, R21

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1. Introduction
Recently, many homeowners have made more money asleep in their homes than at work in the office. The reason why is that their homes have appreciated more per year than the magnitude of their annual salary. These capital gains are indeed sweet since they constitute gifts from the market and appear to be free lunches for the owners. However, some late entrants are weary about their timing and fear that they are exposed to risks of future capital losses. Such losses would indeed be bitter because they appear random and outside of consumer control. At the heart of the matter, lie the questions of forecastability and thus entry timing, market efficiency, time-persistence, and the predictability of breakpoints. Moreover, while market efficiency is a tenet of many economists, housing economists and behavioral economists have claimed that the housing market may not be especially efficient. The position has been both supported and challenged by theory and empirical evidence and so the jury is still debating the verdict. However, it is imperative that we realize that earlier studies and tests may have utilized data with insufficient coverage on important aspects of the housing market, and potentially confounded the time development of house price with the time development of omitted variables. Thus, there is a need for a re-visit of rigorous statistical tests of market efficiency on high-quality and well-suited data. This article attempts exactly that. It asks and answers the simple question: Is the housing market in and around the Norwegian capital, Oslo, efficient?

No. It is not. We can reject the hypothesis of efficiency by utilizing a method developed by Case and Shiller (1989), which constitutes the seminal work on testing housing market efficiency, on a rich data set of transactions in a unique housing market in Oslo. This rejection of the efficiency hypothesis emerges from the discovery that house price indices do not seem to follow martingale processes, which they should have, had the market been efficient. Moreover, returns; i.e. capital gains, housing dividend (avoidance of rent), and interest payments; are forecastable, and this finding is inconsistent with "weak form efficiency". Additionally, we discuss why the development in the housing market is inconsistent with both intra-market and inter-market efficiency. The former emerges with the establishment of the simplest profitable timing rule. The latter arises with the juxtaposition of high returns and low risk. How? We argue, by building upon and extending the reach of Barkham and Geltner's (1996) concept of "price discovery activity", that the combination of higher return and lower risk in the housing market compared to the stock market, over this period, is inconsistent with inter-market efficiency.

Gu (2002) suggests, importantly, that the reason why economists disagree on the question of housing market efficiency may not only be due to methodology. He points toward the different data sources the different studies employ. Potentially, some or much of the conflicting views could have been reconciled had empiricists been in a position to locate ideal data sets. In this article, we cannot say that we utilize a perfect data set, but we do propose that we have found one that is particularly well suited for efficiency tests. The advantages of our data set are of plenty. First, it covers a geographical and economical area that most plausibly functions as one labor market. Thus, analysts avoid the challenging confounding of house price developments in several housing markets and wage developments in several labor markets, which requires disentangling of the two effects. Second, the dataset comprises objects that are fairly homogeneous and are comparable over time. Thus, one may avoid the
difficulties in time series resulting from the influence of different time developments in
different segments of the housing markets, where material standard and unobserved quality
improvements may yield selection biases if the composition of object types are not kept
constant over time. Third, the data set is large and comes with many observations and so we
are able to fine-tune our indices to quarterly entries with small standard errors. Fourth, a
sufficiently long period is covered and ensures that observers may investigate business cycle
effects. Fifth, because the area the data set covers is sufficiently small and may be classified
as one housing region, the inherent up-ward bias of inter-temporal ripple effects in repeated-
sales-models may not be strong; see Sommervoll (2006). Last, but not least, the objects in our
dataset allow close comparison between owner-occupancy and tenant occupancy, which again
insures accurate computation of excess returns. This advantage is related to a caveat that has
not been given much attention in the literature, is the fact that the computations of excess
return in the housing market needs incorporating two different types of indices. One part of
excess returns to housing is capital gains, and they are derived from a house price index.
Another part of excess returns to housing is dividends, or implicit rents, and they are derived
from a rental index. The obvious problem is that the owner-occupied housing market may be
quite different from the rental market, so that indices from the latter do not reflect well the
development in the former. This problem is likely to be larger (smaller) the smaller (larger)
the rental market is compared to the owner-occupied market. To see this, recall that when the
rental market is small, they tend to consist of small objects with one or two bedroom and of
size ranging from 40 to 80 square meters.

Among these six advantages, however, we are tempted to say that the first two are of
particular, but potentially somewhat underestimated, importance. To see the importance,
consider first data sets that cover multiple housing markets and labor markets. When analysts
then observe house price changes, these changes may, but need not, be partial changes in a
price of a given object everything else being the same. Instead, they may originate from
composition effects in changing labor markets. For index purposes, this endogeneity does not
matter, but for efficiency tests, it does. The reason why is that the efficiency hypothesis
implies that the price history cannot be utilized to construct forecasts in a way that beats the
martingale. But if time-persistence and deviations from trends in the labor market spill over
into time-persistence and deviations from trends in the housing market, and observers do not
control for it, unwarranted conclusions of inefficiency may arise.

Consider also the other possibly underemphasized caveat, namely what may happen to a test
of efficiency if, over time, the pool of object types, i.e. the composition of different segments,
also changes. Then, what looks like a partial price change and time-persistence may in reality
be no such thing for a given object type. It may simply be changes in the composition of
object types. Thus, in empirical tests, and especially in efficiency tests, we need to be
extremely careful about the composition of object types over time; see e.g Sommervoll (2006)
and his demonstrations on inherent bias from ripple effects in indices that cover several
regions. In other words, we would like to either break down all object types into a perfect,
exhaustive vector of attributes or, if one cannot, segment all types into pools of specific object
types. This article does the latter, as it employs a data set with fairly homogeneous objects.

This attention to detail is acutely warranted in the housing literature because results and
conclusions are of keen interest to almost any participant in the economy. Knowing whether
housing markets are efficient or not, or more precisely knowing what kind of processes
govern house prices, appears important to any economic agent, and so a substantial literature
has grown on the topic. Englund, Gordon, and Quigley (1999) analyze the temporal pattern of
house prices in Sweden, to test economic theory, to guide agents, and to help build index models by examining the underlying stochastic process. Hill, Sirmans, and Knight (1999) explore the pattern in house price series and seek to uncover what processes govern the time development. Their study starts from the same point of departure as did the article by Case and Shiller, and examine some of the assumptions in it, since, as they say, the Case-Shiller model "has been used by numerous authors". When we inspect the properties of stochastic processes of house prices, we indirectly also join the larger debate on the basis for profits in investment strategies. Shiller (2003) and Malkiel (2003) together highlight the opposing positions in that debate, where Malkiel takes the role of efficiency proponent and Shiller the role of the skeptic. Our investigation can be read as a re-joiner using recent Norwegian evidence.

It is a re-joiner because the debate on housing market efficiency is an old one, but it is intimately related to the on-going discussion of whether or not the housing markets in many countries are bubbles or not. Bubbles require some kind of market inefficiency, so authors have been eager to check whether they are able to explain house price levels and changes by fundamentals. For example, we note that Himmelberg, Mayer, and Sinai (2005) claim to find little evidence of a bubble in the United States. Cameron, Muellbauer, and Murphy detect no evidence for recent bubble in Britain. Rosenthal says there exists little evidence to support notions of inefficiency in the UK owner-occupied housing market over the period 1991-2001.

However, other authors disagree. Englund and Ioannides (1997) say first-differenced real house prices in fifteen OECD countries demonstrate significant structure of autocorrelation. Hort (1998) also finds rich autoregressive structure in real house prices for Sweden in the period 1968-1994, but states that although the results are consistent with speculative behavior, they appear to be well explained by development of fundamental demand conditions. Although they favor an interpretation of high transaction cost to explain their discovery of persistence, Meese and Wallace (1994) cannot rule out the possibility of bubble or non-rational expectations in the 1970-1988-period of residential housing markets in Alameda and San Francisco Counties in California. Barkham and Geltner (1996) find that the UK housing market is not efficient, and Kim (2004) detects some evidence of house price bubbles in South Korea. Clapp and Giaccotto (2002) use several forecasting methods and both uncover some information inefficiency in 1971-1997 data on transactions in Dade County, Miami, Florida. Thus they are able to forecast house prices. Gu (2002) discovers that it would be possible to obtain excess returns by following a suggested trading strategy based on revealed autocorrelation in the Freddie Mac 1975-1999 data set. He detects that house price changes exhibit patterns, even if the size and direction of the autocorrelation change over time.

Recently, Shiller (2006) has joined the debate on the on-going U.S. development and warned that there is substantial risk in the housing market. He says that; contrary to the finding in the study by Himmelberg, Mayer, and Sinai; fundamentals are weak at explaining house prices and he is alarmed due to the "substantial evidence that there is a strong psychological element to the current housing boom". This article cannot, nor aims to, settle the debate even if it hopes to illuminate it. We cannot here offer much more information on the data sets of the mentioned studies and their suitability other than join Gu's suggestion, Implicitly, he calls for a closer examination of the data sets used in the mentioned studies, but that is left to further research. The descriptions do not immediately allow close inspections of whether the housing markets are one or several, whether they are identical to or only related to several labor markets, or whether the composition of object types vary much over time or not. Consequently, what we find is our role here is to substantiate that our data set does meet the criteria and employ it to test efficiency.
It is convenient for the reader to get an overview over how we structure our argument. Let us therefore say where we are headed. In the next section, we give a brief overview of the efficiency-testing methodology and how we construct our repeated-sales indices. The third section describes our data. The fourth section reports empirical results. We proceed to discuss what caveats apply, what qualifications to be made, and what we would like to see, but were unable to accomplish at this stage. The sixth section concludes and presents policy implications. In an appendix, we include useful figures.

2. Theory
Efficiency testing necessarily divides into three separate parts: the establishment of a price index, the establishment of a series of housing returns, and the closer scrutiny of how the series behave. Before we go into details about how to construct a relevant index type, let us briefly consider the term "efficiency". As Gatzlaff and Tirtiroglu (1995) explain, the concept of efficiency often appears in three forms: informational, allocational, and operational. We choose to examine informational efficiency. The seminal definition was put forward by Fama (1970) and is employed in numerous studies. The idea is that in efficient markets, prices fully and instantaneously reflect all relevant information. Fama (1991) clarifies this idea, and states that "prices reflect information to the point where marginal benefits of acting on information (the profits to be made) do not exceed the marginal costs" (op. cit., p. 1575). This leads to the idea that market prices are stochastic processes with certain properties, one of which is stated below in equation (1). The key point in this literature is whether or not the examined process is a martingale, or its special case, a random walk. Following Gatzlaff and Tirtiroglu (1995), a stochastic process is a martingale with respect to the full information set if:

\[ E(y_{t+1} | \phi_t) = y_t, \]

where \( E(.) \) is the expectations operator, \( y_t \) denotes the variable in question at time \( t \) and \( \phi_t \) the full information set at time \( t \). Crucially, it follows that the best forecast of \( y_{t+1} \) at time \( t \) is simply \( y_t \). This article utilizes this definition, and examines the relationship between changes in a house price index at time \( t \) and \( t-1 \), \( y_t - y_{t-1} \) and its relation to the history of the same differences. We repeat the inspection process with a variable on housing returns. Recall, however, that both the house price index, \( y_t \), and its first difference, \( y_t - y_{t-1} \), are stochastic variables. Thus, it may feel natural initially to examine the level, \( y_t \), and its relation to its history, as given in equation (2):

\[ y_t = y_{t-1} + \lambda_t, \]

where \( \lambda_t \) is a stationary, zero-mean, constant variance variable, i.e. white-noise. If, however, \( y_t \) follows a random walk process, its first difference \( y_t - y_{t-1} \) is white noise. Alternatively, \( y_t \) follows another stochastic process, e.g. an AR(1) process. Then, \( y_t \) equals \( \rho y_{t-1} + \lambda_t \), where \( \rho \) is unequal to unity. Notice that \( y_t - y_{t-1} \) may or may not be white noise. The first difference, too, may follow a random walk or an AR(1) process. The essence of this is whether or not analysts can discover a time structure, a pattern, in the propagation of the time series. We follow the Case-Shiller set-up and examine the first differences \( y_t - y_{t-1} \). If the process is a martingale, then forecasting becomes difficult except for observing the magnitude of the last observation. Alternatively, if analysts detect time structure, then it becomes possible to use that time structure to outperform the forecast of the last period's magnitude.
The core of this is that, then, agents would exploit historical data to estimate the parameters and modify \( y_{t-1} \) as predictor. This takes the form of equation (3):

\[
\hat{y}_t = g(d) + f(d) y_{t-1},
\]

where \( g(d) \) and \( f(d) \) are functions of a data set \( d \), for example, but not limited to, least squares estimates of the relationship between \( y_t \) and \( y_{t-1} \). Equation (3) encompasses the possibility that it is fathomable to combine the path history of a variable to beat the martingale forecast, which is inconsistent with efficiency. Moreover, if it is possible to establish estimates of the type presented in equation (3), such estimates would be indicative of time-persistence and inertia. If they occur, they make price development path-dependent such that agents can employ earlier manifestations of price developments to forecast future price developments. Inefficient markets allow patterns in the historical data to be employed so that the analysts can improve make forecasts other than last period's level.

In order to do so, analysts must start by establishing a house price index. We establish ours by constructing a house price index apparatus for objects in the OBOS-system around Oslo and Akershus as explained in Røed Larsen and Sommervoll (2004). Let us briefly outline the procedure. Basically, it follows the structure and error term assumptions introduced by Case and Shiller (1989), in which the logarithm of realized sales price consists of three additive terms: a city-wide price level, which shall be our index, a Gaussian random walk, which we take into account below through controlling for heteroskedasticity, and a classical noise term originating in the usual market imperfections. The former term is this article's focus of attention and constitutes what we aim to examine for time-persistence properties. The middle term is caused by possible time-persistent drift off trend in dwelling value. In this set-up, we assume that the difference between the middle term for the same object sold twice, only at different times, has zero mean and a constant variance and thus allows the treatment presented below. The latter term originates in the idiosyncracy of the process. To see how, recall that potential purchasers arrive at sales events in random fashion, or may be prevented from doing so. The Case-Shiller methodology for constructing housing price indices relies on a three-stage weighted least squares regression model on repeated house sales, which accounts for possible heteroskedasticity. It is summarized in equations (4)-(6):

\[
(4) \quad \log(p_{it}) - \log(p_{is}) = \gamma_2 T_{i2} + \gamma_3 T_{i3} + \ldots + \gamma_46 T_{i46} + \epsilon_{it}, \quad i \in I; t, s, e \{2, \ldots, 46\}, T_{it} \in \{-1,0,1\}
\]

\[
(5) \quad u_i^2 = \alpha_0 + \alpha_1 Q_i + \omega_i, \quad w_i = \sqrt{u_i^2}, \quad i \in I,
\]

\[
(6) \quad (\log(p_{it}) - \log(p_{is})) / w_i = \gamma_2 (T_{i2} / w_i) + \ldots + \gamma_46 (T_{i46} / w_i) + \epsilon_{it} / w_i, \quad i \in I; t, s \{2, \ldots, 46\}, T_{it} \in \{-1,0,1\}.
\]

where \( p \) represents observed sale price, \( T \) is a dummy variable indicating first sale, second sale or no sale, \( t \) is the time period in which the second sale was undertaken, \( s \) the time period in which the first sale was undertaken (and thus \( s < t \)), subscripts \( i \) refer to a sale of a given object in the set of all repeated sales \( I \) such that \( i \) refers to an object sold at least and at most two times, \( \gamma_s \) and \( \gamma_s' \) are index parameters to be estimated, and \( \epsilon \) is an error term with zero-mean, and possibly non-constant variance caused by the drift mentioned above. The dummy variable \( T \) is set to +1 in the second period it was sold and −1 in the first period it was sold for each object, unless this is the first time period, where the dummy variable is set to 0. Parameters \( \alpha \) relate the squared residuals to a counting-variable \( Q \) that denotes the time
interval, i.e. number of quarters, between each sale within transaction pair i. The stochastic variable \( \omega \) is a classic mean-zero, constant variance noise term, and \( w_i \) denotes the inverse of the weight ascribed to each observation in the third step. The larger \( w \) is, the larger is estimated variance, and the smaller is the weight. Equation (4) is the starting OLS-regression, equation (5) estimates the weights, and equation (6) is the resulting FGLS-regression using the weights from (5).

However, as Case and Shiller (1989) explain in detail, one cannot construct one index and examine it for random walk or martingale properties and test for time persistence. The reason why is quite intuitive. The same noise from individual sales of objects would affect both determinants and the left-hand-side variables. There may be serial correlation in the log price index. To solve these challenges, we apply the same simple remedy as did Case and Shiller. We divide the original sample into two random parts and construct two independent indices, each based on its own half. Then we use left-hand-side variables from one index and determinants, i.e. lagged indices, from the other index. That way we circumvent the problem since although both sides of the equation include noise, the two noise sources are not the same, but independent of each other since they emerge from two independent samples. In other words, we allocate each observation in the original sample either to sample A or to sample B, then employ equations (4)-(6), and obtain two independent indices, Index A and Index B, that measure the same underlying price development.

In order to avoid structure from general price development, we compute the real log-index by deflating the log-index with the official CPI, as shown in equation (7):

\[
W_j(t) = \log(I_j(t)) - \log(CPI(t)), \quad j \in \{A, B\}, t \in [1991 III, 2002 IV].
\]

The variable \( W \) is now our real house log-price index. The subscript \( j \) refers to the sub-sample consisting of half the original sample, either sample A or sample B. \( I_j(t) \) is the non-log index for sample \( j \) at time \( t \), which shows the increase of the index at that time in terms of multiples of the index in the starting period \( t=0 \). In other words, \( I_j \) is given by the estimated \( \gamma \)'s, and \( \log(I_j) \)'s are simply the estimates from equation (6) from each of the two samples. Case and Shiller's test comprises regressing the difference of the real log-index from one sample onto a space spanned by the lagged real log-index from the other sample, as given in equation (8):

\[
W_j(t) - W_j(t-4) = \beta_0 + \beta_1(W_k(t-4) - W_k(t-4 - L)) + u(t), \quad j, k \in \{A, B\}, j \neq k,
\]

where the noise term \( u(t) \) is assumed to be a well-behaved zero-mean, constant variance stochastic element, and subscript \( k \) denotes the other half of the original sample, A if \( j \) is B and B if \( j \) is A. \( L \) is short notation for lag, and can be either 0 for no lag or 4 for a 4-quarter lag. Notice, then, that if \( L=4 \), then equation (8) is interpreted as a regression of the real log change in index A on the real log change in index B the previous year. If there is no time-persistence or inertia, i.e. no time structure in index changes, then the market is said to fulfill one of the efficiency criteria. This absence precludes agents to utilize time-persistence in the index history to make money, so it implies an absence of profitable trading-rules. It also precludes forecastability. Alternatively, if the coefficients reveal structure, there will be time-persistence and forecastability. Agents can then use the structure of the process to forecast, which violates the criterion of information efficiency.
However, forecastability of house prices could originate in forecastability of the general price level, interest rates, or rents. The former is controlled for by using real log-indices, as explained above. The latter requires examination of excess returns. We establish series of returns by incorporating capital gains, dividends (i.e. implicit rent for owners), and after-tax interest payments. Estimating housing dividend, however, is non-trivial. Case and Shiller assume that the average dividend-to-price ratio is equal to 0.05, and we make the same assumption. This implicitly presupposes that the purchase price of a given home is $0.05^{-1} = 20$ times the magnitude of annual rent or dividend. We follow Case and Shiller's design (p. 129) and define excess returns in equation (9):

$$ER_j(t) = \left\{ I_j(t + 4) / I_j(t - 1) \right\} + C_j \left\{ (R_t + \ldots + R_{t+4}) / 4 \right\} / I_j(t) - (1 - \tau) r(t)/100,$$

where $R_t$ refers to the increase in a rental index from $t-1$ to $t$, $r(t)$ denotes the mortgage interest rate, and $\tau$ is the proportion of interest payments that is tax deductible. The excess return, then, consists of three elements: i) the capital gains from house price appreciation plus ii) the implicit rent (since an owner avoids paying rent as a tenant to a landlord, and instead is her own tenant and her own landlord), minus iii) the interest payments minus the tax deductable portion. Let us explain the middle element, the housing dividend or avoided rent, in the most transparent way. Assume that a tenant decides to become an owner. She purchases an object at a price $P$ and does not have to pay rent. The value of this dividend, however, depends on what she would have had to pay, counter-factually, in rent had she stayed a tenant. Assume that the rent at purchasing point, $t = 1$, is $E$. Let us say that the development of rent develops following a rental index, and so for the first four quarters it increases to $E*R_1$, $E*R_2$, $E*R_3$, and $E*R_4$, where $R_t$ is the rental index, measured the simplest way, as a multiple of unity. The average avoided rent, then, is $(E(R_1+\ldots+R_4))/4 = E(R_1+\ldots+R_4)/4$. This avoided rent is part of the return, and it is measured as a proportion of purchasing price $P$, $(E(R_1+\ldots+R_4))/P$.

However, the return for the next year measured at $t = 2$, must not only include an update of rent development, but also of house price, e.g. $(E(R_2+\ldots+R_5))/4 = (E(R_2+\ldots+R_5))/4$. This amounts to saying that housing dividends next 4 quarters at $t$ are $C(R_t+\ldots+R_{t+4})/I_t$, where $C$ is the Case-Shiller constant. They calibrate it such that the average over dividends for the number of quarters is equal to 0.05. Thus, 

$$(1/46)\sum_{t=1}^{46} C(R_t+\ldots+R_{t+4})/I_t = 0.05,$$

which implicitly defines $C$. We also compute $C$ in this fashion, and proceed to regress returns on lagged returns to investigate the forecastability of returns as explained below.

3. Data

We employ a data set containing 55 961 sales of housing objects in and around the Norwegian capital, Oslo, in the period from third quarter of 1991 to fourth quarter of 2002. The data are sales data from OBOS, a large Norwegian sales cooperative, which organizes "borettslag", constructs buildings, and functions as a major player in the housing sector. OBOS is also Norway’s largest housing agent. The cooperatives are distributed all over Oslo, from the neighborhoods in the western part to more areas pf the east side. OBOS keeps a register of all objects, each object uniquely identified. Every financial transaction is monitored. From mid-1991 onwards, all information on 60 000 objects of all sizes in approximately 500 cooperatives distributed all over Oslo has been recorded. Since each object is uniquely identified by the cooperative and the apartment number identifying repeated sales is straightforward.

In our analyses, 437 cooperatives were used, and out of the total of 55 961 transactions, 34 025 were identified as repeated sales. Excluding those that were sold 3 times or more resulted...
in 20804 sales of one object sold at least and at most twice. These transactions correspond to 10402 objects rendered available for the Case-Shiller method. 26 observations contained obvious registration errors and were omitted. This left us with 10376 pairs of sales, i.e. 20752 transactions.

Each sales record contains information on size in square meters, number of rooms, number of bedrooms, sales dates, and the amount of common financial liability the cooperative. In addition, we have complete information on geographical coordinates for each object as well as the construction year.

Above, we suggested five criteria for a data set well suited for efficiency tests: it should cover at most one economical area with one housing and one labor market, it should include homogeneous objects, it should contain a rich set of observations, it should span a sufficiently long period in time, and it should be small enough to reduce inter-temporal ripple effects across different sub-areas within the coverage area. The OBOS data appear to satisfy all five, and let us substantiate the first and the second. Oslo is a small city with only a little more than 500000 people, and this indicates that transportation distances are not substantial. Furthermore, it has extremely good coverage of public transportation, including detailed routes of trains, metro, streetcars, and buses. In other words, the public considers it possible to combine any home location within the area with any work location. The homogeneity of the objects is a key facet of the data set. Whereas other house price data set may span objects from 25 square meter 1-room apartments in the inner city to 300 square meter large home residence with a garden in suburban areas, this data set contains mostly homogeneous objects of moderately sized apartments within similarly looking and comparably constructed cooperatives. While many buildings in European cities can by more than a 100 years old, this data set consists mostly of fairly new, rather modern complexes built in the near past. The variance of the material standard is small. This minimizes the challenge emerging from composition biases.

Additionally, because the objects of the OBOS dataset are similar to ones in the rental market, the computation of dividends, or implicit rents, may be more accurate than when the dataset includes larger homes. To see this, recall that in many economies, there is a substantial difference between the type of objects in the owner-occupied market and type of objects in the rental markets. Not only do they often lie in very different regions, settings, and environments, they are often also quite different in size, construction, and material standard. Often, rented objects are small, modest apartments close to universities while owned objects are larger, high-standard homes with gardens in a sub-urban environment. If so, a rental index will not well capture the implicit rent, or dividend, of the owner-occupied market. OBOS objects, however, are typically of modest size and standard and are normally located in areas with many rented objects.

4. Empirical Results

4a. Testing the Efficiency Hypothesis
We regress the changes in real log index from one half of the sample onto changes in real log index from the other half of the sample, with no lag. Theoretically, the slope of such regressions tends towards unity when the number of transactions becomes large. The reason why is that both samples are drawn from the same universe dominated by an identical price
development, and so each half would mirror the other perfectly. Our slope coefficient estimates of 0.92 and 1.04 are more than sufficiently close for us to accept that both samples reflect the same development. After all, changes in one can explain changes in the other 96% of the time.

Then, we proceed to perform regressions with time lags. Observe first that the explanatory power is of the same order of magnitude as what Case and Shiller find; 18% and 19%, respectively. This is substantially more than Case and Shiller could for a somewhat longer time-period in the cities Atlanta, Dallas, and San Francisco, but about the same as what they could for Chicago. It is possible to improve the explanatory power by including more lags, but it is immaterial to the purpose at hand. Second, our intercept estimate is much higher than theirs. The magnitude of the intercept is both statistically significant and economically important. Economically, it is indicative of fairly uniform index growth over the period; i.e. that index changes are of similar magnitude and sign in the real log index in Oslo throughout the period. In other words, the large intercept estimate is evidence of a period of homogeneous price development. It does summarize a period in which most changes in real log index were large, positive, and about the same magnitude.

We go on to notice that while Case and Shiller reported positive slope estimates, our estimated slope coefficients are negative for both regressions. This is largely due to the fact that our intercept estimates are much larger than theirs. However, let us not be confused by the sign of the slope estimate. It reveals a change of tendency of index change magnitude rather than the sign of index change itself. In order to see this, observe that a positive index change would tend to be followed by a positive, but smaller, index change. For example, in our sample most changes in real log index were smaller than 0.20, and many around 0.10, so as an example predicted real log change in index B based on a 0.10-change in the index of sample A, or vice versa, would become 0.166 - 0.281 (0.10) = 0.166 - 0.0281 = 0.1379. A 0.20-change in index of sample A, would yield a prediction of 0.166 - 0.281 (0.20) = 0.110. So large changes are followed by small changes, and small changes by somewhat larger changes. At the same time, negative index changes tend to be followed by positive index changes that are larger than the intercept. For example, an index change of - 0.10 would be followed by 0.166 - 0.281 (-0.10) = 0.1941. In other words, despite the sign of the slope, typically, positive real log increases in one period predict real log increases that are somewhat smaller in the next period.

Table 1. Regression of changes in real log index from one half of the sample onto changes in real log index from the other half of the sample, Oslo, 1991 III - 2002 IV

<table>
<thead>
<tr>
<th>Estimates</th>
<th>j=B, k=A, L=0</th>
<th>j=A, k=B, L=0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept, $\beta_0$</td>
<td>0.0105 (2.00)</td>
<td>-0.0062 (-1.08)</td>
</tr>
<tr>
<td>Slope, $\beta_1$</td>
<td>0.920 (29.4)</td>
<td>1.0393 (29.4)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.956</td>
<td>0.956</td>
</tr>
</tbody>
</table>

L=4, 4-quarter lag

<table>
<thead>
<tr>
<th>Estimates</th>
<th>j=B, k=A, L=4</th>
<th>j=A, k=B, L=4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept, $\beta_0$</td>
<td>0.166 (9.7)</td>
<td>0.171 (9.4)</td>
</tr>
<tr>
<td>Slope 4th lag, $\beta_1$</td>
<td>-0.281 (-2.9)</td>
<td>-0.314 (-2.9)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.184</td>
<td>0.192</td>
</tr>
</tbody>
</table>

Note: We divide the original sample into two halves, randomly. We then estimate indices based on both half-samples and adjusted for price changes. The result is a real log index, $W_j$, where the subscript $j$ refers to either sample A or sample B.
Since it would be interesting and perhaps illuminating to the reader to see how we may utilize a linear time trend in stead, we supplement the Case-Shiller methodology with a simple analysis of fluctuations around a linear trend with the non-log index. The way we go about doing this is straightforward. First, we compute the indices, i.e. the non-log indices, and regress the index-points onto a counting variable of quarters in order to extract a linear trend of the index. We then compute the differences between the index and its trend, and use the deviations in the second stage of regression, reported in Table 2. This second stage involves regressing the deviations extracted from the linear trend of one half of the sample onto similar linear trend deviations from the other half, without or with a lag of 4 quarters. The graphical representation of these trends is presented in Figure 1.

Figure 1. Index A and B and Their Linear Trends

We start out by using no lags because this, again, serves as a check on the similarity of the two halves of our sample. We observe from Table 2 that $R^2$ is as large as 0.97 and that slope coefficients are 1.01 and 0.97.

Doing the analysis in this way, we find even more intuitive estimation evidence for and visual imprints of the existence of inertia. House price index changes do come with time persistence. We can say this on the basis of observing that the slope estimates when lagged index B changes are used to predict (leading) index A changes, and vice versa. The estimated slope coefficients are 0.485 and 0.492, respectively. The interpretation is that any given index change away from trend leads to a subsequent, similar index change. A given index deviation away from trend is followed one year after by a similar deviation away from trend, i.e. same sign of deviation, but $\text{half}$ the size of the original one. The sign is indicative of inertia, and the magnitude, which is smaller than unity, is indicative of a reversion towards trend. The t-values are 4.4 and 4.8, respectively; representing statistically significant estimates. The visual impression is clear: Whenever the index passes its trend, it stays away from the trend for sometime, until it again passes the trend. The index stays above or below trend for quite some time. Recall, conversely, that the visual picture of efficiency is no such pattern, only unsystematic and high-frequent fluctuations around trend, without time persistence. These regressions come with rather large explanatory power, $R^2$, of 0.31 and 0.35, which tells us that even if the apparatus is the simplest possible, it does detect explainable patterns in the index development over time.
\[ DI_a(t) = \beta_0 + \beta_1(DI_b(t-L)) + u, \ t=1991 \text{ III to 2002 IV}, \text{ DI represents deviation from linear trend, DI = linear trend prediction-index point} \]

<table>
<thead>
<tr>
<th>Estimates</th>
<th>Index Diff. A on Index Diff. B</th>
<th>Index Diff. B on Index Diff. A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept, ( \beta_0 )</td>
<td>-6.6214E-17 (0.00)</td>
<td>5.8930E-17 (0.00)</td>
</tr>
<tr>
<td>Slope, ( \beta_1 )</td>
<td>1.00673 (41.03)</td>
<td>0.968 (41.03)</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.974</td>
<td>0.974</td>
</tr>
</tbody>
</table>

\( L=4, 4\text{-quarter lag} \)

<table>
<thead>
<tr>
<th>Estimates</th>
<th>Index Diff. A on Index Diff. B</th>
<th>Index Diff. B on Index Diff. A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept, ( \beta_0 )</td>
<td>0.0356 (1.30)</td>
<td>0.0352 (1.36)</td>
</tr>
<tr>
<td>Slope 4th lag, ( \beta_1 )</td>
<td>0.485 (4.42)</td>
<td>0.492 (4.80)</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.312</td>
<td>0.350</td>
</tr>
</tbody>
</table>

4b. Returns to Housing Investments
The analysis above demonstrates that the housing market's price index does not follow a martingale process since it contains forecastable elements. This is the key issue in the efficiency question. However, a few qualifications must be made. First, the forecastability of index change in Table 2 may be due to forecastability of price increases in general. If general inflation is forecastable, so could house price inflation be, simply as an implication. That is why in our replication of Case and Shiller, our Table 1, we investigated real changes, not nominal. Second, as Case and Shiller point out, the forecastability may also be due to forecastability of interest rates and/or housing dividend. Thus, we account for the excess return to housing by controlling for interest rates and housing dividend.

In order to do so, we sophisticate our technique. Estimating housing dividend is non-trivial. Case and Shiller assume that the average dividend-to-price ratio is equal to 0.05, and we follow their design (p. 129) and defined excess returns above in equation (9).1

For the convenience of the reader, we plot in Figure 2 the relationship between housing dividend, i.e. implicit rent, as proportion of house value over time. We notice that rent, or dividend, does not keep up with the fast appreciation of housing value, so it plays a decreasing role as proportion of the house value over time. By visual inspection, interestingly, the development looks forecastable.

**Figure 2. Time Development of Housing Dividends Measured as Rent's Proportion of House Value, Oslo, 1991/3-2002/4**

---

1 ER\( _j(t) = \{ I_j(t + 4)/I_j{(t)} - 1\} + C_j(\{ R_t + \ldots + R_{t+4}\}/4)/I_j{(t)} - (1 - \tau)r(t)/100. \) In the computation, we set tax deduction rate \( \tau \) equal to 0.28 and we set, for practical purposes, variable mortgage interest rate \( r(t) \) to the central bank rate plus one percentage point.
In Figure 3 we plot excess return against time, and may observe how it reveals periodicity. Both peaks and lows appear to be reached some time after the preceding one. To demonstrate one aspect of the periodicity, we may start with a simple exercise. Average returns in the 1st, 2nd, 3rd (the starting quarter of the dataset, the third quarter of 1991), and the 4th quarter, respectively, for sample A are 0.057 (1), 0.106 (2), 0.129 (3), and 0.131 (4). Even if these 1-year returns average out the different returns for seasons, it illustrates that one may be better off entering the house market at specific times in the year. In particular, entering the market in February, the 1st quarter, gives you the smallest returns the following year. Purchasing just
before Christmas, e.g. appears to lead to a Christmas gift in the form of large 1st-year-return on your investment.

Table 3. Regression Results (t-values) of One-Half Sample Returns on Other Half Sample Return

\[ \text{ER}_j(t) = \beta_0 + \beta_1 \text{ER}_k(t-L) + u(t), \; j \neq k \]

<table>
<thead>
<tr>
<th>Estimates</th>
<th>Returns A on Returns B</th>
<th>Returns B on Returns A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept, ( \beta_0 )</td>
<td>0.00159 (0.2)</td>
<td>0.00918 (1.2)</td>
</tr>
<tr>
<td>Slope, ( \beta_1 )</td>
<td>1.0121 (20.1)</td>
<td>0.907 (20.1)</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.918</td>
<td>0.918</td>
</tr>
<tr>
<td>( R^2 ) Adj.</td>
<td>0.916</td>
<td>0.916</td>
</tr>
</tbody>
</table>

\[ L=4, \text{4-quarter lag} \]

<table>
<thead>
<tr>
<th>Estimates</th>
<th>Returns A on Returns B</th>
<th>Returns B on Returns A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept, ( \beta_0 )</td>
<td>0.154 (6.9)</td>
<td>0.148 (7.2)</td>
</tr>
<tr>
<td>Slope 4th lag, ( \beta_1 )</td>
<td>-0.194 (-1.4)</td>
<td>-0.158 (-1.3)</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.0534</td>
<td>0.0459</td>
</tr>
<tr>
<td>( R^2 ) Adj.</td>
<td>0.0272</td>
<td>0.0194</td>
</tr>
</tbody>
</table>

\[ a \] The estimated standard error is 0.136. The estimated standard error is 0.121.

In Table 3, we cross regress excess returns on lagged excess returns and observe that there exists potential for forecastability, even if not as clear as in the case of index changes. The values of the intercept are large, 6.9 and 7.2, respectively, but those of the slope coefficients smaller at -1.4 and -1.3. Still, the overall impression is one of forecastability. More lags than merely the 4-quarter lag, would increase the explanatory power increases substantially. However, our since our purpose here is not to maximize explanatory power, but demonstrate the existence of it, we do not include such an analysis.

4c. Strategic Trading, Intra-Market Efficiency, and Inter-Market Efficiency

Gatzlaff and Tirtiroglu (1995) emphasize the notion of efficiency being connected to the notion of profitable trading rules or timing rules. However, when the housing market is characterized by rapid appreciation, compared to other assets, it is not obvious exactly why one would or how one would establish a multiple-switching trading rule. Even when the housing asset appreciates less than it has before, or will in the future, it appreciates more than comparable objects in other markets. This is a sometimes overlooked issue, and we suggest below that efficiency analysis include not only an intra-market efficiency concept, but also an inter-market efficiency idea.

We take the former to mean a market that follows a martingale process and disallows profitable trading rules when trading is limited to the market in question. However, when an asset type appreciates as fast as housing did in the period 1991-2002, where our index A increases 246 percent and our index B increases 271 percent, and one has established that the market does not follow a martingale process, it is quite easy to establish a default profitable trading strategy. The strategy is the simplest possible: "Acquire as many assets as early as possible and hold onto them as long as you can." Even if it may be difficult, then, to establish profitable multiple-switching trading strategies that beat the default one, simply because the asset appreciates much in the period of not holding the asset, we would be hard-pressed to categorize such a situation as one consistent with efficiency. However, in order to argue that it is not consistent with efficiency, we need to extend our efficiency idea to the latter, i.e. an inter-market efficiency idea.
With the term inter-market efficiency we understand a collection of markets that all follow martingale processes, disallow profitable trading rules and in addition demonstrates a risk-return relationship over assets. In other words, this term is reserved for markets that do not yield higher return without higher risk.

**Figure 4. The stock market index and housing market index A and B, Norway, 1991-2002**

![Graph showing time development of stock market index and housing market indices](image)

In Figure 4, we show the development of the stock market index and our two housing market indices. We use the housing indices themselves, not the excess return, because in this comparison we do not require agents to live in the objects they purchase for portfolio return reasons.\(^2\)

**Table 4. Risk and Return for Two Norwegian Assets, Stocks and Housing, 1991-2002**

<table>
<thead>
<tr>
<th>Typical Quarterly Return</th>
<th>Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu = (\frac{4\hat{I}<em>{last}}{I</em>{First}} - 1) \times 100 )</td>
<td>( V = (1/45) \sum_{t=2}^{46} (I_t / I_{t-1} - \mu)^2 )</td>
</tr>
</tbody>
</table>

\(^2\) We could, of course, include the difference between rents and interest payments, had we assumed, plausibly, that even investors and speculators rent out their acquired objects to tenants while servicing monthly debt by monthly rent. Notice, however, that this actually would accentuate, not weakened, the results we present. To see this, recall that both acquiring stocks and acquiring housing objects require financing, either from own equity or bank loans. Thus, one could include interest payments in both or exclude them in both. Including them would favor returns to housing because housing dividends recently have been larger than stock dividends. In fact, lately stock dividends are not the preferred method of return; stock buy-backs are, an activity which shows up in the stock price and index themselves.
<table>
<thead>
<tr>
<th>Oslo Stock Index, OSEAX</th>
<th>1.199</th>
<th>131.861</th>
</tr>
</thead>
<tbody>
<tr>
<td>Housing Index A</td>
<td>2.798</td>
<td>38.771</td>
</tr>
<tr>
<td>Housing Index B</td>
<td>2.957</td>
<td>26.339</td>
</tr>
</tbody>
</table>

We observe in Table 4 that although stocks have a respectable quarterly increase in value, it is dwarfed by the increases of housing indices. At the same time, since stocks comprise the more volatile asset, we cannot say these two markets demonstrate inter-market efficiency. The reason why is that one asset, housing, has higher returns while lower risk. Inter-market efficiency would include mechanisms where the housing sector attracted investors from the stock market, and in doing so, equalized the risk-return ratios. This concept is inspired by the idea of a price discovery approach to market efficiency; suggested by Barkham and Geltner (1996) and is fairly obvious: investors compare risk-return relationships across the spectrum of asset types.\(^3\)

5. Discussion
Both Case and Shiller and this article suppress the additional complexity posed by maintenance costs. It is, of course, not necessarily relevant to the martingale hypothesis, unless including it obscures the forecastability substantially. That is highly unlikely. If anything, maintenance is highly forecastable since it is quite constant. However, including maintenance costs, may reduce the level of excess returns to housing, and thus affect our inter-market efficiency idea. Having allowed for that possibility, we believe the effect is likely to be too small to change our results on the inter-market efficiency verdict. It would only modify the discrepancy between housing returns and stock returns. To see why, consider typical maintenance costs. They are likely to be less than half a percentage of the house value per quarter since even a two percent annual maintenance cost may be at the higher end. Then, since the difference between the stock market quarterly return and the returns of our indices are of magnitude 1.6 percent per quarter, an inclusion of a high estimate of maintenance cost would not change our conclusion. In fact, the maintenance costs may most likely be less than what we could call "landlord-profit", namely the mostly positive difference between rents (housing dividend) and interest payments. We left those out of the analyses in Table 4 for transparency and accessibility reasons. Our results are most definitely intact and are not sensitive to maintenance costs.

On the other hand, the way we approach dividend estimation is only one of several possible. For example, the ratio of 0.05 that Case and Shiller use, may be questioned. More importantly, the relationship between the rent tenants pay to landlords and what implicit rent homeowners reap, is a contestable one. First, as Røed Larsen and Sommervoll (2006) demonstrate, rents include risk premia and option prices that do not apply to the owners' market. Thus, the development of observable rent for tenants is not necessarily representative of the development of implicit rent for owners. Second, rental indices are based on rented objects. Rented objects are typically small and with modest standard. They may not represent owned objects, which often are much larger and with higher standard. This would be a general objection to combining house price indices as one part of the excess return formula (the capital gains part) and rental indices as another part of the excess return formula (the dividends part). However, our OBOS dataset includes objects that are most likely fairly

\(^3\) Granted, there are entry-costs in the housing market that are substantially larger than in the stock market, for example transaction fees. However, considering the magnitudes involved, it appears obvious that for periods over more than a few quarters, investors would reap higher returns at lower risk by investing in houses.
similar to typical rental objects. In fact, the OBOS system mostly deals with types of housing objects that lie within the typical spectrum of rented objects, i.e. small, apartments with one, two or three bedrooms of size between 40 and 100 square meters.

This point is an important one, because in many studies the development of the rental index may not well capture the latent, unobservable development of implicit rent for homeowners. Out-of-sample predictions are notoriously difficult, and are most definitely so in the housing market. If the rental index development does not capture well housing dividend development, that part of our excess return analysis may be challengeable.

Last, one may wonder what degree of inefficiency would still count as fairly efficient. We say this because no market will ever attain complete efficiency, if for no other reason so for the logical one: If a market had been completely efficient, then all information would always immediately be included in prices, so no agent could beat the indices. Then, informed agents would know this, and choose not to participate in that activity. But absence of such agents would leave information not priced into market prices and then profit opportunities would emerge, making the markets inefficient. In other words, completely efficient markets preclude the very activity that makes the market efficient. Put differently, attacking market efficiency may be similar to attacking a straw man. The question is not whether or not markets are efficient or not, but rather how inefficient they are. Nobody has shown exactly how to classify markets by degrees of inefficiency. Thus, we are left with discretionary views based on analysts’ sense of relative magnitudes of risk-return differences and forecasting abilities. Our sense, for all it is worth, is that this article shows sufficiently large discrepancies between risk-returns and sufficiently forecastable nature of excess return to say that this housing market in this period actually was quite inefficient.

6. Conclusion and Policy Implications
We demonstrate that house price indices and returns based on the housing market in and around the Norwegian capital, Oslo, for the period 1991-2002 do not appear to follow martingale stochastic processes. Since martingale-processes are hallmarks of efficient markets, this is evidence that the market is inefficient and contains a portion of forecastable elements. The procedure we employ was originally developed in Case and Shiller (1989), in their seminal article on the American housing market's efficiency. It consists of several stages. First, we partition our sample of repeated-sales transactions into two. Second, we construct heteroskedasticity-checked repeated-sales indices for each sample. Third, we use lagged price development from one sample to predict price development in the other sample. This third stage would reveal no forecastability had the process been following a martingale. Conversely, when the process is not following a Martingale, then time structure is revealed. We find the latter, and demonstrate that there do exist forecastable parts of the house price development.

Subsequently, we ask whether the forecastability is due to forecastability of interest rates and/or housing dividends by examining the excess returns to housing. The excess return includes capital gains plus implicit rent minus interest payments, where the latter is adjusted for tax deductions. Again, we reject the null hypothesis of excess return not showing inertia and time-persistence, although not as clearly as in the case of housing index changes. In other words, excess return is somewhat forecastable and displays recognizable patterns over time. Observers may beat the martingale prediction by exploiting the time history of the series. This is evidence consistent with classifying the housing market as inefficient.
We then proceed to explore the possibility of establishing successful strategic trading devices. Since the housing market indices increase 246 and 271, respectively, percent in the 1991-2002 period, the simplest trading rule is profitable. We say this is inconsistent with intra-market efficiency. Moreover, the returns differed greatly across seasons, with early spring being a bad time for purchasing and late fall/early winter being a good time for purchasing. This seasonal effect cannot be consistent with efficient markets. However, because multiple-switch strategies are difficult to construct in a market where the asset appreciates much, compared to other types of assets, even when it appreciates less, compared to its own history, we extend the intra-market concept with an inter-market one. We find that the housing market indices had quarterly increases much above the quarterly increases in the stock market, and with much less volatility. It appears as if the housing market can deliver what is most attractive: high return and low risk.

This behavior of the house prices may seem puzzling to professionals and profit-seeking investors. Normally, as Malkiel (2003) points out, efficient markets lead to a trade-off between risk and return. If an agent seeks higher expected return, she must accept higher risk. The opposite definitely constitutes a violation of this more intuitive sense of efficiency, and in our terminology it is inconsistent with inter-market efficiency.

The ramifications are potentially large. An inefficient housing market may cause large inter-generational equity differences. Speculators may make much money. Latecomers may stay poor over the course of their lifetime. Early entrants may be much wealthier than comparable counterparts from later cohorts. Perhaps more alarming to economists, inefficient housing markets may also lead to macroeconomic disturbances and across-the-spectrum misallocation of scarce production resources if the inefficiency leads first to over-shooting and then under-shooting of prices. The latter can happen for a number of reasons, including simply over-investment in the construction sector. The former can also emerge for several reasons, one being a wealth effect. If the wealth effect from housing wealth is large, non-linear, and heterogeneous across household types, then financial instability may follow dramatic shifts in house prices. Since this article has shown that the housing market displays time-persistence and inertia, a large run-up in prices may very well one day be followed by the opposite. This instability of price development in one market may imply larger financial instability of the whole economy. Thus, knowing whether a market is efficient or inefficient is highly interesting to economists and policy-makers. Intriguingly, potentially, inefficiency markets may be better managed when organized than when left alone. In other words, inefficient markets may inspire policymakers to regulate. The truly difficult question is: How?

References


Appendix

**Figure A1: Quarterly Development of Oslo Stock Index and Housing Index A and B**