Discussion Papers No. 506, June 2007 Statistics Norway, Research Department

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 data from the Norwegian housing market in its capital, Oslo. We employ the Case-Shiller time-persistence-test on a repeated-sales model of a house price index and returns to housing. Our data cover the period 1991-2002 and comprise 20 752 transactions of same-object-repeated-sales. We explain why certain features, sometimes suppressed in earlier tests, of the data set are of importance in efficiency tests, and argue that ours is particularly well-suited for the purpose. We 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. Both the house price index and housing 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 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 over the period, which is inconsistent with inter-market efficiency.

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

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

Acknowledgement: The authors wish to thank participants at the 2007 Annual Meeting of Norwegian Economists in Tromsø for comments and suggestions. In addition, valuable input was obtained from participants at presentations at the 2007 ENHR Meeting in Edinburgh and at Statistics Norway. All merits must be shared with the commentators. In particular, we are grateful to Terje Skjerpen for pointing out several inaccuracies. Any shortcomings are, of course, the full responsibility of the authors.

Address: Erling Røed Larsen, Statistics Norway, Research Department.

E-mail: erling.roed.larsen@ssb.no

Steffen Weum, Statistics Norway, Research Departement. E-mail: steffen.weum@ssb.no

Discussion Papers

comprise research papers intended for international journals or books. A preprint of a Discussion Paper may be longer and more elaborate than a standard journal article, as it may include intermediate calculations and background material etc.

Abstracts with downloadable Discussion Papers in PDF are available on the Internet: http://www.ssb.no http://ideas.repec.org/s/ssb/dispap.html

For printed Discussion Papers contact:

Statistics Norway Sales- and subscription service NO-2225 Kongsvinger

Telephone: +47 62 88 55 00 Telefax: +47 62 88 55 95

E-mail: Salg-abonnement@ssb.no

1. Introduction

Recently, many homeowners have made more money asleep in their homes than at work in their offices. 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 worried 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 (implicit rent), and interest payments; are forecastable, and this finding is inconsistent with "weak form efficiency". Additionally, 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 market, 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 dataset 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 be mostly avoided; 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. To see this, recall that one important part of excess return is the implicit rent. However, the precision of computing developments of implicit rent for owner-occupied housing by using developments in the rental market, depends crucially on the links between the owners' market and the renters' market. This problem of excess return computation has not been given much attention in the literature. For example, Case and Shiller (1989) do not mention it, and a search trough the literature failed to find a precise description of the problem. Thus, let us emphasize the difficulty. 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 challenge is that the owner-occupied housing market may be quite different from the rental market, so that indices from the latter do not well reflect 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, two or three bedrooms and of size ranging from 40 to 100 square meters, mostly situated in city centers or around universities. To get a sense of the issue, consider the fact that in 2001 in Norway, the size of an

average owned object was 127.0 square meters while it was 79.7 for a rented one. In comparison, our dataset on owned objects in Oslo, indicate that average size was 67.4 square meters for the ones sold in 2001. In other words, if size is an indicator of type, our use of the rental index to estimate implicit dividends from avoided rents appears fairly well-grounded.

Nevertheless, the first two criteria mentioned above are of particular, and potentially underestimated, importance. To see the importance, consider first datasets that cover multiple housing markets and labor markets. Then, when analysts 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 may not be too damaging, but for efficiency tests, it is. 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. Then, analysts may not realize that the forecastability of the housing market is due to forecastability of the labor market. In our analysis, we use data only from around Oslo, a region whose modest size of about half a million indicates that it functions as one labor market, within which workers residing in any location can commute to every work-place location.

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, 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 demonstration of inherent bias from ripple effects in indices that cover several sub-regions in what is considered one region. 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 within one specific region. This article does the latter, as it employs a data set with fairly homogeneous objects.

-

¹ Our brief computations are based on Norwegian data. Statistics Norway collected, in an exhaustive scrutiny, information on all housing objects in the economy in 2001. A total of 1 221 570 objects were reported. Of these, 76.7 percent were owned and 23.3 percent were rented. Reports were only available to us for number of objects within size categories, so we used the mid-point for each category in our weighted (using frequency as weight) computations of average size. For the first category, objects below 30 square meters, we used 30, and for the last, objects above 200 square meters, we used 200.

This insistence upon data quality in efficiency tests arises from the importance of the purpose. Knowing whether housing markets are efficient or not, or more precisely knowing what kind of processes govern house prices, appears adamant to every economic agent since purchasing a house is the most important decision most of them ever do. Thus, 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 characterize 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 join the larger debate on the basis for profits in real estate investment strategies. Shiller (2003) and Malkiel (2003) span the spectrum of positions in that debate, the latter taking the role of efficiency proponent and the former the role of the skeptic. Our investigation can be read as a re-joiner using recent Norwegian evidence.

It is convenient for the reader to get an overview over how we structure our reasoning, so let us say where we are heading. In the next section, we give a brief overview of some of the recent literature on the efficiency question. We proceed to introduce the core parts of the efficiency-testing methodology and how we construct our repeated-sales indices. The fourth section describes our data. The fifth section reports empirical results. We go on 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 seventh section concludes and presents policy implications.

2. Efficiencies, price patterns, and bubbles in the literature

The long-standing efficiency debate is intimately connected to today's debate of bubbles. 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 (2006) detect no evidence for any recent bubble in Britain. Rosenthal (2006) 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 a 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 explained by the development in 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 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".

Our 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 of, implicitly, making 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 varies 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.

3. Theory

Efficiency testing necessarily divides into three separate parts, each building upon the preceding element: 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:

(1)
$$E(y_{t+1} | \varphi_t) = y_t,$$

where $E(\cdot)$ is the expectations operator, y_t denotes the variable in question at time t and φ_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):

$$(2) y_t = y_{t-1} + \lambda_t,$$

where λ_t is modeled as 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 ρ is unequal to unity. Notice that $y_1 - y_{t-1}$ may or may not be white noise. The first difference, too, may follow a random walk or an AR(1) process, and if so, it follows that y_t itself has a given stochastic process. The essence of this, however, 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 we detect a time structure governing the process, then it becomes possible to use that time structure to outperform the forecast of the last period's magnitude.

The result of this is that, then, agents would be able to exploit historical data to estimate parameters in relations governing the mechanisms between the present and the past, and thus modify y_{t-1} as predictor. This takes the form of equation (3):

(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, i.e. that variables are above and below the expected value for longer than they should, if the mechanism is a Martingale. 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 timepersistence 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)
$$\log(p_{it}) - \log(p_{is}) = \gamma_2 T_{i2} + \gamma_3 T_{i3} + \dots + \gamma_{46} T_{i46} + \varepsilon_{it}, \quad i \in I; t, s, \in \{2, \dots, 46\}, T_{it} \in \{-1, 0, 1\}$$

(5)
$$u_i^2 = \alpha_0 + \alpha_1 Q_i + \omega_i, \quad w_i = \sqrt{\hat{u}_i^2}, \quad i \in I,$$

(6)
$$\left(\log \left(p_{it} \right) - \log \left(p_{is} \right) \right) / w_i = \gamma_2 \left(T_{i2} / w_i \right) + \dots + \gamma_{46} \left(T_{i46} / w_i \right) + \varepsilon_{it} / w_i, \quad i \in I; t, s \in \{2, \dots, 46\}, T_{it} \in \{-1, 0, 1\}.$$

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, γ and γ 's are index parameters to be estimated, and ε is an error term with zero-mean, and possibly non-constant variance caused by the drift mentioned above. Notice also that, for simplicity, I use the notation u_i^2 for the squared residuals from the OLS-regression in equation (4). 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 α 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 ω is a classic mean-zero, constant variance noise term, and w_i denotes the inverse of the weight applied to each observation in the third step. The larger w is, the larger is estimated variance, and the smaller is the weight, and w is obtained from taking the square root of the fitted variables of the OLS-regression of equation (5). In other words, equation (4) is the starting OLS-regression, equation (5) estimates the weights, and equation (6) is the resulting FGLSregression 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):

(7)
$$W_i(t) = \log(I_i(t)) - \log(CPI(t)), j \in \{A, B\}, t \in [1991III, 2002IV].$$

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 (inverting the log-form) index for sample j at time j, which shows the increase of the index at that time in terms of multiples of the index in the starting period j. Notice that we enumerate quarters using roman numbers. In other words, j is given by the estimated j and j 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):

(8)
$$W_{i}(t) - W_{i}(t-4) = \beta_{0} + \beta_{1} ((t-4) - W_{k}(t-4-L))(W_{k}) + u(t), \quad j,k \in \{A,B\}, j \neq k,$$

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. Observe that we use annual change, not quarterly, in order to avoid picking up seasonal effects. Notice, also, 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, and vice versa of index B on index A. 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. The absence of inertia 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 better than simply using last period's level, 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):

(9)
$$ER_{j}(t) = \left\{ I_{j}(t+4) / I_{j}(t) - 1 \right\} + C_{j} \left(\left\{ R_{t} + \dots + R_{t+4} \right\} / 4 \right) / I_{j}(t) - (1-\tau)r(t) / 100,$$

where R_t refers to the increase in a rental index from t-1 to t, r(t) denotes the mortgage interest rate, and τ is the proportion of interest payments that is tax deductable. The excess return, then, consists of three elements: i) the capital gains from house price appreciation (or capital loss from house price depreciation) 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 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 $(R_1E + ... + R_4E)/4 = E(R_1 + ... + R_4)/4$. This avoided rent is part of the return, and it is measured as a proportion of purchasing price P, $\{E(R_1 + ... + R_4)/4\}/P$. 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. $\{E(R_2 + ... + R_5)/4\}/(P*I_2)$, where house value is multiplied by the house price index. This amounts to saying that housing dividends next 4 quarters at t are $C(R_t + ... + R_{t+4})/I_t$, 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, for our period the computation becomes $(1/46)\sum_{t=0}^{46} C(R_t + ... + R_{t+4})/I_t = 0.05$, 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.

4. 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"², 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. OBOS keeps a register of all objects, each object uniquely identified. Every financial transaction is monitored, and 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 analysis, 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 20 804 sales of one object sold at least and at most twice. These transactions correspond to 10 402 objects rendered available for the Case-Shiller method. 26 observations contained obvious registration errors and were omitted. This left us with 10 376 pairs of sales, i.e. 20 752 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 (shared debt) in the cooperative. In addition, we have complete information on geographical coordinates for each object as well as the construction year.

Above, we suggested six 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, it should be small enough to reduce inter-temporal ripple effects across different sub-areas within the coverage area, and it should consist of objects similar to the object from which the rental index is derived. As far as we can judge, the OBOS data appear to satisfy all six fairly well, and let us re-iterate and expand our substantiation of the first and the second. Oslo is a small city with only a little more than 500 000 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 datasets 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 the 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 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.

5. Empirical Results

5.1. Testing the Efficiency Hypothesis

We start exploring data by replicating Case and Shiller's regression of 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. The regressions then serve as a validity check for the idea of a homogeneous sample of objects. From Table 1, we see that 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, the R^2 is 0.96.

Then, we proceed to perform regressions with time lags, and choose as Case and Shiller to employ 4-quarter lags. Observe first, in Table 1, 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 find for a somewhat longer time-period in the cities Atlanta, Dallas, and San Francisco,

but about the same as what they could find for Chicago. It is possible to improve the explanatory power by including more lags, and we did, but since it is immaterial to the purpose at hand we do not report the results. 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, we should 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 real log index change itself. In order to see this, observe that a positive real log index change would tend to be followed by a positive, but smaller, real log 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, would become 0.166 - 0.281 (0.10) = 0.166 - 0.0281 = 0.1379. A 0.20-change in real log 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 real log index changes tend to be followed by positive real log index changes that are larger than the intercept. For example, a real log 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.

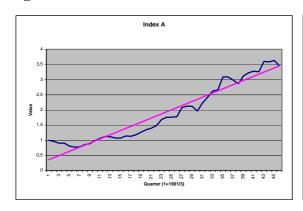
Table 1. Regression of changes in real log index from one half of the sample onto changes in real log index from the other half of the sample, Oslo, 1991 III - 2002 IV

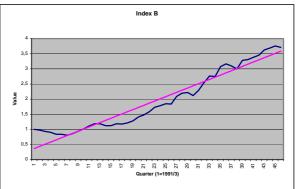
| $W_{j}(t) - W_{j}(t-4) = \beta_{0} + \beta_{1} \left(W_{k}(t-L) - W_{k}(t-4-L) \right) + u(t), t = 1991 \text{ III to } 2002 \text{ IV}; j, k \in \left\{ A, B \right\}, j \neq k$ | | | | |
|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------|-----------------|--|--|
| L=0, no lag | | | | |
| Parameters | j=B, k=A, L=0 | j=A,k=B,L=0 | | |
| Intercept, β_0 | 0.0105 (2.00) | -0.0062 (-1.08) | | |
| Slope, β_1 | 0.920 (29.4) | 1.0393 (29.4) | | |
| \mathbb{R}^2 | 0.956 | 0.956 | | |
| L=4, 4-quarter lag | | | | |
| Intercept, β ₀ | 0.166 (9.7) | 0.171 (9.4) | | |
| Slope 4^{th} lag, β_1 | -0.281 (-2.9) | -0.314 (-2.9) | | |
| \mathbb{R}^2 | 0.184 | 0.192 | | |

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. Estimates are cited for same number of significant digits after the decimal point.

Since it would be interesting and perhaps illuminating to the reader to see how we may utilize a linear time trend instead of the logarithmic model, and since such an exercise would serve as a quick sensitivity check as well, we supplement the Case-Shiller methodology with a simple analysis of fluctuations around a linear trend with the non-log (inverted) 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. The linear trends are depicted in Figure 1. 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.

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 estimated to be 1.01 and 0.97.

Doing the analysis in this way, without the variance-reducing feature of the logarithm, 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 deviations, 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 of smaller size than the original one. The sign is indicative of inertia, and the magnitude of the estimated coefficient, 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. An example clarifies. Say the index change at one point was 0.2 (as it was from the 22nd quarter to 23rd). The predicted next quarter change becomes: 0.036+0.49(0.2)=0.134. The predicted change for the next quarter has the same sign, but smaller size, than does the previous quarter. 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 highfrequent fluctuations around trend, without time persistence. These regressions come with rather large explanatory power, R², 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.

Table 2. Regression Results (t-values) of One-Half Index Changes Estimated with Regressions on Other-Half Index Changes

| $D_a(t) = \beta_0 + \beta_1 (D_b(t-L)) + u$, $t = 1991$ III to 2002 IV, D represents deviation from linear trend, |
|----------------------------------------------------------------------------------------------------------------------|
| i.e. linearly predicted point minus actual index point |

| L=0 , no lag | | | | |
|-------------------------------|----------------------------|-----------------------------------|--|--|
| Estimates | Deviation A on Deviation B | Deviation B on Deviation A | | |
| Intercept, β_0 | -6.6214E-17 (0.00) | 5.8930E-17 (0.00) | | |
| Slope, β_1 | 1.00673 (41.03) | 0.968 (41.03) | | |
| \mathbb{R}^2 | 0.974 | 0.974 | | |
| L = 4 L=4, 4-quarter lag | | | | |
| Intercept, β_0 | 0.0356 (1.30) | 0.0352 (1.36) | | |
| Slope 4^{th} lag, β_1 | 0.485 (4.42) | 0.492 (4.80) | | |
| \mathbb{R}^2 | 0.312 | 0.350 | | |

5.2. 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 in 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 define excess returns above in equation (9).²

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 the same pace as 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. The

18

 $^{^2}$ ER_j(t) = $ER_j(t) = \left\{I_j(t+4)/I_j(t)-1\right\} + C_j\left(\left\{R_t+...+R_{t+4}\right\}/4\right)/I_j(t) - (1-\tau)r(t)/100$. In the computation, we set tax deduction rate τ 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.

clear downward trend is due to the fact that, in this period, rents increase more slowly than houses appreciate, so housing dividends by definition must decline.

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

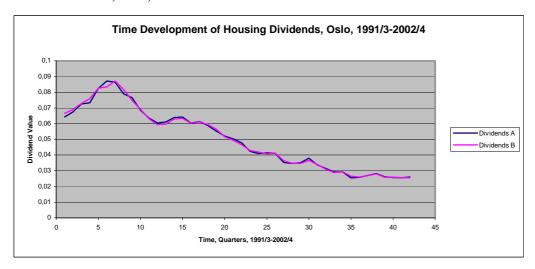
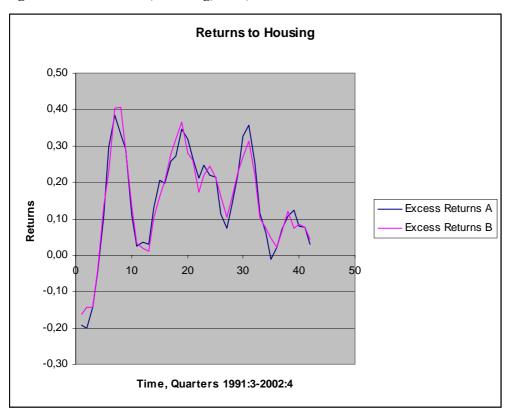


Figure 3. Excess return, Housing, Oslo, 1991/3-2002/4



In Figure 3 we plot excess return against time, and may observe how it reveals periodicity. Both peaks and troughs appear to be reached some time after the preceding one, with some regularity. To demonstrate one aspect of the periodicity, we may start with a simple exercise. Average 4-quarter-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 0.161 (1), 0.154 (2), 0.133 (3), and 0.132 (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.

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

| $ER_{j}(t) = b_{0} + b_{1}ER_{k}(t - L) + u(t), j \neq k$ $L = 0, \text{ no lag}^{a}$ | | | | |
|---------------------------------------------------------------------------------------|-----------------------------|----------------|--|--|
| | | | | |
| Intercept, b ₀ | 0.00795 ^b (0.76) | 0.00817 (0.76) | | |
| Slope, b_1 | 0.965 (19.07) | 0.943 (19.07) | | |
| \mathbb{R}^2 | 0.910 | 0.910 | | |
| R ² Adj. | 0.908 | 0.908 | | |
| | L=4, 4-quarter lag | | | |
| Intercept, b ₀ | 0.218 (8.49) | 0.213 (8.60) | | |
| Slope 4^{th} lag, b_1 | -0.277 (-2.24) | -0.253 (-2.18) | | |
| \mathbb{R}^2 | 0.123 | 0.116 | | |
| R ² Adj. | 0.0984 | 0.0917 | | |

^aWe use n = 38 for comparison, i.e. the same dataset as in L = 4, where the first 4 observations must be deleted.

In Table 3, we regress excess returns from one sample on lagged excess returns from the other sample, and observe that there exists potential for forecasting since both the intercept and the slope coefficients for the lagged version, L=4, demonstrate statistical significance. In fact, we can reject the null hypothesis of a martingale process. The high adjusted R^2 of almost 0.1 for excess returns from sample A on lagged excess returns on sample B, underlines that historical patterns can be exploited for forecasting purposes.³ The interpretation of the estimated magnitudes of the coefficients is also interesting, and uncovers the economic importance. A typical return of 0.16 is followed by a return of

^bWe use 3 significant digits after the decimal point.

⁻

 $^{^{3}}$ Moreover, recall that we may increase R^{2} if we include more lags. That, however, is not the purpose of our study. We aim only at demonstrating the existence of forecastability, not the degree.

0.218 - 0.277 (0.16) = 0.17. According to our estimated process, a small return of 0.05 would be followed by a large one, 0.2; and a large return of 0.2 would be followed by a smaller one, 0.16.

5.3. 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. Why would an investor sell an object that appreciates more than other objects? In our dataset, even when the housing asset appreciates less than it has before, or will in the future, it may appreciate more than comparable objects in other markets. This is a neglected issue, probably because the rarity of an object appreciating as much as housing has done recently, and we suggest below that efficiency analysis should 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 that, at the same time, the same market 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 trivial 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 (buy-sell-buy-...) trading strategies that beat the trivial one, simply because the asset appreciates much compared to other objects even when it appreciates relatively little compared to its own history, 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.

-

⁴ Some economists insist upon the condition that a most-profitable trading rule must involve multiple trades as a hallmark of inefficiency. One argument typically points toward the difficulty of constructing stopping criteria if this condition is ignored. To see why, recall that a multiple-switch trading strategy specifies when to sell and when to buy so that the trader will exit and enter several times, and per definition must be out of the asset once in a while. The trivial rule of purchasing and holding does not demonstrate when to stop; when stop is defined as selling. However, the problem lies not with the trivial strategy but with the insistence upon multiple-switches. To see this, consider two time series of excessive returns to an asset: (... +2, +6, +2, +6, ...) and (... +12, +16, +12, +16, ...). Consider a constant return to the alternative asset of +4. In the former case, a profitable trading rule would involve purchasing at the end of the low-return period, sell (e.g. stop) at the end of the high-return period, then hold the alternative asset for the duration of the low-return period, then repeat. This would not be the case in the latter case, where the trivial rule of purchasing, then holding, is more profitable than selling at the end of the high-return period and entering the alternative asset, despite the same absolute variation of excess returns. It would seem peculiar if one, then, would say that the former passes a criterion of inefficiency because of multiple-switches, but that the latter does not because of no switches.

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 should be reserved for markets that do not yield higher return without higher risk.

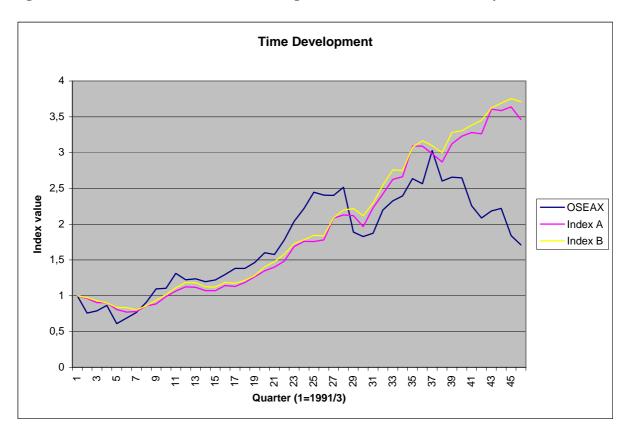


Figure 4. The stock market index and housing market index A and B, Norway, 1991-2002

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.⁵

⁵ 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 weaken, 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 4. Risk and Return for Two Norwegian Assets, Stocks and Housing, 1991-2002

| | Typical Quarterly Return | Volatility |
|-------------------------|--------------------------------------------------------------|----------------------------------------------------|
| | $\mu = \left(\sqrt[45]{I_{last}/I_{First}} - 1\right) * 100$ | $V = (1/45) \sum_{t=2}^{46} (I_t/I_{t-1} - \mu)^2$ |
| Oslo Stock Index, OSEAX | 1.199 | 131.861 |
| Housing Index A | 2.798 | 38.771 |
| Housing Index B | 2.957 | 26.339 |

We observe from 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.⁶

6. 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 quarterly increases in the stock market index and the appreciation of our house price 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 direct flow of "landlord-profit", namely the mostly positive

⁶ 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.

difference between rents (housing dividend) and interest payments. 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. 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, even if our owned objects appear quite similar to rented ones in size, quality, and location. We re-emphasize the importance of this point. 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 excess return analysis may be challengeable.

Of course, it is possible to object to comparing this period's house price appreciation with this period's stock market gains since house prices have gained much in value over this period. Potentially, another period would demonstrate a smaller or a reversed relationship between the appreciation in the two markets. But then again, other periods may be characterized with other efficiencies or inefficiencies. After all, what we argue is that over a substantial period in time, 1991-2002, the housing market consistently outperformed the stock market and the return was less volatile. Granted, over a fifty-year period this may not be the case, and more normal relationships between risk and return may then be found. However, we are not saying in this article that houses always outperform stocks as an asset. We are saying they did in this period. We think this risk-return combination is inconsistent with intermarket efficiency within this period.

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, leading to contradictory statements. Put differently, attacking market efficiency and falsifying a null hypothesis

-

⁷ We left the differences between rents (housing dividend) and interest payments out of the analyses in Table 4 for transparency and accessibility reasons.

of a martingale process may be trivial. The question is not whether or not markets are efficient or not, because they are 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, and surprisingly, inefficient.

7. 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-adjusted 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. In other words, excess return is forecastable and displays recognizable patterns over time. Observers may improve upon the martingale prediction by exploiting the time history of the series. This is evidence inconsistent with classifying the housing market as efficient.

We then proceed to explore the possibility of establishing successful strategic trading devices. Since the housing market indices increase 246 and 271, percent in the 1991-2002 period, respectively, the simplest and trivial trading rule of keeping-and-holding is highly profitable. We say this is inconsistent with intra-market efficiency. Moreover, the returns differ across quarters, which opens up the

possibility of entry-timing. 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 that most attractive combination: high return and low risk. This is inconsistent with inter-market efficiency.

The ramifications, potentially, are large. An inefficient housing market may cause large intergenerational 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. This can happen for a number of reasons, including over-investment in the construction sector and psychologically unstable and self-reinforcing expectations of capital gains (or losses); see Shiller (1990). Macroeconomic disturbances can 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 and volatile aggregate demand may follow 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. Dramatic breakpoints can occur when the time path shows inertia and persistence. If the breakpoint is the most feared one, a price decline, a home may no longer be sweet to the owner, especially not if the owner want to relocate or sell for some other reason. The owner would feel trapped in his or her home because a sale would entail loss of equity. 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

Barkham, R. J. and D. M. Geltner (1996): Price Discovery and Efficiency in the UK Housing Market, *Journal of Housing Economics*, **5**: 1, pp. 41-63.

Cameron, G., J. Muellbauer, and A. Murphy (2006): Was There a British House Price Bubble? Evidence from a Regional Panel, Discussion Paper No. 276, Department of Economics, University of Oxford.

Case, K. E. and R. J. Shiller (1989): The Efficiency of the Market for Single-Family Homes, *American Economic Review*, **79**: 1, pp. 125-137.

Clapp, J. M. and C. Giaccotto (2002): Evaluating House Price Forecasts, *Journal of Real Estate Research*, **24**: 1, pp. 1-26.

Englund, P., T. M. Gordon, J. M. Quigley (1999): The Valuation of Real Capital: A Random Walk down Kungsgatan, *Journal of Housing Economics*, **8**, pp. 205-216.

Englund, P. and Y. M. Ioannides (1997): House Price Dynamics: An International Empirical Perspective, *Journal of Housing Economics*, **6**: 2, pp. 119-136.

Fama, E. F. (1970): Efficient Capital Markets: A Review of Theory and Empirical Work, *Journal of Finance*, **25**, pp. 383-420.

Fama, E. F. (1991): Efficient Capital Markets: II, Journal of Finance, 46, pp. 1575-1617.

Gatzlaff, D. H. and D. Tirtiroglu (1995): Real Estate Market Efficiency: Issues and Evidence, *Journal of Real Estate Literature*, **3**, pp. 157-189.

Gu, A. Y. (2002): The Predictability of House Prices, *Journal of Real Estate Research*, **24**: 3, pp. 213-233.

Hill, R. C., C. F. Sirmans, and J. R. Knight (1999): A Random Walk down Main Street, *Regional Science and Urban Economics*, **29**, pp. 89-103.

Himmelberg, C., C. Mayer, and T. Sinai (2005): Assessing High House Pries: Bubbles, Fundamentals and Misperceptions, *Journal of Economic Perspectives*, **19**: 4, pp. 67-92.

Hort, K. (1998): The Determinants of Urban House Price Fluctuations in Sweden 1968-1994, *Journal of Housing Economics*, **7**: 2, pp. 93-120.

Kim, K.-H. (2004): Housing and the Korean Economy, *Journal of Housing Economics*, **13**: 4, pp. 321-341.

Malkiel, B. G. (2003): The Efficient Market Hypothesis and Its Critics, *Journal of Economic Perspectives*, **17**: 1, pp. 59-82.

Meese, R. and N. Wallace (1994): Testing the Present Value Relation for Housing Prices: Should I Leave My House in San Francisco? *Journal of Urban Economics*, **35**: 3, pp. 245-266.

Rosenthal, L. (2006): Efficiency and Seasonality in the UK Housing Market, 1991-2001, Oxford Bulletin of Economics and Statistics, **68**: 3, pp. 289-317.

Røed Larsen, E. and D. E. Sommervoll (2006): The Impact on Rent from Tenant and Landlord Characteristics and Interaction, Discussion Paper 467, Oslo: SSB

Røed Larsen, E. and D. E. Sommervoll (2004): Inequality of Housing? Evidence from Segmented House Price Indices, *Housing, Theory, and Society*, 2004, **21**: 2, pp. 77-88.

Shiller, R. J. (2006): Long-Term Perspectives on the Current Boom in Home Prices, *The Economists' Voice*, **3**: 4. Available online: http://www.bepress/ev/vol3/iss4/art4.

Shiller, R. J. (2003): From Efficient Markets Theory to Behavioral Finance, *Journal of Economic Perspectives*, **17**: 1, pp. 83-104.

Shiller, R. J. (1990): Speculative Prices and Popular Models, *Journal of Economic Perspectives*, **4**: 2, pp. 55-65.

Sommervoll, D. E. (2006): Temporal Aggregation in Repeated Sales Models, *Journal of Real Estate Finance and Economics* **33**: 2, pp. 151-165.

Appendix

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

