Discussion Paper No. 10-004

Further Evidence on the (In-) Efficiency of the U.S. Housing Market

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Non-technical Summary

Research in real estate finance and economics has been dealing with the topic of efficiency in the U.S. housing market for over 25 years. However, most recent research either examines local markets based on single homes or focuses on the Conventional Mortgage Home Price Indices (CMPHI) and Federal Housing Finance Agency (FHFA) indices. To our knowledge, however, there does not yet exist any study based on the Case-Shiller indices. This is surprisingly given that the Case-Shiller indices have several advantages over the CMPHI and FHFA indices, particularly since they serve as the underlying of derivatives traded at the Chicago Mercantile Exchange.

This study examines the behavior of monthly house price changes for 20 cities in the U.S. and two nationwide indices from January 1987 to June 2009 incorporating both the long-lasting boom and the steep and strong downturn of the U.S. housing market. The conducted analysis gives empirical evidence that house price changes in the U.S. exhibit certain patterns. The results show that the return generating process of U.S. housing markets differs significantly from the theoretical model of the random walk hypothesis. Without any exception, the conducted tests reject the null hypothesis of a random walk for all time series of house price changes. Furthermore, trading strategies are implemented as a robustness check and support the findings by generating excess returns in comparison to a buy-and-hold strategy. In general, we can conclude that investors might be likely to earn excess returns by using past information in the U.S. housing market, in particular when standardized derivatives of the indices are traded on exchange markets. However, due to data limitations, the analysis does not conduct the tests based on prices and price changes in derivatives. This analysis would give further empirical evidence whether inefficiencies in the U.S. housing market are exploitable or whether they are incorporated into the pricing process of tradable products and are thus not exploitable by investors.

Das Wichtigste in Kürze

Die Analyse der Effizienzeigenschaften des US-amerikanischen Häusermarktes war in den letzten 25 Jahren immer wieder Gegenstand von wissenschaftlichen Untersuchungen. Allerdings beziehen sich die meisten Analysen entweder auf einzelne lokale Märkte und basieren auf Daten von Einzelimmobilien oder die Untersuchungen bedienen sich der Conventional Mortgage Home Price Indizes (CMPHI) sowie der Federal Housing Finance Agency (FHFA) Indizes. Dagegen existiert bisher keine Analyse auf Basis der Case-Shiller Indizes für den US-amerikanischen Häusermarkt. Dies ist umso erstaunlicher, da gerade diese Indexfamilie gegenüber den CMPHI und FHFA Indizes einige vorteilhafte Charakteristika besitzt; insbesondere dienen sie als Underlying für an der Chicago Mercantile Exchange gehandelte Derivate.

Dieser Aufsatz untersucht daher das Preisänderungsverhalten der Case-Shiller Indizes für 20 US-amerikanische Städte sowie zwei nationale Indizes über den Zeitraum von Januar 1987 bis Juni 2009. Dieser Zeitraum umfasst sowohl eine Periode stark steigender Hauspreise als auch die Phase stark fallender Hauspreise im Zuge der Finanzmarktkrise. Die durchgeführten parametrischen und nicht-parametrischen Testverfahren liefern empirische Evidenz, dass die Hypothese des Random Walks als Testverfahren auf Markteffizienz für die US-amerikanischen Häusermärkte auf dem 1 %-Signifikanzniveau abgelehnt wird. Als zusätzlicher Test auf die Robustheit der Ergebnisse und auf Grund ihrer praktischen Relevanz werden zwei Handelsstrategien implementiert. In Bezug auf die Prognosefähigkeit deuten die Ergebnisse darauf hin, dass Investoren auf den US-amerikanischen Häusermärkten in der Lage sein könnten, – unter Verwendung von auf historischen Kursen beruhenden Informationen – Überrenditen zu erzielen; insbesondere wenn standardisierte Derivate auf diese Märkte an Börsen gehandelt werden. Auf Grund der eingeschränkten Datenverfügbarkeit basiert die Untersuchung allerdings nicht auf den Preisen der gehandelten Derivate. Eine derartige Analyse würde jedoch weitere Erkenntnisse darüber liefern, ob die aufgedeckten Ineffizienzen tatsächlich in Form von Überrenditen nutzbar sind oder ob diese bei der Bepreisung der Derivate Berücksichtigung finden und somit durch Investoren keine Überrenditen generiert werden können.

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Abstract

Extending the controversial findings from relevant literature on testing the efficient market hypothesis for the U.S. housing market, the results from the monthly and quarterly transaction-based Case-Shiller indices from 1987 to 2009 provide further empirical evidence on the rejection of the weak-form version of efficiency in the U.S. housing market. In addition to conducting parametric and non-parametric tests, we apply technical trading strategies to test whether or not the inefficiencies can be exploited by investors earning excess returns. The empirical findings suggest that investors might be able to obtain excess returns from both autocorrelation- and moving average-based trading strategies compared to a buy-and-hold strategy.

Keywords: Housing market, weak-form market efficiency, random walk hypothesis, variance ratio tests, runs test, trading strategies

JEL Classifications: G12; G14; G15; R31

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1 Introduction

Housing markets are typically characterized by high transaction costs, low turnover volumes, carrying costs, specific tax issues, asymmetric information, and unstandardized, heterogeneous commodities, compared in particular to assets on financial markets. These arguments are repeatedly given as reasons why housing markets might be less efficient than other asset markets.

Nevertheless, the topic of market efficiency is of no less significance for housing markets as already emphasized by Gatzlaff and Tirtiroglu (1995). Around half the net wealth of private households in the U.S. consists of real estate, of which the own home is a substantial part. Furthermore, the origin of the current financial crisis has demonstrated the importance of the housing market for the financial system and the economy quite plainly. Since the burst of the U.S. housing bubble has had worldwide repercussions, a closer look at the pattern of U.S. house prices is well worthwhile. This is particularly necessary because so little is known about identifying turning points in the housing market and how to respond appropriately from an investor's point of view. If housing markets are weak-form efficient, investors, homeowners, mortgage bankers, hedge funds, and others do not have to care about these movements and can not get any further information from analyzing historical prices. However, if there is some indication of inefficiency in the housing markets, historical house prices could contain useful and valuable information with respect to turning points in the markets and on adjusting the position held by real estate in the asset portfolio.

While efficiency in real estate markets has already been the focus of several previous studies, this paper is more oriented towards financial markets and bases its analysis on house price indices whose derivatives are traded on exchanges. The positive impact of futures and options on the housing market for many different types of market players has been thoroughly discussed for almost 20 years now. As early as the 1990s, Case et al. (1991, 1995) recommended the introduction of derivatives on the housing market and emphasized the benefits for various market players with different interests. The main advantages of introducing futures and options on U.S. housing markets are the increase of diversification opportunities such as diversifying the impact of sustained declines in house prices, the improvement of hedging opportunities from real estate risk, the reduction of speculative real estate price movements, diminished information dispersions as they are common at real estate markets, and the decrease of transaction costs which contributes to more efficient housing markets. Thus, index-based futures and options markets in real estate are interesting for homeowners, mortgage banks, insurance companies, hedge funds, and other investment groups. Furthermore, derivatives would be a new vehicle for participating in the housing market. After the introduction of derivatives on 11 housing market indices at the Chicago Mercantile Exchange (CME) in May 2006, Shiller (2008) continues the discussion and emphasizes that “the potential value of such products, once they become established, is seen in consideration of the inefficiency of the market for single family homes” (Shiller, 2008, p. 2).

The trading opportunities at the CME resulted in standardized products, less capital constraints and lumpiness, lower information dispersion, lower transaction costs, lower carrying costs, and less relevant tax issues compared to trading in the direct housing market. Therefore, for the Case-Shiller index futures, the often cited forms of market imperfection presented in previous studies (Gau, 1984 and 1985; Case and Shiller, 1989; Clayton, 1998; Gu, 2002) are valid to a lesser extent only. Thus, one major shortcoming of previous analyses of the U.S. housing market has been mitigated since the studies by Case and Shiller (1989) and Gu (2002). Both analyses found empirical evidence on the inefficiency of U.S. housing markets but could not give a conclusive answer on whether or not these inefficiencies were exploitable for homeowners, professional real estate investors, and mortgage bankers by trading strategies.

Compared to other indices on the U.S. housing market, the Case-Shiller indices have several crucial advantages such as higher marketability, higher data frequency, and the application of the repeated sales method only amongst others. However, to our knowledge, this study is the first analysis to test the weak-form version of market efficiency in the U.S. housing market based on Case-Shiller indices. This study extends the previous literature on the analysis of (weak-form) efficiency of the U.S. housing market in several ways. First, the analysis exclusively applies transaction-based data while other studies like Gu (2002) focus on the Freddie Mac’s Conventional Mortgage Home Price Index (CMHPI) based on both transactions and appraisals. Second, the period from 1987 to 2009 is the largest existing data set on transactions and not only contains a boom cycle of the housing market, but also a bust cycle, which provides further insight into the market behavior. Third, the Case-Shiller indices are calculated on a monthly frequency and thus provide more detailed short-run information. Fourth, the high frequency of data compared to previous studies based mainly on quarterly data allows more robust results from tests on the weak-form version of efficiency. Fifth, as mentioned above, derivatives on the Case-Shiller indices have been traded at the CME since May 2006 which is why the opportunities for exploiting inefficiencies in the housing market improve substantially. With respect to practical relevance, the focus on tradable indices is preferable, the products even allow for short positions in the housing market, thus allowing the investor to participate in falling housing markets.

Beside the standardized and exchange-traded options and futures on the Case-Shiller house price indices, according to the homepage of MacroMarkets LLC, there are also various over-the-counter products based on the Case-Shiller indices. Thus, the universe of derivative products built on the Case-Shiller indices is even larger and might further increase in the future, accompanied by higher liquidity in these instruments. For investors participating in this market and trading these products and for the pricing process of these products, the characteristics of the underlying indices with respect to their market efficiency in the understanding of Fama (1970) are of particular interest.

Referring to Fama (1970, p. 383), "a market in which prices always "fully reflect" available information is called "efficient"." In his two reviewing papers on the theoretical and empirical literature on the efficient market model (Fama, 1970 and 1991), Fama distinguishes three categories of market efficiency differing by the relevant information subset which is considered: (1) weak-form tests, (2) semi-strong form tests, and (3) strong-form tests. The weak-form tests are concerned with the question whether or not prices can be forecasted by past returns. Fama (1990) generalizes the framework compared to his definition in 1970 and replaces the category "weak-form tests" by "tests for return predictability". Semi-strong form tests of the efficient markets model are concerned with whether prices fully reflect all publicly available information. Finally, the strong-form tests are concerned with whether individual investors or groups have access to private information that is not fully reflected in market prices. A more detailed and comprehensive discussion on market efficiency is given by Fama (1970, 1991).

In this paper, the hypothesis of weak-form market efficiency is challenged and tested only. However, if the hypothesis of weak-form market efficiency is rejected, the other two versions of market efficiency are rejected as well, since the information set considered by weak-form tests is a subset of the information sets on which semi-strong form as well as strong-form tests rely.

A widely used test of the weak-from version of market efficiency analyzes whether (housing) market indices follow a random walk or exhibit a certain pattern. If market indices show random walk behavior, investors will be unable to persistently earn excess returns because indices are priced at their equilibrium values. By contrast, if market indices do not follow a random walk process, the pricing of capital and risk would be predictable and investors could achieve excess returns.

For the last 25 years, understanding the behavior of stock prices has been a key topic in financial literature and the efficient market hypothesis and its three versions according to Fama (1970) have been central in many empirical studies on traditional asset markets in a wide range of countries for highly developed markets e.g. Summers (1986), Fama and French (1988), Poterba and Summers (1988), Richardson and Stock (1989), and Fama (1991) but also for less developed markets e.g. Errunza and Losq (1985), Barnes (1986), Laurence (1986), Butler and Malaikah (1992), Agbeyegbe (1994), Huang (1995), Urrutia (1995), Grieb and Reyes (1999), Karemera et al. (1999), Ojah and Karemera (1999), Chang and Ting (2000), Abraham et al. (2002), Ryoo and Smith (2002), Smith et al. (2002), and Lim et al. (2009) amongst others. The studies differ mainly by the market analyzed, the considered time period, and the applied methodology for analyzing market efficiency. However, with regard to real estate markets, the number of studies is much lower. Most research on the securitized real estate sector mainly focuses on the U.S. market, like Mei and Gao (1995), Seck (1996), Graff and Young (1997), Nelling and Gyourko (1998), Kuhle and Alvayay (2000), Kleiman et al. (2002), and Jirasakuldech and Knight (2005). One of the few internationally oriented studies analyzing eleven national real estate stock markets was conducted by Stevenson (2002). Schindler et al. (2009) conduct a more comprehensive study by testing the efficient market hypothesis for 14 national real estate stock markets from January 1990 to December 2006. They conclude that real estate stock markets are less efficient than international stock markets and the empirical findings suggest that investors are likely to earn excess returns by using past information in most of the public real estate markets.

In contrast to the securitized real estate markets, even less empirical evidence exists on the U.S. housing market in its nationwide perspective with respect to the efficient market hypothesis. Many studies focus on selected local markets only. Furthermore, the limitations in data quality are inherent in almost all studies including the following analysis. Thus, conclusions from statistical tests have to been seen in the context of this caveat. A literature review on selected studies related to efficiency in the U.S. housing market is provided in section 2.

The main objectives of this study are (1) to examine the random walk hypothesis for the Case-Shiller indices in 20 regional housing markets, (2) to test for market efficiency across the selected housing markets, and (3), most importantly, for practical relevance, to derive trading strategies if inefficiencies are detected.

The remainder of this paper is organized as follows. The next section provides a literature review. Section 3 discusses the weak-form version of market efficiency (Fama, 1965 and 1970) in conjunction with the random walk hypothesis and deals with the methodology of variance ratio and runs tests. After a data description and descriptive statistics, empirical results of the applied test procedures are presented in section 4. Section 5 tests market efficiency by comparing two trading strategies with a simple buy-and-hold approach. Section 6 draws conclusions and gives an outlook for further research.

2 Literature Review

Although the question of efficiency in housing markets and the resulting implications from market inefficiency are of great importance for professional real estate investors, mortgage bankers, and also for homeowners, the number of empirical studies on this topic has been limited for the last 25 years. However, there are almost innumerable studies considering tests of market efficiency for stock, bond, exchange rate, and commodity markets. The key findings from all analyses are almost similar. In general, the hypothesis at least of weak-form market efficiency by the seminal definition of Fama (1970) is not rejected and even if for some markets and for some time periods the conducted tests reject the efficient market hypothesis, investors trading standardized products on exchanges are not able to exploit these inefficiencies by earning abnormal returns.

One of the first studies analyzing the validity of efficient market hypothesis in real estate markets is conducted by Gau (1984) considering the prices of income-producing properties located in the real estate market of Vancouver in Canada. His results are in support of the random walk-fair game model and thus, in support of the weak-form version of the efficient market hypothesis. In a subsequent study by Gau (1985) – based on the same series of apartment transactions from 1971 to 1980 as in Gau (1984) – the semi-strong form version of the efficient market hypothesis is considered by applying the asset pricing framework of the capital asset pricing model and the arbitrage pricing theory. These models are utilized to estimate the abnormal returns resulting from two types of public information, major changes in government tax shelter and rent control policies as well as unanticipated changes in mortgage interest rates. In conclusion, the results show an absence of significant abnormal returns and thus confirm the semi-strong form version of the efficient market hypothesis. However, Gau (1985) points out some caveats with respect to data problems inherent in his study.

Linneman (1986) focuses his study on the efficiency of the housing market on the housing market of Philadelphia for two points in time (1975 and 1978) using observations on individual homeowner assessments of their house values. By using a hedonic price approach and analyzing the residual information from the estimated model, Linneman (1986) applies this methodology to the Annual Housing Survey for the Philadelphia Standard Metropolitan Statistical Area. From the test results he concludes that the excess returns are insufficient to cover the high transaction costs associated with transacting residential real estate and that no significant arbitrage opportunities exist. Thus, the market can be considered as semi-strong form efficient.

The study by Case and Shiller (1989) extends previous research in several ways. First, it is the first study to use repeated sales price data on individual homes. Second, the total number of observations of 39,210 and the time span from 1970 to 1986 is unique compared to previous studies. Third, Case and Shiller (1989) extend the geographical area by using data from the Society of Real Estate Appraisers for Atlanta, Chicago, Dallas, and San Francisco / Oakland. Fourth, and most importantly for a theoretical perspective, the applied statistical methodology shows several improvements over the analysis by Gau (1984, 1985). The methodology improvements concern testing the random walk hypothesis for housing prices by regressing the change in the index on lagged changes in the index. The suggested method is more robust to spurious serial correlation in price changes. In contrast to Gau (1984, 1985) and Linneman (1986), the results by Case and Shiller (1989) reject weak-form market efficiency for housing markets. Additionally, they implement trading strategies to provide further evidence for the rejection of the weak-form market efficiency. However, forecasting individual housing prices turns out to be much more difficult and is swamped out by noise. Thus, Case and Shiller (1989) emphasize doubts on proving definitively whether or not housing markets are efficient.

Based on the same data set as used by Case and Shiller (1989), Case and Shiller (1990) conduct a more detailed analysis of market efficiency. The forecastability of excess returns is evaluated by regressing home price changes and excess returns on certain identified forecasting variables. The findings give further evidence on inefficiencies in the housing market for single-family homes.

The study by Kuo (1996) focuses mainly on the econometrically and statistically challenging problem of correctly estimating serial correlation and seasonality for infrequently traded assets as in the real estate market. Kuo (1996) shows that the estimators used by Case and Shiller (1989) are not consistent, that they involve an arbitrary partition of the data set, and that the developed Bayesian approach is superior. However, the results from applying the Bayesian approach confirm the result of serial correlation by Case and Shiller. Thus, the rejection of a random walk is supported by Kuo (1996), who points out, however, that "the estimates are sensitive to different estimation techniques" (Kuo, 1996, p. 160).

Two further studies considering the Canadian housing market are conducted by Hosios and Pesando (1991) as well as by Clayton (1998). Hosios and Pesando (1991) construct a quarterly repeated sales price index for the City of Toronto based on data from the Multiple Listing Service from 1974 to 1989. The test results show substantial persistence in house price changes. Furthermore, as Case and Shiller (1989) and Kuo (1996) do for the U.S. housing markets, Hosios and Pesando (1991) find some seasonality in the housing market of Toronto. Thus, the efficient market hypothesis is rejected for the housing market in Toronto as well.

By investigating the market of condominium apartments in the Vancouver metropolitan area from 1982 to 1994, Clayton (1998) extends the topic of efficiency to another segment of the housing market. The results from testing weak-form and semi-strong form efficiency are in line with previous findings on other markets and mainly reject the efficient market hypothesis. However, at least one caveat has to be mentioned. The quarterly data from the Royal Lepage Survey of Canadian House Price might be biased and appraisal-induced smoothing may have occurred, since the data is presented in terms of appraisals rather than market transactions, even if Clayton (1998) argues that these deficiencies are less severe in residential real estate than in commercial real estate.

The most recent analysis on the predictability of house prices is conducted by Gu (2002). This study uses the quarterly published CMHPI for all fifty states, the District of Columbia, separate indices for nine Census Divisions and an aggregate index for the U.S. from the first quarter of 1975 to the first quarter of 1999. It is the most comprehensive analysis of market efficiency in the U.S. housing market to date. In comparison to several studies mentioned above, Gu (2002) examines spatial markets instead of individual homes. Thus, the perspective and implications differ to some extent. While in the short run, price changes in all states show variance ratios less than one, indicating mean reversion, the results from heteroscedasticity-robust variance ratio tests differ across the states when conducting test statistics for more lags and the test statistics become less significant. Similar results can be found when splitting the whole sample in two subsamples and running the variance ratio test for each subsample. Gu (2002) also shows that trading strategies based on estimated autocorrelation are able to generate excess returns supporting the rejection of weak-form market efficiency. However, home values are based on either a sale or an appraisal and for this reason the indices might suffer – at least to some extent – from the same problems as appraisal-based indices.

Besides the U.S. and Canada, there are only a few empirical studies analyzing predictability in housing prices and testing market efficiency in other countries. By applying the methodology suggested by Case and Shiller (1989), Larsen and Weum (2008) conclude that both the repeated sales house price index of the housing market in and around the Norwegian capital, Oslo, and its price changes, contain time structure. Thus, based on data from the housing market in Oslo, they conclude that the efficient market hypothesis is rejected for this market over the period from 1991 to 2002. Ito and Hirono (1993) consider the housing market in Tokyo with respect to its efficiency. Excess returns on the housing market are calculated by applying a hedonic approach. In a next step, these excess returns are tested for their predictability. Ito and Hirono (1993) find that the null hypothesis of no autocorrelation and thus the weak-form market efficiency is rejected when robust standard errors controlling for possible heteroscedasticity are used. However, the results may not be representative considering the data as well as the relatively small and short-period sample. The data are taken from a weekly magazine called Jutaku Joho and the prices are asking prices and not actual transaction prices.

One of the first studies of efficiency in the housing market in the U.K. is conducted by Barkham and Geltner (1996). Their framework of analyzing semi-strong form efficiency is built on examining the linkages between the housing market and the stock market. As a result, the stock market is leading the housing market up to two years and inefficiencies seem to be stronger in the housing market than in the commercial real estate market. However, the limitations in data quality are also pointed out by Barkham and Geltner (1996). The simulations by Meen (2000) also detect inefficiencies in the U.K. housing market by simulating housing cycles and housing model. However, Meen (2000) also points out, that the findings do not necessarily imply that there are exploitable trading rules, if the covered inefficiencies result from high transaction costs. A third, and more recent, analysis of efficiency in owner-occupied housing markets is conducted by Rosenthal (2006), extending the scope to a nationwide, but locally more precise and county-specific examination from 1991 to 2001. Rosenthal (2006) concludes that – at a spatially disaggregated level – the results from the employed autoregressive framework are not indicative of rejecting the weak-form version of efficiency in the owner-occupied housing market of the U.K. By comparing the three studies on the U.K. housing market, it can be seen how conclusions from testing efficiency in the housing market differ. However – as in the case for the U.S. – the tested version of efficiency, statistical methodologies, covered time periods, geographical focus, and level of data aggregation, among other factors are different. Thus, the overall result may not differ to such an extent when the framework of the two studies has been adjusted.

The literature review is summarized by Table 1 which lists the test market, the analyzed time period, the data source as well as the major findings of each study presented above. A comprehensive survey on further empirical findings on efficiency in the housing market is conducted by Gatzlaff and Tirtiroglu (1995).

Concluding, all previous research on the topic of efficiency in the housing market shows that there is no unanimous conclusion and that further research is essential to gain more insight on the housing markets and their characteristics, in particular against the background of ongoing innovations in housing market derivatives and the fact that the recent financial crises had their origin in the housing market. To our knowledge, no study on predicting housing markets and testing the weak-form version of market efficiency based on monthly and quarterly indices consisting of transaction data only and covering both local and national U.S. housing markets exists as yet.

Table 1: Studies on the efficiency of the housing market (listed in chronological order and by geographical focus)

Study	Test Market (Period)	Data Source	Major Findings
Linneman, P. (1986): An Empirical Test of the Efficiency of the Housing Market, *Journal of Urban Economics*.	Philadelphia (1975, 1978)	Annual Housing Survey	Acceptance of semi-strong form market efficiency
Case, K.E., and R.J. Shiller (1989): The Efficiency of the Market for Single-Family Homes, *American Economic Review*.	Atlanta, Chicago, Dallas, San Francisco / Oakland (1970-1986)	Society of Real Estate Appraisers	Rejection of weak-form market efficiency
Case, K.E., and R.J. Shiller (1990): Forecasting Prices and Excess Returns in the Housing Market, *Journal of the American Real Estate and Urban Economics Association*.	Atlanta, Chicago, Dallas, San Francisco / Oakland (1970-1986)	Society of Real Estate Appraisers	Rejection of semi-strong form market efficiency
Kuo, C.-L. (1996): Serial Correlation and Seasonality in the Real Estate Market, *Journal of Real Estate Finance and Economics*.	Atlanta, Chicago, Dallas, San Francisco / Oakland (1971-1986)	Society of Real Estate Appraisers	Rejection of weak-form market efficiency
Gu, A.Y. (2002): The Predictability of House Prices, *Journal of Real Estate Research*.	U.S. (all states) (1975-1999)	Freddie Mac's Conventional Mortgage Price Indices	No consistent result, depending on time period and market

Table 1 continues on the next page

Study	Test Market (Period)	Data Source	Major Findings
Gau, G.W. (1984): Weak Form Test of the Efficiency of Real Estate Investment Markets, *Financial Review*.	Vancouver (1971-1980)	Local Transaction Data	Acceptance of weak-form market efficiency
Gau, G.W. (1985): Public Information and Abnormal Returns in Real Estate Investemnt, *Journal of the American Real Estate and Urban Economics Association*.	Vancouver (1971-1980)	Local Transaction Data	Acceptance of semi-strong form market efficiency
Hosios, A.J., and J.E. Pesando (1991): Measuring Prices in Resale Housing Markets in Canada: Evidence and Implications, *Journal of Housing Economics*.	Toronto (1974-1989)	Multiple Listing Service	Rejection of weak-form market efficiency
Clayton, J. (1998): Further Evidence on Real Estate Market Efficiency, *Journal of Real Estate Research*.	Vancouver (1982-1994)	Royal Lepage Survey of Canadian House Price	Rejection of weak-form and semi-strong form market efficiency

Table 1 continues on the next page

Study	Test Market (Period)	Data Source	Major Findings
Barkham, R.J., and D.M. Geltner (1996): Price Discovery and Efficiency in the UK Housing Market, *Journal of Housing Economics*.	U.K. (1975-1993)	Department of the Environment	Rejection of semi-strong from market efficiency
Meen, G. (2000): Housing Cycles and Efficiency, *Scottish Journal of Political Economy*.	U.K. (1969-1996)	Department of the Environment	Rejection of semi-strong from market efficiency
Rosenthal, L. (2006): Efficiency and Seasonality in the UK Housing Market, 1991-2001, *Oxford Bulletin of Economics and Statistics*.	81 Cities and 51 Counties in the U.K. (1991-2001)	Nationwide Building Society	Acceptance of weak-form market efficiency
Ito, T., and K.N. Hirono (1993): Efficiency of the Tokyo Housing Market, *NBER Working Paper Series*.	Tokyo (1981-1992)	Asking Prices from Magazine "Jutaku Joho"	Rejection of weak-form market efficiency
Larsen, E.R., and S. Weum (2008): Testing the Efficiency of the Norwegian Housing Market, *Journal of Urban Economics*.	Oslo (1991-2002)	OBOS (Oslo Bolig- og Sparelag)	Rejection of weak-form market efficiency

3 Methodology

In its weak form, the efficient market hypothesis proposes that price changes are unpredictable. Thus, a frequently employed test of market efficiency examines whether or not prices follow a random walk. Under the random walk hypothesis, a non-predictable random mechanism generates the behavior of price changes. In the simplest version of a random walk model, the actual index I_t equals the previous index I_{t-1} plus the realization of a random variable ε_t,

$$I_t = I_{t-1} + \varepsilon_t, \tag{1}$$

where I_t is the natural logarithm of the index and ε_t is a random disturbance term at time t which satisfies $E[\varepsilon_t] = 0$ and $E[\varepsilon_t \varepsilon_{t-h}] = 0$, $h \neq 0$ for all t. If the expected index changes are given by $E[\Delta I_t] = E[\varepsilon_t] = 0$, the best linear estimator for index I_t is the previous index value I_{t-1}. Under the assumption that expected index changes μ are constant over time, the random walk model expands to a random walk with drift (μ = drift parameter)

$$I_t = I_{t-1} + \mu + \varepsilon_t \text{ or } \Delta I_t = \mu + \varepsilon_t \qquad \varepsilon_t \sim \text{i.i.d.}(0, \sigma^2). \tag{2}$$

The random walk implies uncorrelated residuals and hence, uncorrelated returns, ΔI_t; $\varepsilon_t \sim$ i.i.d.$(0, \sigma^2)$ denotes that the increments ε_t are independently and identically distributed (i.i.d.) with $E[\varepsilon_t] = 0$ and $E[\varepsilon_t^2] = \sigma_\varepsilon^2$.[1]

In general, the weak-form version of market efficiency and the random walk hypothesis are not equivalent. Nevertheless, if indices are found to follow a random walk process, then the housing market is considerd as weak-form efficient (Fama, 1970). Consequently, the random walk properties of index returns are considered to be an outcome of the efficient market hypothesis.

3.1 Variance Ratio Tests of Random Walk

The traditional random walk tests on the basis of serial correlation and unit roots are vulnerable to errors due to autocorrelation induced by non-synchronous and infrequent trading. A discussion on this topic with respect to real estate indices with a small sample size

[1] A random walk process means that any shock to the index is permanent, and there is no tendency for the index level to return to a trend path over time. In contrast, if indices follow a mean-reverting process, then in general, there exists a tendency for the index level to return to its trend path over time, and investors may be able to forecast future index changes by using information on past returns (Chaudhuri and Wu, 2003).

can be found in Case and Shiller (1989) and in Kuo (1996) respectively. To resolve this shortcoming (for financial time series), Lo and MacKinlay (1988, 1989) developed tests for random walks based on variance ratio estimators.

The variance of the increments of a random walk is linearly time-dependent. Thus, if the natural logarithm of index, I_t, follows a pure random walk with drift (Equation (2)), then the variance of index changes should increase proportionally to the observation interval q. Suppose a series of $nq + 1$ price observations (P_0, P_1, P_2, …, P_{nq}) measured at uniform intervals is available. If this time series follows a random walk, the variance of the qth difference would correspond to q times the variance of first differences. Following the models of Equations (1) and (2), the variance of the first differences, denoted as $\hat{\sigma}^2[I_t - I_{t-1}]$ and $\hat{\sigma}^2[r_t]$ respectively, grows linearly over time so that the variance of the qth difference is

$$\hat{\sigma}^2[I_t - I_{t-q}] = q \cdot \hat{\sigma}^2[I_t - I_{t-1}] \quad \text{or} \quad \hat{\sigma}^2[r_t(q)] = q \cdot \hat{\sigma}^2[r_t]. \tag{3}$$

For the qth lag in I_t, where q is any integer greater than one, the variance ratio, VR(q), is defined as

$$VR(q) \equiv \frac{\hat{\sigma}^2[r_t(q)]}{q \cdot \hat{\sigma}^2[r_t]} = 1 + 2\sum_{h=1}^{q-1}\left(1 - \frac{h}{q}\right) \cdot \hat{\rho}(h), \tag{4}$$

where $\hat{\sigma}^2[\cdot]$ is an unbiased estimator of the variance. The expected value of VR(q) is one under the null hypothesis of a random walk for all values of q. While I_t describes the logarithmic price process, $r_t(q)$ is a q period continuously compounded return with $r_t(q) \equiv r_t + r_{t-1} + \ldots + r_{t-q+1} = I_t - I_{t-q}$. $\hat{\rho}(h)$ is the estimator of the hth serial correlation coefficient. Alternatively, values for VR(q) greater than one imply mean aversion while values smaller than one imply mean reversion. Equation (4) shows that VR(q) is a particular linear combination of the first h-1 autocorrelation coefficients with linearly declining weights. If q behaves as a random walk, VR(q) = 1 because $\hat{\rho}(h) = 0$ for all $h \geq 1$ (Campbell et al., 1997).

Under the null hypothesis of a homoscedastic increments random walk, Lo and MacKinlay (1988) derive an asymptotic standard normal test statistic for the VR. The standard z-test statistic is

$$Z_1(q) = \frac{VR(q)-1}{\sqrt{\hat{\theta}_1(q)}} = \frac{M_r(q)}{\sqrt{\hat{\theta}_1(q)}} \overset{a}{\sim} N(0,1), \tag{5}$$

where $\hat{\theta}_1(q) = \frac{2(2q-1)(q-1)}{3q(nq)}$, and $\overset{a}{\sim}$ denotes that the distributional equivalence is asymptotic.

Many time series have time-varying volatilities, with returns deviating from normality. When index changes are conditionally heteroscedastic over time, there may not exist a linear relation over the observation intervals. Hence, Lo and MacKinlay (1988) suggest a second test statistic $Z_2(q)$ with a heteroscedasticity-consistent variance estimator $\hat{\theta}_2(q)$:

$$Z_2(q) = \frac{VR(q)-1}{\sqrt{\hat{\theta}_2(q)}} = \frac{M_r(q)}{\sqrt{\hat{\theta}_2(q)}} \overset{a}{\sim} N(0,1), \tag{6}$$

with $\hat{\theta}_2(q) = \sum_{j=1}^{q-1} \left[\frac{2(q-j)}{q} \right]^2 \cdot \hat{\delta}(j)$ and $\hat{\delta}(j) = \frac{\sum_{t=j+1}^{nq} (I_t - I_{t-1} - \hat{\mu})^2 (I_{t-j} - I_{t-j-1} - \hat{\mu})^2}{\left[\sum_{t=1}^{nq} (I_t - I_{t-1} - \hat{\mu})^2 \right]}$.

If the null hypothesis is true, then the modified heteroscedasticity-consistent test statistic in Equation (6) has an asymptotic standard normal distribution (Liu and He, 1991). The $Z_2(q)$-statistic is robust to heteroscedasticity as well as to non-normal disturbance terms and it allows for a more efficient and powerful test than the tests of Box and Pierce (1970) or of Dickey and Fuller (1979, 1981) (Lo and MacKinlay, 1989).

The variance ratio test of Lo and MacKinlay (1988) considers one VR for a single aggregation interval q by comparing the test statistics $Z_1(q)$ and $Z_2(q)$ with the critical value of a standard normal distribution. By contrast, the random walk model requires that $VR(q) = 1$ and hence $VR_r(q) = VR(q)-1 = 0$ for all selected aggregation intervals q simultaneously. Neglecting the joint nature of the hypothesis may lead to inaccurate inferences. To solve this problem, Chow and Denning (1993) suggest a multiple variance ratio (MVR) test. It is based on a multiple comparison similar to a classical joint F-test. In conjunction with a set of primary Lo and MacKinlay test statistics, $\{Z_1(q_i) \mid i = 1, \ldots, m\}$ and $\{Z_2(q_i) \mid i = 1, \ldots, m\}$, the random walk hypothesis is rejected if any of the estimated VRs differs significantly from one. For this test, it is only necessary to consider the maximum absolute value of the test statistics (Chow and Denning, 1993):

$$Z_1^*(q) = \max_{1 \le i \le m} |Z_1(q_i)| \quad \text{and} \quad Z_2^*(q) = \max_{1 \le i \le m} |Z_2(q_i)|. \tag{7}$$

The multiple variance ratio approach controls the size of the joint test and defines a joint confidence interval for the $VR(q_i)$ estimates by applying the Studentized Maximum Modulus (SMM) distribution theory. The upper α point is used instead of the critical values of the standard normal distribution,

$$SMM(\alpha, m, \infty) = Z_{\alpha^+/2}, \tag{8}$$

where $\alpha^+ = 1 - (1 - \alpha)^{1/m}$.

According to Equation (8), the asymptotic SMM critical value can be calculated from the conventional standard normal distribution for a large number of observations. In essence, the Chow and Denning's test is conservative by design (i.e., the critical values are larger), but even so, it has the same, or even more, power than the conventional unit root tests against an AR(1) alternative. At the same time, the MVR-test is robust with respect to many forms of heteroscedasticity and non-normality of the stochastic disturbance term.

3.2 Runs Test of Market Efficiency

Both autocorrelation and VR tests are based on the assumption of a linear return generating process and thus, both approaches test for linear dependencies in the price series by definition when challenging the random walk hypothesis and the hypothesis of weak-form market efficiency. Consequently, even if the efficient market hypothesis is not rejected by autocorrelation and VR tests, it does not necessarily imply market efficiency. Thus, it is important to apply a direct test of the weak-form version of market efficiency. The non-parametric runs test investigates the independence of successive returns and does not require normality or a linear return generating process. These characteristics of testing methods are especially useful for investigating returns of house price indices, which are frequently non-normally distributed.

A runs test determines whether the total number of runs in the sample is consistent with the hypothesis that changes are independent. If the return series exhibits a greater tendency of change in one direction, the average run will be longer and, consequently, the number of runs will be lower than generated by a random process. In the Bernoulli case, the total number of runs is referred to as N_{Runs} and the total expected number of runs is given by

$$E[N_{Runs}] = 2n\pi(1-\pi) + \pi^2 + (1-\pi)^2, \tag{9}$$

where $\pi = \Pr(r_t > 0) = \Phi\left(\frac{\mu}{\sigma}\right)$, μ is the expected index change, and σ is the standard deviation of index changes. For large (N > 30) the sampling distribution of E $[N_{Runs}]$ is approximately normal, and a continuity correction is produced.

When the actual number exceeds (falls below) the expected runs, a positive (negative) Z-value is obtained. Consequently, a positive (negative) Z-value indicates a negative (positive) serial correlation in the series of index changes.

Table 2 summarizes the conclusions of the various test approaches which are applied to test for weak-form market efficiency and predictability of price changes in the U.S. housing market.

Table 2: Null and Alternative Hypotheses of Weak-Form Market Efficiency Tests

Significance Test	**Autocorrelation Coefficient**	**Variance Ratio**	**Runs**
Random Walk	$\rho(h) = 0 \;\; for \; h \neq 0$	$VR(h) = 1 \;\; for \; h \neq 0$	$Z = 0$
Mean Aversion	$\rho(h) > 0 \;\; for \; h \neq 0$	$VR(h) > 1 \;\; for \; h \neq 0$	$Z < 0$
Mean Reversion	$\rho(h) < 0 \;\; for \; h \neq 0$	$VR(h) < 1 \;\; for \; h \neq 0$	$Z > 0$

4 Empirical Results of Weak-Form Market Efficiency Tests

4.1 Data

The data set used in this study is based on the Case-Shiller indices.[2] As mentioned above, these indices are the underlying of the futures on the U.S. housing market traded at the CME. Thus, with respect to its practical relevance and the implementation of the trading strategies, these indices are more suitable than the CMPHI or the Federal Housing Finance Agency (FHFA) indices. However, the latter cover a broader market and are calculated for each state,

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[2] See Standard and Poor's (2006) for further information on index construction methodology.

while the Case-Shiller indices are based on 20 large cities only. However, the cities are spread throughout the U.S. with the exception of the sparsely populated states in the Mountain and West North Central Census Division, such as Wyoming, North Dakota, Idaho, and Kansas amongst others. But in support of the Case-Shiller indices, it is worth to mention that the number of transactions is very low in these states compared to the ones on the coast and in the highly populated areas, which might result in certain index construction problems and spurious autocorrelation, as described in the studies by Case and Shiller (1989, 1990) and Kuo (1996). Furthermore, the CMPHI and FHFA indices are calculated based on both transactions and appraisals and are thus not restricted to considering transactions only. There could also be some biases due to the fact that the appraisers are often paid based on the appraisal value of the house. However, the Case-Shiller indices consider transactions only and thus reflect the market more precisely. One further limitation of the FHFA indices is their focus on homes financed by government sponsored enterprises (GSEs), such as Fannie Mae and Freddie Mac. The eligibility of financing housing via GSEs depends on the house price beside other criteria. Thus, the CMPHI and FHFA indices do not consider house prices above given price limits varying according to year and state. This results in some skewness to the lower end of the housing market.

Additionally, the CMPHI and FHFA indices based on states are reported quarterly only. This might result in some smoothing and distortion on the average return for the quarter if there is some non-adjusted seasonality, e.g., higher price increases in June than in April in the second quarter. Due to the monthly frequency of the index calculation, this feature is less likely for the Case-Shiller indices. All these facts support the application of the Case-Shiller indices for analyzing housing market efficiency with data most closely related to the market and are thus representative for the housing market.[3]

The data set includes monthly house price indices from January 1987 to June 2009. There are indices for 20 cities and two aggregate indices for the U.S. The availability of index data is limited for some cities resulting in a shortened period. The different indices and their availability are presented in Table 2. One of the aggregate indices comprises ten cities and has been calculated since 1987, the other one is constituted of 20 cities and has been

[3] However, the monthly indices are moving averages of the actual month and the two preceding months. Thus, the results from short-term autocorrelation like autocorrelation of order one and two are highly influenced by this index construction methodology. This has to be considered when analyzing the results in section 4.3. Furthermore, the variance ratio with lag interval q = 2 suffers from the same problem. As a robustness check, higher order autocorrelation and variance ratios with higher lag intervals are calculated as well.

calculated since 2000. The 20 cities cover 17 states allocated throughout the U.S. Thus, the indices offer an appropriate representation of the main regional and local U.S. housing markets relevant for investors.

Table 3: List of the Case-Shiller Indices on the U.S. Housing Market

City	State	Index	Data availability since
Atlanta	Georgia	AT	01/1991
Boston*	Massachusetts	BO	01/1987
Charlotte	North Carolina	CR	01/1987
Chicago*	Illinois	CH	01/1987
Cleveland	Ohio	CE	01/1987
Dallas	Texas	DA	01/2000
Denver*	Colorado	DN	01/1987
Detroit	Michigan	DE	01/1991
Las Vegas*	Nevada	LV	01/1987
Los Angeles*	California	LA	01/1987
Miami*	Florida	MI	01/1987
Minneapolis	Minnesota	MN	01/1989
New York*	New York	NY	01/1987
Phoenix	Arizona	PX	01/1989
Portland	Portland	PO	01/1987
San Diego*	California	SD	01/1987
San Francisco*	California	SF	01/1987
Seattle	Washington	SE	01/1990
Tampa	Florida	TP	01/1987
Washington*	Washington D.C.	WD	01/1987
Composite of 10*		CS10	01/1987
Composite of 20		CS20	01/2000

Notes: * indicates indices on that futures and options are traded at the Chicago Mercantile Exchange.

4.2 Descriptive Statistics

The descriptive statistics for the monthly returns of the Case-Shiller indices are presented in Table 4 and are based on continuously compounded monthly returns from the first date from which data are available for each series to June 2009.[4] The coastal cities in the West and Washington D.C. show the highest average returns while the lowest, but still positive average return can be found in Detroit. Cities such as Las Vegas, San Francisco, Phoenix, Los Angeles, and San Diego in the western part of the U.S. exhibit the most volatile housing markets as well. With respect to the higher moments, all local housing markets are characterized by negative skewness and excess kurtosis. According to the test statistic by Jarque and Bera (1980), the null hypothesis of normally distributed returns is rejected for all markets except the ones in Boston and New York. The evidence of non-normally distributed index changes corresponds to the findings by Young and Graff (1996) on commercial real estate and is more apparent than by Gu (2002) probably caused by monthly data instead of quarterly data.

Futhermore, Gu (2002) concludes that more volatile house price indices are associated with lower rates of return. By replicating the regressions employed by Gu (2002) and by regressing index changes on volatility, the coefficients are not significant; thus, there is no evidence of either a positive or a negative relation between index changes and volatility. Considering simple Sharpe ratios, the housing markets in Portland, Denver, Charlotte, and Seattle have the best risk-return profile, while Detroit, Las Vegas, and Phoenix exhibit the least beneficial risk-return characteristics. However, the reasons for the relatively high Sharpe ratios are mixed as well and confirm the results from the regession analysis. While the high Sharpe ratio for the housing market in Seattle and Portland is driven by high mean returns, the markets in Denver and Charlotte benefit from their low standard deviation.

[4] Log differences of prices are used because, for small changes, they approximately equal the rate of return from continuous compounding. The descriptive statistics for the non-overlapping quarterly returns of the Case-Shiller indices are presented in Appendix 1.

Table 4: Descriptive Statistics of Monthly Index Returns

Index	Mean	Min.	Max.	Std.dev.	Skewness	Kurtosis	No. of Obs.
AT	0.0020	-0.0320	0.0144	0.0066	-2.6156	12.1746	221
BO	0.0029	-0.0264	0.0261	0.0089	-0.2403	3.1704	269
CR	0.0024	-0.0259	0.0170	0.0054	-1.0464	7.2259	269
CH	0.0032	-0.0475	0.0263	0.0088	-1.6235	9.9343	269
CE	0.0026	-0.0511	0.0410	0.0082	-0.8148	13.9580	269
DA	0.0016	-0.0250	0.0268	0.0080	-0.5047	5.0945	113
DN	0.0034	-0.0275	0.0251	0.0071	-0.7898	5.0750	269
DE	0.0008	-0.0497	0.0251	0.0104	-2.2650	9.5114	221
LV	0.0018	-0.0524	0.0587	0.0144	-0.4490	7.5854	269
LA	0.0037	-0.0436	0.0379	0.0130	-0.5303	4.0259	269
MI	0.0028	-0.0461	0.0274	0.0118	-1.3055	6.0539	269
MN	0.0024	-0.0599	0.0310	0.0105	-2.5451	13.5815	245
NY	0.0031	-0.0243	0.0233	0.0078	-0.2249	3.1492	269
PX	0.0018	-0.0566	0.0477	0.0139	-1.0698	7.7657	245
PO	0.0048	-0.0301	0.0313	0.0081	-0.7234	6.1072	269
SD	0.0037	-0.0367	0.0518	0.0124	-0.3005	4.5632	269
SF	0.0037	-0.0517	0.0406	0.0140	-0.7844	5.2265	269
SE	0.0040	-0.0370	0.0440	0.0094	-0.3868	7.2297	233
TP	0.0022	-0.0448	0.0285	0.0102	-1.0455	6.5840	269
WD	0.0037	-0.0276	0.0315	0.0101	-0.3063	4.0373	269
CS10	0.0033	-0.0283	0.0227	0.0091	-0.8709	4.3493	269
CS20	0.0030	-0.0282	0.0197	0.0115	-1.1180	3.4894	113

4.3 Results from Autocorrelation Tests

At least in the short-run, positive autocorrelations are a well-studied phenomenon for asset market returns and various possible explanations have been proposed. Lo and MacKinlay (1988) as well as French and Roll (1986) explain autocorrelations in the returns of stock indices by referring to the common risk factor of stocks that comprise the index. Thus, systematic risk drives the autocorrelation.

As can be depicted from Table 5, the results from estimating autocorrelations of the monthly index changes show significant coefficients for all markets and all considered lags indicating a general upward trend and mean aversion processes. In particular, the short-run autocorrelations are very high, have a positive sign and are highly significant. In the long-run, persistence weakens slightly but is still significant. The exceptions are the housing markets in Charlotte and Cleveland, the latter of which exhibits slightly negative, but still significant autocorrelation for lag three. By considering higher-order autocorrelations both eight out of 20 local house price indices and the nationwide index consisting of 20 cities exhibit significant negative autocorrelations. However, with the exception of the housing markets in Miami, Phoenix and Tampa, the negative autocorrelations with a lag of 36 months are very low and thus indicate a slight long-run mean reversion only. In general, according to the autocorrelation analysis, housing markets in the U.S. exhibit a highly significant positive autocorrelation; this indicates both short- and long-run mean aversion and thus suggests the rejection of the efficient market hypothesis in its weak-form version. However, at least three points of criticism of analyzing the random walk hypothesis by autocorrelation have to be addressed. First, estimated autocorrelation may not be accurate if the index changes are not normally distributed. Second, Case and Shiller (1989, 1990) and Kuo (1996) refer to biased serial correlation coefficients estimated for infrequently traded assets as in the housing market. Due to the index construction criteria, the monthly indices are calculated based on three month moving averages resulting in artificially high autocorrelation coefficients of order one and two. However, according to Gu (2002), the indices are based on such a large sample that the problem of spurious autocorrelation should not exist; thus, the estimators should be consistent but at least the last argument should still persists. Additionally, because of the emphasized deficiencies, the following tests can be seen as a robustness check on the findings from autocorrelation.

Table 5: Autocorrelation of Monthly Index Returns

Index	ρ_1	ρ_2	ρ_3	ρ_6	ρ_{12}	ρ_{24}	ρ_{36}
AT	**0.8241**	**0.6595**	**0.3964**	**0.0425**	**0.5064**	**0.2185**	**0.0975**
BO	**0.7835**	**0.5870**	**0.3170**	**0.0664**	**0.6576**	**0.5268**	**0.3575**
CR	**0.5843**	**0.4891**	**0.0950**	**-0.1176**	**0.3454**	**0.2351**	**0.0912**
CH	**0.7297**	**0.5614**	**0.2996**	**0.1500**	**0.4691**	**0.1541**	**0.0455**
CE	**0.5656**	**0.3325**	**-0.0580**	**-0.2391**	**0.4374**	**0.2947**	**0.2414**
DA	**0.9585**	**0.9108**	**0.8560**	**0.7302**	**0.6180**	**0.2705**	**0.0467**
DN	**0.7686**	**0.5826**	**0.3035**	**-0.0218**	**0.5963**	**0.3688**	**0.1773**
DE	**0.8167**	**0.6570**	**0.5309**	**0.3864**	**0.5519**	**0.2583**	**0.1171**
LV	**0.8590**	**0.7742**	**0.6699**	**0.5172**	**0.4313**	**0.0807**	**-0.0706**
LA	**0.9347**	**0.8635**	**0.7683**	**0.5729**	**0.6019**	**0.2202**	**-0.0097**
MI	**0.8918**	**0.8509**	**0.7664**	**0.7218**	**0.5559**	**0.0348**	**-0.2069**
MN	**0.7478**	**0.5958**	**0.3519**	**0.0897**	**0.5099**	**0.2295**	**0.1258**
NY	**0.8907**	**0.7629**	**0.6254**	**0.4086**	**0.5822**	**0.3484**	**0.1529**
PX	**0.9539**	**0.9040**	**0.8242**	**0.6472**	**0.4669**	**0.0139**	**-0.2862**
PO	**0.7589**	**0.6484**	**0.4131**	**0.2217**	**0.3618**	**0.0809**	**-0.0643**
SD	**0.8501**	**0.8078**	**0.7017**	**0.5391**	**0.5520**	**0.2756**	**0.0592**
SF	**0.8850**	**0.7373**	**0.5822**	**0.3701**	**0.4079**	**0.1803**	**-0.0025**
SE	**0.9940**	**0.9874**	**0.9803**	**0.9568**	**0.8883**	**0.6943**	**0.4918**
TP	**0.8324**	**0.7601**	**0.6395**	**0.5677**	**0.4843**	**0.0262**	**-0.1830**
WD	**0.8889**	**0.7802**	**0.6499**	**0.4444**	**0.5798**	**0.2258**	**-0.0208**
CS10	**0.9435**	**0.8458**	**0.7253**	**0.4970**	**0.6366**	**0.2840**	**0.0428**
CS20	**0.9531**	**0.8658**	**0.7580**	**0.5421**	**0.5930**	**0.1833**	**-0.0872**

Notes: Bold figures indicate significance of the autocorrelation coefficients for lag h at a 1 % significance level with critical values from the χ^2 distribution with h degrees of freedom.

4.4 Results from Variance Ratio Tests

The variance ratios are computed in intervals of two, three, and six months as well as for 12 and 24 months. With the exception of Charlotte, Cleveland, and Dallas, all housing markets exhibit systematically increasing and highly significant variance ratios for all considered lags, which confirms the mean aversion and the rejection of the weak-form version of market efficiency (see Table 6). The empirical findings from both homoscedasticity- and heteroscedasticity-robust variance ratio tests as well as multiple variance ratio tests are basically consistent with the results from autocorrelations. Even the decreasing variance ratios for lag 12 in contrast to lag 6 for Charlotte and Cleveland correspond with the findings of negative autocorrelation for some higher lags. The highest variance ratios are detected for the cities in California, Florida, Las Vegas, Phoenix, New York, and Washington D.C. The housing market in these cities exhibits relatively high volatility as well (see Table 4) and thus seems to be more cyclical and contains smoother trends. California and Florida, at least, are both characterized by a high number of second homes. This sector of the housing market might be more volatile and cyclical than the housing market where secondary residences are less common. Furthermore, Greater New York and California are densely populated areas with above-average house transactions. This feature of the housing market can have a smoothing character and allows for less noise in the time series of house price changes compared to areas and cities with fewer house transactions.

While Gu (2002) depicts mostly significant variance ratios less than one in the short-run indicating mean reversion and variance ratios greater than one in the long-run only, our results consistently present variance ratios greater than one being higher on average than those found by Gu (2002). These differences could be caused by the differences in the covered data set with respect to data frequency, geographical focus, and house price appraisals. However, there are also some similarities to the findings by Gu (2002). First, as indicated above, positive autocorrelation seems to increase over the time horizon according to variance ratio tests. Compared to other Census Divisions, the variance ratios are higher on average in the Pacific Census Division and California, in particular.

With the exception of Cleveland again, the results from comparing homoscedasticity- and heteroscedasticity-consistent test statistics indicate the rejection of the random walk hypothesis at the same assumed level of significance. However, the differences in the values of the test statistics suggest that all analyzed housing markets are characterized by heteroscedasticity in the time series of house price changes.

Table 6: Variance Ratio Estimates and Variance Ratio Test Statistics for Monthly Index Returns

Index	**Number q of Base Observations (Lags) Aggregated to form Variance Ratio**					**SMM for *m* = 5**
	q = 2	q = 3	q = 6	q = 12	q = 24	max $Z_1^*(2,\ldots, 24)$ max $Z_2^*(2,\ldots, 24)$
AT	1.83	2.56	4.00	4.63	5.92	
	(12.32)***	(15.59)***	(18.03)***	(14.40)***	(13.34)***	(18.03)***
	[3.74]***	[4.84]***	[6.14]***	[5.84]***	[6.42]***	[6.42]***
BO	1.78	2.44	3.68	5.20	9.79	
	(12.85)***	(15.87)***	(17.78)***	(18.37)***	(26.31)***	(26.31)***
	[8.80]***	[11.07]***	[13.30]***	[15.27]***	[23.39]***	[23.39]***
CR	1.59	2.13	2.82	2.62	2.73	
	(9.71)***	(12.39)***	(12.07)***	(7.10)***	(5.19)***	(12.39)***
	[4.45]***	[5.71]***	[5.95]***	[4.06]***	[3.50]***	[5.71]***
CH	1.73	2.37	3.55	4.26	5.14	
	(12.04)***	(15.05)***	(16.89)***	(14.26)***	(12.38)***	(16.89)***
	[4.40]***	[5.62]***	[6.97]***	[7.03]***	[7.20]***	[7.20]***
CE	1.54	1.87	2.06	1.82	2.94	
	(8.78)***	(9.54)***	(7.04)***	(3.60)***	(5.80)***	(5.80)***
	(3.83)***	[4.31]***	[3.22]***	[1.79]*	[3.21]***	[4.31]***
DA	1.64	2.11	2.28	1.33	1.80	
	(6.82)***	(7.93)***	(5.51)***	(0.93)	(1.55)	(7.93)***
	[3.80]***	[4.58]***	[3.53]***	[0.65]	[1.19]	[4.58]***
DN	1.76	2.41	3.54	4.69	7.97	
	(12.49)***	(15.51)***	(16.82)***	(16.16)***	(20.87)***	(20.87)***
	[6.66]***	[8.52]***	[9.95]***	[10.60]***	[14.76]***	[14.76]***
DE	1.83	2.57	4.30	6.24	9.75	
	(12.34)***	(15.64)***	(19.84)***	(20.77)***	(23.73)***	(23.73)***
	[4.71]***	[6.08]***	[8.19]***	[9.58]***	[12.41]***	[12.41]***
LV	1.87	2.68	4.76	7.73	10.84	
	(14.24)***	(18.51)***	(24.92)***	(29.45)***	(29.44)***	(29.45)***
	[5.51]***	[7.27]***	[10.36]***	[13.71]***	[15.73]***	[15.73]***
LA	1.95	2.86	5.31	9.35	14.75	
	(15.56)***	(20.51)***	(28.62)***	(36.52)***	(41.14)***	(41.14)***
	[8.23]***	[11.01]***	[16.22]***	[22.78]***	[28.75]***	[28.75]***
MI	1.91	2.80	5.27	9.55	14.27	
	(14.86)***	(19.77)***	(28.32)***	(37.39)***	(39.73)***	(39.73)***
	[6.46]***	[8.69]***	[12.95]***	[18.07]***	[20.87]***	[20.87]***
MN	1.75	2.40	3.69	4.55	6.86	
	(11.67)***	(14.73)***	(17.02)***	(14.81)***	(16.74)***	(17.02)***
	[4.13]***	[5.22]***	[6.25]***	[6.21]***	[8.10]***	[8.10]***
NY	1.90	2.73	4.65	7.36	13.09	
	(14.79)***	(19.01)***	(24.24)***	(27.83)***	(36.18)***	(36.18)***
	[9.18]***	[12.09]***	[16.53]***	[21.23]***	[30.73]***	[30.73]***
PX	1.97	2.92	5.51	9.26	12.52	
	(15.17)***	(20.18)***	(28.54)***	(34.48)***	(32.91)***	(34.48)***
	[5.66]***	[7.62]***	[11.29]***	[14.95]***	[16.16]***	[16.16]***

Table 6 continues on the next page

Index	Number q of Base Observations (Lags) Aggregated to form Variance Ratio					SMM for m = 5 max $Z_1^*(2,\ldots,24)$ max $Z_2^*(2,\ldots,24)$
	q = 2	q = 3	q = 6	q = 12	q = 24	
PO	1.77	2.48	3.96	5.36	6.76	
	(12.65)***	(16.27)***	(19.61)***	(19.08)***	(17.25)***	(19.61)***
	[5.70]***	[7.42]***	[9.53]***	[10.55]***	[11.05]***	[11.05]***
SD	1.86	2.71	5.00	8.86	14.20	
	(14.14)***	(18.81)***	(28.24)***	(34.37)***	(39.52)***	(39.52)***
	[7.87]***	[10.56]***	[15.52]***	[21.71]***	[27.55]***	[27.55]***
SF	1.89	2.69	4.65	7.37	9.90	
	(14.57)***	(18.61)***	(24.20)***	(27.89)***	(26.64)***	(27.89)***
	[7.07]***	[9.21]***	[12.72]***	[15.88]***	[16.71]***	[16.71]***
SE	1.81	2.49	3.60	4.28	5.53	
	(12.34)***	(15.29)***	(16.05)***	(13.35)***	(12.62)***	(16.05)***
	[5.25]***	[6.72]***	[7.95]***	[7.89]***	[8.81]***	[8.81]***
TP	1.85	2.66	4.81	8.18	12.64	
	(13.87)***	(18.22)***	(25.27)***	(31.42)***	(34.85)***	(34.85)***
	[6.05]***	[8.06]***	[11.87]***	[16.37]***	[19.96]***	[19.96]***
WD	1.89	2.72	4.84	8.19	13.08	
	(14.62)***	(18.93)***	(25.44)***	(31.44)***	(36.15)***	(36.15)***
	[7.93]***	[10.45]***	[14.97]***	[20.38]***	[25.36]***	[25.36]***
CS10	1.95	2.86	5.16	8.62	13.70	
	(15.66)***	(20.45)***	(27.62)***	(33.33)***	(38.01)***	(38.01)***
	[7.82]***	[10.36]***	[14.79]***	[19.71]***	[24.68]***	[24.68]***
CS20	1.98	2.94	5.53	9.67	16.44	
	(10.46)***	(13.84)***	(19.49)***	(24.60)***	(29.94)***	(29.94)***
	[5.83]***	[7.83]***	[11.69]***	[16.48]***	[22.20]***	[22.20]***

Notes: ***, **, * indicate significance at the 99 %, 95 %, and 90 % confidence level (rejection of the RWH). One month is taken as a base observation interval; the varaince ratios, VR(q)'s, are reported in the main rows. The homoscedasticity- and heteroscedasticity-consistent test results are reported in parentheses ($Z_1(q)$, $Z_1^*(q)$) and brackets [$Z_2(q)$, $Z_2^*(q)$], respectively. The critical values for multiple variance ratio tests $Z_1^*(q)$ and $Z_2^*(q)$ at the 1 %, 5 % and 10 % significance level are 3.089, 2.569, and 2.311, respectively, according to Hahn and Hendrickson (1971) and Stoline and Ury (1979).

4.5 Results from Runs Tests

As mentioned above, both the autocorrelation tests and the variance ratio tests contain some shortcomings when applying these tests for analyzing market efficiency. Moreover, if the return generating process is non-linear, the autocorrelation coefficients and variance ratio tests are not a reliable measure to detect market (in-) efficiency. Therefore, a direct test for market efficiency is employed that requires neither the assumption of normality of the underlying distribution nor a linear return generating process. The results of the non-parametric runs test of independence between successive events in the time series of index changes are presented in Table 7.

According to the runs test, all indices show significant negative test statistics as can be seen in Table 7. This indicates a mean aversion process because the number of observed runs is below the statistically expected number. Thus, the results of the different tests are consistent for each market. Again, the test statistics are much higher for the housing markets in California and Phoenix than for the other markets. Furthermore, Cleveland, Charlotte, Dallas, and Portland feature the lowest test statistic. With the exception of Portland, these results are consistent with the empirical findings from the variance ratio tests and autocorrelations.

Table 7: Results from the Runs Test for Monthly Index Returns

Index	**Runs**		**Probability**	**Test Statistics**
	actual $\mathbf{N_{Runs}}$	**expected E[Runs]**	π	
AT	43	105	0.6174	-7.8089***
BO	60	126	0.6282	-7.5125***
CR	78	120	0.6700	-4.5208***
CH	51	124	0.6405	-8.2703***
CE	70	127	0.6229	-6.4663***
DA	31	56	0.5792	-4.3333***
DN	46	116	0.6872	-7.6291***
DE	43	111	0.5307	-8.9245***
LV	70	134	0.5495	-7.5707***
LA	31	128	0.6125	-11.2174***
MI	57	130	0.5939	-8.5312***
MN	58	119	0.5903	-7.4392***
NY	39	122	0.6549	-9.2765***
PX	30	122	0.5512	-11.4739***
PO	49	108	0.7235	-6.2646***
SD	40	128	0.6173	-10.0642***
SF	29	129	0.6031	-11.6519***
SE	53	120	0.6660	-7.4170***
TP	65	131	0.5869	-7.7002***
WD	39	124	0.6442	-9.5485***
CS10	27	124	0.6429	-10.9499***
CS20	5	54	0.6060	-8.7577***

Notes: ***, ** and * indicate significance at the 99 %, 95 %, and 90 % confidence level; critical values for the runs test at the 1 %, 5 %, and 10 % significance level are derived from standard normal distribution.

4.6 Results from Quarterly Data as a Further Robustness Check

As a further robustness check of the empirical results above, the analogous analysis is conducted by using quarterly non-overlapping data from the Case-Shiller indices. The shortcoming of the monthly Case-Shiller data for statistical analysis might derive from the index construction methodology applying moving averages over three months for calculating monthly index values. To avoid the bias resulting from monthly data, non-overlapping quarterly data are used. However, as it turned out, the empirical findings support the results and conclusions from monthly data in general.

There is strong evidence of highly significant and positive autocorrelation for the first eight lags (two years) for all markets except the markets in Charlotte, Cleveland, Dallas as well as Portland and Seattle (see Appendix 2). While the latter two markets – both located in the Northeast of the U.S. – show mainly positive and significant autocorrelation and negative autocorrelation for order 6 and 7 only, Cleveland and Dallas do not exhibit significant first-order autocorrelation and significant higher-order autocorrelation of mixed signs. The housing market in Charlotte shows mixed, but highly significant results from autocorrelation tests as well.

Conducting variance ratio tests gives further evidence on these results. In general, the variance ratios reported in Appendix 3 are greater than one, increasing with the lag length, significant in both the homo- and heteroscedastic setting, and thus, indicate strong mean aversion. Again, the pattern of the housing market in Charlotte, Cleveland, and Dallas is exceptional. While Charlotte shows insignificant variance ratios, but still greater than one for lags up two eight quarters, Cleveland and Dallas exhibit insignificant variance ratios being less than one or slightly above. Implementing heteroscedasticity-robust variance ratio tests changes the proposition on the efficient market hypothesis for the housing markets in Atlanta, Chicago, and Minneapolis only slightly. While all three markets show variance ratios greater than one and being significant at the one percent level when applying homoscedastic variance ratio tests, the variance ratios up to lag eight are significant at the five and ten percent level respectively only when controlling for potential heteroscedasticity in the index returns.

Conducting runs tests, the test statistics (see Appendix 4) for the U.S. housing markets are significant at the one percent level and indicate strong mean aversion with the exception of Charlotte, Cleveland, and Dallas again. Thus, the results based on quarterly data are mainly consistent with the previous results and support the rejection of the efficient market hypothesis for all markets with the exception of the three markets in Charlotte, Cleveland, and Dallas. However, these markets already show the lowest test statistics based on monthly data and therefore, seem to be less characterized by inefficiencies as the other 17 local housing markets and the two nationwide housing markets in the U.S.

Summing up, while the results from Gu (2002) based on variance ratio tests are mixed, the results of the different tests are consistent for each market and indicate the rejection of the null hypothesis of the weak-form version of market efficiency for all markets. Moreover, all 20 of the U.S. housing markets covered exhibit a significant mean aversion based on monthly data.

5 Implications for Trading Strategies

The strong (mainly positive) autocorrelation suggests that there might be a pattern of house price movements and that investors would therefore be able to develop some trading strategies to exploit the pattern and to earn excess returns compared to a buy-and-hold strategy. However, following the definition by Fama (1970), even if the efficient market hypothesis is rejected by statistical tests and housing prices do not reflect all relevant market information, (housing) markets can be weak-form efficient from a more practical perspective. Thus, the rejection of the weak-form version of market efficiency alone, however, does not postulate market inefficiency by itself. Although inefficiencies seem to be statistically detected, they might be too small for investors yielding excess returns by implementing trading strategies based upon historical price information. This means that autocorrelation is not necessarily contradictory to the efficient market hypothesis as long as the implementation of a trading strategy is not beneficial. Thus, further methods must be introduced to evaluate particular strategies and to provide more direct evidence of market inefficiencies. Technical analysis can therefore serve as a control of, or complement, the earlier statistical testing methods.

In contrast to the CMPHI and FHFA indices mainly used in previous analysis such as Gu (2002), the Case-Shiller indices are partly traded at the CME and therefore offer investors and speculators more opportunities to exploit market inefficiencies. However, this study focuses on the underlying indices and not on the traded derivatives. Thus, the question if these inefficiencies are priced in the derivatives or not is left for further research. However, one further advantage compared to non-traded indices is the possibility of shortening the indices; Gu (2002) does not allow for short selling in his analysis. This issue is also mentioned by Case and Shiller (1989). In Case et al. (1991, 1995) and Shiller (2008) the advantages of establishing futures and options markets for residential real estate prices are well described and discussed. Since the introduction of such products in May 2006 the notional trading value was on the rise until November 2007 (Shiller, 2008). However, although the futures open interest has fallen and the market suffers from low liquidity, Shiller (2008) is optimistic that liquidity will increase when more products are established and emphasizes the benefits of such market in many respects such as reducing the amplitude of speculative price movements, dampening the business cycle, diversification benefits, and hedging characteristics, among others.

In order to analyze the profitability of trading strategies compared to a simple buy-and-hold strategy, we apply two different methodologies. First, a trading strategy based on the estimated autocorrelations of the indices is considered as suggested by Gu (2002), but we explicitly allow for short selling in consideration of the changed market environment. Second, trading strategies based on moving averages are tested. On comparing the two strategies, the latter one is built on less crucial assumptions. While the strategy suggested by Gu (2002) explicitly assumes linear return generating processes and is afflicted with problems from estimating autocorrelations, the application of moving averages does not require any assumption on linearity in returns and is thus less restrictive. Both trading strategies are simply constructed, allow for out-of-sample analysis, and are thus well suited as a basis for investor's strategies. Tax effects and transaction costs are not considered in both strategies, but due to the trading at the CME transaction costs should be low compared to transactions costs in the direct real estate market. Furthermore, the number of transactions indicated by the strategies is very low and should not influence the comparison of buy-and-hold and the applied trading strategy substantially.

5.1 Results from Autocorrelation-based Trading Strategy

The empirical results of applying the trading strategy suggested by Gu (2002) and extending it by assuming short selling opportunities are shown in Table 8. For the purpose comparison only, the total nominal returns from a buy-and-hold strategy are presented as well. The starting point of implementing the trading strategy is February 1988 if data are available since January 1987, since 12 monthly returns are needed in advance to have a basis. In general, the returns from the trading strategy are much higher than those from a buy-and-hold strategy, confirming the results from the test on housing market efficiency above. It also becomes apparent that the excess return is negatively related to the employed order of autocorrelation for the trading strategy. Thus, the lower the order of autocorrelation, the higher the excess return. With the exception of Las Vegas, Miami, Phoenix, Tampa, and the U.S. index containing 20 cities, the strategy based on autocorrelations with a lag of half a year performs the worst. This finding might be an indication of seasonality, even if excess returns are still persistent for most of the indices. Las Vegas, Miami, Phoenix, and Tampa are located in the South and have a more stable climate with less severe winter seasons than cities such as Chicago or New York in the North. Thus, seasonality might be less distinctive in these areas. Due to the negative autocorrelation in the case of Charlotte (lag 6), Cleveland (lag 3 and lag 6), and Denver (lag 6) the strategy is reversed for these lag structures. This means that negative (positive) index changes indicate a buying (selling) signal. However, as can be seen from Table 8, applying this strategy excess returns are not possible; also a slightly positive total nominal return is found for Cleveland (6 lags) only. Cleveland is also the city which discloses the highest negative autocorrelation. For all the other three cases, a trading strategy based on positive autocorrelation instead of a negative one would result in higher total nominal returns, but even then excess returns cannot be realized.

The relative comparison between a buy-and-hold strategy and the trading strategies might be of relevance because the strategies are based on different time spans for the housing markets. The influence of the time span on the absolute superiority of trading strategies becomes obvious when focusing on the housing market of Detroit in particular. While the total nominal returns from both the buy-and-hold strategy and the applied trading strategy are much less than for other markets such as New York, the relative superiority of the trading strategy is much higher for Detroit than for New York. One reason for this result could be the different time period and thus the different stage in the cycle of the real estate market. While the return of 366.45 % for the housing market in New York based on the AR(1)-strategy is around 3.5 times the return of the buy-and-hold strategy only, the return of 256.25 % for the housing market in Detroit according to the AR(1)-strategy is around 15 times the return of the buy-and-hold strategy.

While investors can earn excess returns for almost all cities at least by focusing on the short-term pattern (see Table 8), Gu (2002) points out that excess returns can be earned by investors exclusively for the housing market in California, based on his data. However, the cities in California (Los Angeles, San Diego, and San Francisco) exhibit the most pronounced absolute excess returns as well. Furthermore, the advantage of trading strategies compared to a buy-and-hold strategy is more pronounced in volatile markets and periods characterized by market up- and downturns. However, as can be seen from Exhibit 2 in Gu (2002), the considered period is mainly dominated by an upward moving market, for the six presented markets at least. There is only one period where markets decrease of around 10 percent. In contrast, the cyclical pattern is more pronounced in the period from 1987 to 2009 and additionally driven by monthly, transaction-based data.

Table 8: Total Nominal Returns from Buy-and-Hold Strategy Compared to Trading Strategies Based on Autocorrelation Pattern

Index	Buy-and-Hold	AR(1)	AR(2)	AR(3)	AR(6)	AR(12)
AT	53.49 %	143.09 %	125.83 %	85.96 %	49.93 %	143.17 %
BO	105.26 %	368.88 %	236.41 %	100.85 %	41.16 %	354.84 %
CR	78.46 %	97.71 %	87.54 %	35.73 %	-14.68 %	88.74 %
CH	104.23 %	274.48 %	214.74 %	146.63 %	110.72 %	238.34 %
CE	88.48 %	180.87 %	129.39 %	-26.18 %	6.58 %	179.16 %
DA	12.39 %	56.29 %	32.45 %	8.82 %	-28.41 %	56.03 %
DN	157.18 %	313.01 %	232.94 %	140.46 %	-41.33 %	293.01 %
DE	16.67 %	256.25 %	196.65 %	138.06 %	129.20 %	219.91 %
LV	61.03 %	575.28 %	427.58 %	360.59 %	413.02 %	387.25 %
LA	134.34 %	1,168.71 %	1,051.58 %	851.06 %	694.88 %	835.82 %
MI	102.86 %	561.36 %	545.10 %	433.57 %	452.59 %	347.64 %
MN	77.76 %	274.56 %	211.99 %	124.81 %	117.46 %	244.04 %
NY	103.86 %	366.45 %	302.24 %	240.31 %	183.65%	281.80 %
PX	57.35 %	635.69 %	641.27 %	594.70 %	577.37 %	540.03 %
PO	256.81 %	406.53 %	342.96 %	243.96 %	201.30 %	310.61 %
SD	146.09 %	817.40 %	786.71 %	669.02 %	516.60 %	629.45 %
SF	138.71 %	1,187.08 %	825.07 %	516.76 %	300.84 %	506.49 %
SE	128.19 %	262.52 %	230.16 %	145.10 %	115.62 %	212.17 %
TP	77.55 %	364.00 %	325.21 %	261.90 %	335.56 %	255.76 %
WD	135.34 %	533.38 %	446.75 %	351.65 %	277.52 %	340.68 %
CS10	117.46 %	536.70 %	453.36 %	374.80 %	270.43 %	406.77 %
CS20	26.22 %	171.19 %	161.86 %	157.36 %	147.02 %	143.20 %

5.2 Results from Moving Average-based Trading Strategy

As a further robustness check on the rejection of the hypothesis of housing market efficiency in section 4 and to control for possible spurious autocorrelation and the assumption of linear return generating processes, we implement a technical analysis based on simple moving averages for the 22 housing markets. Moving averages are applied to distinguish between long-term trends and short-term oscillations, thus acting as trend indicators. In practice, the average index price is calculated from past index prices. The number of relevant historical index values depends on the selected period under investigation. In order to recognize mid- to long-term trends, the 12-month line is used. However, moving averages do not only differ with respect to the length of period (e.g., 3, 6, 12 months), but also with regard to the calculation of the mean. In the simplest form, the arithmetic mean is used. More sophisticated models by applying linearly or exponentially weighted averages might be possible as well, but the differences between these approaches are rather small. In addition to the 12-month window, moving-averages for 3 and 6 months are calculated. This might be advantageous for indices that are more volatile and less persistent.

The sample period ranges from January, 1987 to June, 2009, which is identical to the sample for the tests of the random walk hypothesis. The time period from January, 1987 to December, 1987 is needed to compute the moving average based on the 12-month line. Therefore, the moving averages of December, 1987 serve as starting points and decision criteria for the positioning. For indices with a shorter historical time series, the sample period is adjusted accordingly as for the tests of weak-form market efficiency.

A trading signal occurs directly at the breakthrough of the moving average line. A so-called buying signal occurs if the index value breaks through its moving average bottom-up; a selling signal occurs when the moving average is breached top-down. Allowing for short-term and long-term pattern in the indices, moving averages of 3 months, 6 months, and 12 months, respectively, are considered. When a selling signal occurs, a short position is assumed. The chart-technical model is compared with the buy-and-hold strategy. The technical model is advantageous when it generates higher returns than a simple buy-and-hold strategy.

The total nominal returns of both strategies are shown in Table 9. With the exception of the housing market in Dallas, all housing market indices analyzed show higher returns for all strategies based on moving averages than for a continuous market investment. It is also apparent that strategies built on relatively short-term indicators perform better than long-term oriented indicators for the vast majority of housing markets. The 6- and 12-month moving average strategy, respectively, is superior to the 3-month moving average strategy for the markets in Denver, Las Vegas, Portland, and Seattle only. However, the difference in the total nominal returns between the three approaches is small when calculating annual returns in particular.

Again, the three housing markets in California (Los Angeles, San Diego, and San Francisco) exhibit the highest absolute total nominal returns resulting from trading strategies while the markets in Atlanta, Charlotte, Cleveland, and Dallas feature the lowest returns for the period considered in each case. The picture changes slightly when focusing on the relative superiority of the trading strategies in comparison to a buy-and-hold investment. In that case, the lowest return can be detected in Charlotte, Denver, and Portland, while the housing markets in Detroit and Phoenix are the relatively best performing markets.

On comparing the findings to the conclusions from the statistical tests, it can be stated that the results correspond to each other and confirm the rejection of market efficiency. Judging the superiority of the two implemented trading strategies is nontrivial since they are built on different information sets. However, one could choose to compare the results from the 3-month moving average strategy and the mean return from the trading strategies build on autocorrelations of order one, two, and three. Alternatively, the returns from the AR(3)-trading strategy can be compared to the performance of the strategy built on 3-month moving averages. Regardless of which comparison is conducted, the moving average strategies result in higher total nominal returns for all housing markets. The difference of one month in the time span can be neglected and is not crucial for the performance.

Table 9: Total Nominal Returns from a Buy-and-Hold Strategy Compared to Trading Strategies Based on Moving Averages (MA)

Index	Buy-and-Hold	3-Month MA	6-Month MA	12-Month MA
AT	53.82 %	142.72 %	135.85 %	130.98 %
BO	104.32 %	339.91 %	261.24 %	242.20 %
CR	79.58 %	117.92 %	104.54 %	102.22 %
CH	107.28 %	296.69 %	253.42 %	258.48 %
CE	88.68 %	196.27 %	115.37 %	127.97 %
DA	12.69 %	47.55 %	33.13 %	10.27 %
DN	154.55 %	307.60 %	243.86 %	190.42 %
DE	16.24 %	251.44 %	250.66 %	265.97 %
LV	60.98 %	572.42 %	550.02 %	586.46 %
LA	136.93 %	1,209.08 %	1,103.76 %	1,021.75 %
MI	103.57 %	619.44 %	589.97 %	577.41 %
MN	76.35 %	279.15 %	233.08 %	268.65 %
NY	103.16 %	356.49 %	306.17 %	288.17 %
PX	57.70 %	644.02 %	634.29 %	609.83 %
PO	254.51 %	411.53 %	397.21 %	423.66 %
SD	148.00 %	951.89 %	839.78 %	844.04 %
SF	139.67 %	1,080.09 %	818.05 %	680.95 %
SE	125.26 %	253.46 %	255.46 %	220.81 %
TP	78.02 %	383.40 %	365.71 %	372.67 %
WD	137.43 %	528.79 %	439.21 %	401.45 %
CS10	118.17 %	520.08 %	447.84 %	400.12 %
CS20	27.14 %	174.12 %	165.60 %	162.64 %

In addition to the trading strategies based on monthly data and as a further robustness check of the findings, the same strategies are implemented considering quarterly data. The findings in Appendix 5 and Appendix 6 strongly support the drawn conclusions above and suggest that excess returns might be earned by investors at most of the markets. When applying the trading strategy with respect to the autocorrelation coefficient of lag 6, the strong negative returns for Atlanta, Charlotte, Cleveland, Denver, Portland, and Seattle result from the negative autocorrelation coefficient of lag 6. By contrast, the trading strategy based on the negative autocorrelation coefficient is superior for Dallas. However, the autocorrelation coefficient for Dallas has the highest negative value and thus might be more powerful and predictive. This holds for both lag 2 and lag 6. Considering the results from quarterly moving averages, Dallas is the only market, where the trading strategy is not superior to a buy-and-hold strategy at any implemented moving average. This result is consistent with the variance ratio and runs test. Both tests do not reject the null hypothesis of market efficiency for Dallas only. Furthermore, the strategy based on the 3-quarter moving average is not generating excess returns for Cleveland and Denver. However, for all the other markets the rejection of the efficient market hypothesis also results in excess returns compared to a buy-and-hold-strategy when applying simple trading strategies.

In summary, the results from the statistical testing methods on housing market efficiency are confirmed by the implementation of two different trading strategies. Thus, the rejection of the efficient market hypothesis is not only a statistical artifact but also exploitable by investors. In general, short-term persistence is more pronounced and trading strategies based on short-term indicators result in higher excess returns than do long-term oriented strategies. There are also differences in the degree of superiority of the trading strategies compared to a buy-and-hold strategy. While the housing markets in California, Phoenix, and Miami exhibit the highest excess returns, the excess returns for Atlanta, Charlotte, Cleveland, and Dallas are the lowest. This is consistent with the results from statistically testing market efficiency. Besides differing periods, the differences might also be caused by varying seasonality effects as milder winter seasons in California and Florida compared to the Midwest or to New York.

However, even if all the results strongly support the rejection of the efficient market hypothesis, there are still some limitations on a final judgment of housing market (in-) efficiency in the U.S. The trading strategies in particular assume that derivatives on the indices are tradable and short selling is possible. At present, derivatives are traded for ten local indices and one U.S index, but liquidity is still small and the experience with these instruments is limited since they have only been traded for a few years. Furthermore, analysis of how the derivatives are priced and whether or not the inefficiencies might be incorporated into the pricing process has not yet been made.

6 Conclusion

Research in real estate finance and economics has been dealing with the topic of efficiency in the housing market for more than 25 years. However, most past research has either focused on local markets with the analyses based on single homes or has focused on the CMPHI and FHFA indices. To our knowledge, there does not already exist any study based on the Case-Shiller indices. As mentioned above, these indices consider more locally concentrated markets than the CMPHI and FHFA indices, but contain some advantageous characteristics compared to the FHFA indices.

While in general, the efficient market hypothesis deals with the question of whether or not prices fully reflect all the information available at a specific point in time, the study tests the weak-form efficient market hypothesis focusing on the information set of historical index series or index changes. The tests utilize single and multiple variance ratio tests because they possess greater power and a lower sensitivity against type-II error than conventional tests such as autocorrelation and unit root tests, even if the time series are not normally distributed. Variance ratio tests also allow the random walk hypothesis to be tested jointly for all observation intervals. Since the rejection of the random walk hypothesis does not necessarily imply inefficiency in a market, a non-parametric runs test for market efficiency is also conducted. Additionally, the practical relevance of rejecting the efficient market hypothesis is tested by implementing trading strategies based on results from autocorrelation tests as well as on moving averages.

This study examines the behavior of monthly house price changes for 20 cities and two nationwide indices for the period of January 1987 to June 2009, incorporating both the long lasting boom and the steep and strong downturn of the U.S. housing market. The conducted analysis gives empirical evidence that house price changes in the U.S. exhibit certain patterns. The results show that the price changing generating process of U.S. housing markets differs significantly from the theoretical model of the random walk hypothesis. Without any exception, the conducted tests reject the null hypothesis of a random walk for all time series of house price changes. Furthermore, the implemented trading strategies support the findings by generating excess returns in comparison to a buy-and-hold strategy. In general, we can conclude that investors might be likely to earn excess returns by using past information in the U.S. housing market, in particular when standardized derivatives of the indices are traded on exchange markets. However, due to limitations in the data, the analysis does not conduct the tests based on prices and price changes of the derivatives.

The findings support the conclusions by previous research e.g. by Case and Shiller (1989) and Gu (2002). In comparison to the most recent study by Gu (2002), the results are in even of stronger support of the inefficiency of the U.S. housing market. This might be caused by higher data frequency and the focus on transaction data, among other reasons. However, all the studies focus on different areas and markets, differ in their focus on markets or single houses, apply different methodologies and data frequencies, use partly appraisal data, and are conducted over different time periods. Thus, the general qualitative conclusions might be comparable, but not the quantitative results.

In terms of the shortcomings of the index construction methodology for monthly data, the tests on the efficient market hypothesis are also conducted by applying quarterly data. The findings mainly confirm the results from the analysis based on monthly data in a qualitative way. Furthermore, even if short-term dependencies are artificially biased due to the index construction methodology, the analysis of long-term persistence without overlapping time periods supports the rejection of the efficient market hypothesis at a very high significance level for all considered housing markets with the exception of Charlotte, Cleveland, and Dallas. The empirical results from implementing trading strategies confirm long-term persistence as well. In fact, the excess returns from trading strategies – based on three-month moving averages in particular – compared to a buy-and-hold strategy could be even higher when the monthly indices are not constructed on moving averages because trend reversals of the market would be detected faster and reflected in the indices.

Knowing the inefficiencies of the U.S. housing market, the next step for investors interested in exploiting these inefficiencies consists of focusing on the pricing process of the traded derivatives on the Case-Shiller indices. Further research should conduct analyses on the interdependence of the underlying market and its derivatives traded at the CME. This type of analysis would give further empirical evidence on whether inefficiencies in the U.S. housing market are exploitable or whether they are incorporated into the pricing process of tradable products and are thus not exploitable by investors. This work is left for further research.

Appendix

Appendix 1: Descriptive Statistics of Quarterly Index Returns

Index	Mean	Min.	Max.	Std.dev.	Skewness	Kurtosis	No. of Obs.
AT	0.0061	-0.0824	0.0331	0.0188	-2.8421	12.8164	73
BO	0.0088	-0.0505	0.0684	0.0242	-0.2416	3.0703	89
CR	0.0071	-0.0633	0.0409	0.0137	-1.5591	10.1246	89
CH	0.0093	-0.1143	0.0666	0.0237	-2.2213	12.1198	89
CE	0.0077	-0.0827	0.0938	0.0211	-0.6154	9.0407	89
DA	0.0043	-0.0546	0.0629	0.0206	-0.1940	4.7929	37
DN	0.0104	-0.0554	0.0528	0.0192	-0.7296	4.3853	89
DE	0.0026	-0.1312	0.0334	0.0294	-2.5617	10.4512	73
LV	0.0052	-0.1466	0.1616	0.0410	-0.5666	8.0295	89
LA	0.0111	-0.1179	0.1010	0.0380	-0.5886	3.9211	89
MI	0.0083	-0.1037	0.0802	0.0342	-1.2786	5.7249	89
MN	0.0074	-0.1415	0.0477	0.0289	-2.9519	14.2168	81
NY	0.0091	-0.0556	0.0585	0.0220	-0.1966	2.9547	89
PX	0.0054	-0.1485	0.1298	0.0411	-1.0605	7.6053	81
PO	0.0144	-0.0707	0.0703	0.0219	-0.9867	7.3872	89
SD	0.0110	-0.0959	0.1052	0.0354	-0.5074	3.9300	89
SF	0.0109	-0.1167	0.1058	0.0405	-0.8415	4.7553	89
SE	0.0114	-0.0759	0.0886	0.0251	-0.7111	5.9410	77
TP	0.0067	-0.0987	0.0810	0.0288	-1.1622	6.9561	89
WD	0.0110	-0.0790	0.0873	0.0292	-0.3433	3.9008	89
CS10	0.0098	-0.0753	0.0665	0.0266	-0.9267	4.4365	89
CS20	0.0089	-0.0723	0.0583	0.0343	-1.1214	3.4354	37

Appendix 2: Autocorrelation of Quarterly Index Returns

Index	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7	ρ_8
AT	**0.4769**	**0.0723**	**0.2668**	**0.5342**	**0.2264**	**-0.0809**	**0.0019**	**0.2210**
BO	**0.4727**	**0.1050**	**0.4005**	**0.7048**	**0.3528**	**0.0324**	**0.2705**	**0.5417**
CR	**0.2903**	*-0.0868*	*0.1218*	**0.4521**	**0.0539**	**-0.2774**	**-0.0641**	**0.1882**
CH	**0.4514**	**0.1857**	**0.2650**	**0.4891**	**0.1830**	**0.0114**	**0.0221**	**0.1486**
CE	0.0301	*-0.2547*	0.0979	**0.5929**	**0.0849**	**-0.2272**	**0.0225**	**0.3736**
DA	0.0741	**-0.5167**	**0.0345**	**0.5666**	**0.0245**	**-0.3940**	**-0.1003**	**0.3234**
DN	**0.4135**	**0.0547**	**0.3416**	**0.6490**	**0.2769**	**-0.0606**	**0.1681**	**0.3957**
DE	**0.6599**	**0.4328**	**0.5053**	**0.5981**	**0.4052**	**0.2632**	**0.3341**	**0.2836**
LV	**0.7798**	**0.6010**	**0.5343**	**0.4815**	**0.3655**	**0.2159**	**0.1315**	**0.0989**
LA	**0.8196**	**0.6271**	**0.6251**	**0.6145**	**0.4344**	**0.2561**	**0.2346**	**0.2138**
MI	**0.8576**	**0.7850**	**0.6947**	**0.5835**	**0.4358**	**0.2963**	**0.1769**	**0.0420**
MN	**0.4624**	**0.1450**	**0.3603**	**0.5531**	**0.2581**	**0.0915**	**0.1715**	**0.2561**
NY	**0.7310**	**0.4854**	**0.5323**	**0.6296**	**0.4817**	**0.2893**	**0.3171**	**0.3681**
PX	**0.8638**	**0.6896**	**0.5774**	**0.4760**	**0.3090**	**0.1522**	**0.0703**	**0.0083**
PO	**0.5794**	**0.3139**	**0.3465**	**0.4259**	**0.1761**	**-0.0761**	**-0.0081**	**0.0784**
SD	**0.7958**	**0.6111**	**0.5986**	**0.5956**	**0.4222**	**0.2440**	**0.2725**	**0.2831**
SF	**0.6428**	**0.4110**	**0.4101**	**0.4351**	**0.2037**	**0.0427**	**0.1140**	**0.1877**
SE	**0.4992**	**0.1573**	**0.2653**	**0.4676**	**0.1730**	**-0.0904**	**-0.0184**	**0.1149**
TP	**0.7739**	**0.6393**	**0.6116**	**0.5494**	**0.3865**	**0.2523**	**0.1414**	**0.0438**
WD	**0.6978**	**0.4935**	**0.5629**	**0.6056**	**0.3421**	**0.1768**	**0.2002**	**0.2268**
CS10	**0.7669**	**0.5451**	**0.5944**	**0.6457**	**0.4343**	**0.2374**	**0.2541**	**0.2776**
CS20	**0.7795**	**0.5795**	**0.5842**	**0.6008**	**0.4164**	**0.2360**	**0.1947**	**0.1810**

Notes: Bold figures indicate significance of the autocorrelation coefficients for lag h at a 1 % significance level with critical values from the χ^2 distribution with h degrees of freedom. Italic figures indicate significance of the autocorrelation coefficients for lag h at 5 % significance level with critical values from the χ^2 distribution with h degrees of freedom.

Appendix 3: Variance Ratio Estimates and Variance Ratio Test Statistics for Quarterly Index Returns

Index	**Number q of Base Observations (Lags) Aggregated to form Variance Ratio**					**SMM for *m* = 5** max $Z_1^*(2, \ldots, 8)$ max $Z_2^*(2, \ldots, 8)$
	q = 2	q = 3	q = 4	q = 6	q = 8	
AT	1.51	1.72	1.80	2.32	2.32	
	(4.36)***	(4.14)***	(3.67)***	(4.57)***	(3.81)***	(4.57)***
	[1.67]*	[1.74]*	[1.67]*	[2.27]**	[2.00]**	[2.00]
BO	1.49	1.75	2.10	3.17	3.96	
	(4.60)***	(4.75)***	(5.53)***	(8.29)***	(9.43)***	(9.43)***
	[3.65]***	[4.02]***	[4.89]***	[7.50]***	[8.66]***	[8.66]***
CR	1.31	1.36	1.32	1.52	1.38	
	(2.95)***	(2.28)**	(1.60)	(2.00)**	(1.22)	(2.95)**
	[1.57]	[1.32]	[1.00]	[1.36]	[0.87]	[1.57]
CH	1.48	1.70	1.82	2.23	2.22	
	(4.52)***	(4.40)***	(4.14)***	(4.68)***	(3.90)***	(4.68)***
	[2.09]**	[2.22]**	[2.25]**	[2.73]***	[2.39]**	[2.73]**
CE	0.95	0.83	0.81	1.28	1.33	
	(-0.45)	(-1.07)	(-0.95)	(1.05)	(1.06)	(-1.07)
	(-0.19)	[-0.49]	[-0.47]	[0.57]	[0.60]	[0.60]
DA	1.01	0.72	0.59	0.93	0.80	
	(0.03)	(-1.15)	(-1.33)	(-0.17)	(-0.41)	(-1.33)
	[0.03]	[-0.89]	[-1.02]	[-0.13]	[-0.33]	[-1.02]
DN	1.42	1.64	1.91	2.78	3.24	
	(3.94)***	(4.03)***	(4.61)***	(6.80)***	(7.15)***	(7.15)***
	[2.58]***	[2.77]***	[3.29]***	[4.97]***	[5.30]***	[5.30]***
DE	1.70	2.14	2.48	3.36	3.84	
	(5.97)***	(6.55)***	(6.75)***	(8.16)***	(8.19)***	(8.19)***
	[2.57]**	[3.06]***	[3.37]***	[4.34]***	[4.54]***	[4.54]***
LV	1.79	2.43	2.96	3.86	4.20	
	(7.49)***	(9.03)***	(9.87)***	(10.91)***	(10.21)***	(10.91)***
	[3.27]***	[4.13]***	[4.71]***	[5.54]***	[5.47]***	[5.54]***
LA	1.86	2.59	3.29	4.57	5.24	
	(8.08)***	(10.09)***	(11.55)***	(13.62)***	(13.52)***	(13.62)***
	[4.96]***	[6.45]***	[7.64]***	[9.43]***	[9.80]***	[9.80]***
MI	1.90	2.72	3.47	4.69	5.29	
	(8.44)***	(10.87)***	(12.44)***	(14.06)***	(13.68)***	(14.06)***
	[3.95]***	[5.19]***	[6.06]***	[7.10]***	[7.20]***	[7.20]***
MN	1.49	1.72	1.89	2.58	2.74	
	(4.43)***	(4.34)***	(4.27)***	(5.76)***	(5.74)***	(5.76)***
	[1.74]*	[1.89]*	[2.02]**	[2.92]***	[2.98]***	[2.98]**
NY	1.74	2.28	2.80	4.00	5.00	
	(6.95)***	(8.10)***	(9.07)***	(11.46)***	(12.75)***	(12.75)***
	[5.31]***	[6.53]***	[7.63]***	[10.08]***	[11.54]***	[11.54]***
PX	1.91	2.66	3.28	4.20	4.50	
	(8.18)***	(10.03)***	(10.96)***	(11.66)***	(10.65)***	(11.66)***
	[3.51]***	[4.46]***	[5.05]***	[5.69]***	[5.50]***	[5.69]***

Appendix 3 continues on the next page

Index	Number q of Base Observations (Lags) Aggregated to form Variance Ratio					SMM for $m = 5$ max $Z_1^*(2, \ldots, 8)$ max $Z_2^*(2, \ldots, 8)$
	q = 2	q = 3	q = 4	q = 6	q = 8	
PO	1.61	2.00	2.27	2.80	2.87	
	(5.80)***	(6.32)***	(6.38)***	(6.87)***	(5.96)***	(6.87)***
	[2.79]***	[3.26]***	[3.49]***	[4.06]***	[3.74]***	[4.06]***
SD	1.84	2.57	3.26	4.53	5.30	
	(7.88)***	(9.94)***	(11.41)***	(13.48)***	(13.71)***	(13.71)***
	[4.73]***	[6.18]***	[7.31]***	[9.04]***	[9.61]***	[9.61]***
SF	1.67	2.21	2.68	3.43	3.65	
	(6.33)***	(7.65)***	(8.45)***	(9.28)***	(8.44)***	(9.28)***
	[3.59]***	[4.46]***	[5.05]***	[5.76]***	[5.48]***	[5.76]***
SE	1.47	1.73	1.91	2.44	2.54	
	(4.16)***	(4.28)***	(4.29)***	(5.12)***	(4.55)***	(5.12)***
	[2.47]**	[2.71]***	[2.86]***	[3.64]***	[3.41]***	[3.64]***
TP	1.81	2.51	3.11	4.25	4.87	
	(7.68)***	(9.55)***	(10.64)***	(12.41)***	(12.34)***	(12.41)***
	[3.79]***	[4.97]***	[5.73]***	[6.91]***	[7.09]***	[7.09]***
WD	1.72	2.33	2.92	4.06	4.71	
	(6.78)***	(8.41)***	(9.70)***	(11.68)***	(11.83)***	(11.83)***
	[4.38]***	[5.66]***	[6.70]***	[8.26]***	[8.61]***	[8.61]***
CS10	1.80	2.44	3.04	4.23	4.90	
	(7.54)***	(9.12)***	(10.31)***	(12.33)***	(12.43)***	(12.43)***
	[4.42]***	[5.61]***	[6.55]***	[8.10]***	[8.46]***	[8.46]***
CS20	1.86	2.63	3.34	4.83	5.81	
	(5.25)***	(6.64)***	(7.60)***	(9.42)***	(9.89)***	(9.89)***
	[3.55]***	[4.73]***	[5.64]***	[7.25]***	[7.89]***	[7.89]***

Notes: ***, **, * indicate significance at the 99 %, 95 %, and 90 % confidence level (rejection of the RWH). One month is taken as a base observation interval; the varaince ratios, VR(q)'s, are reported in the main rows. The homoscedasticity- and heteroscedasticity-consistent test results are reported in parentheses ($Z_1(q)$, $Z_1^*(q)$) and brackets [$Z_2(q)$, $Z_2^*(q)$], respectively. The critical values for multiple variance ratio tests $Z_1^*(q)$ and $Z_2^*(q)$ at the 1 %, 5 % and 10 % significance level are 3.089, 2.569, and 2.311, respectively, according to Hahn and Hendrickson (1971) and Stoline and Ury (1979).

Appendix 4: Results from the Runs Test for Quarterly Index Returns

Index	**Runs** Actual N_{Runs}	**Runs** expected E[Runs]	**Probability** π	**Test Statistics**
AT	15	35	0.6266	-4.1349^{***}
BO	27	41	0.6414	-2.6681^{***}
CR	33	38	0.6979	-0.7666
CH	21	41	0.6519	-3.7198^{***}
CE	33	41	0.6422	-1.4682
DA	15	19	0.5830	-0.7979
DN	19	37	0.7069	-3.2899^{***}
DE	12	37	0.5347	-5.5504^{***}
LV	19	45	0.5509	-5.1502^{***}
LA	11	43	0.6147	-6.2063^{***}
MI	18	43	0.5964	-4.9896^{***}
MN	21	39	0.6006	-3.7191^{***}
NY	18	40	0.6605	-4.1900^{***}
PX	7	41	0.5521	-7.1598^{***}
PO	17	34	0.7449	-3.0268^{***}
SD	19	42	0.6223	-4.4965^{***}
SF	19	43	0.6060	-4.6841^{***}
SE	17	34	0.6751	-3.3871^{***}
TP	24	44	0.5915	-3.8045^{***}
WD	19	41	0.6463	-4.1911^{***}
CS10	19	41	0.6444	-4.2164^{***}
CS20	3	18	0.6026	-4.5016^{***}

Notes: ***, ** and * indicate significance at the 99 %, 95 %, and 90 % confidence level; critical values for the runs test at the 1 %, 5 %, and 10 % significance level are derived from standard normal distribution.

Appendix 5: Total Nominal Returns from Buy-and-Hold Strategy Compared to Trading Strategies Based on Quarterly Autocorrelation Pattern

Index	**Buy-and-Hold**	**AR(1)**	**AR(2)**	**AR(3)**	**AR(6)**	**AR(8)**
AT	50.40 %	114.46 %	58.85 %	76.71 %	-33.26 %	94.07 %
BO	105.03 %	204.08 %	88.57 %	160.29 %	49.11 %	272.54 %
CR	71.10 %	59.05 %	-23.03 %	60.63 %	-14.87 %	70.38 %
CH	78.74 %	176.83 %	107.75 %	148.66 %	63.62 %	129.13 %
CE	73.34 %	46.46 %	5.16 %	71.54 %	-7.06 %	180.67 %
DA	6.51 %	-2.87 %	24.64 %	9.33 %	24.50 %	31.39 %
DN	168.16 %	156.24 %	92.72 %	177.91 %	-45.86 %	248.74 %
DE	13.55 %	184.99 %	156.81 %	186.62 %	80.22 %	117.80 %
LV	53.37 %	493.01 %	423.53 %	448.51%	176.56 %	122.08 %
LA	78.10 %	662.13 %	496.46 %	503.62 %	176.13 %	158.77 %
MI	88.79 %	444.52 %	486.98 %	421.10 %	227.61 %	136.50 %
MN	76.79 %	217.88 %	214.64 %	214.67 %	124.13 %	174.66 %
NY	105.94 %	259.28 %	199.15 %	254.75 %	130.57 %	192.23 %
PX	62.12 %	590.87 %	535.75 %	513.19 %	349.40 %	191.66 %
PO	233.19 %	328.82 %	268.05 %	259.95 %	-69.11 %	237.99 %
SD	99.28 %	586.58 %	438.95 %	498.80 %	247.99 %	329.91 %
SF	92.91 %	525.79 %	241.53 %	276.23 %	146.30 %	149.69 %
SE	125.94 %	242.72 %	180.90 %	202.87 %	-52.55 %	94.63 %
TP	72.74 %	323.50 %	334.16 %	288.11 %	200.66 %	125.67 %
WD	97.78 %	273.97 %	218.70 %	269.52 %	124.21 %	156.29 %
CS10	93.63 %	352.32 %	248.62 %	281.47 %	145.51 %	180.75 %
CS20	15.99 %	139.23 %	133.55 %	128.28 %	93.97 %	60.44 %

Appendix 6: Total Nominal Returns from a Buy-and-Hold Strategy Compared to Trading Strategies Based on Quarterly Moving Averages (MA)

Index	Buy-and-Hold	3-Quarter MA	6-Quarter MA	12-Quarter MA
AT	44.77 %	101.07 %	107.53 %	107.53 %
BO	109.13 %	165.07 %	255.62 %	218.56 %
CR	66.47 %	76.66 %	80.54 %	71.18 %
CH	81.38 %	173.84 %	192.86 %	191.05 %
CE	63.81 %	41.48 %	103.15 %	102.17 %
DA	5.15 %	-19.95 %	-6.92 %	0.40 %
DN	164.09 %	133.00 %	174.64 %	155.80 %
DE	7.92 %	226.44 %	224.90 %	224.90 %
LV	43.10 %	491.52 %	497.05 %	450.59 %
LA	61.09 %	572.38 %	554.17 %	467.83 %
MI	84.62 %	452.67 %	418.93 %	375.95 %
MN	72.44 %	240.56 %	266.62 %	247.36 %
NY	110.88 %	226.48 %	275.05 %	242.18 %
PX	58.80 %	582.21 %	563.17 %	468.49 %
PO	205.05 %	349.70 %	355.29 %	319.75 %
SD	76.31 %	456.31 %	519.58 %	405.91 %
SF	70.78 %	430.49 %	289.13 %	355.35 %
SE	121.62 %	224.97 %	234.61 %	211.54 %
TP	71.72 %	308.24 %	308.93 %	266.23 %
WD	88.17 %	231.00 %	255.41 %	179.25 %
CS10	86.04 %	283.88 %	307.44 %	234.28 %
CS20	4.96 %	111.35 %	106.58 %	95.87 %

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