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Forecasting Dynamic Investment Timing under the Cyclic Behavior in Real Estate

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This paper applies the Hodrck-Prescott (HP) filter to forecast short-term residential real estate prices under cyclical movements. We separate the trend component from the cyclical component. We show that each regional residential market reacts not only to previous price movements, but also that these regional markets react to previous shocks under Auto Regressive Integrated Moving Average (ARIMA) modeling. Using the S&P Case-Shiller Home Price Index, we compare our forecast to index values from the Chicago Mercantile Exchange (CME) Housing Futures and Options. Our study identifies possible systematic errors from the different price adjustments reflecting current market situations.

Keywords

Real estate investment; Real estate cycle; residential housing futures contract; Real estate risk hedging

1. Introduction

Although real estate has been regarded as an asset class for investment in various previous research papers, it does not have the appropriate hedging tool to account for its own risk. This conditional state is especially evident in dealing with residential properties as noted by Shiller (2003). In comparing securities markets with a broad delineation of risk, he determines that the major risk to individuals is their potential loss of income and their expenditures on housing. The latter exposure may occur as either deficient flows or wealth erosion. He further notes that despite the potential frequency and magnitude of loss that can be encountered, no readily available hedging devises or strategies are available or operating.

The Chicago Mercantile Exchange (CME) has created an innovation enabling hedging tool that provides derivative products such as futures and options to hedge risk in the residential real estate that is available. As more sophisticated risk-hedging tools are developed, there will be an increasing demand to accurately forecast fluctuations in the real estate market. Accurately forecasting the future price of housing, while considering aggregate market behavior, would offer substantial benefits to both investors and owners seeking to hedge a major component of their personal wealth.

Regarding cyclic behavior in the real estate market, it is generally assumed that real estate markets go through both physical and financial market cycles and that these have differing effects on property prices. Fisher, Hudson-Wilson, and Wurtzebach (1996) used comparative statistics to investigate the separate and integrated impact that these cycles have on space and capital markets. Their work offers theoretical foundations for the cyclical descriptions promulgated by Mueller (1999) and other generalized studies of property cycles.

The recursive relationship between market structures and cycles is important to understanding property markets and cycles as it allows a dynamic rather than a comparatively static approach to modeling and developing the analytics of property. Forecasting the accuracy of property markets cannot be separated from a market's cyclical patterns. However, the forecasting of cyclical behavior has been challenging given that real estate's cyclic integration with the assumptions of pure market efficiency is inconclusive in terms of the effects on pricing.

Differences in cyclic studies premised on housing market efficiencies have produced different findings and conclusions in the literature. For instance, Case and Shiller (1990) found that the residential housing market was not efficient in predicting annual changes in prices and tended to be followed by changes in the same direction as in the preceding year. This conflicts with the concept of rational expectations, which Gau (1987) contends is a primary assumption and the foundation of the efficient market hypothesis (EMH). Case and Shiller's findings suggest that residential property markets are a function of adaptive expectations. The conjecture of adaptive expectations implies that knowledge of prior prices can influence current prices, and this knowledge can help predict future price behavior.

In a similar context, Clapp and Giaccotto (1994) show evidence that housing prices do not quickly reflect publicly available information. Local unemployment statistics, expected levels of inflation, changes in mortgage rates, income levels, the average age of the population, or other exogenous factors operate to offset “pure” adaptive price patterns. This suggests a possible lag and/or an endogenous affect on the dynamics of property prices.

Academic findings as to the occurrence of real estate market efficiency are still inconclusive, and fundamental financial analysis remains the dominant approach used to predict real estate market performance. As practiced, fundamental analysis is based on a microeconomic framework that often employs macroeconomic variables and policies that are applied using representative agent models. Variables are often combined to simulate cash flow measures. These include multiple inflation measures, volatility in mortgage interest rates, regional population and income growth, and changes in money supplies and other capital market activities.

Analysts often use more complicated forecasting models than the parsimonious model proposed in this study to characterize the effects of macroeconomic variables as likelihood variables that best specify real estate asset and market behavior. While offering exogenous likelihood models using the variables identified above, the technique usually used is often termed fundamental analysis. In this context, it tends to concentrate on the variables quantifying systematic risk that do not fit the asset specific measures that traditional fundamental analysis focuses on.

The following constraints challenge the validity of both types of fundamental analysis. First, the model must employ the right fundamentals with the right specifications and the right set of exogenous variables. It should then be able to forecast the economic variables included in the model. The forecasts of the fundamentals must differ at least in part from those of the market. The model used in this study is a reduced form, which offers a less complex alternative to the complicated forecasting models used by most analysts. Nevertheless, it still requires the consideration of an adaptive lagged relationship, which is difficult to identify. For this reason, it is subject to the dynamics of time variation.

This study applies analytics that focus on past prices while ignoring the exogenous economic and political factors characteristic of the arbitrage and fundamental econometric model. In this context, successful modeling depends on the discovery of price patterns that repeat themselves or are within the range of expected amplitude. Variations in or the failure to comply with the criteria expected may assist in identifying anomalies. Identification of anomalies requires further specialized inquiry. This study attempts to test for more sensitive forecasting models that integrate real estate cyclic behavior.

2. Purposes of Research

The purpose of this study is to develop an alternative to the linear market models that focus on systematic risk models. Assuming that the residential real estate market has adaptive expectations of price patterns, we attempt to investigate endogenous time series components by focusing on trends and cyclical relationships with autoregressive structures and temporal lag patterns.

Hodrick – Prescott (1997) hypothesized that the growth component of aggregate economic time series would vary smoothly over time. We believe that an application of the Hodrick–Prescott (HP) filter to property is consistent with their conjecture that the real estate market – as major component of a macro-economy – will grow smoothly over time.

Following the methodology adopted by Hodrick and Prescott, we attempt in this paper to determine if cyclical behavior does, in fact, exist in residential markets. By separating the trend component from the cyclical component in the time series of prices using their filter, we attempt to achieve decomposition.

Another purpose of this research is to determine the best fitting model among the Auto Regressive Integrated Moving Average (ARIMA) models given the endogenous adaptive expectations noted above. The ARIMA model selected is identified by those that performed well in relatively short-term market predictions. The fit of the method selected supports the use of eight parsimonious models to decompose short-term cyclical series as created by Box-Jenkins. ARIMA-based models have been widely used in short-term forecasts, which are likely a good fit for adaptive expectations. Support for the ARIMA methodology is consistent with the form of S&P/Case-Shiller housing price data and index. The S&P/C-S index is used as a reference for CME housing futures and options. The index is designed to be updated monthly using the transacted data from the previous three months.

The third purpose of this paper is to measure the systematic errors occurring between the real estate cycle forecasting model suggested by this study and the actual outcomes. The sample test logically follows the general rule for cash assessment derived from CME housing futures transactions. Thus, the main study objective is not to generate an optimal forecasting model, but rather to identify the systematic behaviors of forecast errors estimated by variations between the forecast model and the outcomes and observations of actual market fluctuations.

3. Literature Review

The real estate cycle has been the topic of a number of academic studies. Pyhrr, Webb, and Born (1990) provide a typical trend model for real estate analysis, with a theoretical cyclical model based on demand, supply, and inflation. Their conclusions on the benefits of real estate investment timing suggest an endogenous or inefficient market attribute with real estate assets benefiting from market timing. In this regard, they have, unlike securities markets, which are more exogenous, a more efficient market.

Pyhrr, Webb, and Born (1990) also compare traditional methods such as the traditional correlation of inflation against a model using cyclical assumptions such as demand, supply, absorption, occupancy rates, and rental rate differences between newly constructed and existing properties. They conclude that a cyclical model may be a better indicator of investment value maximizing expected “real” returns in comparison to market value without taking inflation cycles into consideration. This means that the real estate market cycle is based on its temporal position, which is delineated by physical components. Changes in vacancy rates, rental prices, existing stock, and new construction are all seen as cyclical descriptors of the market. They further suggest that the physical descriptors should be compared with financial capital market factors.

With regard to the residential real estate market cycle, studies by Chinloy (1996) of multifamily housing in Tucson and Phoenix, Arizona, in the United States, suggest that cycles are characterized by upside and downside lags of three years. Abraham and Hendershott (1996) propose a model with housing prices appreciating along with equilibrium prices and the adjustment procedure in the equilibrium price process. Capozza et al (2002) investigate the dynamics of housing prices using a time-series analysis, which estimates serial correlations as well as means reversion parameters of the housing price index. They suggest that variations in the cyclical behavior of real housing prices depend on variations in local economic variables along with construction costs and the growth rate of the metropolitan area.

Grissom and DeLisle (1999) find that the fluctuation characteristics of cycles can be segmented into temporally delineated economic regimes, which are defined as consistent return behaviors that are associated with key systematic variables. Although the returns are consistent in the direction of the trends calculated with the use of spline analysis, they delineate the segments of the splines linked to specific turning points. The direction of the returns is proven to be relative to the splines for the span of a regime. The technical shifts that are conditional to these systematic variables are used to designate inflection points that signify structural changes and fundamental relationships. The regimes represent long-term structural trends, which enable the separation of return cycles that characterize unsystematic components of property assets in time.

Using short-term cyclical behavior, Witkiewicz (2002) examines the use of the H-P filter to identify the impact of indicators on the real estate cycle. Similarly, Matysiak, and Tsolacos (2003) attempt to investigate short-term cycles in office rental markets and their leading relationship with other macro-economic variables. They also apply H-P filters to isolate the sensitivity of a rental index to corresponding economic variables. Crawford and Frantantoni (2003) construct invariant time series models for housing prices. This technique allows for a comparison of the forecasts of home price changes using three techniques: an ARIMA model, a Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) model, and a Regime-Switching model. Crawford and Frantontoni (2003) conclude that while regime-switching models tend to perform better in sample studies, the ARIMA models generally forecast better in terms of short-term predictions.

4. Data and Methodology

The period under study runs from January 1987 to October 2006. Data were drawn from the S&P/Case-Shiller Home Price Index, which was launched in May 2006 by the CME to provide information on price housing futures and options on residential housing markets in 10 metropolitan regions across the United States. It is calculated monthly, using three-month moving average tracking data. Its value for each month is based on sales pairs found for that month and the preceding two months.

The H-P filter is widely used by macroeconomists to obtain a smooth estimate of the long-term trend component of a series. We use it to identify short-term cyclical behavior and long-term trends The deviation of this trend from the actual rental value is defined as the short-term cyclical volatility. We use the H-P filter specification proposed by Witkiewicz (2002). In this form, the filter is useful for decomposing a time series, y_t, into a cyclical component, y_t^c, and a trend component y_t^g,

$$y_t = y_t^c + y_t^g \tag{1}$$

The HP-filter sets the minimization of variance of the cyclical component subject to a penalty constraining the variation by the second difference of the growth component. Thus, the method results in solving the following minimization problem:

$$\{y_t^g\}_{t=0}^{T+1} = \min \sum_{t=1}^{T} [(y_t - y_t^g)^2 + \lambda[(y_{t+1}^g - y_t^g) - (y_t^g - y_{t-1}^g)]^2] \tag{2}$$

where λ controls the smoothness of the series by penalizing the growth component, y_t^g

The first order condition from the minimization problem results in

$$y_t = [1 + \lambda(1-L)^2(1-L^{-1})^2]y_t^g \tag{3}$$

The first order condition for $y_t^g = H^g(L)y_t$ is given by

$$H^g(L) = [1 + \lambda(1-L)^2(1-L^{-1})^2]^{-1} \tag{4}$$

where L is the lag operator and the cyclical component, where

$$y_t^c = y_t - y_t^g = (1 - H^g(L))y_t = H^c(L)y_t \tag{5}$$

HP(L) y_t is given by:

$$HP^c(L) = \frac{\lambda[1-L]^2[1-L^{-1}]^2}{1+\lambda[1-L]^2[1-L^{-1}]^2} = \frac{\lambda L^{-2}(1-L\ )^4}{1+\lambda L^{-2}(1-L)^2} = \frac{L^{-2}(1-L)^4}{(1/\lambda)+L^{-2}(1-L)^4} \tag{6}$$

As λ approaches infinity, the growth component y_t^g approaches a trend line.

Hodrick and Prescott (1997) recommend that λ = 100 for annual data, 1,600 for quarterly data, and 14,400 for monthly data. In this study, the frequency power rule methodology was suggested by Ravan and Uhlig (1997).

All regional series are filtered to remove the long-term trends and isolate the cyclical components of the series. The cycles obtained from this procedure are then used as input for forecasting. The first step of the analysis decomposes the long-term trend and short-term cycle.

Table 1 presents descriptive statistics for long-term trends and short-term cycles for the 10 regions traded in CME real estate futures and options. The calculation shows that Las Vegas, Nevada; San Diego, California; Los Angeles, Califonria; and Miami, Florida, have a higher standard deviation on short-term cycles while San Diego, Los Angeles, Miami, and San Francisco, California, have greater fluctuations in long-term trends.

The short-term analysis used for technical modeling is critical because the periodic adjustments needed for indexing require monthly data measurements using an algorithm for a three-month moving average. To forecast the effects of the short-term cycle, we apply an ARIMA model. The ARIMA model contrasts directly with the methodology of property analysts, who use fundamental analysis based on exogenous economic variables. ARIMA models are generalizations of the simple AR model, which uses the following tools for modeling the serial correlation in the disturbance.

ARIMA's first component is the autoregressive or AR term. Each AR term corresponds to the use of a lagged value in the forecasting equation. Therefore, the lagged value can reflect the current market situation. An autoregressive model of order *p*, AR (*p*) has the form:

$$y_t = \beta\, y_{t-1} + \beta_2 y_{t-2} + ... + \beta_p y_{t-p} + \varepsilon_t \tag{7}$$

The second component is the moving average (MA) term. With an MA, the forecasting model uses lagged values of the forecast error to improve the current forecast. A first-order moving average term uses the most recent forecast error; a second-order term uses the forecast error from the two most recent periods, and so on. The error can reflect any newly introduced shocks to current housing markets. The MA (*q*) has the form:

$$y_t = \theta\, \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + ... + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{8}$$

Thus, the auto regressive and moving average specifications can be combined to form an ARMA (*p,q*) specification:

$$y_t = \beta\, y_{t-1} + \beta_2 y_{t-2} + ... + \beta_p y_{t-p} + \varepsilon_t + \theta\, \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + ... + \theta_q \varepsilon_{t-q_t} \tag{9}$$

Table 1 Descriptive Statistics for Long-term Trends and Short-term Cycles

	Short term Cycle						Long Term Trend					
	Mean	**Max**	**Min**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Mean**	**Beginning**	**Ending**	**Std. Dev.**	**Skewness**	**Kurtosis**
Boston	2.92E-11	5.88	-7.23	1.89	-0.18	4.48	99.41	64.60	182.95	39.81	0.94	2.32
Chicago	3.95E-10	4.34	-4.62	1.56	0.17	3.72	96.85	58.17	169.95	30.20	0.86	2.61
Denver	2.55E-10	6.80	-4.71	2.35	0.62	3.37	84.70	48.11	141.43	32.38	0.38	1.62
Las Vegas	3.84E-10	23.48	-20.47	7.28	-0.18	5.61	107.86	64.30	244.47	44.47	1.58	4.45
Los Angeles	2.85E-10	15.43	-12.32	6.08	0.18	2.54	114.39	67.39	280.12	54.50	1.61	4.38
Miami	3.26E-10	20.41	-13.47	5.45	1.11	7.52	112.54	70.17	276.37	52.45	1.64	4.57
New York	4E-10	8.23	-8.53	2.52	-0.05	4.55	106.68	75.67	221.71	41.85	1.34	3.48
San Diego	2.85E-10	20.99	-22.66	6.24	0.73	5.28	111.09	58.16	266.70	56.73	1.36	3.53
San Francisco	3.74E-10	15.18	-10.87	5.38	0.71	3.44	100.63	50.85	224.53	47.71	1.14	2.99
Washington	3.79E-10	18.49	-14.84	4.94	0.94	6.23	115.41	71.59	258.39	47.60	1.58	4.26

Note: Begins January 1987 and ends October 2006. The data are on sales of specific single-family homes. Each sales price is considered a data point. To specify for smoothing parameter, λ , the study followed the method suggested by Ravan and Uhlig (2002)

The method applied for short-term cyclic behavior is a function of the AR and MA processes. On the one hand, the AR represents the behavior of current values as functions of recent past values. The technique to decompose the MA component, on the other hand, provides the processes in which past innovations continue to reverberate for a number of periods. The study follows the structure of the Box-Jenkins model. This model allows for a choice of lagged variables to maintain the degrees of freedom.

5. Results

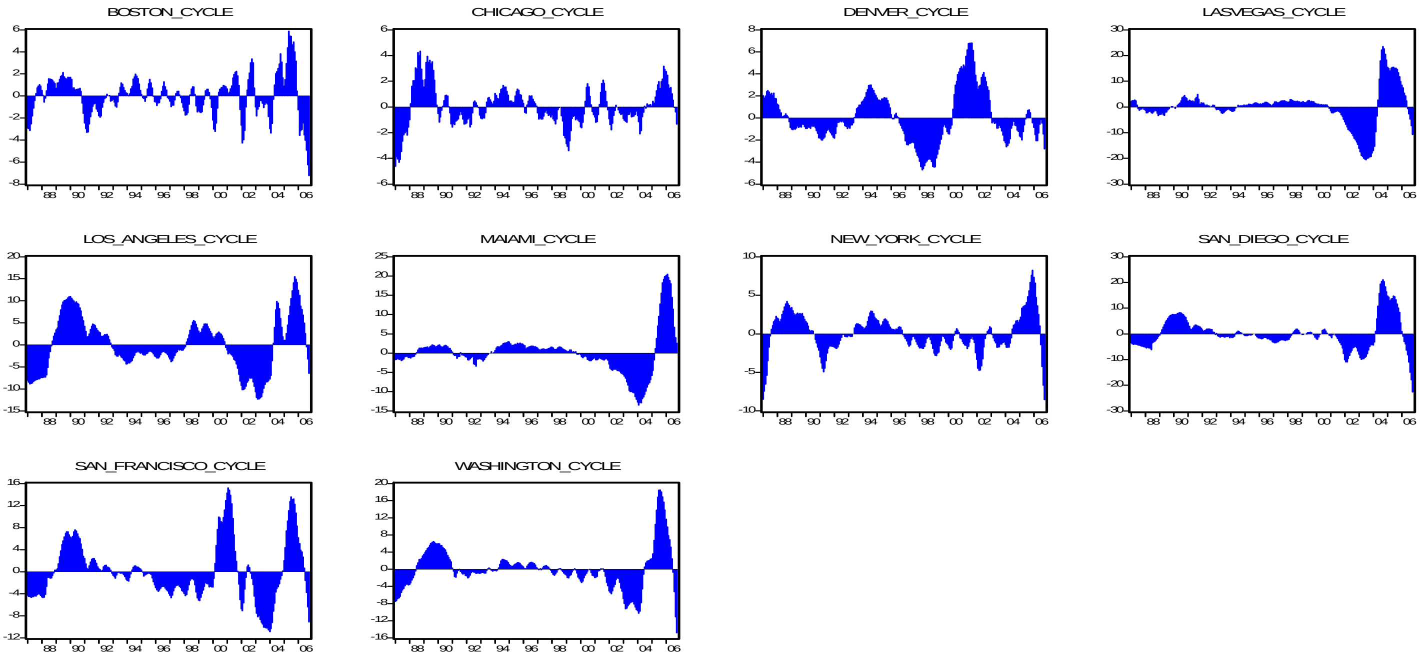
As examples, Figures 1 and 2 show the short-term cycles and long-term trends, respectively, in Los Angeles after applying the H-P filter. The fluctuations of short-term cycles are detected from 1988 to 1990 and from 2003 to 2005 over most of the regions included in the study. The up-cycles observed in the late 1980’s are associated with the massive speculation in construction that peaked in 1989-1990. The market started to slide in the early 1990’s for both residential and commercial properties until vacancy exceeded 30% nationwide. Throughout the 1990’s, the real estate market experienced largely increasing development, with the nationwide inventory nearly tripling. In the up-cycle of the early 2000’s, there were increasing concerns about the development of a national real estate bubble.

The traditional observations and the implications of past occurrences support the application of two forecasting techniques in the specification of trends and cycles. An exponential smoothing technique is applied in this study to forecast long-term trends. This approach is utilized because the trend decomposed using the HP filters shows stability to be positive and on an upward graphical pattern. The second approach used for short-term cycles is the ARIMA models. Unit root testing is considered to be the first stage for ARIMA modeling to check whether the absolute value of the parameter is less than one. The unit root results are reported in Table 2.

The test data reveal strong evidence of stationary conditions in the short-term cycle series. The study shows that eight of the 10 regions are significant at the 1% level in the Augmented Dickey-Fuller test. Los Angeles and San Diego are exceptions, being significant at the 5% level. In addition, most regions exhibit strong evidence of a stationary condition at the 5% level in the Phillips – Perron test. While a popular approach for testing the stationary condition involves carrying out consecutive differencing on the data series and then fitting the ARIMA model to them, the short-term cycles are enough to confirm the stationary condition without a differencing process. Therefore, the strict model definition in our study necessarily applies the Auto Regressive Moving Average Model (ARMA) as a stringent methodology term.

As a model selection rule, we employ the Akaike Information Criterion (AIC) to ensure that the most accurate model is selected from the class of eight possible models suggested by the Box-Jenkin’s methodology. In Table 3, four models are sorted and selected using the AIC criteria.

Figure 1 Short-term Cycles for MSAs



Note: The SandP/Case-Shiller Home Price Indices from January 1987 to October 2006 were used to identify the short-term cyclic behavior. The data were collected from 10 Regions. Eight of them are based on the Metropolitan Statistical Area as defined by the U.S. Office of Management and Budget. To smooth parameter, λ , the study followed the method suggested by Ravan and Uhlig (2002).

Figure 2 Long –Term Trend for MSAs

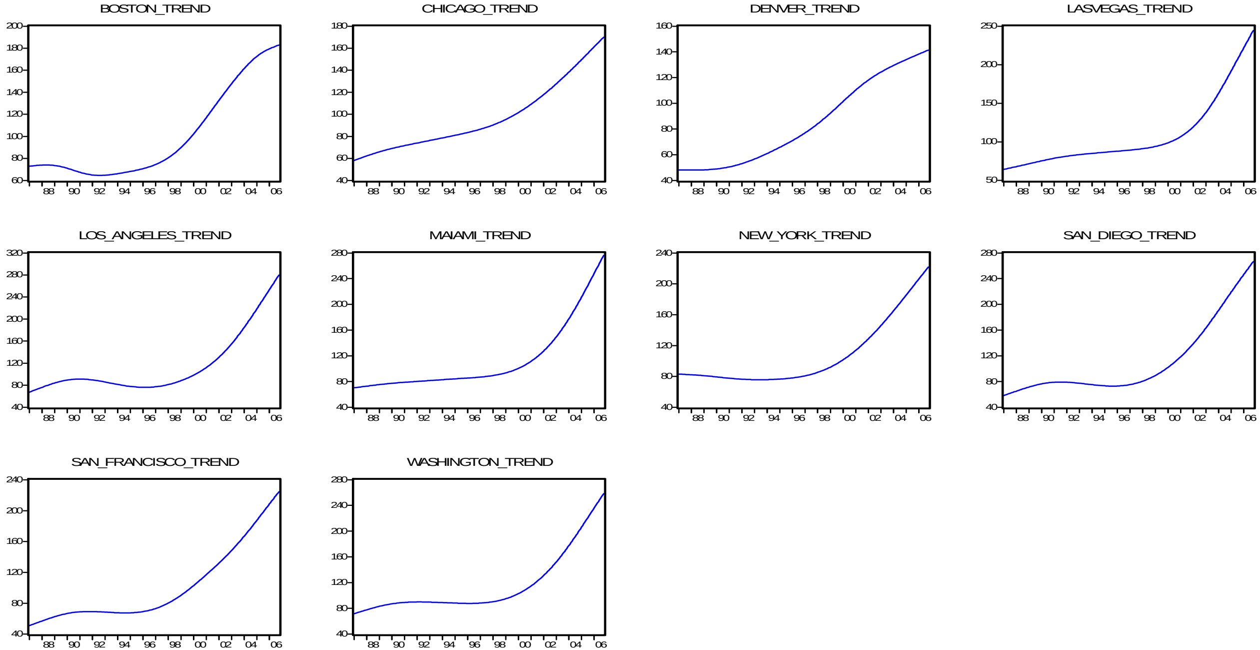


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Table 2 Unit Roots Test for Short-term Cycles

	ADF Test		PP Test	
	t-statistic	*p*-value	t-statistic	*p*-value
Boston	-5.256*	0.000	-3.378*	0.001
Chicago	-5.017*	0.000	-3.876*	0.000
Denver	-3.979*	0.000	-1.995**	0.044
Las Vegas	-4.125*	0.000	-2.784*	0.005
Los Angeles	-2.479**	0.013	-2.544**	0.011
Miami	-5.883*	0.000	-2.700*	0.007
New York	-3.494*	0.001	-3.737*	0.000
San Diego	-1.934**	0.050	-2.032**	0.041
San Francisco	-3.527*	0.001	-2.886*	0.004
Washington	-3.505*	0.001	-2.832*	0.005

Note: Augmented Dickey- Fuller test statistic (ADF), Phillips-Perron test statistic (PP test)* and ** indicate significance at the 1% and 5% levels.

Table 3 shows that the ARMA (2, 2) model is the best forecasting model for Boston, Massachusetts; Los Angeles; Miami; New York, New York; San Francisco, and Washington, DC. The ARMA (1, 2) model is the best predictive structure in Chicago, Illinois, and ARMA (2, 1) model achieves the appropriate forecasting structure for Las Vegas. The simpler AR (2) with 2 short-term lag offers an appropriate forecasting procedure for Denver, Colorado, and San Diego.

Forecasting out-of-sample periods (2005 1Q – 2006 3Q) are presented in Table 4. We constructed the forecast index from two components: short-term cycle forecasts generated by the best-fitting model from Exhibit 5 and the long-term trend forecasts generated by double exponential smoothing. The monthly forecasts are shown for the period from April 2005 to October 2006. However, to make things smple, we only present four data points per year with monthly data observations. The magnitude of error can be realized from the inequality between the actual index observed and the forecast index constructed. The last column in Table 4 shows the dollar amount of gains and losses from the magnitude of error in forecast models with associated cash assessment.

Table 3 Alternative ARIMA Models

	β_1	β_2	ϕ_1	ϕ_2	AIC		β_1	β_2	ϕ_1	ϕ_2	AIC
Boston						Miami					
ARMA(2,2)	**1.210***	**-0.358***	**0.525***	**0.579***	**1.214**	**ARMA(2,2)**	**1.695***	**-0.718***	**0.007***	**0.304***	**1.420**
ARMA(1,2)	0.864*		0.825*	0.685*	1.232	AR(2)	1.777*	-0.798*			1.490
AR(2)	1.614*	-0.721*			1.419	AR(1)	0.989*				2.464
ARMA(2,1)	1.616*	-0.724	-0.006**		1.427	MA(1)			0.936*		4.975
Chicago						New York					
ARMA(1,2)	**0.859***		**0.620***	**0.543***	**0.891**	**ARMA(2,2)**	**1.498 ***	**-0.557***	**0.509***	**0.547***	**0.516**
ARMA(2,2)	0.873*	-0.015*	0.602*	0.538*	0.894	AR(2)	1.809*	-0.853*			0.620
AR(2)	1.451*	-0.527*			1.014	ARMA(2,1)	1.798*	-0.842*	0.037*		0.627
ARMA(2,1)	1.513*	-0.586*	-0.085*		1.018	MA(1)			0.971*		3.423
Denver						San Diego					
AR(2)	**1.658***	**-0.679***			**0.414**	**AR(2)**	**1.845***	**-0.864***			**2.020**
ARMA(2,1)	1.687*	-0.707*	-0.050*		0.420	ARMA(2,1)	1.871*	-0.890*	-0.081*		2.022
MA(2)			1.413*	0.893*	2.357	MA(2)			1.243*	0.989*	4.381
MA(1)			0.936*		3.331	MA(1)			0.953*		5.262
Las Vegas						San Francisco					
ARMA(2,1)	**1.832***	**-0.858***	**-0.013***		**2.151**	**ARMA(2,2)**	**1.697***	**-0.733***	**0.411***	**0.299***	**1.398**
ARMA(1,1)	0.983*		0.652*		2.725	ARMA(2,1)	1.805*	-0.837*	0.236*		1.450
MA(2)			1.429*	0.969*	4.539	AR(2)	1.855*	-0.887*			1.505
MA(1)			0.989*		5.497	MA(1)			0.987*		4.874
Los Angeles						Washington					
ARMA(2,2)	**1.760***	**-0.787***	**0.148***	**0.370***	**1.337**	**ARMA(2,2)**	**1.764***	**-0.800***	**0.225***	**0.268***	**1.372**
AR(2)	1.858*	-0.881*			1.468	ARMA(2,1)	1.846*	-0.877*	0.131*		1.409
ARMA(2,1)	1.839*	-0.863*	0.075**		1.469	MA(2)			1.466*	0.981*	3.755
MA(1)			0.981*		5.132	MA(1)			0.959*		4.760

Note: AIC results for the alternative ARMA models over the estimation period. The lower the statistic the better the model fits.
* and ** indicate significance at the 1% and 5% levels, respectively. The best fitting model are in bold for presentation.

Table 4 Performance of Forecast Index and S&P/CS

	Period	Forecast Trends (T)	Forecast Cycles (C)	Forecast Index (FI)	S&P/CS	Forecast Error (FE)	Dollar amount of gains and losses
		(Trend)	(Cycle)	(FI=T+C)	(SPCS)	(FI-SPCS)	(FE/0.2)* $250
Boston							
2005	1Q	173.33	0.677	174.01	174.76	-0.751	-$1,000
	2Q	175.35	4.865	180.22	181.17	-0.954	-$1,250
	3Q	177.09	4.491	181.58	181.67	-0.088	$0
	4Q	178.58	3.114	181.70	181.69	0.006	$0
2006	1Q	179.88	-2.528	177.35	176.27	1.084	$1,250
	2Q	181.07	-2.151	178.92	178.61	0.307	$500
	3Q	182.20	-4.213	177.99	175.72	2.268	$2,750
Chicago							
2005	1Q	150.57	0.263	150.84	151.02	-0.184	-$250
	2Q	153.47	0.356	153.82	154.72	-0.897	-$1,000
	3Q	156.37	1.815	158.19	157.81	0.375	$500
	4Q	159.28	2.038	161.32	162.44	-1.121	-$1,500
2006	1Q	162.19	2.696	164.89	164.67	0.218	$250
	2Q	165.10	1.255	166.36	166.61	-0.251	-$250
	3Q	168.01	0.727	168.74	167.99	0.751	$1,000
Denver							
2005	1Q	134.36	-1.913	132.45	132.63	-0.182	-$250
	2Q	135.44	-0.695	134.75	134.82	-0.073	$0
	3Q	136.51	0.576	137.09	137.19	-0.101	-$250
	4Q	137.58	0.274	137.85	137.53	0.319	$500
2006	1Q	138.63	-1.142	137.49	137.12	0.369	$500
	2Q	139.68	-2.018	137.66	138.31	-0.645	-$750
	3Q	140.73	0.158	140.89	140.27	0.623	$750
Las Vegas							
2005	1Q	194.39	12.649	207.04	209.31	-2.271	-$2,750
	2Q	201.91	15.553	217.46	217.28	0.183	$250
	3Q	209.44	14.201	223.64	224.51	-0.868	-$1,000
	4Q	216.97	11.885	228.85	228.77	0.083	$0
2006	1Q	224.48	7.018	231.50	231.94	-0.440	-$500
	2Q	231.98	3.212	235.20	234.39	0.806	$1,000
	3Q	239.48	-4.327	235.15	234.78	0.370	$500

(Continue...)

Table 4 Continued

	Period	Forecast Trends (T)	Forecast Cycles (C)	Forecast Index (FI)	S&P/CS	Forecast Error (FE)	Dollar amount of gains and losses
		(Trend)	**(Cycle)**	**(FI=T+C)**	**(SPCS)**	**(FI-SPCS)**	**(FE/0.2)* $250**
L A							
2005	1Q	221.23	0.390	221.62	222.29	-0.672	-$750
	2Q	230.00	6.346	236.34	236.68	-0.338	-$500
	3Q	238.82	11.709	250.53	251.1	-0.573	-$750
	4Q	247.67	16.301	263.97	262.56	1.406	$1,750
2006	1Q	256.52	10.643	267.16	267.75	-0.586	-$750
	2Q	265.37	6.961	272.33	272.12	0.214	$250
	3Q	274.22	0.180	274.40	273.8	0.601	$750
Miami							
2005	1Q	214.15	-4.754	209.40	209.67	-0.275	-$250
	2Q	223.27	3.749	227.01	227.10	-0.085	$0
	3Q	232.52	11.447	243.97	245.24	-1.272	-$1,500
	4Q	241.87	19.961	261.83	261.00	0.826	$1,000
2006	1Q	251.26	19.959	271.22	271.68	-0.463	-$500
	2Q	260.67	17.619	278.29	278.68	-0.390	-$500
	3Q	270.09	8.141	278.23	276.80	1.430	$1,750
New York							
2005	1Q	187.12	2.117	189.24	189.29	-0.048	$0
	2Q	192.32	3.432	195.75	195.96	-0.209	-$250
	3Q	197.52	4.363	201.88	202.33	-0.447	-$500
	4Q	202.72	7.321	210.04	210.30	-0.261	-$250
2006	1Q	207.91	5.925	213.83	214.47	-0.636	-$750
	2Q	213.09	2.536	215.63	215.59	0.036	$0
	3Q	218.26	-3.679	214.58	214.01	0.574	$750
San Diego							
2005	1Q	221.41	13.015	234.42	235.64	-1.219	-$1,500
	2Q	228.37	13.882	242.25	242.00	0.248	$250
	3Q	235.25	13.833	249.08	248.45	0.633	$750
	4Q	242.06	8.503	250.57	250.34	0.226	$250
2006	1Q	248.82	-2.019	246.80	247.89	-1.089	-$1,250
	2Q	255.54	-4.736	250.80	249.15	1.654	$2,000
	3Q	262.24	-13.177	249.06	247.30	1.765	$2,250

(Continue...)

Table 4 Continued

	Period	Forecast Trends (T)	Forecast Cycles (C)	Forecast Index (FI)	S&P/CS	Forecast Error (FE)	Dollar amount of gains and losses
		(Trend)	(Cycle)	(FI=T+C)	(SPCS)	(FI-SPCS)	(FE/0.2)* $250
San Francisco							
2005	1Q	189.08	3.907	192.99	193.50	-0.513	-$750
	2Q	194.40	10.175	204.58	205.52	-0.943	-$1,250
	3Q	199.74	13.730	213.47	212.86	0.607	$750
	4Q	205.07	11.121	216.19	215.70	0.490	$500
2006	1Q	210.39	4.384	214.77	215.50	-0.727	-$1,000
	2Q	215.70	3.383	219.08	218.37	0.711	$1,000
	3Q	221.00	-3.562	217.44	217.23	0.208	$250
Washington							
2005	1Q	208.60	2.512	211.11	212.24	-1.128	-$1,500
	2Q	216.07	13.835	229.90	229.87	0.031	$0
	3Q	223.56	19.175	242.73	242.06	0.671	$750
	4Q	231.04	15.436	246.48	246.70	-0.219	-$250
2006	1Q	238.52	9.391	247.91	248.39	-0.479	-$500
	2Q	245.98	5.950	251.93	251.13	0.800	$1,000
	3Q	253.43	-3.644	249.78	248.17	1.613	$2,000

Note: S&P/CS represents S&P/Case Shiller home price indices. Dollarization follows the CME Futures contract rule in terms of minimal increments called "ticks" with the value of 0.20 index point, and $250 as a product multiplier. Therefore, 0.20 of differences in two index values cause $250 x 0.20 =$50.0 gains or losses for investors holding short future position. The quarter presented in Table follows the CME trading month (February, May, August, and November) except 3rd quarter of 2006. Oct 2006 replaced the 3rd quarter basis. For Short-term cycles, the best model selected from table 3 was applied to forecast the series. Double exponential smoothing method was applied for Long-term trend.

Table 4 follows the transaction process used in the CME housing futures market when an investor sells one future contract at the forecast index value. The unit of change is derived by comparing the CME method, with errors observed by the forecast being adjusted by 0.2. This adjustment is consistent with the minimum unit changes in CME housing futures. The contract is valued at $250, which is the same value applied in a CME housing futures contract. Thus, the best forecast model is the model that yields the cumulative error closest to zero where the dollar amount of gains and losses is closest to zero. In addition, the forecast errors can explain the amount of divergence from rational expectation based on previous existing market information and the reflection of additional shocks. Therefore, the pattern and insight gained from the forecast errors will contribute to proper investment timing. If the real estate market is fundamentally efficient, the fluctuation of current market estimates can be expected to converge toward the actual value of moderate market conditions without any additional shocks taking place in the expected model.

The generated series, the differences between the forecasted model, and the reference index show that there is a consistent pattern and cyclical behavior. The changes in market direction are observed in subsequent periods, and decay is on a serial basis. The negative forecast errors in out-of-sample data are captured in the housing price index beginning in early 2005. We find that a cyclical behavior in negative forecast error that started in the previous month increasingly occur in subsequent months. Thus, even though the forecast model is weak in identifying a large upward or downward movement, changes in the number of forecast errors will provide information on market direction. They will also yield further insight regarding investment timing.

In Table 4, if the value of the S&P/CS index for Los Angeles was reported as 222.2 in the first quarter of 2005, the contract value would equal $55,550 (= $250 x 222.2). The negative forecast error would result in a $750 loss on the futures transaction. The negative forecast errors observed in the first quarter of 2005 would be followed in subsequent periods with a loss of $500 in the second quarter of 2005 and a loss of $750 in the third quarter. The negative forecast errors would occur when the real S&P C-S index increased to a value that was higher than expected from the forecast index for Boston, Chicago, Los Angeles, Miami, New York, and San Francisco. These regions were suspected of having potential housing bubbles in late 2004 and early 2005.

In up-markets, the forecast model calls for conservative guidelines. This could be the result of real market movements that exceeded the market forecasts, which, in turn, would result in cash losses for CME futures contracts. This would occur when market demand increases as the trading volume increases. In this case, the forecast model would systematically project lower forecasting values than the real outcome from S&P Case Shiller index. As shown in early 2005, most regions would have losses on CME futures contracts if guided by our forecast model. These systematic negative errors occur in up-markets or seller’s markets, when the bid prices offered by buyers rapidly move to the seller’s asking price because of increased trading volumes.

While consecutively negative additive or multiplicative errors are observed in up-markets, negative additive errors have also occurred in down-markets such as in early 2006. Most regions have positive cash values on selling a future contract when guided by our forecast. These systematic negative errors are typically observed in down-markets or buyers’ markets, when the asking prices offered by sellers rapidly move to the buyer’s bid price owing to lower trading volumes. The additive or multiplicative errors observed in down-markets can be attributed to these systematic negative errors. Thus, the test results suggest that once a real estate market passes the turning point, the pattern shows serially additive or multiplicative movement.

6. Conclusion

Various prior studies have regarded real estate as a distinct asset class for investment. However, unlike other financial asset classes, real estate does not have appropriate exogenous hedging tools to reduce the risk. As with other financial asset classes, risk-hedging tools are offered for real estate through the housing derivative program of the Chicago Mercantile Exchange (CME). Demand for relative short-term forecasts is expected to increase as the housing derivative market expands.

This study has compared the validity of the forecasting model constructed for 10 regions across the United States. The H-P filtering technique was applied to test for sensitive forecasting models incorporating real estate cyclical behavior and market reflection by decomposing the trend component of aggregated market growth from the cyclical component in a time series. The study used the decomposed short-term cyclical series as an alternative to ARIMA modeling. The results show that although the ARIMA model is limited to identifying large upward and downward changes, it does sufficiently capture the market direction and pattern of the systematic errors presented in Table 5. The study further shows that the forecast errors decayed serially and expanded additively while the amount of forecast errors stated in previous months has also occurred in subsequent observations.

Although the main purpose of this study was not to generate an optimal forecasting model, these systematic behaviors from errors estimated by forecast model and real market fluctuation will be useful for designating a market proxy that adequately fits the needs of hedging loss exposure for investors interested in market timing. While the forecasting developed within data from the prior month impact subsequent observations, the effects reflect an additive pattern with the autoregressive and moving average effects are consistent with adaptive expectation.

Though the proxy time series model in this study is a reduced form model of a highly complex situation, significant insights can be derived from it. Market timing in residential properties can significantly impact investor benefits, but these benefits at any given point in time would have a relatively short-term impact.

Given the relevance of market timing to the residential property market, appropriate forecasting techniques would have to consider the use of adaptive explanations as a straightforward form of the local property market. This study accepted a modeling conjecture of AR and supported the quantitative equipment of AR and MA components in the Box Jenkins tradition of time series analysis. This study also employed theoretically premised quantitative techniques to decompose time series into a cyclical as risk component as variance around a relatively defined short on long term growth trend enables insights to assist hedging to cover the significant risk exposure to housing expenditure.

The implication of adaptive pricing expectation from endogenous variables also sets a foundation for future research into decomposed patterns to identify useful indicators related to the real estate market. Future research is needed to adopt useful indicators related to the real estate market. The economic variables will also be a helpful tool for forecasting market turning points only if they can play a role as a leading indicator.

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Appendix

Table 1A Metro Areas for the Original 10 S&P/Case-Shiller Home Price Indices*

	MSA	Represented Counties
1	**Boston**	Essex MA, Middlesex MA, Norfolk MA, Plymouth MA, Suffolk MA, Rockingham NH, Strafford NH
2	**Chicago**	Cook IL, Dekalb IL, Du Page IL, Grundy IL, Kane IL, Kendal IL, McHenry IL, Will IL
3	**Denver**	Adams CO, Arapahoe CO, Broomfield CO, Clear Creek CO, Denver CO, Douglas CO, Elbert CO, Gilpin CO, Jefferson CO, Park CO
4	**Las Vegas**	Clark NV
5	**Los Angeles**	Los Angeles CA, Orange CA
6	**Miami**	Broward FL, Miami-Dade FL, Palm Beach FL
7	**New York City**	Fairfield CT, New Haven CT, Bergen NJ, Essex NJ, Hudson NJ, Hunterdon NJ, Mercer NJ, Middlesex NJ, Monmouth NJ, Morris NJ, Ocean NJ, Passaic NJ, Somerset NJ, Sussex NJ, Union NJ, Warren NJ, Bronx NY, New York NY, Orange NY, Putnam NY, Queens NY, Richmond NY, Rockland N, Suffolk NY, Westchester NY, Pike PA
8	**San Diego**	San Diego CA
9	**San Francisco**	Alameda CA, Contra Costa CA, Marin CA, San Francisco CA, San Mateo CA
10	**Washington**	District of Columbia DC, Calvert MD, Charles MD, Frederick MD, Montgomery MD, Prince Georges MD, Alexandria City VA, Arlington VA, Clarke VA, Fairfax VA, Fairfax City VA, Falls Church City VA, Fauquier VA, Fredericksburg City VA, Loudoun VA, Manassas City VA, Manassas Park City VA, Prince William VA, Spotsylvania VA, Stafford VA, Warren VA, Jefferson VA

Source: Standard & Poor's Data Web Site