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Abstract

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Introduction

This paper describes a research attempt to use the analytical framework of the dynamic Gordon growth model to test the present value relation (PVR) in a number of large housing markets. The PVR hypothesis implies two testable hypotheses: first, housing markets must be at least weakly efficient; and, second, there is a cointegrating relationship between price and rent series in the long run. On the basis of the results of the tests, it also addresses possible implications for the sensitivity of housing prices to changes in expected returns. The paper ends with a discussion of the rates of adjustment in expected housing inflation and overall inflation as a key factor in short run housing market dynamics.

In a pioneering study, Case and Shiller (1989) reject the efficient market hypothesis in four large metropolitan statistical areas (MSA), Atlanta, Chicago, Dallas, and San Francisco. Meese and Wallace (1994) extend previous work in the field by successfully testing for a *long run* cointegrating relationship between prices and rents in a number of local Bay Area housing markets. The presented research attempts to make two contributions to the study of housing markets: first, the dynamic Gordon growth model is applied to the analytical framework developed by Meese and Wallace (1994); and, second, it extends the applicability of the PVR analytical framework to large housing markets by testing it in the context of 23 large metropolitan housing markets.

Data and Variables

The dataset includes biannual data for a set of 23 large MSA's for the period 1986-2003. It incorporates price, rent, return, cost of capital, non-shelter, and shelter inflation series. The price series is based on the quarterly MSA housing price index (HPI) developed by the Office of Federal Housing Enterprise Oversight (OFHEO). The inflation data is retrieved from the Bureau of Labor Statistics (BLS). The constant-quality HPI conforms to the weighted repeated sales (WRS) framework introduced by Case and Shiller (1987). The price of individual house **i** at time **t** is represented as:

$$\ln(P_{it}) = \beta_t + H_{it} + N_{it}, \quad (1)$$

where P_{it} is price of **i** at time **t**, β_t the market price index, H_{it} a Gaussian random walk, and N_{it} is house specific white noise assumed to be constant over time[1]. While the HPI loses some nuances intrinsic to the WRS index developed by Shiller and Case (1987), it provides estimates of comparable quality and is used even by the creators of the WRS index methodology, Case and Shiller (2003).

The availability of rental data requires the use of only two observations per year, second and fourth quarters. The HPI can be used to form a nominal housing inflation series with 1995 as a base year. Then, the real housing inflation is calculated as the difference of the nominal housing inflation with the first half (1H) of 1995 as a base period and the overall MSA inflation less shelter with 1H 1995 as a base period. Finally, the real price series is estimated using reported MSA housing prices for 2Q 2003 (4Q 2001 for Detroit and 3Q 2003 for San Jose) and expressing prices in constant 1H 1995 US dollars.

In the context of housing markets, the dividend payment is defined as housing services, which are approximated by rental payments. The lack of publicly available and aggregated rental data for MSA's requires the use of a proxy for housing rents. Since the

[1] Unlike the OFHEO HPI, Case and Schiller do not make such a simplifying assumption about the characteristics of the white noise.

services provided by a two-bedroom apartment and the services provided by the median house can be regarded as substitutes, in this study apartment rents are used as a proxy for the implicit flow of rental (housing services) payments. The biannual MSA apartment nominal rent series for two-bedroom apartments was provided graciously by the Federal Reserve Bank of San Francisco as a follow-up on previous research. Similarly to the estimation of real housing inflation, the rent data can be used to calculate nominal rent inflation with 1H 1995 as a base period. The real rent inflation in 1H 1995 US dollars can be estimated by subtracting shelter inflation with 1H 1995 as a base period from the nominal rent series with 1H 1995 as a base period. Finally, the real rent series is calculated using 1H 1995 rent prices.

The use of apartment rents as a proxy for housing dividends raises two concerns which must be addressed. The first one is that the rental property differs qualitatively from owned property, so the flow of services differs, too. While such an argument may be applicable to small markets, in the context of large MSA rental property have comparable characteristics to the characteristics of owned property. Large MSA have higher labor mobility than their small counterparts and, as a result, a larger pool of people willing to enjoy the same quality of housing services as homeowners but for a limited time period. Related to the first one, the second concern is that housing rents and apartment rents may differ, which would lead to uninformative conclusions about the behavior of the series; as pointed out above, the results of the study will depend on the positive correlation between housing and apartment rental payments, which may cast doubt on a possible rejection of the long run cointegrating relationship between prices and rents.

The housing returns are defined according to the standard setting used in financial literature:

$$R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t} - 1, \qquad (2)$$

where R_{t+1} is housing return for the period from time **t** to time **t+1**, which becomes known at time **t+1**; P_t is housing price at time **t** and P_{t+1} the price at time **t+1**; finally, D_{t+1} is the rental payment/dividend for the period from time **t** to time **t+1**, which also becomes known at time **t+1**. In other words, the purchase of a house at time **t** is a transfer of the ownership rights to claim the housing services for the next period but not to the housing services for the preceding period. An alternative specification of the return is the lognormal returns or continuously compounded returns:

$$\begin{aligned} r_{t+1} &= \ln(1 + R_{t+1}) \\ r_{t+1} &= \ln(P_{t+1} + D_{t+1}) - \ln(P_t) = \\ &= p_{t+1} - p_t + \ln(1 + \exp(d_{t+1} - p_{t+1})), \qquad (3) \end{aligned}$$

where lowercase variables are in lognormal form. This specification is employed to analyze the case of non-constant returns under the dynamic Gordon growth model (Campbell, Lo and McKinley, 1997).The estimation of the return series is based on the price and rent series described above.

A possible problem, indicated by Case and Shiller (1989), arises from the characteristics of the noise in the price series. A simple example illustrates the point: suppose that the HPI is based on the sales of three houses A, B, and C. A is sold at time 0 and time **3**, B at time **0** and time **3**, and C at time **1** and time **3**. Using (1), one concludes that the change for the corresponding periods is:

$$period\ 0-1:(P_{A3}-P_{A0})-(P_{C3}-P_{C1})$$

$$period\ 1-2:(P_{B2}-P_{B0})-\{(P_{3A}-P_{0A})-(P_{C3}-P_{C1})\}$$

$$period\ 2-3:(P_{A3}-P_{A0})-(P_{B2}-P_{B0})$$

As obvious from these expressions, we observe negative autocorrelation between any two adjacent periods and positive autocorrelation for periods **0-1** and **2-3**. Practically, one may expect that property sold in period **t** would not be sold in period **t+1** due to high transaction costs, which will lead to some methodologically-introduced negative autocorrelation in the series. Such a negative autocorrelation may be expected to dampen the effect of any genuine autocorrelation, if present. Several factors are expected to mitigate the effect on the tests for autocorrelation: the relatively large sample, as well as the theoretically and empirically confirmed expectations that significant autocorrelations exist within a period of six months to a year.

The PVR hypothesis implies that expected return equals cost of capital, K_t. Kearl (1979), Dougherty and Van Order (1982) adjust the cost of capital for mortgage rate, state and federal income taxes, depreciation, specific risk, and expected shelter inflation:

$$K_t = E(R)_t = i_t(1-\tau_t^y(y_t)) + \delta + \tau_t^p(p_t)(1+\tau_t^y(y_t)) - \pi_t^e + \alpha_t, \qquad (4)$$

where i_t is real mortgage rate, $\tau_t^y(y_t)$ combined federal and state income tax, δ depreciation, $\tau_t^p(p_t)$ property tax, π_t^e expected shelter inflation, and α_t specific housing market risk. This relationship provides a way for estimating expected returns. Unfortunately, the lack of aggregated data on state income and property taxes allows only for an approximation of the cost of capital series. As tax rates and the housing specific risk remain relatively stable, one may approximate changes in cost of capital as the difference of tax adjusted real mortgage rate and the expected shelter inflation, which allows for an alternative way to test the efficient market hypothesis.

Consequently, the estimation of cost of capital depends on data for mortgage rates, shelter inflation and overall inflation less shelter. Fannie Mae provides regional weekly mortgage rates for 80% loan-to-value (LTV) loans with 2 points, which for the purposes of this research were transformed into average mortgage rates for the first and second half of year ***t***. The MSA overall inflation less shelter and the shelter inflation series are taken from the Bureau of Labor Statistics (BLS). The combined federal and state income tax is assumed to be 20%.

Summary of the Dynamic Gordon Growth Model

Campbell and Shiller (1989) have developed a PVR with time-varying returns on the basis of the classical Gordon growth model. They provide a loglinear approximation of the nonlinear relationship between prices and rents implied by the non-constant returns. It allows the estimation of asset price behavior under any model of expected returns and has the additional advantage of being tractable under the empirically plausible assumption of loglinear dividend and return processes (Campbell, 1991). Equation (3) for the returns can be approximated around the mean value, using first-order Taylor expansion:

$$r_{t+1} \approx k + \rho * p_{t+1} + (1-\rho) * d_{t+1} - p_t, \; where$$
$$\rho = \frac{1}{(1+\exp(avg(d-p)))},$$
$$k = \ln(1+\exp(avg(d-p))) - \left(1 - \frac{1}{(1+\exp(avg(d-p)))}\right) * (avg(d-p)). \quad (5)$$

Solving forward (5), one obtains the following relations for the lognormal price at time **t**:

$$p_t = \frac{k}{1-\rho} + \sum_{i=0}^{\infty} \rho^i \{(1-\rho)d_{t+1+i} - r_{t+1+i}\},$$
$$provided\ that\ \lim_{i\to\infty} \rho^i * p_{t+i} = 0 \qquad (6)$$

Taking expectations, one obtains Campbell and Shiller's dynamic Gordon growth model or dividend-ratio model:

$$p_t = \frac{k}{1-\rho} + E_t\left[\sum_{i=0}^{\infty} \rho^i \{(1-\rho)d_{t+1+i} - r_{t+1+i}\}\right], \qquad (7)$$

The relation implies that housing prices will be high when housing rents are expected to grow rapidly or when dividends are discounted at a low rate. Furthermore, the impact of the dividend growth or a decline in the discount rate depends on the expected duration of these trends. Simplifying the notation, one obtains:

$$p_t = \frac{k}{1-\rho} + p_{dt} - p_{rt}, \qquad (8)$$

where p_{dt} equals the expected discounted value of the product of $1-\rho$ and the future lognormal dividends, while p_{rt} equals the expected discounted value of future lognormal returns. Equation (7) can be transformed into the following cointegrating relationship for prices and rents:

$$d_t - p_t = \frac{k}{1-\rho} + E_t\left[\sum_{i=0}^{\infty} \rho^i \{r_{t+1+i} - \Delta d_{t+1+i}\}\right] \qquad (9)$$

In short, the dynamic Gordon growth model implies two testable hypotheses. The first one is that in the long run prices and rents are cointegrated, as suggested by equation (9). The second one is that housing markets are at least weakly efficient. This hypothesis is rejected if future returns are even partially predictable on the basis of only past returns. One of the most frequently performed procedures to test the efficient market hypothesis is a test for significant serial correlation between two observations at time **t** and **t+n**, (Campbell, Lo, McKinely, 1997).

Cointegrating Relation for Prices and Rents

A cointegrating relationship for prices and rents must include series of the same order. The integration order of the price, rent, and cost of capital series is determined through a set of Augmented Dickey Fuller (ADF) tests (Table 1). The ADF tests are applied to the logarithmic specifications of the variables, which is consistent with the dynamic Gordon growth model and is empirically suggested to be appropriate. In the case of the price and rent series, the ADF test is performed with an estimated time trend to take account of the likely non-zero drift. There are no theoretical reasons to expect a drift in the cost of capital series, so the ADF specification includes only a constant. The number of possible lags is restricted to 2 because empirical and anecdotal evidence indicates that carry-over effect in housing markets is not likely to last for more than one year.

The small number of observations and the relatively small power of the ADF test (Cook, 2001) allows only for tentative conclusion about the stationarity of the series. In particular, the ADF test does not make a distinction between nonstationary and highly persistent stationary processes, as indicated by Faust (1993). Yet, as Meese and Wallace

(1994) point out, whether the price, rent, and cost of capital series are unit root or borderline stationary process is not relevant to the present discussion; if the PVR holds in the long run, then deviation from the cointegrating relationship should be less persistent than the component series. The empirical results suggest that most price and rent series are integrated of order 1, I(1), while cost of capital series appear to be well approximated by unit root processes.

Table 1: ADF unit-root tests for prices (level and first differences), rents (level and first differences), and cost of capital (level).

MSA	Log Rents		Log Prices		Log Cost of Capital, constant	
	Trend		Trend		Constant	
	One lag	Two lags	One lag	Two lags	One lag	Two lags
Atlanta	-0.66	-1.1	-3.21	-0.73	-2.008	-1.728
Boston	-2.20	-2.31	-3.14	-1.34	-0.990	-0.544
Chicago	-1.13	-2.13	-2.27	-1.20	-2.056	-2.096
Cincinnati	-1.64	-2.29	-3.17	-1.89	-3.176	-2.843
Cleveland	-1.84	-1.17	-4.45	-4.41	-2.86	-2.462
Dallas	0.23	-0.49	-4.48	-1.51	-1.286	-0.996
Denver	-0.18	-0.76	-2.21	-1.85	-1.429	-1.747
Detroit	-1.27	-1.49	-2.55	-2.91	-2.981	-2.507
Houston	-2.81	-2.97	-3.25	-1.35	-2.242	-1.951
Kansas City	-1.64	-1.34	-3.39	-0.22	-1.903	-1.616
Los Angeles	-3.31	-2.94	-1.21	-1.44	-0.855	-1.148
Miami	-2.1	-2.16	-3.08	2.00	-1.889	-1.620
Milwaukee	-2.42	-2.23	-4.89	-0.12	-3.365	-2.868
Minneapolis	-0.55	-0.42	-3.14	1.30	-1.384	-1.396
New York	-2.53	-2.02	-2.92	-1.98	-1.715	-0.744
Philadelphia	-2.35	-2.47	-1.64	-2.11	-2.766	-2.169
Pittsburgh	-1.99	-1.25	-3.64	-2.05	-2.765	-2.051
Portland	-2.67	-2.81	-2.48	-1.48	-2.402	-2.209
Saint Louis	-1.27	-1.26	-2.81	-0.06	-1.565	-1.457
San Diego	-2.51	-2.39	-1.44	-0.59	-0.784	-0.199
San Francisco	-1.85	-1.39	-1.92	-2.45	-2.101	-1.621
San Jose	-2.08	-2.24	-3.01	-2.39	-2.101	-1.621
Seattle	-2.15	-2.00	-3.21	-2.50	-2.415	-2.428

Significance level, 35 obs.	10%	5%	1%
Trend	-3.21	-3.54	-4.23
Constant	2.62	-2.95	3.63

Meese and Wallace (1994) propose a cointegrating relationship which is a variation of McCallum's technique (McCallum, 1976). They define the forecast error as follows:

$$e_{t+1} = P_{t+1} + D_{t+1} - E_t\{(P_{t+1} + D_{t+1}) \mid I_t\}, \qquad (10)$$

where e_{t+1} is the discrepancy between expected and actual values and I_t is the information set available at time **t.** Using equation (4) and the asset pricing relationship

Table 2: ADF unit root test for the discrepancy term under the dynamic Gordon growth model		
MSA	Discrepancy (Cost of Capital), constant	
	One lag	Two lags
Atlanta	-4.054	-3.351
Boston	-3.017	-1.997
Chicago	-3.369	-3.458
Cincinnati	-2.484	-1.817
Cleveland	-4.011	-3.421
Dallas	-3.452	-3.033
Denver	-3.184	-2.910
Detroit	-2.276	-2.801
Houston	-2.78	-3.794
Kansas City	-3.463	-3.221
Los Angeles	-2.057	-2.029
Miami	-3.008	-3.008
Milwaukee	-3.567	-4.418
Minneapolis	-4.777	-6.165
New York	-2.055	-2.011
Philadelphia	-3.024	-2.707
Pittsburgh	-3.563	-3.811
Portland	-2.218	-3.123
Saint Louis	-2.880	-2.785
San Diego	-2.601	-2.319
San Francisco	-2.429	-2.466
San Jose	-4.099	-2.679
Seattle	-3.01	-2.221
Significance level, 35 obs.	10%	5%
Constant	-2.62	-2.95

$$P_t = E\left[\frac{P_{t+1} + D_{t+1}}{(1+R_t)} \middle| I_t\right],$$

and assuming that expectations coincide with the linear projection, Meese and Wallace (1994) arrive at the following expression for the discrepancy term:

$$e_{t+1} = P_{t+1} + D_{t+1} - P_t(1 + K_t),$$

In the context of the dynamic Gordon growth model, Meese and Wallace (1994) use equations (1) and (5) of Cambell and Shiller (1988) to rewrite the discrepancy term as:

$$e_{t+1} = \ln(P_{t+1} + D_{t+1}) - \ln(P_t) - 1/(1 + K_t), \qquad (11)$$

Equation (11) may be interpreted as a possible cointegrating linear combination for prices and rents with unit coefficients, provided that the discrepancy term is stationary. Table 2 reports the results of the ADF unit-root test for no-trend specification of the series. The coefficients have been theoretically restricted to 1 or -1, so the discrepancy term is not subject to problems arising from the bias associated with the ADF test for cointegrating relation. The results suggest that (11) can be interpreted as a cointegrating relationship for prices, rents, and cost of capital series, where the order of the series allows for a cointegrating relation. Thus, in most markets deviations from the PVR are not permanent and the discrepancy term is mean-reversing.

Serial Correlations

The efficient market hypothesis is tested by two procedures: a regression of present values of covariance stationary processes on lagged values and the Portmanteau statistic[2]. The tests are performed for the return, cost of capital, and the first-differences of the price series. Both the F-statistics for the autoregressive processes and the Portmanteau statistics indicate that there is significant serial correlation in all of the investigated series. Thus, we reject the efficient market hypothesis for the set of 23 large MSA's.

The regression results indicate that significant autocorrelations are observed within a one-year horizon with persistence coefficients in the range 0.5-0.75 for the first six months. The Portmanteau statistic is reported for 2 lagged periods and as theoretically suggested for approximately ln(N), where N equals the number of observations in the series (in this case ln(N) falls between 4 and 5). For all markets, except those in the Midwest, the Portmanteau Statistic is significant and the null hypothesis of no autocorrelation is rejected (Table 3, 4, 5). The regression results and the Portmanteau statistic are especially significant for markets in California, the Northeast, Denver and Atlanta.

Noticeable exceptions are the housing markets of Los Angeles, New York, San Francisco, San Diego and, surprisingly Cincinnati. An investigation of the plots of the discrepancy terms in these markets suggests that the most recent boom of housing prices in contrast to falling or stagnant rents may have contributed to the rejection of the proposed cointegration relationship; given the small number of observations, recent trends for the period 1998-2003 are likely to be influential. Alternatively, one may focus on a case-by-case study of government restrictions on rents in MSAs as a source of

[2] An alternative route is to investigate the variance ratios. This approach exploits one of the major properties of random walks, which are used to model market efficient financial time series: the variance of random walk increments is a linear function of the time elapsed. This procedure is suitable for all three major types of random walks in the context of market efficiency because of the relatively few structure imposed on the behavior of the series. In the context of the relatively short long run series employed in this study, however, testing for autocorrelation suffice. For more details on the various testing procedures and their applications, please see Campbell, Lo, and McKinley (1997).

exogenous restrictions on rent series. Unfortunately, such an exhaustive study of the impact of municipal regulations on housing market dynamics is beyond the scope of this paper.

* * *

The significant six-month horizon serial correlations in the return series and cost of capital series conform to the expectations of relatively high persistence of shock effects in housing markets. Yet as indicated in the preceding section, in the long run there exists a cointegrating relationship between prices and rents. In short the discussion so far implies that periods of abnormally high returns are typically followed by periods of downward adjustment.

Table 3. Regression output and Portmanteau statistic for log prices.								
MSA	Log Price differences, AR(1) specification		Log Price differences, AR(2) specification			Portmanteau Statistic		
	AR(1) coeff.	F-stat	AR(1) coeff.	AR(2) coeff.	F-stat.	Two lags	Four lags	Five lags
Atlanta	0.39	6.173	0.213	0.389	6.607	14.84	21.36	21.56
Boston	0.775	60.33	0.723	0.057	29.41	35.55	48.7	50.24
Chicago	0.403	5.998	0.290	0.261	4.087	9.83	20.06	20.29
Cincinnati	0.135	0.624	0.065	0.231	1.138	2.67	4.49	8.13
Cleveland	0.006	0.001	0.024	-0.118	0.243	0.51	2.28	4.36
Dallas	0.546	14.26	0.432	0.206	8.232	18.21	26.11	26.89
Denver	0.534	14.94	0.374	0.420	17.48	24.72	40.58	41.95
Detroit	0.625	21.76	0.612	0.017	12.62	20.49	22.19	22.66
Houston	0.231	2.116	0.218	0.391	5.893	9.36	12.49	12.95
Kansas City	0.534	12.37	0.326	0.391	10.47	19.94	29.57	31.46
Los Angeles	0.828	50.8	0.731	0.120	24.35	33.87	45.92	47.37
Miami	0.553	13.18	0.528	0.231	11.10	14.62	22.23	24.0
Milwaukee	-0.177	0.868	-0.174	-0.127	0.532	0.95	2.52	2.52
Minneapolis	0.579	14.34	0.343	0.428	11.09	20.44	42.12	48.61
New York	0.850	110.0	0.814	-0.009	48.38	92.70	56.02	56.69
Philadelphia	0.823	56.99	0.885	-0.092	27.53	33.56	45.42	45.63
Pittsburgh	0.175	1.029	0.171	0.015	0.527	1.92	3.13	3.21
Portland	0.317	4.358	0.089	0.224	3.945	7.21	9.25	9.39
Saint Louis	0.402	5.965	0.248	0.381	5.939	12.70	20.01	20.11
San Diego	0.771	37.68	0.542	0.314	21.19	32.21	47.43	50.65
San Francisco	0.797	59.66	0.873	-0.091	28.38	37.49	47.19	47.64
San Jose	0.679	29.13	0.881	-0.296	16.45	20.71	21.08	21.16
Seattle	0.506	11.65	0.577	-0.139	5.89	10.32	10.46	11.36
Significance level		5%				1%		
F(1,35)		4.12				7.72		
F(2,34)		3.27				5.27		

Table 4. Regression output and Portmanteau statistic for log return series

MSA	Log Returns, AR(1) specification		Log Returns, AR(2) specification			Portmanteau Statistic		
	AR(1) coeff.	F-stat	AR(1) coeff.	AR(2) coeff.	F-stat.	Two lags	Four lags	Five lags
Atlanta	0.459	10.05	0.249	0.382	7.603	16.71	23.45	23.63
Boston	0.790	82.91	0.768	0.044	35.72	39.55	57.03	59.92
Chicago	0.430	7.995	0.287	0.266	4.878	12.38	21.65	21.92
Cincinnati	-0.134	0.451	-0.122	0.150	0.506	1.15	6.38	7.95
Cleveland	0.003	0.000	-0.034	-0.264	0.862	1.67	2.80	3.32
Dallas	0.481	8.628	0.479	0.217	11.33	23.65	34.46	35.81
Denver	0.534	14.67	0.386	0.399	15.93	23.53	35.37	35.8
Detroit	0.628	17.02	0.541	0.138	8.142	16.81	20.91	21.21
Houston	0.290	3.447	0.248	0.381	6.492	10.95	14.24	14.3
Kansas City	0.593	14.40	0.399	0.267	7.675	17.36	21.48	22.98
Los Angeles	0.835	57.64	0.738	0.117	27.480	37.01	51.47	53.39
Miami	0.580	13.69	0.497	0.185	7.351	14.20	19.32	20.03
Milwaukee	-0.260	-1.29	-0.333	-0.243	1.785	2.14	2.18	2.26
Minneapolis	0.443	7.581	0.290	0.343	5.990	13.4	29.17	33.66
New York	0.794	70.15	0.837	0.020	37.11	35.79	51.75	54.88
Philadelphia	0.827	69.91	0.872	-0.081	32.17	37.41	51.20	51.55
Pittsburgh	0.154	0.709	0.191	-0.122	0.569	0.95	4.61	5.04
Portland	0.621	17.15	0.477	0.196	8.974	18.68	25.61	28.12
Saint Louis	0.332	3.446	0.157	0.352	3.153	7.67	13.42	13.55
San Diego	0.762	38.34	0.534	0.303	21.27	33.55	49.65	52.92
San Francisco	0.807	65.49	0.894	-0.102	31.14	38.97	49.51	49.97
San Jose	0.609	19.93	0.798	-0.256	9.922	12.81	14.71	15.39
Seattle	0.578	17.07	0.640	-0.109	8.282	14.96	15.51	15.64
Significance level			5%			1%		
F(1,35)			4.12			7.72		
F(2,34)			3.27			5.27		

Table 5. Regression output and Portmanteau statistic for log cost of capital series.								
MSA	Log Cost of Capital, AR(1) specification		Log Cost of Capital, AR(2) specification			Portmanteau Statistic		
	AR(1) coeff.	F-stat	AR(1) coeff.	AR(2) coeff.	F-stat.	Two lags	Four lags	Five lags
Atlanta	0.304	3.503	0.130	0.507	7.297	13.34	29.40	30.70
Boston	0.717	32.59	0.348	0.530	25.86	31.25	49.17	53.98
Chicago	0.662	33.12	0.254	0.515	24.83	31.25	51.16	56.19
Cincinnati	0.400	8.418	0.196	0.277	4.239	10.65	17.51	22.25
Cleveland	0.444	9.29	0.283	0.219	4.129	10.31	23.26	27.88
Dallas	0.622	25.07	0.212	0.643	29.87	34.96	62.05	70.32
Denver	0.737	39.58	0.316	0.520	27.03	36.75	54.46	61.03
Detroit	0.504	14.66	0.307	0.307	6.08	14.96	23.47	29.04
Houston	0.710	52.35	0.485	0.268	23.46	31.15	49.21	55.08
Kansas City	0.748	49.66	0.523	0.258	23.24	33.39	54.73	67.45
Los Angeles	0.728	47.86	0.435	0.475	37.53	36.71	51.69	55.79
Miami	0.345	5.642	0.089	0.626	14.25	17.13	24.61	26.04
Milwaukee	0.281	2.769	0.162	0.128	0.971	3.19	4.24	4.27
Minneapolis	0.684	31.19	0.394	0.429	20.93	31.29	54.89	63.98
New York	0.649	38.92	0.330	0.473	24.74	24.28	31.88	32.49
Philadelphia	0.201	1.404	0.068	0.355	2.776	5.29	7.16	7.17
Pittsburgh	0.545	18.42	0.231	0.393	11.1	21.58	31.72	35.78
Portland	0.449	10.4	0.139	0.522	12.81	20.96	36.61	37.29
Saint Louis	0.469	9.89	0.233	0.511	10.74	18.26	23.84	25.37
San Diego	0.730	34.31	0.418	0.481	24.69	33.85	57.09	66.02
San Francisco	0.750	49.98	0.837	-0.082	24.19	32.50	50.84	55.49
San Jose	0.750	49.98	0.837	-0.082	24.19	32.50	50.84	55.49
Seattle	0.651	34.41	0.363	0.347	17.61	29.02	37.65	39.12
Significance level			5%			1%		
F(1,35)			4.12			7.72		
F(2,34)			3.27			5.27		

Housing Price Sensitivity to Changes in Returns

The autocorrelation test and the likely existence of long run cointegration relationship between prices and rents suggest that a PVR relation consistent with the analytical framework of the dynamic Gordon growth model is applicable to large housing markets. The rest of the paper examines the implications for price sensitivity to changes in return series and the role of adjustment in shelter inflation in the short run housing market dynamics.

A simple and empirically relevant expected returns model, which is compatible with the dynamic Gordon growth model, can be defined, as follows:

$$k_{t+1} = E_t(r_{t+1}) = r + \varepsilon_t, \qquad (12)$$

$$\varepsilon_t = \phi * \varepsilon_{t-1} + \xi_t \qquad (13)$$

where ε_t is zero mean variable following an AR(1) process, ϕ is the persistence coefficient (theoretically belonging to (-1, 1) and expected to by close to 1), and ξ_t is the innovation at time **t** (Campbell, Lo and McKinely, 1997). Equation (13) implies that

$$\sigma_\varepsilon^2 = \frac{\sigma_\xi^2}{(1-\phi^2)} \qquad (14)$$

Under (12), (13), and (14),

$$p_{rt} = E\left[\sum_{i=0}^{\infty} \rho^i * r_{t+1+i}\right] = \frac{r}{1-\rho} + \frac{\varepsilon_t}{1-\rho * \phi} \qquad (15)$$

This formula suggests that housing prices are likely to be highly sensitive to changes in expected returns, when the expected return series are highly persistent. For example, when ρ is close to one and ϕ=0.5, a 1% increase in the expected returns reduces housing prices by 2% and by 4% if ϕ=0.75[3].

Campbell (1991) shows that substituting (9) into (5) yields the following relationship for unexpected returns:

$$r_{t+1} - E_t(r_{t+1}) = E_{t+1}\left[\sum_{i=0}^{\infty}\rho^i \Delta d_{t+1+i}\right] - E_t\left[\sum_{i=0}^{\infty}\rho^i \Delta d_{t+1+i}\right] - \left(E_{t+1}\left[\sum_{i=0}^{\infty}\rho^i r_{t+1+i}\right] - E_t\left[\sum_{i=0}^{\infty}\rho^i r_{t+1+i}\right]\right) \qquad (16)$$

Equations (12), (13), and (14) also yield:

$$E_{t+1}\left[\sum_{i=0}^{\infty}\rho^i r_{t+1+i}\right] - E_t\left[\sum_{i=0}^{\infty}\rho^i r_{t+1+i}\right] = \frac{\rho * \xi_{t+1}}{1-\rho * \phi} \qquad (17)$$

Equation (17) allows for a simplification of the general expression for one period returns, equation (16):

$$r_{t+1} = r + \varepsilon_t + E_{t+1}\left[\sum_{i=0}^{\infty}\rho^i \Delta d_{t+1+i}\right] - E_t\left[\sum_{i=0}^{\infty}\rho^i \Delta d_{t+1+i}\right] - \frac{\rho * \xi_{t+1}}{1-\rho * \phi} \qquad (18)$$

Then, under assumption of independence of news on rents and on housing returns[4], the variance of r_{t+1} can be expressed as:

$$Var(r_{t+1}) \approx \sigma_*^2 + \frac{2\sigma_\varepsilon^2}{1-\phi}, \qquad (19)$$

[3] For more details on the sensitivity of prices to changes in expected returns and price volatility in general can be found in Summers (1986).
[4]. If news about future housing services and the innovation for expected returns are allowed to be autocorrelated and the correlation between the two terms is sufficiently high, then the return serial correlation is positive. For more details on the simplifications and a discussion of the non-restricted model, see Campbell, Lo, and McKinley (1997), particularly Chapter 12.

where σ_*^2 is the variance of the first two terms in (16) that indicate the change in expected future rents[5]. Equations (13) and (18) can be used to express realized housing returns as an ARMA (1, 1) process. Similarly, expected returns modeled as an AR(2) correspond to realized returns expressed as an ARMA(2, 2).

Unfortunately, the precise modeling of the return series is not possible due to the methodologically introduced noise in the price and return series. Yet, as pointed out previously, under the PVR hypothesis cost of capital must equal expected returns. Consequently, the persistence coefficients of cost of capital may be used as a proxy for the persistence coefficients of expected returns. In short, the existing data allows for some cautious inferences about the behavior of returns based on modified cost of capital series.[6]

The positive AR coefficient(s) for the expected return series is (are) also present in the return series. However, a positive innovation in future expected returns leads to contemporaneous capital loss, which introduces negative autocorrelation in the return series represented by a negative moving average (MA) coefficient. Thus, one may expect that the observed autocorrelation in the return series is less than or equal to the autocorrelation in the expected return series. If the MA coefficient is close in absolute value to the AR coefficient for a given market, then returns may not exhibit signs of serial correlation, and yet expected returns may follow an autoregressive process. For example, the fact that realized returns in Cincinnati, Cleveland, and Milwaukee appear to exhibit no serial correlations may be due not to market efficiency but to large negative

[5] For more details on the model: Campbell, Lo, and McKinley (1997).
[6]The lack of data necessitates the approximation of the cost of capital series. On average, one may expect that the cost of capital equals expected returns. Thus, modified cost of capital series include a long run constant equal to the average actual returns and the short run variations, caused by changes in mortgage rates and shelter inflation.

MA. In short, the return autocorrelation coefficients are likely to be smaller than the autocorrelation coefficients for expected return series, which are approximated by the cost of capital series. The serial autocorrelation in the cost of capital series indicate high sensitivity of housing prices to changes in expected returns in Los Angeles, San Diego, San Francisco, San Jose, New York, Philadelphia, Boston, Denver, and Atlanta. These results conform with previous studies and anecdotal evidence.

The remaining question is what may be the causes of the short-run deviations. Meese and Wallace (1994) discuss at great length the possible causes of the discrepancy between the actual and theoretically predicted values. They conclude that the most likely cause is the high transaction costs in housing markets. In particular, deviation from the optimal decision rule implied by equation (7) may arise because any change in utility must exceed transaction costs before any adjustment in housing service consumption takes place.[7] The survey of public expectations concluded by Case and Shiller (2004) suggests that exuberant expectations for future housing appreciation may be an alternative explanation worth exploring. A third possibility, advanced in this paper, is related to the interaction between shelter and non-shelter inflation.

[7] Akerlof and Yellen (1985) develop a framework for the analysis of near rational behavior, which implies that for constant expected returns the asset pricing relationship imposes only second-order utility loss.

Table 6. ADF unit-root tests for shelter and non-shelter inflation.								
MSA	Log Shelter Inflation, constant		Log Shelter Inflation, constant and trend		Log Non-Shelter Inflation, constant		Log Non-Shelter Inflation, constant and trend	
	One lag	Two lags	One lag	Two lags	One lag	Two lags	One lag	Two lags
Atlanta	-1.548	-2.042	-1.494	-1.986	-2.975	-2.717	-3.493	-3.286
Boston	-2.089	-1.304	-2.278	-1.62	-3.148	-2.656	-3.496	-2.952
Chicago	-4.133	-3.491	-4.564	-4.098	-2.980	-2.424	-3.813	-3.344
Cincinnati	-5.153	-4.172	-5.083	-4.131	-3.189	-2.982	-3.287	-3.216
Cleveland	-5.414	-4.346	-5.441	-4.259	-3.385	-3.436	-3.544	-3.686
Dallas	-2.106	-2.317	-2.197	-3.146	-2.925	-3.479	-3.110	-3.771
Denver	-1.027	-1.752	-0.189	-1.211	-3.119	-2.599	-3.242	-2.748
Detroit	-3.803	-4.108	-3.988	-4.439	-3.529	-2.423	-3.567	-2.454
Houston	-2.603	-2.253	-2.372	-2.178	-3.730	-3.437	-3.834	-3.675
Kansas City	-2.671	-2.156	-3.263	-2.767	-3.144	-3.284	-3.421	-3.682
Los Angeles	-1.361	-1.792	-1.335	-1.740	-1.821	-1.704	-2.496	-2.467
Miami	-3.449	-2.787	-3.477	-2.992	-3.518	-3.588	-3.862	-4.115
Milwaukee	-3.734	-3.380	-3.837	-3.604	-4.024	-2.552	-4.256	-2.814
Minneapolis	-3.027	-2.609	-3.683	-3.735	-3.006	-3.500	-3.230	-3.785
New York	-2.394	-2.109	-2.360	-2.072	-2.950	-1.920	-3.685	-2.505
Philadelphia	-3.329	-2.088	-3.609	-2.186	-2.789	-2.227	-3.294	-2.750
Pittsburgh	-3.193	-3.363	-3.205	-3.399	-3.326	-2.630	-3.451	-2.807
Portland	-1.545	-1.462	-1.733	-1.616	-4.076	-2.346	-4.324	-2.533
Saint Louis	-3.609	-3.086	-3.517	-2.950	-2.906	-3.298	-3.054	-3.549
San Diego	-1.788	-1.264	-2.411	-2.153	-2.506	-2.682	-2.657	-2.965
San Francisco	-2.261	-2.092	-2.154	-2.214	-2.809	-2.046	-3.331	-2.752
San Jose	-2.261	-2.092	-2.154	-2.214	-2.809	-2.046	-3.331	-2.855
Seattle	-2.056	-3.483	-1.895	-3.349	-2.709	-2.689	-2.682	-2.698
Significance level, 35 obs.	10%			5%			1%	
Constant and Trend	-3.21			-3.54			-4.23	
Constant	-2.62			-2.95			-3.62	

Table 7. Regression output and Portmanteau statistic for shelter inflation series.								
MSA	Log Shelter Inflation, AR(1) specification		Log Shelter Inflation, AR(2) specification			Portmanteau Statistic		
	AR(1) coeff.	F-stat	AR(1) coeff.	AR(2) coeff.	F-stat.	Two lags	Four lags	Five lags
Atlanta	0.154	0.698	0.094	0.569	6.528	13.34	29.40	30.70
Boston	0.479	9.831	0.298	0.343	6.927	31.25	49.17	53.98
Chicago	0.174	1.126	0.192	-0.103	0.712	31.25	51.16	56.19
Cincinnati	-0.070	0.147	-0.091	-0.279	1.263	10.65	17.51	22.25
Cleveland	-0.060	0.128	-0.079	-0.394	1.866	10.31	23.26	27.88
Dallas	0.421	7.020	0.261	0.358	5.861	34.96	62.05	70.31
Denver	0.674	20.71	0.450	0.384	13.30	36.75	54.46	54.46
Detroit	0.086	0.224	0.095	-0.058	0.158	14.96	23.47	23.47
Houston	0.452	10.85	0.158	0.464	10.35	31.15	49.21	55.08
Kansas City	0.136	0.666	0.074	0.361	2.762	33.39	54.73	67.45
Los Angeles	0.727	40.76	0.447	0.395	26.22	36.71	51.69	55.78
Miami	-0.167	1.054	-0.163	0.337	3.175	17.13	24.61	26.04
Milwaukee	-0.057	0.068	-0.045	-0.047	0.050	3.19	4.24	4.27
Minneapolis	0.138	0.690	0.103	0.230	1.266	31.29	54.88	63.98
New York	0.395	6.708	0.261	0.312	5.153	24.28	31.88	32.49
Philadelphia	0.158	0.916	0.118	0.160	0.834	5.29	7.16	7.17
Pittsburgh	0.170	0.923	0.171	0.021	0.452	21.58	31.72	35.78
Portland	0.256	2.422	0.174	0.503	5.779	20.96	36.61	37.29
Saint Louis	-0.003	0.000	-0.005	0.187	0.667	18.26	23.84	25.37
San Diego	0.555	15.02	0.354	0.365	10.55	33.85	57.09	66.02
San Francisco	0.732	37.63	0.823	-0.121	18.76	32.50	50.84	55.49
San Jose	0.732	37.63	0.823	-0.121	18.76	32.50	50.84	55.49
Seattle	0.457	9.480	0.321	0.308	6.16	29.02	37.65	39.12
Significance level	10%			5%			1%	
F(1,35)/F(1,27)	-3.21			-3.54			-4.23	
F(2,34)/F(2,26)	-2.62			-2.95			-3.62	

Table 7. Regression output and Portmanteau statistic for non-shelter inflation series.

MSA	Log Non-Shelter Inflation, AR(1) specification		Log Non-Shelter Inflation, AR(2) specification			Portmanteau Statistic		
	AR(1) coeff.	F-stat	AR(1) coeff.	AR(2) coeff.	F-stat.	Two lags	Four lags	Five lags
Atlanta	0.054	0.099	0.03	0.277	1.41	1.32	4.35	5.56
Boston	0.378	5.988	0.36	0.033	2.845	0.83	7.63	8.16
Chicago	0.138	0.699	0.112	0.226	1.259	3.25	6.34	6.37
Cincinnati	0.141	0.700	0.106	0.181	0.858	0.07	2.17	4.15
Cleveland	0.291	3.320	0.291	0.0210	1.662	0.81	4.58	5.7
Dallas	0.148	0.810	0.122	0.242	1.523	1.63	5.06	6.38
Denver	0.172	0.969	0.138	0.147	0.778	0.93	2.86	2.96
Detroit	0.335	4.396	0.359	-0.076	2.172	0.82	4.99	10.77
Houston	0.290	3.603	0.345	0.170	2.078	0.71	4.06	4.19
Kansas City	0.229	1.895	0.205	0.100	1.099	0.78	3.54	6.23
Los Angeles	0.386	5.519	0.182	0.489	7.562	9.21	23.9	24.32
Miami	0.206	1.572	0.198	0.038	0.768	1.21	3.14	3.34
Milwaukee	0.339	4.502	0.408	-0.203	2.937	0.58	4.94	5.75
Minneapolis	0.300	3.509	0.268	0.117	1.931	1.32	6.26	7.22
New York	0.567	17.27	0.620	-0.087	8.429	5.17	20.84	21.7
Philadelphia	0.323	4.225	0.257	0.197	2.704	3.05	10.33	10.78
Pittsburgh	0.358	5.303	0.354	0.000	2.436	0.51	6.13	6.71
Portland	0.247	2.265	0.285	-0.142	1.432	0.91	3.36	4.30
Saint Louis	-0.028	0.028	-0.131	0.345	2.349	3.72	8.79	15.41
San Diego	0.25	2.332	0.171	0.323	3.152	0.81	8.21	11.0
San Francisco	0.381	5.608	0.388	0.059	3.039	2.32	8.17	8.24
San Jose	0.381	5.608	0.388	0.059	3.039	2.32	8.17	8.24
Seattle	0.527	13.35	0.518	0.021	6.396	0.62	14.07	14.85
Significance level	10%			5%			1%	
F(1,35)/F(1,27)	-3.21			-3.54			-4.23	
F(2,34)/F(2,26)	-2.62			-2.95			-3.62	

If shelter and non-shelter inflation have different rates of adjustment, then the discrepancy between these rates may introduce an unsustainable in the long run housing market dynamics. As pointed out above, housing prices in some markets are highly sensitive to even small changes in returns, which may induce an unsustainable, in the long run, appreciation of houses. Tables 5 indicates that most shelter and non-shelter inflation series are well approximated by unit root processes. Table 6 and 7 summarize the significance of the serial correlation found in the shelter and non-shelter inflation for the 23 MSAs. The results indicate that while the impact of any shock on non-shelter inflation diminishes in the following 6 months, the impact of any shock on shelter inflation is still significant after 6 months. In several MSAs, both series exhibit significant autocorrelations, but the autocorrelation coefficients for shelter inflation are noticeably higher than their counterparts for overall inflation less shelter. Since overall inflation is the weighted average of the two inflation series, overall inflation exhibits lower persistence than shelter inflation alone.

These results suggest the opportunity for future investigation of the impact of economic shocks on the economy as a whole viz. housing markets.

Conclusion

Significant serial correlations in all of the 23 large MSAs indicate that housing markets depart from the optimal relation between prices, cost of capital, and rents in the short run. The long-run cointegrating relationship between prices and rents, however, imply that the short-run deviations are not permanent. While the rejection of the efficient market hypothesis in the short run is hardly a surprise, especially in the context of high transaction costs in housing market, the persistence coefficients provide valuable insights into the sensitivity of housing prices to changes in expected returns. First, the autocorrelation in the housing returns is significant for a period of 6 to 12 months. Second, the different magnitude of the persistent coefficients may be used to approximate the sensitivity of housing prices to changes in expected returns. Third, the results indicate some regional differences: Los Angeles, San Diego, San Francisco, San Jose, Boston, Atlanta, New York, Philadelphia, and Denver have relatively high sensitivity to changes in expected returns. Along with the dominant explanation in terms of transaction costs, the different rates of adjustment of overall and shelter inflation may provide some insights into the short-run dynamics of housing markets.

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Set of MSA Housing Markets

The dataset includes biannual data for a set of 23 large MSA's for the period 1986-2003: Atlanta (1986-2003), Boston(1986-2003), Chicago (1986-2003), Cincinnati (1989-2003), Cleveland (1989-2003), Dallas(1986-2003), Denver(1986-2003), Detroit(1986-2003), Houston (1989-2003), Kansas City (1989-2003), Los Angeles(1986-2003), Miami (1989-2003), Milwaukee(1989-2003), Minneapolis(1989-2003), New York (1987-2003), Philadelphia (1989-2003), Pittsburgh(1989-2003), Portland(1989-2003), Saint Louis(1989-2003), San Diego (1986-2003), San Francisco(1986-2003), San Jose(1986-2003), and Seattle(1989-2003). The size of the set and the time span depend on the availability of data, particularly rental data.