Dynamic Correlation and Its Determinants: Challenge or a New Tool for Hedging House-Price Risk?

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Abstract: Dynamic correlation models estimated in this paper demonstrate that the relationship between interest rates and housing prices is typically non-constant. The estimates reveal statistically significant time fluctuations in correlations between house-price indexes and Treasury bonds, the S&P 500 Index and the stock prices of mortgage-related companies at different time lags. Regressions of the correlation time series reveal a number of systematic predictors: the difference between the interest rate and GDP growth, stock market growth, and the employment rate. Most home owners have few financial instruments available to them that provide direct hedging against house-price risk, whether defined in terms of volatility or downside risk. For those who wish to develop new hedging strategies, the assumption of constant correlation between interest rates and housing prices, which is common in the existing mortgage-pricing literature, is an important issue. The results point to the possibility that the incorrect assumption of constant correlation leads to mortgage mis-pricing and that the hedging problem may be more challenging than has been previously acknowledged. Prospects for using dynamic correlation models to develop new hedging tools are considered.

Introduction

This study estimates bivariate dynamic correlation models for housing price indexes and financial-market time-series. These include Treasury bond rates, the S&P 500 and individual common stocks sensitive to defaults on residential home mortgages. The primary motivation for analyzing these correlations is to provide a quantitative description of how stable linear relationships between housing-market variables and financial markets are, and to look for potential cross-hedging instruments against the risk of house-price declines in different regions of the U.S. over different time horizons. The consequences of homeowners' lack of access to insurance against declines in home values and the broader economic impact of sharp movements in mortgage-default rates have been described by Case, Shiller, and Weiss (1996). This paper relaxes their assumption that correlations between home values and other assets are constant with respect to time, a maintained assumption in nearly all the literature in this area. There are practical policy consequences for mortgage-industry decision-makers whose job it is to price risk if real and financial asset markets have time-varying correlation. Difficult-to-forecast dynamical correlation may help explain why financial-market innovators have so far provided very few practical hedging instruments for average home owners.

The major stakeholders in developing new hedging instruments include homeowners, builders, mortgage holders, insurers, and mortgage-backed securities companies. Although major home finance firms such as FNMA and FHLMC have "risk sharing" operations, these transactions are all over-the-counter, creating significant transaction costs and illiquidity. Case, Shiller and Weiss (1996) have suggested the establishment of futures or options markets for residential real estate prices, but these markets are unlikely to emerge in the foreseeable future. There is a possibility that the futures and options markets for the S&P 500 and for U.S. Treasury Bonds may provide a partial solution through their correlations with house prices. With the aid of dynamical correlation models, the hope is that cross-hedging strategies could be built using relatively liquid instruments such as S&P 500 and T-bond futures and options based on their predicted time paths and the relevant correlations. In this paper, those frequently studied hedging instruments are augmented by the inclusion of publicly traded REITs and the common stocks of firms in the homebuilding and mortgage insurance industries. We attempt to describe how dynamic hedging strategies could be implemented by financial professionals with frequent re-estimation and updating. Therefore, financial market variables' correlations with region-specific home values would seem to be a worthwhile research priority.

A small but growing collection of empirical studies on the relation between housing prices and the stock market indexes has emerged in recent decades. Research examining the relation between securitized real estate indexes (REITs) and the stock market has arrived at conflicting views. Okunev and Wilson (1997) report that securitized REITs and stock markets are segmented when examined using conventional cointegration tests, and are fractionally integrated when examined with a nonlinear model. Wilson, Okunev, Plessis and Ta (1998) report that property and stock markets are not cointegrated in Australia but somewhat cointegrated in South Africa. Gyourko and Keim (1992), and Eichholtz and Hartzell (1996) report that lagged values of real-estate stock-portfolio returns help predict the returns of appraisal-based real-estate indexes. These researchers use stock-price indexes of real-estate-related firms, however, which makes the relation between house prices and stocks somewhat indirect. Takala and Pekka (1991) suggest that using lagged changes in the stock index can improve house price prediction in Finland. Using repeat-sales price indexes, Goetzmann (1993) finds negative correlation between housing and bond returns, and small negative correlations with the S&P 500.

Several recent studies investigate correlation between different financial markets using dynamical correlation models. For example, using GARCH models, Christofi and Pericli (1999), Engle (2000), and Tse (2000) demonstrate time-varying correlations between stock markets. Tse reports constant correlation for spot futures and foreign exchange data. Ball and Torous (2000), use an integration-based filtering method to uncover dynamic correlation between stock markets.

This paper tests dynamic conditional correlation (DCC) models against more standard constant correlation models. The second step of this paper's empirical investigation seeks to explain the estimated DCC in terms of multiple return series thereby establishing the partial correlations needed for portfolio analysis of risk-return trade-offs among these instruments. The explanatory factors include volatility measures, seasonality and macroeconomic variables. The results aim to improve upon available methodologies for risk management in the housing and home-finance industry. Ultimately, improvements in risk management methodology are intended to help improve housing-market and financial-market efficiency together with the economic well-being of individual homeowners.

II. Data and Methodologies

2.1 The Data

The house-price data is published by Fannie Mae (Federal National Mortgage Association) and Freddie Mac (Federal Home Loan Mortgage Corporation). The data includes quarterly housing price indexes for 163 metropolitan areas, the 50 states plus the District of Columbia, the nine Census Divisions, and the United States as a whole from the first quarter of 1975 to the last quarter of 2001. The indexes are built as repeat-sales weighted averages. Details about the building of the indexes are described by Wang and Zorn (1997). The repeat-sales method is based on the approach of Bailey, Muth, and Nourse (1963). Successful applications and modifications of the method are provided by Case and Shiller (1987), Shiller (1991), and Wang and Zorn (1997). The method takes differences in prices of the same house at different times of sale. Once constructed from the Fannie Mae and Freddie Mac data, the index represents the largest and, we believe, best data available for this study. The data we use are immune to the well-known problem of seasonal bias that afflicts appraisal-based house-price indexes. The returns of composite REITs, equity REITs, mortgage REITs and hybrid REITs, are from the National Association of Real Estate Investment Trusts (NAREIT). One finds methodological details for the calculation of these indexes at the NAREIT website: www.nareit.com. House-related firms include Centex Corporation (CTX, NYSE), Heady Lennar (LEN, NYSE), Fannie Mae (FNM, NYSE), Freddie Mac (FRE, NYSE), NVR, Inc. (NVR, AMEX), and Pulte Homes, Inc. (PHM, NYSE). Data for U.S. Treasury bond rates, GDP growth and employment growth are from "International Financial Statistics" published by the International Monetary Fund.

2.2 Methodologies

2.2.1 Constant correlation

In order to determine the optimal hedging portfolio within a standard mean-variance framework, a hedger needs to know the correlation between returns on potential instruments and returns on home values, along with the expected return for instruments and home values. Under the assumption that instrument and home-price correlations are constant with respect to time, they can be estimated from the following equation:

$$R_{H,t} = \alpha + \beta R_{I,t+j} + \varepsilon_t, \tag{1}$$

where $R_{H,t}$ represents the period-t return on a house-price index, $R_{I,t+j}$ represents returns on a potential instrument at time $t+j$, j = -2, -1, 0, 1, 2, and ε_t is a zero-mean error term. Constant correlation is estimated by the expression $\beta(\text{var}(R_{H,t})/\text{var}(\text{R}_\text{I}))^{.5}$. Return is calculated as differenced natural logarithms of consecutive quarters' index value. Defining P as the value of an individual's house or portfolio of housing, and A as the current value of the assets underlying one futures contract, the number of contracts (shares) to long or short can be expressed as $\beta^*(P/A)$.

Whether homeowners take long or short positions depends on the direction of the correlation. For example, suppose the expected (constant) correlation between house-price returns and the S&P 500 returns is -1.0. Also suppose a home is worth $300,000 and the value of the S&P 500 index is 1,000. Then the homeowner can obtain insurance against fluctuations in the value of the home over three and six month time horizons by buying three call option contracts (100 futures per contract) with a strike price of 1,000. If the expected correlation is 0.333, only one contract should be bought.

2.2.2 Dynamic Correlation

The constant correlation approach assumes that the variance-covariance matrix is constant. For the dynamic correlation approach, we apply the dynamic conditional correlation (DCC) model proposed by Engle (2000). The DCC model is a multivariate GARCH estimator with the following specification:

$$E_{t-1}(r_t r_t^{'}) = H_t = D_t R_t D_t, \qquad (2)$$

where r_t is an nx1 vector of mean zero residuals obtained from the AR models and D_t is a diagonal matrix given by:

$$D_t = diag\{\sqrt{E[r_{it}^2]}\}. \qquad (3)$$

The steps for estimating the DCC are as follows:

Step 1: Estimate a univariate AR-GARCH(1,1) model of each variable. This produces consistent estimates of the time-varying variance (D_t) for the hedging instrument.

Step 2: Calculate the standardized residuals $\varepsilon_t = D_t^{-1} r_t$, where r_t is the residual from the AR_GARCH model.

Step 3: Estimate an ARMA(1,1) model on $e_{i,j,t} = \varepsilon_{i,t}\varepsilon_{j,t}$, $e_{i,i,t} = \varepsilon_{i,t}\varepsilon_{i,t}$, and $e_{j,j,t} = \varepsilon_{j,t}\varepsilon_{j,t}$ jointly:

$$e_{i,j,t} = \alpha_0 + \alpha_1 e_{i,j,t-1} + u_t - \beta_1 u_{t-1}. \qquad (4)$$

The parameters for the covariance and variance processes are assumed to be the same. Thus the parameters in Equation 3 are estimated by stacking the variance and covariance series of

$e_{i,i,t}$ together. Equation 3 is derived from the following GARCH(1,1) process of the covariance between instruments i and j:

$$q_{i,j,t} = \bar{\rho}_{i,j} + \alpha(e_{i,j,t-1} - \bar{\rho}_{i,j}) + \beta(q_{i,j,t-1} - \bar{\rho}_{i,j}), \tag{5}$$

where $\bar{\rho}_{i,j} = \alpha_0 /(1-\alpha_1)$, $\alpha = \alpha_1 - \beta_1$, and $\beta = \beta_1$.

Step 4: Calculate the variances of instruments i and j and the covariance between instruments i and j ($q_{i,j,t}$).

Once the parameters in Equation 3 are estimated, one can calculate the covariance from Equation 4 using initial values of $q_{i,j,t}$ set to $\alpha_0 /(1-\alpha_1)$:

Step 5: Calculate the correlation between instruments i and j

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}}.$$

III. Estimated Models

3.1 Estimated constant correlation

Table 1 presents estimated constant-correlation regressions of U.S. and state-specific house-price indexes and potential hedging instruments. Representative results were chosen from a much larger list of combinatorial possibilities involving regional house-price indexes and potential hedging instruments. The tabled results result from bivariate regressions of house-price returns on a single financial-market variable's return at lags of -2, -1, 0, +1 and +2. For example, the first entry of Table 1 indicates that the regression coefficient of U.S. Treasury Bond returns on aggregate U.S. house-price-index returns is -0.156 and statistically insignificant.

If correlations were stronger, Treasury Bonds and the S&P 500 would be convenient instruments because of their well-developed options markets. Goetzmann (1993) found negative correlation between housing and bond returns and a small negative correlation with the S&P 500. The results in Table 1 indicate, however, that the relation between house-price indexes and T-bond returns varies for different areas: for the US national house index, the relation is negative and insignificant. For the Illinois index, the relation is significantly negative for t=0 and t-1. For the New York index, on the other hand, the relation is significantly positive for t=0 and t+1. Few reliable patterns can be found in Table 1 for other major states. For example, the relation between house prices and Treasury Bonds is weakly negative in California and Florida but positive in Texas. The relation between the US national house index and the S&P 500 is negative and statistically significant with lag t – 2 and lead t + 1. Noticeable correlations hold for the U.S. national house index and the four REITs indexes (All, Equity, Mortgage, and Hybrid REITs). As one might expect, these correlations are all positive and statistically significant at the 1% level with lag t -1, indicating that REIT indexes respond with a lag to changes in home prices. The U.S. national index also has large correlations with some stock-price returns: for example, (statistically) significantly negative for FNM at t + 1; significantly positive for FRE at t – 1; and significantly positive for LEN at t – 1. Individual stocks also appear to have predictive power for certain states' house-price indexes: for example, negative correlation between the Illinois index and NVR and PHM; positive correlation between the Florida index and LEN and PHM; and positive correlation between the Texas index and CTX, NVR and PHM. It is a little surprising that returns of house-price indexes of some major states and metropolitan areas, such as California and New York, Chicago, Los Angelis, San Francisco, and New York City, did not exhibit significant correlation with returns on individual stocks. None of the major states' house-price index returns is significantly correlated with the S&P 500. And only the Florida house-price index return is significantly positively correlated to the four REITs indexes returns at t – 1.

Even where statistical significance prevails, the magnitudes of the estimated correlation are rather small, ranging from 0.002 to 0.103 in absolute value. Therefore, the potential instruments cannot be efficient and effective for hedging house-price risk. Even when multiple hedging instruments are combined, their joint predictive power is weak.

3.2 Estimated dynamic correlation

The estimated dynamic correlation models indicate that most of the bivariate relationships considered in Table 1 actually fluctuate significantly over time. Figures 1a through 1f show the time paths of correlations between Treasury Bonds and house-price returns for the U.S. as a whole and the States of Florida, Illinois, Texas, New York and California, respectively. According to Figure 1a, housing and bond prices are positively correlated from 1979 to 1982 and from 1991 to 1997, but negatively correlated with large-magnitude correlation coefficients from 1983 to 1985 and from 2000 to 2002. The time-pattern of housing-and-T-bond correlation is clearest in Figures 1a and 1f, which correspond to the U.S. national and California house-price indexes. T-bond correlations for Florida and New York (Figures 1b and1e) exhibit fewer negative values. The T-bond correlation for Illinois (Figure 1c) is mostly negative before 1987 and mostly positive after 1987. The dynamic correlation path for Texas (Figure 1d) is the most volatile. Correlations between house price returns and next (t+1) period's T-bond rate are generally the largest (except for New York and Texas), consistent with the idea that expected interest-rate changes are a driving source of variation in home prices.

Correlations between house-price returns and individual stocks (not presented in the Figures or Tables) also fluctuate over time and across region. Those correlations tend to be significantly negative around 1980 and then positive in the early 1980s and early 1990s. The correlation between housing and the S&P 500 index is significantly negative from the late 1990s onward, possibly indicating that investors use real estate as a broad-based hedge against financial equity risk.

Overall, no clear and consistent pattern characterizes the estimated dynamic correlations aside from the fact that they appear strongly non-constant. The question then is whether the dynamic correlations are predictable. Predictability is required to make hedging feasible.

IV. Factors Determining the Dynamics of the Correlation

It is generally expected that interest rates, economic growth, employment growth and stock-market growth are closely related to housing prices. House-price increases have often been observed during low-interest-rate periods, which offer lower borrowing costs to home buyers. Because willingness to pay for housing probably goes up with home buyers' income, *ceteris paribus* housing prices should be positive correlated with economic growth and employment growth in lock step with demand for housing. Also, housing prices and the stock market should be positively correlated since stock-market growth increases households' wealth and enables them to buy more housing.

These factors interact in determining the level and volatility of the correlations, (i.e., one can observe negative and positive, and significant and insignificant correlations between house prices and these macroeconomic factors during different time periods). The literature has not produced stable or consistent estimates of the relationships among these variables. One can, however, say that housing demand generally increases more during periods of economic growth and low interest rates.

To reveal the relations between the dynamic correlations and macroeconomic factors over time, we conduct regression analyses of the correlations on macroeconomic time series. In the regressions, the estimated DCC (between housing prices and one potential hedging instrument) is the dependent variable. As for the independent variables, we hypothesis that when interest rates are rising faster than GDP growth and when interest rates are declining faster than GDP is declining, negative correlation between house price and interest rate should be observed. When interest rates are rising slower than GDP growth and when interest rates are declining more slowly than GDP is declining, positive correlation between house price and interest rate should be observed. Hence, the first independent variable in the regression is the absolute value of the difference between the rate of interest rate and the rate of GDP growth, and the coefficient of the variable is expected to have a negative sign. The second independent variable is the rate of employment growth, and the third independent variable is the return of the S&P 500 Index.

The estimated regressions are reported in Table 2. As expected, the difference between interest-rate- and GDP growth is negatively related to the dependent variable for the U.S. national, California and Illinois housing price series. The connection is significantly positive for New York, perhaps because higher interest rates benefit parts of the finance industry that is concentrated in New York City. The predictive effect of employment growth on the dependent variable also varies by region with surprisingly negative effects in Texas and Florida and effects conforming to expectations in New York and elsewhere. The predictive relationships between growth in the S&P500 and the DCCs are positive across all regions as expected.

V. Conclusion

This study reports dynamic correlations between the returns of house-price indexes and certain securities at leads and lags and during various time periods. The level and direction of the correlations change markedly over time. Although some of the estimated correlations are statistically significant, they are not economically significant because the correlation is too small for effective and efficient hedging of house-price risk. Furthermore, the instruments considered would serve as effective hedging tools only if historical patterns of dynamic correlation are themselves fairly stable through time, which is not yet known. Thus, we still have a long way to go for hedging house price risk. Nevertheless, the large magnitude of the dynamic correlations, which are considerably larger than those estimated in the constant-correlation models, suggests some hope of leveraging time-variation in correlations to better hedge against housing risk.

Macroeconomic factors such as the interest rate, GDP growth, employment rate and stock-market growth are statistically significant predictors of the estimated dynamic correlations between house price returns and T-bond rate. The predictive relationships vary, however, across different cross different regions. Further study is needed to understand the factors that drive the dynamics of correlation between house prices and the potential hedging instruments. In particular, we need to further examine whether the lead and lag relationships or the simultaneous correlations are more important, and which of these could best be exploited using existing financial derivatives. Historical analysis of the dynamic correlations would also provide a useful check on the reliability of estimated dynamic correlations.

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Table 1. Estimated Constant Correlations in Regressions of House-Price Indexes on Potential Hedging Instruments

									t-values=	2.39***	2**	1.67*
	coefficient	**t-value**	**adj. R2**	**coefficient**	**t-value**	**adj. R2**	**coefficient**	**t-value**	**adj. R2**	**coefficient**	**t-value**	**adj. R2**
	(US)T-b			(US)S&P			(US)FNM			(US)FRE		
t0	-0.156	-0.939	-0.001	-0.003	-0.215	-0.009	-0.006	-1.016	0.000	0.000	-0.017	-0.019
t-1	***-0.238***	-1.439	0.010	0.006	0.485	-0.007	0.001	0.158	-0.010	0.013	**1.854***	0.044
t-2	-0.157	-0.961	-0.001	-0.024	**(-2.076)****	0.030	-0.008	-1.414	0.010	-0.002	-0.222	-0.019
t+1	-0.047	-0.287	-0.009	-0.022	**(-1.846)***	0.022	-0.009	**(-1.684)***	0.018	-0.004	-0.569	-0.013
t+2	0.005	0.033	-0.010	-0.019	-1.551	0.013	-0.008	-1.382	0.009	-0.004	-0.491	-0.015
	(US)All REITs			(US)Equity REITs			(US)Mortgage REITs			(US)Hybrid REITs		
t0	0.012	0.992	0.000	0.020	1.502	0.011	0.005	0.604	-0.006	0.012	1.307	0.006
t-1	0.038	**3.228*****	0.080	0.042	**3.167*****	0.076	0.023	**2.631*****	0.052	0.024	**2.652*****	0.052
t-2	-0.014	-1.181	0.004	-0.010	-0.707	-0.005	-0.012	-1.434	0.010	-0.012	-1.348	0.008
t+1	-0.018	-1.404	0.009	-0.015	-1.077	0.001	-0.009	-0.940	-0.001	-0.012	-1.252	0.005
t+2	-0.010	-0.721	-0.004	-0.012	-0.881	-0.002	-0.006	-0.606	-0.006	-0.001	-0.128	-0.009
	(FL)All REITs			(FL)Equity REITs			(FL)Mortgage REITs			(FL)Hybrid REITs		
t0	0.050	1.147	0.003	0.069	1.491	0.011	0.016	0.524	-0.007	0.044	1.364	0.008
t-1	0.103	**2.577**	0.050	0.091	**2.029**	0.028	0.061	**2.096**	0.030	0.066	**2.208**	0.035
t+1	-0.056	-1.315	0.007	-0.061	-1.340	0.007	-0.011	-0.350	-0.008	-0.037	-1.155	0.003
	(US)LEN			(FL)LEN			(FL)PHM			(IL)NVR		
t0	-0.001	-0.275	-0.011	0.014	**2.566*****	0.060	0.008	1.597	0.023	-0.001	-0.422	-0.012
t-1	0.009	**2.749*****	0.070	0.008	1.596	0.017	0.012	**2.371****	0.065	0.001	0.868	-0.004
t-2	0.002	0.668	-0.006	0.000	-0.081	-0.012	0.004	0.743	-0.007	0.000	0.024	-0.016
t+1	-0.005	-1.343	0.009	0.004	0.643	-0.007	-0.003	-0.642	-0.009	-0.003	**(-1.978)***	0.042
t+2	0.000	-0.109	-0.012	-0.003	-0.504	-0.009	-0.006	-1.225	0.008	-0.002	-1.163	0.005
	(IL)PHM			(TX)CTX			(TX)NVR			(TX)PHM		
t0	-0.006	**(-1.705)***	0.028	0.018	**1.932***	0.040	0.009	**3.249*****	0.126	0.017	**2.234****	0.057
t-1	0.001	0.257	-0.014	0.015	1.618	0.024	0.005	1.613	0.024	0.020	**2.615*****	0.082
t-2	-0.003	-0.886	-0.003	0.001	0.053	-0.016	-0.001	-0.257	-0.015	0.002	0.223	-0.015
t+1	-0.002	-0.639	-0.009	0.007	0.698	-0.008	0.004	1.179	0.006	-0.006	-0.704	-0.008
t+2	-0.003	-0.894	-0.003	-0.003	-0.327	-0.014	0.000	0.107	-0.015	0.001	0.090	-0.015

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Table 2. Estimated Impacts

	Intercept	i - gGDP	gEmploy	gS&P500	adj. R^2
US	0.1920	-2.9349	-8.1531	0.6795	0.0308
(t-value)	(1.590)	(-1.878)*	(-1.111)	(1.539)	
California	0.3978	-3.8032	-19.4137	0.2935	0.0074
(t-value)	(1.978)	(-1.483)	(-1.596)	(0.399)	
Florida	-0.0146	0.4214	2.5001	0.5938	0.0102
(t-value)	(-0.178)	(0.403)	(0.504)	(1.979)**	
Illinois	0.3558	-4.9826	-5.2393	0.444	0.1218
(t-value)	(3.642)	(-4.00)***	(-0.887)	(1.242)	
New York	-0.086	2.8073	20.5046	0.5817	0.1207
(t-value)	(-0.952)	(2.434)**	(3.749)***	(1.757)*	
Texas	0.0125	0.0938	-14.4008	0.2673	0.0509
(t-value)	(0.136)	(0.080)	(-2.604)**	(0.799)	

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 2 presents the estimated predictive effects of the independent variables (difference between real interest rate and GDP growth, employment growth, and S&P500 growth) on the dynamic conditional correlation between returns of house-price indices (US national and five states) and T-bond rates.

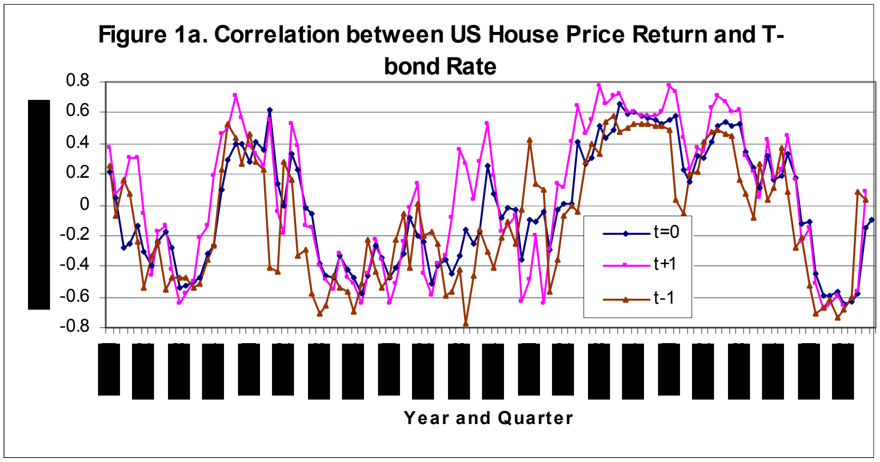

Figure 1a. Correlation between US House Price Return and T-bond Rate

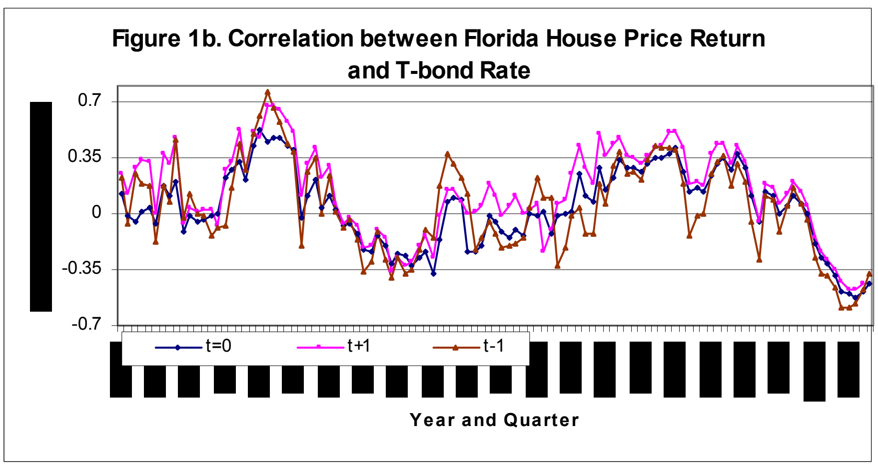

Figure 1b. Correlation between Florida House Price Return and T-bond Rate

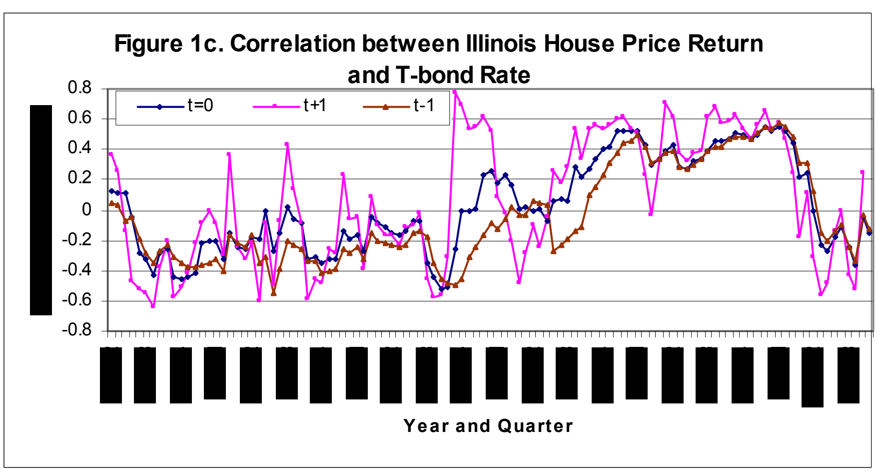

Figure 1c. Correlation between Illinois House Price Return and T-bond Rate

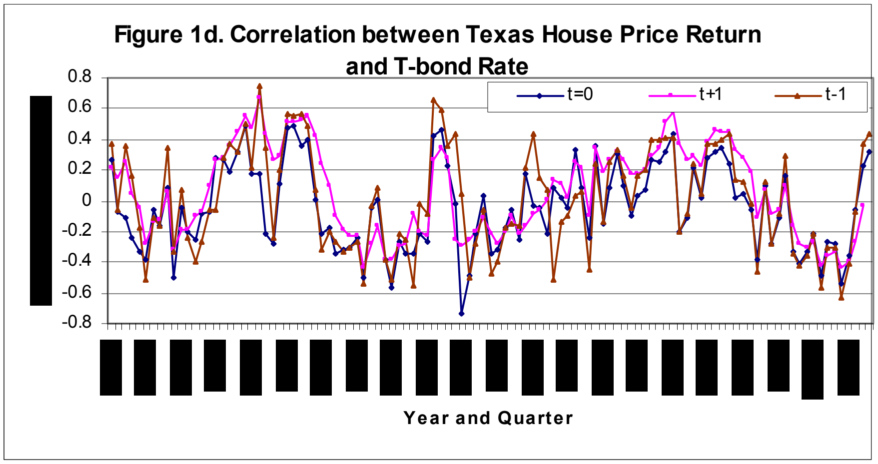

Figure 1d. Correlation between Texas House Price Return and T-bond Rate

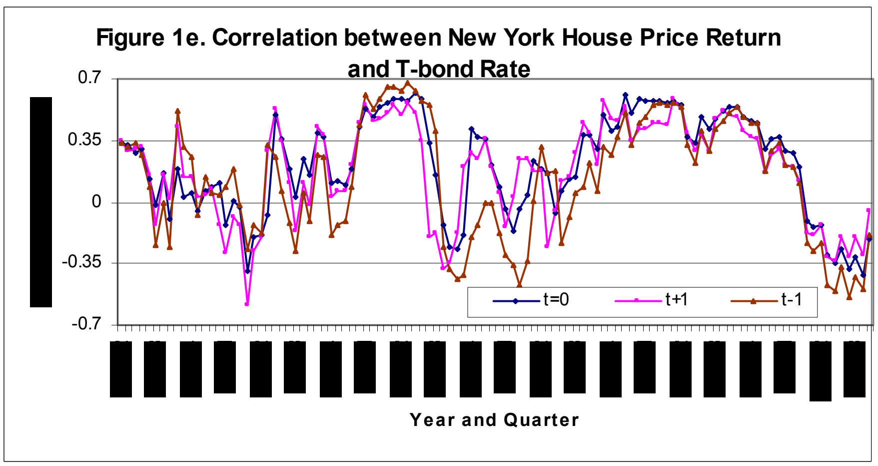

Figure 1e. Correlation between New York House Price Return and T-bond Rate

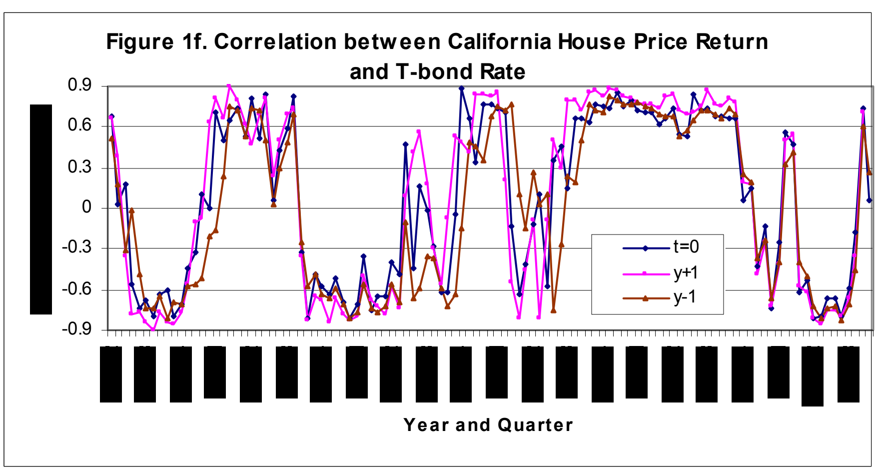

Figure 1f. Correlation between California House Price Return and T-bond Rate