Dynamic correlation: A tool hedging house-price risk?

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Dynamic Correlation: A Tool for Hedging House Price Risk?

Executive Summary. *Dynamic correlation models demonstrate that the relationship between interest rates and housing prices is non-constant. Estimates reveal statistically significant time fluctuations in correlations between housing price indexes and Treasury bonds, the S&P 500 Index, and stock prices of mortgage-related companies. In some cases, hedging effectiveness can be improved by moving from constant to dynamic hedge ratios. Empirics reported here point to the possibility that incorrect assumptions of constant correlation could lead to mis-pricing in the mortgage industry and beyond.*

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This study estimates bivariate dynamic correlation models for housing price indexes and financial market time series. The latter 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 twofold: first, to provide a quantitative description of time patterns in the linear relationships between housing market variables and financial markets; and, second, to look for potential cross-hedging instruments against housing price volatility in different regions of the United States. No attempt is made to estimate a structural model. Rather, the goal is to see whether correlations used in previous studies of hedging in housing markets are statistically constant with respect to time and, if not, whether dynamic correlations can be predicted (in a forecasting rather than structural sense) using highly liquid securities that are easily used as hedging instruments and thought to be structurally linked to home prices.

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 would likely be shifts in policy for mortgage industry decision makers, whose job it is to price risk, if real and financial

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asset markets were found to have systematically time-varying correlation. Difficult-to-forecast dynamic correlation may also help explain why financial-market innovators have so far provided few practical hedging instruments for average homeowners.

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 liquid markets for options based on region-specific indexes seem unlikely to emerge in the foreseeable future.[1]

There is a possibility, however, that existing futures and options markets for the S&P 500 and U.S. Treasury Bonds might provide a partial solution because of their correlations with home prices. With the aid of dynamical correlation models, one hopes to discover cross-hedging strategies that could be built using relatively liquid instruments, such as the S&P 500 and T-bond futures and options, based on their predicted time paths and the relevant correlations. In this paper, these frequently studied hedging instruments are augmented by the inclusion of publicly traded real estate investment trusts (REITs) and the common stocks of firms in the homebuilding and mortgage insurance industries.

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 produced 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, and Du Plessis (1998) report that property and stock markets are not cointegrated in Australia but are 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. 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 the 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 correlations between stock markets. Berg (2003) investigates changes in correlation structure within a single city's housing market.

This paper tests dynamic conditional correlation (DCC) models against the null hypothesis of constant correlation. The second step of this empirical investigation is to forecast estimated DCCs using a basket of housing-related equities and financial market indexes. Forecastability is a pre-condition for DCCs to have any utility in illuminating relationships needed for hedging housing risk. The predictors include volatility measures, seasonality, and macroeconomic variables. Nonstructural forecasting models reported here are intended to provide evidence concerning whether the precondition of DCCs' forecastability holds sufficiently well to think that further work with DCCs might provide practical hedging tools. To pursue the issue, measures of hedging effectiveness are compared for dynamic hedging portfolios, whose hedge ratios change each period based on a covariance/variance ratio from the period before, versus static hedging strategies, whose hedge ratio is estimated by linear regression as is standard in the hedging literature. Ultimately, methodological improvements in risk management for the housing and home-finance industry are intended to help improve housing market and financial market efficiency together with the economic well-being of individual homeowners.

Data and Method

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. Owing to space considerations, only results that incorporate regional indexes from the five most populous states are reported. The indexes are built as repeat-sales weighted averages. Details about the building of the indexes have been 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 (1999). 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 best data available for this study. The data 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.

Methods

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 $t + j$, $j = -1, 0, 1$, and $_t$ is a zero-mean error term. Constant correlation is estimated by the expression β(var($R_{H\ t}$)/var(R_I))[5]. Return is calculated as differenced natural logarithms of consecutive quarters' index values. Defining P as the value of an individual's house or portfolio of housing, and A as the current value of the assets underlying a single 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.

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

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

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:

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

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:

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

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:

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

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.

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

Estimated Models

Estimated Constant Correlation

Exhibit 1 presents estimated constant-correlation regressions of U.S. and state-specific house price indexes on 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 are bivariate regressions of house price returns on a single financial market variable's return at lags of -1, 0, and $+1$. For example, the first entry of Exhibit 1 indicates that the regression coefficient of U.S. Treasury bond returns on aggregate U.S. house price returns is -0.16 and statistically insignificant.

The results in Exhibit 1 imply that the relation between house price indexes and potential hedging instruments is generally weak and geographically unstable. Standard correlation computations based on the data show that REITs have only modest predictive power for U.S. and Florida indexes. There are also several statistically significant non-dynamic correlations for Texas and Illinois indexes. Even where statistical significance prevails, however, the magnitudes of estimated correlations are rather small, ranging from 0.002 to 0.10. Therefore, these potential instruments cannot be efficient and effective for hedging house price risk.

When multiple hedging instruments are combined, their joint predictive power remains weak. If these non-dynamic correlations were stronger, Treasury bonds and the S&P 500 would be convenient instruments because of their well-developed options markets. Dynamic correlation models are examined next to look for possible improvements in hedging strategies.

Estimated Dynamic Correlation

The estimated dynamic correlation models indicate that most of the bivariate relationships considered in Exhibit 1 fluctuate significantly through time. Exhibits 2a–f show the time paths of dynamic correlations between Treasury bonds and house price returns for the U.S. as a whole and for the five largest states by population (Florida, Illinois,

Exhibit 1

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

Subscript on Hedging Instrument	Coeff.	*t*-Stat.	Adj. R^2	Coeff.	*t*-Stat.	Adj. R^2	Coeff.	*t*-Stat.	Adj. R^2	Coeff.	*t*-Stat.	Adj. R^2
	(U.S.) Regressed on T-b			(U.S.) Regressed on S&P			(U.S.) Regressed on FNM			(U.S.) Regressed on FRE		
t	−0.16	−0.9	0.00	0.00	−0.2	−0.01	−0.01	−1.0	0.00	0.00	0.0	−0.02
$t-1$	−0.24	−1.4	0.01	0.01	0.5	−0.01	0.00	0.2	−0.01	0.01	1.9*	0.04
$t+1$	−0.05	−0.3	−0.01	−0.02	(−1.8)*	0.02	−0.01	(−1.7)*	0.02	0.00	−0.6	−0.01
	(U.S.) Regressed on all REITs			(U.S.) Regressed on Equity REITs			(U.S.) Regressed on Mortgage REITs			(U.S.) Regressed on Hybrid REITs		
t	0.01	1.0	0.00	0.02	1.5	0.01	0.01	0.6	−0.01	0.01	1.3	0.01
$t-1$	0.04	3.2***	0.08	0.04	3.2***	0.08	0.02	2.6***	0.05	0.02	2.7***	0.05
$t+1$	−0.02	−1.4	0.01	−0.02	−1.1	0.00	−0.01	−0.9	0.00	−0.01	−1.3	0.01
	(FL) Regressed on all REITs			(FL) Regressed on Equity REITs			(FL) Regressed on Mortgage REITs			(FL) Regressed on Hybrid REITs		
t	0.05	1.1	0.00	0.07	1.5	0.01	0.02	0.5	−0.01	0.04	1.4	0.01
$t-1$	0.10	2.6***	0.05	0.09	2.0**	0.03	0.06	2.1**	0.03	0.07	2.2**	0.04
$t+1$	−0.06	−1.3	0.01	−0.06	−1.3	0.01	−0.01	−0.4	−0.01	−0.04	−1.2	0.00
	(U.S.) Regressed on LEN			(FL) Regressed on LEN			(FL) Regressed on PHM			(IL) Regressed on NVR		
t	0.00	−0.3	−0.01	0.01	2.6***	0.06	0.01	1.6	0.02	0.00	−0.4	−0.01
$t-1$	0.01	2.7***	0.07	0.01	1.6	0.02	0.01	2.4**	0.07	0.00	0.9	0.00
$t+1$	−0.01	−1.3	0.01	0.00	0.6	−0.01	0.00	−0.6	−0.01	0.00	(−2.0)*	0.04
	(IL) Regressed on PHM			(TX) Regressed on CTX			(TX) Regressed on NVR			(TX) Regressed on PHM		
t	−0.01	(−1.7)*	0.03	0.02	1.9*	0.04	0.01	3.2***	0.13	0.02	2.2**	0.06
$t-1$	0.00	0.3	−0.01	0.02	1.6	0.02	0.01	1.6	0.02	0.02	2.6***	0.08
$t+1$	0.00	−0.6	−0.01	0.01	0.7	−0.01	0.00	1.2	0.01	−0.01	−0.7	−0.01

Notes: The dependent variable is the house price index in parentheses always with time subscript *t*. The time subscript on the independent variable is then moved backward and ahead to investigate the possibility of leading and lagged correlations.

*Significant at the 10% level.

**Significant at the 5% level.

***Significant at the 1% level.

Exhibit 2a
Correlation between U.S. House-Price Return and T-Bond Rate

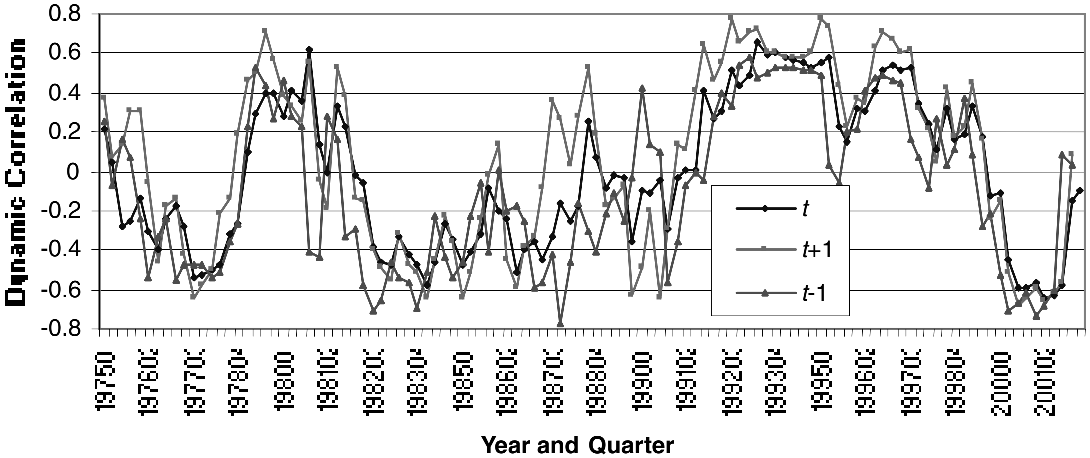


Exhibit 2b
Correlation between Florida House-Price Return and T-Bond Rate

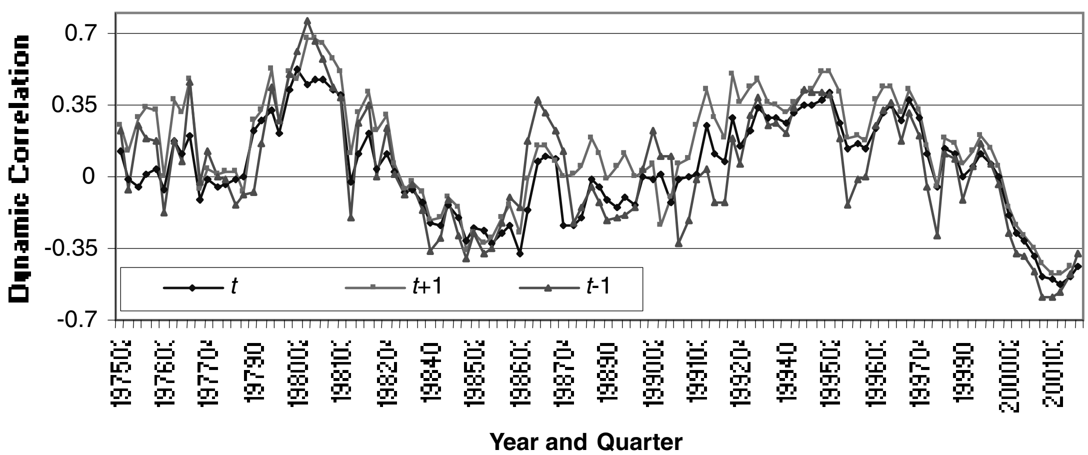


Exhibit 2c
Correlation between Illinois House-Price Return and T-Bond Rate

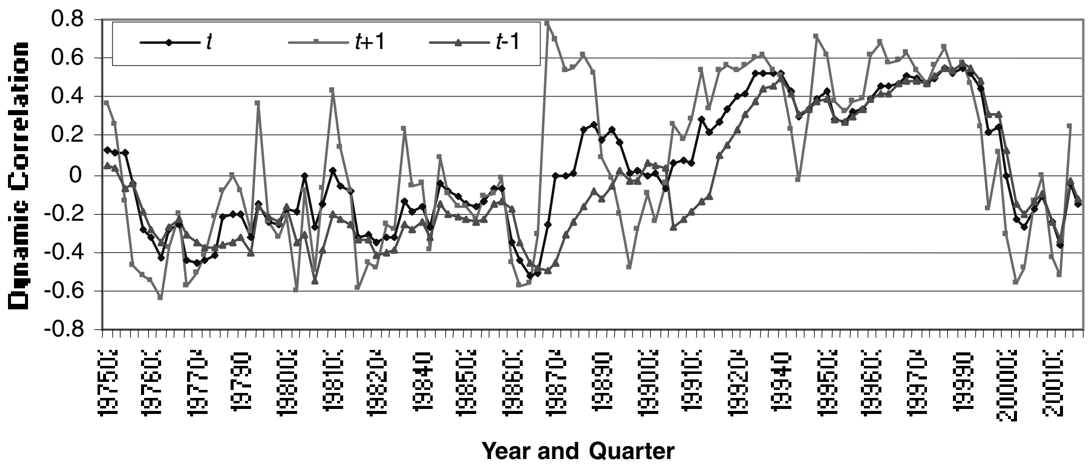


Exhibit 2d

Correlation between Texas House-Price Return and T-Bond Rate

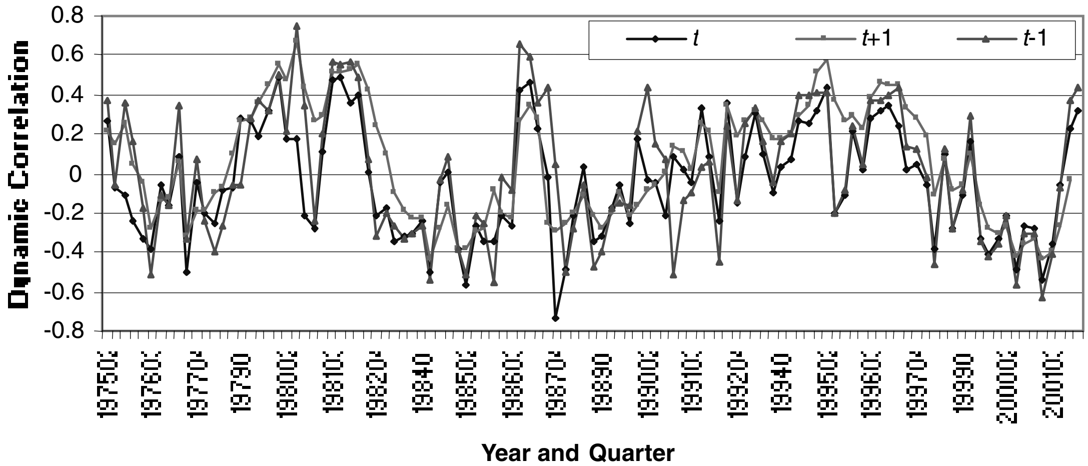


Exhibit 2e

Correlation between New York House-Price Return and T-Bond Rate

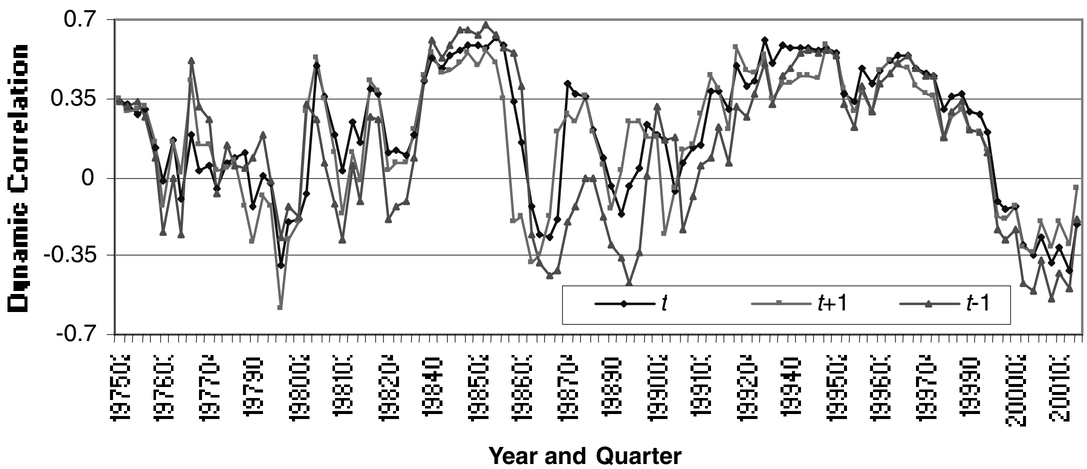
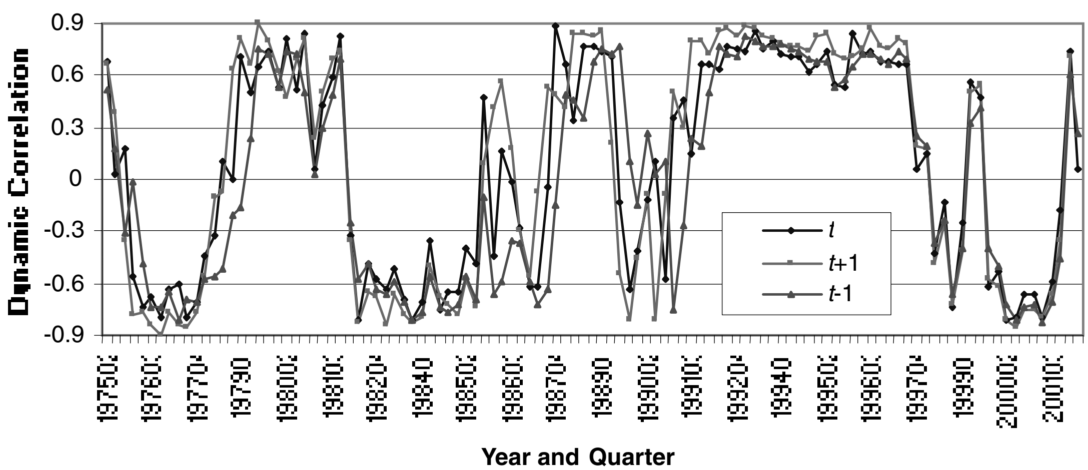


Exhibit 2f

Correlation between California House-Price Return and T-Bond Rate



Texas, New York, and California). According to Exhibit 2a, U.S. 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 Exhibits 2a and 2f, which correspond to the U.S. and California house price indexes. Treasury bond correlations for Florida and New York (Exhibits 2b and 2e) exhibit fewer negative values. The T-bond correlation for Illinois (Exhibit 2c) is mostly negative before 1987 and mostly positive after 1987. The dynamic correlation path for Texas (Exhibit 2d) 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 exhibits) 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 for hedging to be possible.

Predictors of Dynamic 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 positively correlated with economic growth and employment growth in lockstep 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 alternatively negative and positive, and alternatively 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 during periods of economic growth and low interest rates.

Regression analyses of the correlations on macroeconomic time series were conducted to reveal the relations between dynamic correlations and macroeconomic factors over time. In the regressions, the estimated DCC (between housing prices and one potential hedging instrument) is the dependent variable. As for the independent variables, it is hypothesized 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 prices and interest rates 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 prices and interest rates 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 Exhibit 3. As expected, the difference between interest rate growth and GDP growth is negatively related to

Exhibit 3
Estimated Prediction Models

	Intercept	i - gGDP	gEmploy	gS&P500	Adj. R^2
U.S.	0.19	−2.93	−8.15	0.68	0.03
t-Stat	−1.6	(−1.9)*	(−1.1)	−1.5	
California	0.40	−3.80	−19.41	0.29	0.01
t-Stat	−2.0	(−1.5)	(−1.6)	−0.4	
Florida	−0.01	0.42	2.50	0.59	0.01
t-Stat	(−0.2)	−0.4	−0.5	(2.0)**	
Illinois	0.36	−4.98	−5.24	0.44	0.12
t-Stat	−3.6	(−4.0)***	(−0.9)	−1.2	
New York	−0.09	2.81	20.50	0.58	0.12
t-Stat	(−1.0)	(2.4)**	(3.7)***	(1.8)*	
Texas	0.01	0.09	−14.40	0.27	0.05
t-Stat	−0.1	−0.1	(−2.6)**	−0.8	

Notes: This table 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 (U.S. national and five states) and T-bond rates.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

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, which are 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&P 500 and the DCCs are positive across all regions as expected.

Dynamic versus Static Hedging

Correlations between housing market indexes and financial-market indexes are clearly dynamic. Previous literature and the data considered in this paper both suggest that housing markets present individual investors and portfolio managers with risks that are difficult to hedge against. It may appear that dynamic correlation makes that difficulty even worse. Insofar as the search for hedging tools is restricted to a space spanned by models that assume constant correlation, the performance of resulting hedging strategies will be limited, since those models impose a restriction clearly falsified by time-varying correlations in the data.

One measure of potential value as a practical tool is hedging effectiveness, i.e., the percentage of variance in the housing index return x_t that can be reduced by constructing a hedging portfolio using the hedging instrument y_t. To pursue the question of DCC's value as a hedging tool, an attempt was made to run a horse race between regression-based hedging strategies in which the hedge ratio $\theta_{reg} = -\text{cov}(x,y)/\text{var}(y)$ is constant, versus dynamic hedging strategies, in which the hedge ratio is based on time-varying covariances and variances estimated by the DCC: $\theta t_{DCC} = -\text{cov}_{t-1}(x,y)/\text{var}_{t-1}(y)$.

The regression-based hedging portfolio is defined as $x_t + \theta_{reg} y_t$, whereas the DCC hedging portfolio is defined as $x_t + \theta t_{DCC}\, y_t$. Hedging effectiveness can be computed for both strategies: he_{reg} = 1-var($x_t + \theta_{reg} y_t$)/var(x_t), and he_{DCC} = 1-var($x_t + \theta t_{DCC} y_t$)/var(x_t).

The more effective a hedging strategy is, the smaller is var($x_t + \theta_t y_t$) relative to var(x_t), and the greater the percentage reduction is, as measured by he_{reg} and he_{DCC}, with a maximum of 100%.

Exhibit 4 reports values of he_{reg} and he_{DCC} in the third and fourth columns for the six housing market indexes whose DCCs were shown in Exhibits 2a–f. In each case, the hedging tool y_t (i.e., the other asset in the bivariate hedging portfolio) is U.S. Treasury bonds, either contemporaneous with housing prices or lagged by one period so that treasuries are used to predict one-period-ahead housing market returns. Of the six housing-price indexes for which the hedging effectiveness of T-bonds is reported in Exhibit 4, there is one case, Florida, in which the DCC would appear to provide an economically significant reduction in volatility. For the Florida time series, dynamic hedging with the DCC leads to a 28% reduction in variance, whereas a hedging portfolio based on static regression reduces volatility by, at most, one-tenth of 1%. In other cases, such as the U.S. series and Texas, where the absolute magnitude of reduction is smaller, the *relative* reduction, he_{DCC}/he_{reg}, is still

Exhibit 4
Hedging Effectiveness Using Bivariate DCC Versus Constant Regression to Hedge Home-Price Indexes with Treasuries

Housing Price Index		he_{reg} (Constant Hedge Ratio)	he_{DCC} (Dynamic Hedge Ratio)	Dynamic Stability of the DCC
U.S.	contemporaneous	0.0094	0.0478	1.21
	1-step ahead	0.0009	0.0519	
Florida	contemporaneous	0.0003	0.2834	1.39
	1-step ahead	0.0012	0.2842	
Illinois	contemporaneous	0.0298	0.0107	1.09
	1-step ahead	0.0216	0.0168	
Texas	contemporaneous	0.0019	0.0317	1.14
	1-step ahead	0.0121	0.0323	
New York	contemporaneous	0.0317	0.0036	1.08
	1-step ahead	0.0346	−0.0022	
California	contemporaneous	0.0018	−0.0038	0.79
	1-step ahead	0.0003	0.0038	

quite large. Exhibit 4 also shows cases where dynamic hedging increases volatility relative to the unhedged housing price index, indicated by negative values of hedging effectiveness. With that caveat in mind, Exhibit 4 provides at least tentative evidence that DCC has potential as a volatility reduction tool.

This is not overwhelming progress, of course, because the daunting challenge of regional heterogeneity remains as before. Therefore, the issue of regional heterogeneity was further investigated to try understanding whether something more systematic could be said about why, for instance, Florida appears so different than, say California, in terms of the hedging effectiveness of the DCC. Rather than classical statistics, one further statistic is reported that seemed potentially interesting after visually inspecting the DCCs at different leads and lags, as shown in Exhibits 2a–f. The development of quantitative measures motivated by visual inspection of data follows the data-to-statistical-tools methodology advocated by Tukey (1977). In Exhibits 2a–f, it appears that cases where hedging effectiveness is high, e.g., the U.S. and Florida series in Exhibits 2a and 2b, the DCCs at different lags look approximately like horizontally-shifted translations of each other. On the other hand, in cases where hedging effectiveness is low, e.g., California and New York in Exhibits 2e and 2f, the DCCs at different lags appear much more unstable, crossing at many irregular spots. Because the DCCs appear to track one another more closely at different lags in cases where DCC hedging effectiveness is large, the stability of dynamic correlation was determined by two criteria:

- Correlations at different lags are different by a meaningful magnitude; and
- Differences in correlation at different lags do not change much through time.

If correlation were constant and the DCC were therefore wrong, then $\text{cor}_t\ (x_t,y_{t-1}) = \text{cor}_t\ (x_t,y_t) = \text{cor}_t\ (x_t,y_{t+1})$, and the first criterion would be violated. For dynamics to matter, time-dependent correlations must be different to an appreciable extent. Second, insofar as dynamical correlation can be captured with a parsimonious parametric model, the time paths of $\text{cor}_t\ (x_t,y_{t-1})$ and $\text{cor}_t(x_t,y_{t+1})$ should be linked in a simple way, implying that their difference should not vary erratically.

To measure these features simultaneously, the absolute difference in lag-differenced correlations were computed at each point in time: $d_t = |\text{cor}_t\ (x_t,y_{t-1}) - \text{cor}_t(x_t,y_{t+1})|$. And then, for each pair of indexes, computed the coefficient of variation for d_t, referring to the result as dynamic stability: dynamic stability = $\text{mean}(d_t)/\text{var}(d_t)$.

The last column of Exhibit 4 reports dynamic stability for the six price series, each paired with the Treasury bond time series. Ranking housing price indexes by dynamic stability reveals an ordering that matches almost perfectly the same variables' ranking by hedging effectiveness, depending on whether one looks at contemporaneous or 1-period-ahead measures of hedging effectiveness. The finding admittedly leaves one with an as yet incomplete picture of the structural causes of DCC hedging effectiveness. Nevertheless, the pattern is suggestive of an implementable diagnostic for understanding regional heterogeneity and predicting the effectiveness of dynamic hedging.

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, there is still 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 the T-bond rate. The predictive relationships vary, however, across different regions. Further study is needed to understand the factors that drive the dynamics of correlation between house prices and potential hedging instruments. In particular, there needs to be further examination of 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.

Correlation analyses of potential hedging instruments have been published *ad nauseam* in many areas of asset pricing and risk management. Correlation itself is not novel; however, the correlations presented in this paper do effectively argue for the structural claim that constant-correlation models used in the vast majority of empirical studies of hedging possibilities are incorrect for housing markets, because they impose a static constraint on an inherently dynamic structure. The DCC is used here as a tool for observing whether the correlation between house price and financial market returns fluctuates through time. Indeed it does.

The first implication of dynamic correlation is to drop the search for static correlation hedging strategies that predominate in much of the portfolio hedging literature. A second implication based on these data is that, at least in select cases, DCC can be used as a tool for variance reduction. Dynamic hedging strategies would appear to work best when dynamic effects are sizeable (i.e., changes in correlation through time are of large magnitude), and when those differences are relatively stable through time, so that they can be effectively exploited with a minimum of statistical parameters.

Endnotes

1. An encouraging development in the form of newly available hedging instruments is the "hedgelet" (see hedgestreet.com), which allows individual investors to bet on upward or downward movements in six city-specific real estate indexes. The indexes for which options trading are now available are the National Association of Realtors' (NAR) Median Sales Prices of Existing Single-Family Homes for Chicago, Los Angeles, Miami, New York, San Diego, and San Francisco.

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