The Time-Series Properties of House Prices: A Case Study of the Southern California Market

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Abstract We examine the time-series relationship between house prices in eight Southern California metropolitan statistical areas (MSAs). First, we perform cointegration tests of the house price indexes for the MSAs, finding seven cointegrating vectors. Thus, the evidence suggests that one common trend links the house prices in these eight MSAs, a purchasing power parity finding for the house prices in Southern California. Second, we perform temporal Granger causality tests. The Santa Anna MSA temporally causes house prices in six of the other seven MSAs, excluding only the San Luis Obispo MSA. The Oxnard MSA experiences the largest number of temporal effects from six of the seven MSAs, excluding only Los Angeles. The Santa Barbara MSA proves the most isolated. It temporally causes house prices in only two other MSAs (Los Angeles and Oxnard) and house prices in the Santa Anna MSA temporally cause prices in Santa Barbara. Third, we calculate out-of-sample forecasts in each MSA, using various vector autoregressive and vector error-correction models, as well as Bayesian, spatial, and causality versions of these models with various priors. Different specifications provide superior forecasts in the different MSAs. Finally, we consider how theses time-series models can predict out-of-sample peaks and declines in house prices after in 2005 and 2006. Recursive forecasts, where we update the sample each quarter, provide reasonably good forecasts of the peaks and declines of the house price indexes.

Keywords House prices, Cointegration, Temporal causality, Forecasting

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Introduction

This paper considers the dynamics of house prices and the ability of different pure time-series models to forecast house prices in eight Southern California metropolitan statistical areas (MSAs) – Bakersfield, Los Angeles, Oxnard, Riverside, San Diego, San Luis Obispo, Santa Anna, and Santa Barbara.[1] Earlier papers examine the efficiency and diffusion of house prices across contiguous geographic regions. For example, see the analysis of Tirtiroglu (1992) and Clapp and Tirtiroglu (1994) for the Hartford MSA.

The Southern California area provides an excellent case study with its large, mobile population. That is, the vast highway network, albeit frequently overrun with commuters, facilitates the separation of home and work location. Thus, we anticipate that house prices in one MSA at the margin will reflect housing market conditions in other MSAs, especially where the demand-side effect of commuting plays a significant role. But, more generally, house prices reflect the interaction of the demand and supply sides of the market. In the past, the experience of run-ups in house prices followed by falling house prices confined itself primarily to the East and West coasts of the US. The most recent run-up and decline, however, affected housing markets around the country (Shiller 2007), suggesting that the examination of the Southern California market may provide insights into other US markets.

The Law of One Price (LOOP) states that a homogeneous good that sells in two different markets should sell for the same price, ignoring transaction and transportation costs. Fundamentally, the LOOP requires the arbitrage of goods prices between markets or, in other words, that one can transport the good between markets at relatively low cost. Clearly, housing fails in, at least, two important areas – lack of homogeneity in housing goods and lack of transportability between markets. In addition, when one compares house price indexes, rather than individual home prices, across geographic regions, the Purchasing Power Parity (PPP) approach, which extends the LOOP to price indexes, applies. PPP implies that trade between geographic regions of goods leads to a convergence of the regions' price indexes. Once again, the operation of PPP requires the arbitrage of goods between regions.

Housing economists address the issue of a non-homogeneous good by appealing to the characteristics of housing. Hedonic models allow the researcher to compare house prices based on the characteristics imbedded into the sales, such as number of bedrooms and baths, square footage, and so on. In addition, researchers want to insure that the house price index accommodates the quality of the house. A "repeat sales" index based on multiple sales of the same home attempts to address this issue. To do so successfully requires that the repeat sales include information on renovations and depreciation. A "constant quality" index allows the proper comparison of house prices across time and space. Typically, the geographic reach of the housing market reflects the commuting shed for the metropolitan area. That is, houses compete with each other within the same metropolitan area. Tirtiroglu (1992) and Clapp and Tirtiroglu (1994) provide some of the earliest tests of whether the housing market exhibits efficiency in a spatial market in Hartford, Connecticut.

A significant literature exists that examines the "ripple effect" in house prices in the UK. The ripple effect refers to the observation that house price increases in the southeastern UK generally lead with some time lag to house price increases in the Northwest UK (Meen 1999). More recent work on the ripple effect in the UK includes Cook (2003; 2005) and Holmes and Grimes (2008). Cook (2003; 2005) tests for convergence and cointegration in house prices, introducing asymmetric responses to house price increases and decreases. Holmes and Grimes (2008) apply unit root tests to the first principal component of the set of regional to national house price differentials.

Since we cannot transport houses from one metropolitan market to another necessarily imply that the housing markets in the MSAs do not exhibit linkages? Trade theory demonstrates that although labor and capital frequently do not move between countries, factor prices equalize (Samuelson 1948), if goods and services flow freely between countries. That is, flows of goods and services between countries act as surrogates for labor and capital flows and cause the prices of labor and capital to equalize even though capital and labor do not move between countries. Since housing cannot flow between markets, do other flows exist that can cause PPP to hold? First, the migration of home buyers between metropolitan areas can link the housing markets. Second, home builders can also move their operations between metropolitan areas in response to differential returns on home building activity. In sum, the movement of home buyers and home builders between regions in response to price differences can arbitrage the prices of homes, even though the homes themselves cannot move between regions.

In sum, borrowing from Meen's (1999) analysis of the UK housing market, we argue that house prices between geographic regions affect each other if either home buyers or home builders move between the markets in response to price incentives. On the home buyer side, different types of buyers or motivations may assist in the arbitrage process. One, within the Southern California MSAs, commuters can choose to purchase a home that trades off the home price and related amenities with the commuting cost. Thus, commuting across MSAs by some will

[1] We exclude the El Centro MSA because the length of the time series on house prices proves too limited.

exert some pressure to equalize home prices, adjusting for commuting costs and differences in amenities. Two, equity conversion may allow some longtime residents of areas that experienced significant appreciation to cash in their accumulated equity and buy a “better” home in an area with lower home prices and probably higher commuting costs. Three, investors may use spatial arbitrage to allocate their housing investment funds.[2]

Home builders face two basic components in their cost of supplying new housing -- construction (replacement) costs and land value. If the demand for housing rises in one region, that will draw resources, including construction labor, from other regions. As a result, construction costs in both regions will rise. It rises first in the market where the demand for housing rises to attract more construction workers. And as a consequence, as the supply of construction workers in the other region falls, their wages will rise. The equalizing of construction costs tends to equilibrate house prices across regions.

Just as we cannot transport housing between regions, we cannot transport land as well. Thus, if a region faces a fixed, or extremely inelastic, supply of land, then that regions house prices and land values will rise. That is, since house prices include construction (replacement) costs and land prices, higher land prices will drive up house prices even though construction (replacement) costs may equilibrate between regions. All eight metropolitan areas face land restrictions to varying degrees that respond in this manner. That is, all eight regions experienced run-up in house prices in recent years that fell recently (see Figure 1).

In fact, Southern California experienced two run-ups and subsequent falls in house prices – the late 1980s and early 1990s and the late 2000s. The run-up and decline in the late 1980s and early 1990s bucked the national trend, which did not experience the same movement. The run-up and decline in the late 2000s, and our focus, occurred in conjunction with the national data. We note that the two MSAs at the periphery of the commuting sheds to employment concentrations experienced the least run-up and fall in prices. As Figure 1 illustrates, Bakersfield did not see any run-up and decline in the late 1980s and early 1990s and Riverside falls below the other six MSAs. But, in the late 2000s, both Bakersfield and Riverside mimic the rest of the MSAs in run-ups and falls, although they show the smallest movement with Bakersfield showing the smallest run-up.

Finally, a debate exists on whether the run-up and decline in house prices in recent years represent a bubble and its collapse. That is, did the rise and fall in house prices reflect changes in fundamentals or did they respond to non-fundamental, psychological factors?[3] Shiller (2007) argues that US house prices reflect psychological factors or a social epidemic based on behavioral economic analysis. Earlier, Case and Shiller (2003) conclude that house price increases generally reflect fundamental factors, except for possible psychological factors for East and West coast prices. McCarthy and Peach (2003) and Himmelberg, Mayer, and Sinai (2004) find that fundamental factors can explain recent house price increases in the US. The existence of a bubble and its collapse in recent house price movements proves irrelevant for our paper, since we focus on trying to forecast the peak in the house price movement that exists in the Southern California data, no matter the cause.

Gabriel, Mattey, and Wascher (1999) analyze price differentials and dynamics in the Los Angeles and San Francisco metropolitan areas with data ending in 1997. They conclude that for the Los Angeles Metropolitan area, household mobility moderated house price differences between regions, especially those experiencing significant constraints on the supply of land. Moreover, the longer-run price differences largely reflect differences in amenities and housing quality, as the standard theories argue.

This paper, first, tests for cointegration between real house prices in the eight MSAs, using the Johansen (1991) technique. We find seven cointegrating relationships between the real house prices, a purchasing power parity (PPP) result for house prices in Southern California. Block exogeneity tests on the vector error correction (VEC) model reveal an intricate temporal causality pattern between house prices for these MSAs. The Santa Anna MSA leads the pack in temporally causing house prices in six of the other seven MSAs, excluding only the San Luis Obispo MSA. The Oxnard MSA experienced the largest number of temporal effects from other MSAs, six of the seven, excluding only Los Angeles. The Santa Barbara MSA proved the most isolated in that it temporally caused house prices in only two other MSAs (Los Angeles and Oxnard) and house prices in the Santa Anna MSA temporally caused prices in Santa Barbara.

We next compare the out-of-sample forecasting performance of various time-series models – vector autoregressive (VAR), vector error-correction (VEC), and various Bayesian time-series models. For the Bayesian models, we estimate Bayesian VAR (BVAR) and VEC (BVEC) models as well as BVAR and BVEC models that

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[2] Meen (1999) offers a similar discussion of UK for house price arbitrage between the Southeast to the Northwest, which he calls the “ripple effect.” He defines four explanations -- migration, equity conversion, spatial arbitrage, and exogenous shocks with different timing of spatial effects.

[3] Stiglitz (1990) defines a bubble as follows. A high price exists because buyers anticipate that future prices will rise to even higher levels, not based on movements in fundamental factors.

include spatial and causality priors (LeSage 2004; Gupta and Miller 2009). A causality BVEC model performs the best across all eight MSAs, although the forecasting performances in the individual MSAs do differ. That is, none of the MSAs perform the best in this causality BVEC model that performs the best across all eight MSAs.

Finally, we consider whether pure time-series models can predict the peak and decline of house prices in the Southern California market, no easy task. Our findings prove more accurate than we anticipated, when we update the model with new data as it becomes available. We can forecast the peaks and declines in the house price indexes with a lead time of up to three quarters and as low a lead time of zero quarters.

We organize the rest of the paper as follows. Section 2 specifies the various time-series models estimated. Section 3 discusses the findings from the various estimations. Section 4 concludes.

VAR, VEC, BVAR, BVEC, SBVAR, and SBVEC Specification and Estimation[4]

Following Sims (1980), we can write an unrestricted VAR model as follows:

$$y_t = A_0 + A(L)y_t + \varepsilon_t, \quad (1)$$

where y equals a $(n\times 1)$ vector of variables to forecast; A_0 equals an $(n\times 1)$ vector of constant terms; $A(L)$ (= $A_1L + A_2L^2 + ... + A_pL^p$) equals an $(n\times n)$ polynomial matrix in the backshift operator L with lag length p, and ε equals an $(n\times 1)$ vector of error terms. In our case, we assume that $\varepsilon \sim N(0,\sigma^2 I_n)$, where I_n equals an $(n\times n)$ identity matrix. The applicability of this standard-normal error specification requires that either the vector of variables in y proves stationary or, if non-stationary, then the vector exhibits cointegration. Non-stationary variables (i.e., integrated of order one) do not possess a finite variance. Nonetheless, non-stationary variables may exhibit cointegration, contain a common trend (Granger 1986; Engle and Granger 1987). The existence of the long-run common trend ensures that the short-run movements in the variables will eventually converge back to this long-run trend relationship.

With cointegrated (non-stationary) series, we can transform the standard VAR model into a VEC model. The VEC model builds into the specification the cointegration relations so that they restrict the long-run behavior of the endogenous variables to converge to their long-run, cointegrating relationships, while at the same time describing the short-run dynamic adjustment of the system. The cointegration terms, known as the error correction terms, gradually correct through a series of partial short-run adjustments.

More explicitly, for our eight variable system, if each series y_t is integrated of order one, [i.e., *I(1)*],[5] then the error-correction counterpart of the VAR model in equation (1) converts into a VEC model as follows.[6]

$$\Delta y_t = \pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-1} + \varepsilon_t, \quad (2)$$

where $\pi = -[I - \sum_{i=1=}^{p} A_i]$ and $\Gamma_i = -\sum_{j\ i+1}^{p} A_j$.

VAR and VEC models typically use equal lag lengths for all variables in the model, which implies that the researcher must estimate many parameters, including many that prove statistically insignificant. This over-parameterization problem can create multicollinearity and a loss of degrees of freedom, leading to inefficient estimates, and possibly large out-of-sample forecasting errors. Some researchers exclude lags with statistically insignificant coefficients (see Dua and Ray 1995; Dua and Miller 1996; Dua, Miller, and Smyth 1999). Alternatively, researchers use near VAR models, which specify unequal lag lengths for the variables and equations (Doan 2007, pp. 342, 345).

Litterman (1981), Doan *et al.,* (1984), Todd (1984), Litterman (1986), and Spencer (1993), use a Bayesian VAR (BVAR) model to overcome the over-parameterization problem. Rather than eliminating lags, the Bayesian

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[4] The discussion in this section relies heavily on LeSage (1999), Gupta and Sichei (2006), Gupta (2006), and Gupta and Miller (2009).

[5] See LeSage (1999) and references cited therein for further details regarding the non-stationarity of most macroeconomic time series.

[6] See Dickey *et al.* (1991) and Johansen (1995) for further technical details.

method imposes restrictions on the coefficients across different lag lengths, assuming that the coefficients of longer lags may approach more closely to zero than the coefficients on shorter lags. If, however, stronger effects come from longer lags, the data can override this initial restriction. Researchers impose the constraints by specifying normal prior distributions with zero means and small standard deviations for most coefficients, where the standard deviation decreases as the lag length increases. The first own-lag coefficient in each equation is the exception with a unitary mean. Finally, Litterman (1981) imposes a diffuse prior for the constant. We employ this "Minnesota prior" in our analysis, where we implement Bayesian variants of the classical VAR and VEC models.

Formally, the means and variances of the Minnesota prior take the following form:

$$\beta_i \sim N(1, \sigma_{\beta_i}^2) \text{ and } \beta_j \sim N(0, \sigma_{\beta_j}^2) \ , \tag{3}$$

where β_i equals the coefficients associated with the lagged dependent variables in each equation of the VAR model (i.e., the first own-lag coefficient), while β_j equals any other coefficient. In sum, the prior specification reduces to a random-walk with drift model for each variable, if we set all variances to zero. The prior variances, $\sigma_{\beta_i}^2$ and $\sigma_{\beta_j}^2$, specify uncertainty about the prior means $\overline{\beta}_i = 1$, and $\overline{\beta}_j = 0$, respectively.

Doan *et al.,* (1984) propose a formula to generate standard deviations that depend on a small numbers of hyper-parameters: *w, d*, and a weighting matrix *f*(*i, j*) to reduce the over-parameterization in the VAR and VEC models. This approach specifies individual prior variances for a large number of coefficients, using only a few hyper-parameters. The specification of the standard deviation of the distribution of the prior imposed on variable *j* in equation *i* at lag *m*, for all *i, j* and *m*, equals $S_1(i, j, m)$, defined as follows:

$$S_1(i,j,m) = [w \times g(m) \times f(i,j)] \frac{\hat{\sigma}_i}{\hat{\sigma}_j} \ , \tag{4}$$

where $f(i, j) = 1$, if $i = j$ and k_{ij} otherwise, with ($0 \le k_{ij} \le 1$), and $g(m) = m^{-d}$, with $d > 0$. The estimated standard error of the univariate autoregression for variable *i* equals $\hat{\sigma}_i$. The ratio $(\hat{\sigma}_i / \hat{\sigma}_j)$ scales the variables to account for differences in the units of measurement and, hence, causes specification of the prior without consideration of the magnitudes of the variables. The term *w* indicates the overall tightness and equals the standard deviation on the first own lag, with the prior getting tighter as the value falls. The parameter *g(m)* measures the tightness on lag *m* with respect to lag 1, and equals a harmonic shape with decay factor *d*, which tightens the prior at longer lags. The parameter *f*(*i, j*) equals the tightness of variable *j* in equation *i* relative to variable *i*, and by increasing the interaction (i.e., the value of k_{ij}), we loosen the prior.[7] The overall tightness (*w*) and the lag decay (*d*) hyper-parameters equal 0.1 and 1.0, respectively, in the standard Minnesota prior, while k_{ij} = 0.5, implying a weighting matrix (*F*) for our eight MSAs that includes 1.0 in every diagonal element and 0.5 in every off-diagonal position.[8]

Since researchers believe that the lagged dependant variable in each equation proves most important, *F* imposes $\overline{\beta}_i = 1$ loosely. The β_j coefficients, however, that associate with less-important variables receive a coefficient in the weighting matrix (*F*) that imposes the prior means of zero more tightly. Since the Minnesota prior treats all variables in the VAR, except for the first own-lag of the dependent variable, in an identical manner, several researchers attempt to alter this fact. Usually, this means increasing the value for the overall tightness (*w*) hyper-parameter from 0.10 to 0.20, so that more influence comes from other variables in the model. In addition, Dua and Ray (1995) introduce a prior that imposes fewer restrictions on the other variables in the VAR model (i.e., *w* = 0.30 and *d* = 0.50).

Some researchers believe that the standard BVAR model leaves out relevant information when it assumes symmetry of the *F* matrix. Asymmetry can arise because of spatial relationships or time-series causal effects. We consider, in turn, these two possible sources of asymmetry. First, LeSage and Pan (1995) propose spatial BVAR (SBVAR) and BVEC (SBVEC) models. They adopt a weight matrix that uses the first-order spatial contiguity

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[7] For an illustration, see Dua and Ray (1995).

[8] A longer version of this paper provides more details about the analysis and explicitly includes the weight matrices, *F.* See http://ideas.repec.org/p/nlv/wpaper/0912.html.

(FOSC) prior, implying a non-symmetric *F* matrix with more importance given to variables from neighboring MSAs than those from non-neighboring MSAs. Figure 2 maps the locations of the eight MSAs. They impose a value of 1.0 for both the diagonal elements of the weight matrix, as in the Minnesota prior, as well as for place(s) that correspond to variable(s) from MSAs with which the specific MSA shares a common border(s). For the elements in the *F* matrix that correspond to variable(s) from MSAs that do not share common borders, Lesage and Pan (1995) impose a weight of 0.1. In sum, the 0.5 weights in the specification of the F matrix become 1.0 for neighbors and 0.1 for non-neighbors.

Second, Gupta and Miller (2009) propose new specifications, causality BVAR (CBVAR) and BVEC (CBVEC) models, where the weight matrix depends on tests for Granger temporal causality –- the temporal causality (TC) prior. They modify the LeSage and Pan (1995) first-order spatial-contiguity (FOSC) prior in that they consider some neighbors as more important than other neighbors. In fact, non-neighbors may exert more influence than neighbors. If one MSA's home prices temporally cause another MSA's home prices, then they code the weight matrix for that off-diagonal entry at 1.0. If no temporal causality exists, then they code the off-diagonal entry as 0.1.

LeSage and Krivelyova (1999) develop another approach to remedy the equal treatment in the Minnesota prior, called the "random-walk averaging" (RWA) prior. As noted above, most attempts to adjust the Minnesota prior focus mainly on alternative specifications of the prior variances. The RWA prior requires that both the prior mean and variance incorporate the distinction between important variables, neighbors and non-neighbors, for each equation in the VAR and VEC models. In this specification, neighbors and non-neighbors receive weights of 1.0 and 0.0, respectively, in the weight matrix. Using 1.0 on the main diagonal of the *F* matrix for the RWA prior, however, does not always prove obvious. LeSage and Krivelyova (1999) provide the exposition for when the autoregressive influences do not influence importantly certain variables. For example, in matrix F, Bakersfield and San Luis Obispo receive a weight of 1.0, because they share a common border (i.e., they are neighbors), while San Luis Obispo and San Diego receive a weight of 0.0, because they do not share a common border (i.e., they are not neighbors). We then standardize the weight matrix, C, so that each row sums to unity.

We can interpret the *C* matrix as generating a pseudo random-walk process with drift, where the random-walk component averages across the important variables in each equation *i* of the VAR. Formally,

$$y_{it} = \delta_i + \sum_{j=1}^{3} C_{ij} y_{jt-1} + u_{it} \text{ , } i = 1, 2, \text{ and } 3. \tag{5}$$

Expanding equation (5), we observe that by multiplying y_{jt-1} ,containing the house prices of the eight metropolitan areas at *t-1,* with *C* produces a set of explanatory variables for the VAR equal to the mean of observations from the important variables (neighboring house prices) in each equation *i* at *t-1*. Just as with the constant in the Minnesota Prior, δ is also estimated based on a diffuse prior. This also suggests that the prior mean for the coefficients on the first own-lag of the important variables equals $(1/c_i)$, where c_i equals the number of important variables in a specific equation *i* of the VAR model (i.e., c_i equals 3, 4, 5, and 6 in our application).[9] As in the Minnesota prior, the RWA prior uses a prior mean of zero for the coefficients on all lags, except for the first own lags. The RWA approach of specifying prior means requires that the researcher scale the variables to similar magnitudes, since otherwise it does not make intuitive sense to say that the value of a variable at *t* equals the average of values from the important variables at *t-1*. This issue does not affect our analysis, since our variables are all scaled in the same fashion.

In sum, the prior variances for the parameters under the RWA prior, as proposed by LeSage and Krivelyova (1999), retaining the distinction between important (i.e., neighbors) and unimportant (i.e., non-neighbors) variables, require the following ideas:

(i) Assign a smaller prior variance to parameters associated with unimportant variables, imposing zero prior means with more certainty;

(ii) Assign a small prior variance to the first own-lag of the important variables so that prior means force averaging over the first own-lags of such variables;

(iii) Impose the prior variance of parameters associated with unimportant variables at lags greater than one such that it becomes smaller as the lag length increases, imposing decay in the influence of the unimportant variables over time;

(iv) Assign larger prior variances on lags other than the first own-lag of the important variables, allowing those

[9] See the longer version of this paper at http://ideas.repec.org/p/nlv/wpaper/0912.html for more details.

lags to exert some influence on the dependant variable; and

(v) Assign decreasing prior variances on the coefficients of lags, other than the first own-lag of the important variables.

Thus, in the specification of the RWA, as in the Minnesota prior, longer lag influences decay irrespective of whether we classify the variable as important or unimportant.

Given *(i)* to *(v)*, we adopt a flexible form, where the RWA prior standard deviations $S_2(i,j,m)$ for a variable *j* in equation *i* at lag length *m* equal the following:

$$\begin{aligned} S_2(i,j,m) &\sim N\left(1/c_i, \sigma_c\right); \quad j \in C; \quad m = 1; \quad i,j = 1,\ldots,n; \\ S_2(i,j,m) &\sim N\left(0, \eta\, \sigma_c/m\right); \quad j \in C; \quad m = 2,\ldots,p; \quad i,j = 1,\ldots,n; \text{ and} \\ S_2(i,j,m) &\sim N\left(0, \rho\, \sigma_c/m\right); \quad j \neg\in C; \quad m = 1,\ldots,p; \quad i,j = 1,\ldots,n; \end{aligned} \tag{6}$$

where $0 < \sigma_c < 1$, $\eta > 1$, $0 < \rho \le 1$, and c_i equals the number of important variables in equation *i*. For the important variables in equation *i* (i.e., $j \in C$), the prior mean for the lag length of 1 equals the average of the number of important variables in equation *i*, and equals zero for the unimportant variables (i.e., $j \neg\in C$). With $0 < \sigma_c < 1$, the prior standard deviation for the first own lag imposes a tight prior mean to reflect averaging over important variables. For important variables at lags greater than one, the variance decreases as *m* increases, but the restriction that $\eta > 1$ allows for the loose imposition of the zero prior means on the coefficients of these variables. We use $(\rho\sigma_c/m)$ for lags on unimportant variables, with prior means of zero, to indicate that the variance decreases as *m* increases. In addition, since $0 < \rho \le 1$, we impose the zero means on the unimportant variables with more certainty. In our model, however, we do not include any unimportant variables.

Gupta and Miller (2009) propose a weighted random-walk averaging (WRWA) prior. That is, they extend the specification of LeSage and Krivelyova (1999) by assuming that the first own-lagged value proves more important than the other important variables (neighbors).[10] They impose the condition that the first own-lagged variable proves twice as important as the other important variables.

$$\begin{aligned} S_3(i,j,m) &\sim N\left\{ 2/\left(c_i'+1\right), \sigma_c \right\}; \quad j \in C'; \quad m = 1; \quad j = i \quad i,j = 1,\ldots,n; \\ S_3(i,j,m) &\sim N\left\{ 1/\left(c_i'+1\right), \sigma_c \right\}; \quad j \in C'; \quad m = 1; \quad j \neq i \quad i,j = 1,\ldots,n; \\ S_3(i,j,m) &\sim N\left\{ 0, \eta\, \sigma_c/m \right\}; \quad j \in C'; \quad m = 2,\ldots,p; \quad i,j = 1,\ldots,n; \text{ and} \\ S_3(i,j,m) &\sim N\left\{ 0, \rho\, \sigma_c/m \right\}; \quad j \neg\in C'; \quad m = 1,\ldots,p; \quad i,j = 1,\ldots,n. \end{aligned} \tag{7}$$

Thus, in our eight-variable system, c_i' equals 3, 4, 5, or 6, depending on the MSA, and the prior means for the first own lag equals $\left[2/(c_i'+1)\right]$ and the first lags of the other important variables in each equation equal $\left[1/(c_i'+1)\right]$. We also adopt the values for the hyperparameters used by Gupta and Miller (2009): $\sigma_c = 0.1, \eta = 8$, and $\rho = 0.5$.[11]

We estimate the BVAR, BVEC, SBVAR, SBVEC, CBVAR, and CBVEC models, based on the FOSC, TC, RWA, and WRWA priors, using Theil's (1971) mixed estimation technique. Specifically, we denote a single

[10] Kuethe and Pede (2008) specify a similar prior, where they assume that the coefficient of the own-lagged term equals one and the sum of the lags of the other important variables, not including the own-lagged term, sums to one as well. Thus, their weighting scheme doubles the weight as compared to our scheme as well as requiring the own-lagged term to retain the coefficient of one, which reflects the essence of the random-walk averaging (RWA) prior.

[11] LeSage (1999) suggested ranges for the values for these hyperparameters.

equation of the VAR model as: $y_1 = X\beta + \varepsilon_1$, with $Var(\varepsilon_1) = \sigma^2 I$. Then, we can write the stochastic prior restrictions for this single equation as follows:

$$\begin{bmatrix} r_{111} \\ r_{112} \\ . \\ . \\ . \\ r_{nnp} \end{bmatrix} = \begin{bmatrix} \sigma/\sigma_{111} & 0 & . & . & . & 0 \\ 0 & \sigma/\sigma_{112} & 0 & . & . & 0 \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ 0 & . & . & . & . & 0 \\ 0 & 0 & . & . & 0 & \sigma/\sigma_{nnp} \end{bmatrix} \begin{bmatrix} \beta_{111} \\ \beta_{112} \\ . \\ . \\ . \\ \beta_{nnp} \end{bmatrix} + \begin{bmatrix} u_{111} \\ u_{112} \\ . \\ . \\ . \\ u_{nnp} \end{bmatrix} \tag{8}$$

Note that $Var(u) = \sigma^2 I$, and the prior means r_{ijm} and the prior variance σ_{ijm} [12] take the forms shown in equations (3) and (4) for the Minnesota prior; in equations (3), (4), and the LeSage-Pan weight matrix for the FOSC prior; in equations (2), (3) combined with the Gupta-Miller weight matrix for the TC prior, with the specification in equation (6) for the RWA prior, and with the specification in equation (7) for the WRWA prior. With equation (8) written as follows:

$$r = \Sigma\beta + u \ , \tag{9}$$

we derive the estimates for a typical equation as follows:

$$\hat{\beta} = (X'X + \Sigma'\Sigma)^{-1}(X'y_1 + \Sigma'r) \tag{10}$$

Essentially then, the method involves supplementing the data with prior information on the distribution of the coefficients. The number of observations and degrees of freedom increase artificially by one for each restriction imposed on the parameter estimates. Thus, the loss of degrees of freedom from over-parameterization in the classical VAR or VEC models does not emerge as a concern in the BVAR, BVEC, SBVAR, SBVEC, CBVAR, and CBVEC models.

Model Estimation and Results

This section briefly describes the data and then reports our econometric findings. First, we describe the sources of data. Second, we determine whether cointegration exists between the variables in our model. Third, we select the optimal model for forecasting each market's house price, using the minimum root mean square error (RMSE) for the average of the one-, two-, three-, and four-quarter-ahead out-of-sample forecasts. Finally, we examine the ability of the optimal forecasting models to detect the peaks and declines in the house price indexes in our-of-sample forecasts.

Data

The nominal house price data for the eight MSAs come from the Freddie Mac. Using matched transactions on the same property over time to account for quality changes, the Conventional Mortgage Home Price Index (CMHPI) of the Freddie Mac provides a means of measuring typical price inflation for houses within the U.S. The Freddie Mac data consist of both purchase and refinance-appraisal transactions, and include over 33 million homes. We deflate the MSA-level nominal CMHPI house price by the personal consumption expenditure (PCE) deflator from the Bureau of Economic Analysis (BEA) to generate our real house price series. As Hamilton (1994, p. 362) notes, we seasonally adjust the data, since the Minnesota-type priors do not perform well with seasonal data.

Evidence on Cointegration

The first step in our analysis tests for Granger temporal causality between the eight house price series (Granger

[12] Note σ_{ijm} in equation (8) is a generic term used to describe $S_k(i, j, m)$, $k=1, 2, 3$.

1969). Temporal causality tests emerge from VAR or VEC models. For example, we estimate a VAR model of the eight house price indexes. For each equation in the VAR, we then calculate chi-squared (Wald) statistics for the joint significance of each of the other lagged endogenous variables in that equation. Then, the San Diego house price index temporally (Granger) causes the Los Angeles house price index, if all lagged values of the San Diego house price index prove jointly significant in the Los Angeles house price index equation. We first consider various lag-length selection criteria for the VAR specification, including the sequential modified likelihood ratio (LR) test statistic (each test at the 5-percent level), the final prediction error (FPE), the Akaike information criterion (AIC), the Schwarz information criterion (SIC), and the Hannan-Quinn information criterion (HQIC). All criteria choose six lags. Table 1 reports the results.

We next run the Johansen test for cointegration with five lags, since the test is performed on the first difference of endogenous variables (i.e., the real house prices of the eight MSAs). Cointegration tests – the trace statistic and maximum eigen-value test – both indicate seven cointegrating vector. Table 2 tabulates the findings. Cointegration between regional house price indexes implies that a long-run equilibrium relationship exists as described by our PPP discussion above (Cook 2005). Alternatively, convergence of regional house prices should occur over time for cointegrated house price indexes (Cook 2003).

Running the VEC specification and using the block exogeneity test, we discover that house price indexes in Los Angeles temporally cause (lead) house price indexes in Bakersfield, Riverside, San Diego, and San Luis Obispo, the two inland MSAs and the most distant coastal MSAs. At the same time, Oxnard, San Diego, San Luis Obispo, Santa Ana, and Santa Barbara house price indexes temporally cause Los Angeles house price index. In other words, each coastal MSA house price index temporally causes the Los Angeles index.[13]

The most isolated MSA in causality terms is Santa Barbara, where Santa Ana's house price index temporally causes Santa Barbara's house price index and the house price index in Santa Barbara temporally causes (leads) the house price indexes in Los Angeles and Oxnard. The Oxnard MSA house price index responds to the most other MSA house price indexes – Bakersfield, Riverside, San Diego, San Luis Obispo, Santa Ana, and Santa Barbara. Further, the Santa Ana MSA house price index temporally leads the most other MSA house price indexes – Bakersfield, Los Angeles, Oxnard, Riverside, San Diego, and Santa Barbara.[14]

On a bivariate basis, we observe seven pairs of MSAs with no causality between their house price indexes and seven pairs with two-way causality. No causality exists between Bakersfield-Riverside, Bakersfield-Santa Barbara, Riverside-San Diego, Riverside-Santa Barbara, San Diego-Santa Barbara, San Luis Obispo-Santa Ana, and San Luis Obispo-Santa Barbara. Neither Los Angeles nor Oxnard appear in the list of no bivariate causality, implying that these two MSAs always exhibit a causality relationship between their house price indexes and house price indexes with each other MSA. On the other hand, Santa Barbara, the most isolated MSA, exhibits no causality with four of the other MSAs.

Two-way temporal causality exists between Bakersfield-Santa Ana, Los Angeles-San Diego, Los Angeles-San Luis Obispo, Oxnard-San Luis Obispo, Oxnard-Santa Ana, San Diego-San Luis Obispo, and San Diego-Santa Ana. Neither Riverside nor Santa Barbara exhibit two-way causality of their house price indexes with the house price indexes of any other MSA. The Santa Ana, San Diego, and San Luis Obispo MSAs each exhibit two-way causality of their house price indexes with the house price indexes in three other MSAs, where house price index in Santa Ana causes house price indexes in the most other MSAs.

Examining the no bivariate causality findings, we see that unexpectedly four pairs of MSAs that geographically share portions of their borders exhibit no causality between their house price indexes in either direction -- Bakersfield-Riverside, Bakersfield-Santa Barbara, Riverside-San Diego, and San Luis Obispo-Santa Barbara.[15] In addition, five pairs of MSAs that exhibit two-way temporal causality do not share a common border -- Bakersfield-Santa Ana, Los Angeles-San Diego, Los Angeles-San Luis Obispo, Oxnard-Santa Ana, and San Diego-San Luis Obispo.

In sum, we find more evidence of temporal causality occurring for non-adjacent MSAs and not occurring for adjacent MSAs much more frequently than we would have hypothesized. We also find that Santa Barbara forms a more isolated geographic area than the rest of the Southern California MSAs. Los Angeles and Oxnard share the characteristic that they each link in a causal way to every other MSA in Southern California.

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[13] Since the VEC specification constitutes the first differenced form of the three endogenous variables, and the optimal lag length used for the VAR is 6, we estimate all VEC models with 5 lags.

[14] The Santa Ana house price index just falls short of significantly causing house price index in San Luis Obispo at the 10-percent level.

[15] Here, we assume that Oxnard and San Luis Obispo share a portion of their border. In fact, they do not. But, we feel that they are close enough to justify the assumption.

One- to Four-Quarter-Ahead Forecast Accuracy

Given the specification of priors in Section 2, we estimate numerous Bayesian, spatial, causality, and random-walk VAR and VEC models based on the FOSC, TC, RWA, and WRWR priors for Bakersfield, Los Angeles, Oxnard, Riverside, San Diego, San Luis Obispo, Santa Ana, and Santa Barbara over the period 1977:Q2 to 1994:Q4 using quarterly data. We then compute out-of-sample one- through four-quarters-ahead forecasts for the period of 1995:Q1 to 2004:Q4, and compare the forecast accuracy relative to the forecasts generated by an unrestricted VAR and VEC models.[16] Note that the choice of the in-sample period, especially, the starting date depends on data availability. The starting point of the out-of-sample period follows Rapach and Strauss (2009), who observe marked differences in house price growth across U.S. regions since the mid-1990s. Finally, we choose the end-point of the horizon as 2005:Q4, since we also use our alternative models to predict the turning point(s) in the real house prices of these eight MSAs and, hence, stop prior to the date where the turning point actually occurred. In our case, the real house prices peaked in each market as follows: Bakersfield, 2006:Q4; Los Angeles, 2006:Q4; Oxnard, 2006:Q2; Riverside, 2006:Q4; San Diego, 2006:Q1; San Luis Obispo, 2006:Q1; Santa Ana, 2006:Q2; and Santa Barbara, 2005:Q4.

The models include house price indexes for the above mentioned eight MSAs. Each equation of the various VAR (VEC) models includes 49 (41) parameters with the constant, given that we estimate the models with 6 (5) lag(s) of each variable. We estimate the eight-variable models for a given prior for the period 1977:Q2 to 1994:Q4, and then forecast from 1995:Q1 through to 2004:Q4. Since we use six (five) lags, the initial six (five) quarters from 1977:Q2 to 1978:Q3 (1978:Q2) feed the lags. We re-estimate the models each quarter over the out-of-sample forecast horizon in order to update the estimate of the coefficients, before producing the 4-quarters-ahead forecasts. We implemented this iterative estimation and the 4-quarters-ahead forecast procedure for 40 quarters, with the first forecast beginning in 1995:Q1. This produced a total of 40 one-quarter-ahead forecasts, …, up to 40 four-quarters-ahead forecasts.[17] We calculate the root mean squared errors (RMSE)[18] for the 40 one-, two-, three-, and four-quarters-ahead forecasts for the eight home prices of the models. We then examine the average of the RMSE statistic for one-, two-, three-, and four-quarters ahead forecasts over 1995:Q1 to 2004:Q4. We follow the same steps to generate forecasts from the Bayesian, spatial, random-walk, and causality versions of VAR and VEC models based on the FOSC, TC, RWA, and WRWA priors.

For the BVAR models, we start with a value of $w = 0.1$ and $d = 1.0$, and then increase the value to $w = 0.2$ to account for more influences from variables other than the first own lags of the dependant variables of the model. In addition, as in Dua and Ray (1995), Gupta and Sichei (2006), Gupta (2006), and Gupta and Miller (2009), we also estimate a BVAR model with $w = 0.3$ and $d = 0.5$. We also introduce $d = 2$ to increase the tightness on lag m. Finally, we specify $\sigma_c=0.1$, $\eta=8$, $\theta=0.5$ for the random-walk models with the two different specifications for causality and spatial priors. We select the model that produces the lowest average RMSE values as the ‘optimal’ specification for a specific metropolitan area.

Table 4 in the last column reports the average RMSE across the eight MSAs. For each MSA, the average RMSE occurs across the one-, two-, three, and four-quarter-ahead forecasts. The spatial BVEC model with $w=0.1$ and $d=2.0$ provides the lowest average RMSE, which we identify as the optimal specification. This specification deviates from the Minnesota prior in that the decay factor reduces the influence of lagged values more quickly.

Table 4 also reports the findings for Bakersfield, Los Angeles, Oxnard, Riverside, San Diego, San Luis Obispo, Santa Ana, and Santa Barbara, respectively. Focusing on the average RMSE across the one-, two-, three-, and four-quarter-ahead forecasts, we observe the following findings. First, the optimal specification for Los Angeles, Riverside, and San Luis Obispo corresponds to a spatial BVEC with $w=0.1$ and $d=2.0$, $w=0.2$ and $d=1.0$, and $w=0.2$ and $d=2.0$, respectively. That is, the specifications for Los Angeles and Riverside reflect less importance for other variables and lagged values, respectively, than the Minnesota prior. San Luis Obispo imposes less importance on lags and more importance on other variables relative to the Minnesota prior. Second, the optimal specification for Oxnard and Santa Ana equals the causality BVEC with $w=0.1$ and $d=1.0$, or the Minnesota prior.

[16] Note that the initial estimation period does not include the dramatic run up in home prices at the end of the out-of-sample forecast period.

[17] For this, we used the algorithm in the Econometric Toolbox of MATLAB, version R2006a.

[18] Note that if A_{t+n} denotes the actual value of a specific variable in period $t + n$ and ${}_tF_{t+n}$ equals the forecast made in period t for $t + n$, the RMSE statistic equals the following: $\sqrt{\left[\sum_1^N \left({}_tF_{t+n} - A_{t+n}\right)^2 / N\right]}$ where N equals the number of forecasts.

Third, the optimal specification for Riverside equals the BVEC and allows more importance for both other variables and lagged values with *w=0.3* and *d=0.5*. Fourth, the optimal specification for Santa Barbara equals the causality BVAR with *w=0.2* and *d=2*.0. Finally, the optimal specification for San Diego equals the standard VAR model and the use of Bayesian models increases the RMSE.

In sum, different specifications yield the lowest RMSE in different MSAs. No common pattern emerges. Comparing the forecasting performance across MSAs, however, we see that they rank from best to worst forecasting performance as follows: Oxnard (0.010), San Diego (0.012), San Luis Obispo (0.016), Los Angeles (0.018), Santa Ana (0.021), Santa Barbara (0.026), Riverside (0.039), and Bakersfield (0.043) experiences the lowest average RMSE across the one-, two-, and three-quarter-ahead forecast horizon. Viewed differently, the forecasting performance in all the coastal MSAs beat the performance in the two inland MSAs.

Forecasting House Price Peaks and Declines

Figure 1 illustrates that each housing market experiences a marked reversal of real house prices after the peaks in 2005 and 2006, depending on the MSA. That is, the house price peaks and then declines in the various MSAs. We expose our optimal forecast models to the acid test – predicting the peaks and declines in house prices. We estimate the optimal models based on the average RMSE from Table 4, using data through the fourth quarter of 2004. Next, we forecast the price in the first quarter of 2005. Then we update the data by one quarter and repeat the forecasting exercise with a model estimated through the first quarter of 2006 and forecast the second quarter of 2006. We then continue the updating and forecasting process until the end of the sample in the second quarter of 2008. Table 5 reports one-quarter-ahead forecasts.

The various models perform well when forecasting the peaks and declines in the house price indexes in each MSA in that the overall the performance exceeds our prior expectation. First, Los Angeles, Oxnard, San Luis Obispo, and Santa Ana all predict the peaks and declines in house prices, using data with a one-quarter lead. That is, for example, using data through 2006:Q3, we forecast the peak in the Los Angeles house price index that occurred in 2006:Q4 and then using data through 2006:Q4, we forecast the decline in the Los Angeles house price index that occurred in 2007:Q1.

Second, the Bakersfield and Riverside MSA forecasting models predict both peaks and declines in their house price indexes with a three-quarter lead. That is, we forecast the peaks and declines in the house price indexes in these MSAs, using data nine months prior to the actual peaks and declines.

Finally, the forecasting models for San Diego and Santa Barbara perform the worst of all the MSAs. That is, we can only forecast the peaks and declines in the house price indexes in these MSAs, using data through the same quarter as the actual peaks and declines.

Conclusion

House prices rose dramatically in Southern California MSAs in the early 2000s, peaking in 2005 or 2006 depending on the MSA. This paper considers the time-series relationships between the house prices in the Bakersfield, Los Angeles, Oxnard, Riverside, San Diego, San Luis Obispo, Santa Ana, and Santa Barbara MSAs, using Freddie Mac data from 1977:Q2 to 2008:Q2. First, we test for Granger temporal causality. Second, we generate out-of-sample forecasts using VAR, VEC and Bayesian, spatial, and causality VAR and VEC models with various priors. Finally, we explore the ability of these models to forecast the peaks and declines of house price indexes that occurred in 2005 and 2006.

The Los Angeles house price index temporally causes the house price indexes in Bakersfield, Riverside, San Diego, and San Luis Obispo, the two inland MSAs and the most distant coastal MSAs. At the same time, the Oxnard, San Diego, San Luis Obispo, Santa Ana, and Santa Barbara house price indexes temporally cause the Los Angeles index. In other words, each coastal MSA house price index temporally causes the Los Angeles index. Santa Barbara proves the most isolated MSA in causality terms. The Oxnard MSA house price index responds to the most other MSA house price indexes and the Santa Ana MSA house price index temporally leads the most other MSA house price indexes. More evidence exists of temporal causality occurring with non-adjacent MSAs than with adjacent MSAs, an unexpected result. The Los Angeles and Oxnard house price indexes each causally link to the house price index in every other Southern California MSA.

Different time-series models prove better at forecasting house price indexes in the different MSAs. Comparing the forecasting performance across MSAs, however, we see that they rank from best to worst forecasting performance as follows: Oxnard, San Diego, San Luis Obispo, Los Angeles, Santa Ana, Santa Barbara, Riverside, and Bakersfield. That is, the forecasting performance in all the coastal MSAs beat the performance in the two inland MSAs.

Forecasting the peaks and declines in the house price indexes proves a difficult task. Our one-quarter-ahead recursive forecasts perform much better than we anticipated. That is, when we updated our data set with new information and forecast one-quarter ahead, we anticipate the peaks and downturns in the house price indexes for Bakersfield and Riverside with a three-quarter lead time. For Los Angeles, Oxnard, San Luis Obispo, and Santa Ana, we anticipate the peaks and declines with a one-quarter lead. Finally, for San Diego and Santa Barbara, the prediction of the peaks and declines occur simultaneously with the actual peaks and declines.

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Table 1 Lag-Length Selection Tests

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1473.6	NA	3.59e-30	-45.10	-44.83	-44.99
1	1962.9	843.1	7.56e-36	-58.18	-55.77	-57.23
2	2090.0	187.8	1.18e-36	-60.12	-55.58	-58.33
3	2180.0	110.7	6.72e-37	-60.92	-54.23	-58.28
4	2290.2	108.6	2.66e-37	-62.35	-53.51	-58.86
5	2498.8	154.1	8.11e-39	-66.79	-55.82	-62.47
6	2687.4	92.8*	1.13e-39*	-70.63*	-57.51*	-65.45*

The star indicates lag order selected by the criterion. The criterion include the sequential modified likelihood ratio (LR) test statistic (each test at 5% level), the final prediction error (FPE), the Akaike information criterion (AIC), the Schwarz information criterion (SIC), and the Hannan-Quinn information criterion (HQIC). See Doan (2007, p. 203)

Table 2 Johansen Cointegration Tests

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.948	542.96	159.53	0.00
At most 1 *	0.823	350.38	125.62	0.00
At most 2 *	0.710	237.80	95.75	0.00
At most 3 *	0.626	157.27	69.82	0.00
At most 4 *	0.510	93.29	47.86	0.00
At most 5 *	0.348	46.98	29.80	0.00
At most 6 *	0.246	19.16	15.49	0.01
At most 7	0.013	0.82	3.84	0.36
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.948	192.58	52.36	0.00
At most 1 *	0.823	112.59	46.23	0.00
At most 2 *	0.710	80.52	40.08	0.00
At most 3 *	0.626	63.99	33.88	0.00
At most 4 *	0.510	46.31	27.58	0.00
At most 5 *	0.348	27.82	21.13	0.00
At most 6 *	0.246	18.34	14.26	0.01
At most 7	0.013	0.82	3.841	0.36

The trace and maximum eigen-value tests both indicate 7 cointegrating vectors at the 5-percent level. See Johansen (1999).
* denotes rejection of the hypothesis at the 0.05 level and ** is the MacKinnon-Haug-Michelis (1999) p-values

Table 3 Granger Temporal Causality Tests

MSA	Bakers-field	Los Angeles	Oxnard	Riverside	San Diego	San Luis Obispo	Santa Ana	Santa Barbara
Bakers-field		10.52**	7.042	7.90	13.358*	16.03*	9.52**	8.16
Los Angeles	7.31		14.13*	5.60	9.96**	14.68*	12.42*	11.188*
Oxnard	16.86*	7.27		13.96*	18.47*	9.47**	16.67*	11.79*
Riverside	3.19	10.19**	7.92		2.97	14.21*	10.01**	2.00
San Diego	1.817	18.178*	5.27	8.35		17.86*	21.12*	8.82
San Luis Obispo	7.19	16.30*	9.40**	7.83	11.47*		9.22	3.12
Santa Ana	18.24*	4.09	15.96*	5.81	11.65*	8.57		5.95
Santa Barbara	6.46	7.20	9.09	3.29	2.96	6.39	12.12*	

Numbers are χ^2, chi-squared, test statistics with 5 degrees of freedom for the null hypothesis that the lagged values of the column variable do not prove jointly significant in the equation for the row variable. For example, in the first row, we reject the null hypotheses that lagged values of the Los Angeles, San Luis Obispo, and Santa Ana MSA house prices do not significantly affect house prices in the Bakersfield MSA at the 5- and 10-percent levels. See Doan (2007, p. 350).
* and ** mean rejection of the null-hypothesis at the 5- and 10-percent levels.

Table 4 Forecast Results for All Eight MSAs

Parameterization	Models	Average RMSEs Bakers-field	Los Angeles	Oxnard	Riverside	San Diego	San Luis Obispo	Santa Ana	Santa Barbara	MSA Average
	VAR	0.086	0.498	0.409	0.102	**0.012**	0.122	0.226	0.133	0.199
	VEC	0.099	0.477	0.481	0.109	0.448	0.329	0.202	0.192	0.292
w=0.3, d=0.5	**BVAR**	0.097	0.402	0.295	0.102	0.042	0.101	0.179	0.115	0.167
	BVEC	0.161	0.332	0.224	**0.039**	0.282	0.171	0.103	0.206	0.190
	Causality BVAR	0.216	0.350	0.200	0.211	0.070	0.195	0.171	0.033	0.181
	Spatial BVAR	0.105	0.229	0.095	0.216	0.031	0.137	0.195	0.086	0.137
	Causality BVEC	0.243	0.233	0.218	0.106	0.170	0.272	0.112	0.113	0.183
	Spatial BVEC	0.057	0.087	0.205	0.096	0.152	0.056	0.145	0.358	0.145
w=0.2, d=1	**BVAR**	0.128	0.244	0.117	0.156	0.022	0.054	0.128	0.107	0.119
	BVEC	0.159	0.220	0.040	0.055	0.151	0.065	0.041	0.274	0.126
	Causality BVAR	0.187	0.261	0.112	0.165	0.093	0.095	0.176	0.039	0.141
	Spatial BVAR	0.137	0.105	0.101	0.264	0.033	0.136	0.208	0.154	0.142
	Causality BVEC	0.211	0.182	0.113	0.085	0.105	0.173	0.066	0.140	0.134
	Spatial BVEC	**0.043**	0.045	0.224	0.087	0.124	0.051	0.139	0.412	0.141
w=0.1, d=1	**BVAR**	0.094	0.132	0.016	0.144	0.035	0.031	0.097	0.111	0.083
	BVEC	0.113	0.103	0.095	0.056	0.037	0.022	0.021	0.292	0.092
	Causality BVAR	0.126	0.206	0.043	0.135	0.078	0.040	0.127	0.059	0.102
	Spatial BVAR	0.109	0.046	0.157	0.200	0.050	0.111	0.177	0.137	0.123
	Causality BVEC	0.122	0.117	**0.010**	0.054	0.041	0.069	0.027	0.149	0.074
	Spatial BVEC	0.053	0.018	0.209	0.069	0.039	0.022	0.092	0.403	0.113
w=0.2, d=2	**BVAR**	0.068	0.078	0.032	0.102	0.043	0.033	0.098	0.133	0.073
	BVEC	0.136	0.116	0.114	0.052	0.087	0.023	**0.021**	0.347	0.112
	Causality BVAR	0.076	0.144	0.032	0.091	0.081	0.038	0.120	**0.026**	0.076
	Spatial BVAR	0.097	0.038	0.175	0.167	0.044	0.127	0.140	0.221	0.126
	Causality BVEC	0.152	0.122	0.028	0.058	0.029	0.028	0.026	0.190	0.079
	Spatial BVEC	0.053	0.036	0.212	0.062	0.070	**0.016**	0.072	0.406	0.116

Table 4 Forecast Results for All Eight MSAs (Continued)

Parameterization	Models	Average RMSEs								MSA Average
		Bakers-field	Los Angeles	Oxnard	Riverside	San Diego	San Luis Obispo	Santa Ana	Santa Barbara	
w=0.1, d=2	**BVAR**	0.115	0.035	0.142	0.052	0.026	0.040	0.032	0.126	0.071
	BVEC	0.100	0.046	0.152	0.053	0.036	0.063	0.030	0.327	0.101
	Causality BVAR	0.138	0.099	0.154	0.054	0.030	0.034	0.035	0.037	0.073
	Spatial BVAR	0.118	0.043	0.177	0.083	0.032	0.113	0.086	0.149	0.100
	Causality BVEC	0.059	0.072	0.094	0.063	0.024	0.039	0.035	0.176	**0.070**
	Spatial BVEC	0.058	**0.018**	0.226	0.058	0.032	0.017	0.039	0.405	0.106
σ=0.1, τ=8, θ=0.5	**RBVAR Causality1**	0.165	0.170	0.067	0.166	0.084	0.043	0.091	0.199	0.123
	RBVAR Causality2	0.169	0.180	0.064	0.171	0.074	0.042	0.086	0.211	0.125
	RBVAR Spatial1	0.123	0.168	0.093	0.258	0.082	0.051	0.163	0.119	0.132
	RBVAR Spatial2	0.118	0.157	0.120	0.262	0.041	0.046	0.150	0.143	0.130
	RBVEC Causality1	0.119	0.132	0.209	0.197	0.181	0.145	0.159	0.243	0.173
	RBVEC Causality2	0.119	0.132	0.209	0.197	0.181	0.145	0.159	0.243	0.173
	RBVEC Spatial1	0.088	0.166	0.415	0.156	0.235	0.233	0.218	0.349	0.232
	RBVEC Spatial2	0.118	0.173	0.368	0.180	0.200	0.143	0.208	0.284	0.209

VAR and VEC refer to vector autoregressive and vector error-correction models. BVAR and BVEC refer to Bayesian VAR and VEC models. The text discusses the various priors and parameterizations. RMSE means root mean square error. The entries measure the average RMSE across all forecasts at each horizon – one-, two-, three-, and four-quarter-ahead forecasts. The column Average computes the average RMSE across the one-, two-, three-, and four-quarter-ahead forecast RMSEs. Bold numbers equal the minimum values in each column.

Table 5 Recursive Forecasts: 2005:Q1 to 2008:Q2

Date	Bakersfield		Los Angeles		Oxnard		Riverside		San Diego		San Luis Obispo		Santa Ana		Santa Barbara	
	Act.	Fcst.	Act.	Fcst.	Act.	Fcst.	Act.	Fcst.	Act.	Fcst.	Act.	Fcst.	Act.	Fcst.	Act.	Fcst.
2004:Q4	213.8	213.8	315.3	315.3	329.4	329.4	289.6	289.6	374.9	374.9	345.9	345.9	336.4	336.4	377.2	377.2
2005:Q1	226.1	220.0	325.7	330.2	336.8	352.2	300.0	299.1	383.5	376.2	359.1	355.5	343.5	357.4	393.5	396.1
2005:Q2	239.5	242.5	342.5	344.5	347.7	358.3	312.9	326.6	391.8	399.4	367.8	377.1	360.2	364.3	408.1	409.1
2005:Q3	253.5	257.8	357.5	364.1	360.4	359.1	325.5	330.3	396.2	405.4	381.2	372.3	371.9	377.5	412.8	417.5
2005:Q4	268.1	271.7	377.5	373.4	374.6	371.4	342.0	338.3	401.7	395.6	391.0	386.5	386.9	385.4	**427.8**	426.2
2006:Q1	278.4	288.5	391.0	401.6	382.5	391.0	354.1	366.1	**402.1**	420.0	**392.0**	**401.1**	400.0	406.8	424.3	**436.0**
2006:Q2	282.6	**301.0**	398.2	409.9	**383.8**	**398.7**	357.7	**377.7**	398.4	**421.7**	386.4	400.8	**403.0**	**416.8**	422.5	433.1
2006:Q3	283.9	300.0	403.5	410.3	379.8	394.2	361.3	374.5	395.4	396.5	379.7	393.6	402.3	412.4	417.1	424.7
2006:Q4	**286.6**	294.8	**405.6**	**411.4**	373.6	384.8	**363.7**	369.3	391.4	391.1	374.0	378.1	400.1	406.1	405.7	412.5
2007:Q1	283.5	292.0	401.5	406.0	364.3	370.8	359.7	364.6	383.2	377.7	367.4	366.0	392.2	396.7	396.6	398.1
2007:Q2	275.3	283.3	398.3	396.6	356.6	357.4	354.9	352.9	373.9	363.0	359.0	358.3	385.6	384.8	376.4	383.5
2007:Q3	265.8	278.1	391.1	394.0	346.0	350.4	341.4	351.6	361.8	363.1	351.9	345.2	372.8	379.6	357.6	364.3
2007:Q4	251.3	257.5	376.8	382.1	331.5	333.2	322.3	332.1	347.9	342.8	345.2	344.3	358.8	361.2	334.3	342.9
2008:Q1	228.7	240.4	350.7	364.3	307.8	319.2	292.6	311.0	329.1	335.4	329.8	337.8	331.0	345.4	318.8	318.8
2008:Q2	207.6	211.4	321.5	327.9	284.2	290.9	253.7	270.0	302.8	308.0	319.0	320.0	306.8	307.6	296.0	295.8

Act. means the actual data and Fcst. means the forecast data. Bold numbers equal the maximum values in each column.

Fig 1 House Price Indexes: Bakersfield, Los Angeles, Oxnard, Riverside, San Luis Obispo, Santa Ana, and Santa Barbara

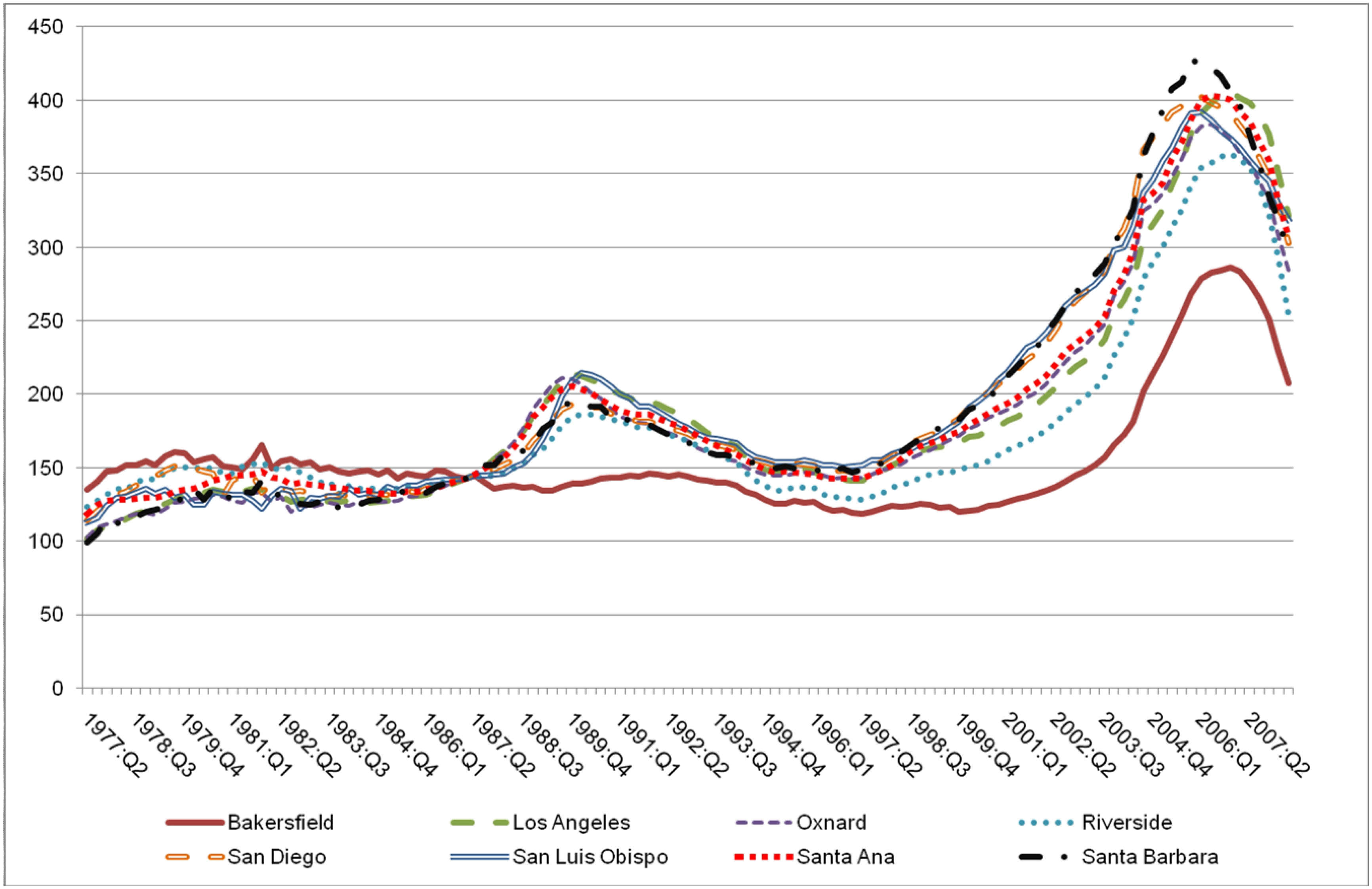

Fig 2 MSA Map: Bakersfield, Los Angeles, Oxnard, Riverside, San Luis Obispo, Santa Ana, and Santa Barbara