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

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Abstract

We examine the time-series relationship between housing prices in eight Southern California metropolitan statistical areas (MSAs). First, we perform cointegration tests of the housing price indexes for the MSAs, finding seven cointegrating vectors. Thus, the evidence suggests that one common trend links the housing prices in these eight MSAs, a purchasing power parity finding for the housing prices in Southern California. Second, we perform temporal Granger causality tests revealing intertwined temporal relationships. The Santa Anna MSA leads the pack in temporally causing housing 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 housing prices in only two other MSAs (Los Angels and Oxnard) and housing prices in the Santa Anna MSA temporally caused prices in Santa Barbara. Third, we calculate out-of-sample forecasts in each MSA, using various vector autoregressive (VAR) and vector error-correction (VEC) 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 the ability of theses time-series models to provide accurate out-of-sample predictions of turning points in housing prices that occurred in 2006:Q4. Recursive forecasts, where the sample is updated each quarter, provide reasonably good forecasts of turning points.

Keywords: Housing prices, Forecasting

JEL classification: C32, R31

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1. Introduction

This paper considers the dynamics of housing prices and the ability of different pure time-series models to forecast housing 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 housing prices across contiguous geographic regions. For example, see the analysis of Tirtirglou 1992; and Clapp and Tirtirglou 1994 on the Hartford MSA.

This paper, first, tests for cointegration between real house prices in the eight MSAs, using the Johansen technique (1991). We find seven cointegrating relationships between the real house prices, a purchasing power parity (PPP) result for housing prices in Southern California. Block exogeneity tests on the vector error correction (VEC) model reveal an intricate temporal causality pattern between housing prices for these MSAs. The Santa Anna MSA leads the pack in temporally causing housing 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 housing prices in only two other MSAs (Los Angels and Oxnard) and housing 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 include spatial and causality priors

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[1] We exclude the El Centro MSA because of too short a time series on housing prices.

(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.

We organize the rest of the paper as follows. Section 2 examines the potential linkage of housing prices across geographic regions. Section 3 specifies the various time-series models estimated in Section 4. Section 5 concludes.

2. Housing Demand and Supply and Spatial Price Arbitrage

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 housing 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 housing prices based on the characteristics imbedded into the sales, such as number of bedrooms and baths, square footage, and so on. 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. Tirtirglou (1992) and Clapp and Tirtirglou (1994) provided some of the earliest tests of whether the housing market exhibited efficiency in a spatial market in Hartford, Connecticut.

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, we argue that housing 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 with the commuting cost. Thus, commuting across MSAs by some will exert some pressure to equalize home prices, adjusting for commuting costs. 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 housing 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 housing prices and land values will rise. That is, since housing prices include construction (replacement) costs and land prices, higher land prices will drive up housing prices even though construction (replacement) costs may equilibrate between regions. All eight metropolitan areas in this paper face land restrictions that respond in this manner. That is, all eight regions experienced a housing "bubble" in recent years that deflated recently. See Figure 1.

In sum, we argue that the housing "bubbles" in the eight MSAs in the Southern California housing market reflect, in large measure, run ups and then crashes in land values. While other factors such as construction costs also played a role, land values dominated the movement in home prices.

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[2] Meen (1999) offers a similar discussion of UK for housing 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. VAR, VEC, BVAR, BVEC, SBVAR, and SBVEC Specification and Estimation[3]

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

$$y_t = A_0 + A(L) y_t + \varepsilon_t \text{ (1),}^4 \qquad (1)$$

where *y* equals a ($n \times 1$) vector of variables to forecast; *A(L)* 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.

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[5] of order one, (i.e., *I(1)*),[6] then the error-correction counterpart of the VAR model in equation (1) converts into a VEC model as follows.[7]

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

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

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

[4] $A(L) = A_1 L + A_2 L^2 + ... + A_p L^p$; and A_0 equals an ($n \times 1$) vector of constant terms.

[5] A series is integrated of order *q*, if it requires *q* differences to transform it into a zero-mean, purely non-deterministic stationary process.

[6] See LeSage (1990) and references cited therein for further details regarding the non-stationarity of most macroeconomic time series.

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

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. Alternatively, researchers use near VAR models, which specify unequal lag lengths for the variables and equations.

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 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:

$$\beta_i \sim N(1, \sigma^2_{\beta_i}) \text{ and } \beta_j \sim N(0, \sigma^2_{\beta_j}) \quad (3)$$

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, $\sigma^2_{\beta_i}$ and $\sigma^2_{\beta_j}$, 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.[8]

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*)

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

for our eight MSAs:

$$F = \begin{bmatrix} 1.0 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 1.0 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 1.0 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 1.0 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 1.0 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 1.0 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 1.0 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 1.0 \end{bmatrix}. \quad (5)$$

Since researchers believe that the lagged dependant variable in each equation proves most important, F imposes $\bar{\beta}_i = 1$ 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 $d = 0.50$).

Alternatively, LeSage and Pan (1995) propose spatial BVAR (SBVAR) and BVEC (SBVEC) models. They adopt a weight matrix that uses the first-order spatial contiguity (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.[9] They impose a value of one 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

[9] We exclude the El Centro MSA because of too short a time series on housing prices.

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 shown in equation (5) become 1.0 for neighbors and 0.1 for non-neighbors.

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.

Consider the weight matrix *F* in equation (5). The order of inclusion of MSAs in the matrix is as follows: Bakersfield, Los Angeles, Oxnard, Riverside, San Diego, San Luis Obispo, Santa Ana, and Santa Barbara. In addition, we continue with 1.0 down the main diagonal of the *F* matrix, to emphasize the importance of the autoregressive influences from the lagged values of the dependant variable (house price of a specific metropolitan area).[10] In sum, the weight matrix *F* in our application becomes as follows:

$$F = \begin{bmatrix} 1.0 & 1.0 & 1.0 & 1.0 & 0.0 & 1.0 & 0.0 & 1.0 \\ 1.0 & 1.0 & 1.0 & 1.0 & 0.0 & 0.0 & 1.0 & 0.0 \\ 1.0 & 1.0 & 1.0 & 0.0 & 0.0 & 1.0 & 0.0 & 1.0 \\ 1.0 & 1.0 & 0.0 & 1.0 & 1.0 & 0.0 & 1.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 1.0 & 1.0 & 0.0 & 1.0 & 0.0 \\ 1.0 & 0.0 & 1.0 & 0.0 & 0.0 & 1.0 & 0.0 & 1.0 \\ 0.0 & 1.0 & 0.0 & 1.0 & 1.0 & 0.0 & 1.0 & 0.0 \\ 1.0 & 0.0 & 1.0 & 0.0 & 0.0 & 1.0 & 0.0 & 1.0 \end{bmatrix}. \qquad (6)$$

We then standardize the weight matrix in equation (6) so that each row sums to unity. Formally, we write the standardized *F* matrix, called *C*, as follows:

$$C = \begin{bmatrix} 0.167 & 0.167 & 0.167 & 0.167 & 0.0 & 0.167 & 0.0 & 0.167 \\ 0.2 & 0.2 & 0.2 & 0.2 & 0.0 & 0.0 & 0.2 & 0.0 \\ 0.2 & 0.2 & 0.2 & 0.0 & 0.0 & 0.2 & 0.0 & 0.2 \\ 0.2 & 0.2 & 0.0 & 0.2 & 0.2 & 0.0 & 0.2 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.33 & 0.33 & 0.0 & 0.33 & 0.0 \\ 0.25 & 0.0 & 0.25 & 0.0 & 0.0 & 0.25 & 0.0 & 0.25 \\ 0.0 & 0.25 & 0.0 & 0.25 & 0.25 & 0.0 & 0.25 & 0.0 \\ 0.25 & 0.0 & 0.25 & 0.0 & 0.0 & 0.25 & 0.0 & 0.25 \end{bmatrix}. \qquad (7)$$

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,

$$y_{it} = \delta_i + \sum_{j=1}^{3} C_{ij} y_{jt-1} + u_{it}\text{ , } i = 1, 2, \text{ and } 3. \qquad (8)$$

Expanding equation (8), we observe that by multiplying y_{jt-1} ,containing the house prices of the

[10] 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.

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*.[11] 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 (=3, 4, 5, or 6) equals the number of important variables in a specific equation *i* of the VAR model.[12]

In sum, the prior variances for the parameters under the RWA prior, as proposed by LeSage and Krivelyova (1999), retaining the distinction between important and unimportant 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 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

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[11] Just as with the constant in the Minnesota Prior, δ is also estimated based on a diffuse prior.

[12] 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.

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:

$$\begin{aligned} &S_2(i, j, m) \sim N(1/c_i, \sigma_c); \quad j \in C; \quad m = 1; \qquad i, j = 1, ..., n; \\ &S_2(i, j, m) \sim N(0, \eta \sigma_c/m); \quad j \in C; \quad m = 2, ..., p; \quad i, j = 1, ..., n; \text{ and} \\ &S_2(i, j, m) \sim N(0, \rho \sigma_c/m); \quad j \neg \in C; \quad m = 1, ..., p; \quad i, j = 1, ..., n; \end{aligned} \qquad (9)$$

where $0 < \sigma_c < 1$, $\eta > 1$, $0 < \rho \leq 1$, 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 $0 < \rho \leq 1$, 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).[13] They

[13] 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

impose the condition that the first own-lagged variable proves twice as important as the other important variables.

$$
\begin{aligned}
&S_3(i,j,m) \sim N\left\{ 2\big/(c_i^{'}+1), \sigma_c \right\}; \; j \in C'; \quad m=1; \quad j=i \quad i,j=1,\ldots,n; \\
&S_3(i,j,m) \sim N\left\{ 1\big/(c_i^{'}+1), \sigma_c \right\}; \; j \in C'; \quad m=1; \quad j \neq i \quad i,j=1,\ldots,n; \\
&S_3(i,j,m) \sim N\left\{ 0, \eta \, \sigma_c / m \right\}; \qquad j \in C'; \quad m=2,\ldots,p; \quad i,j=1,\ldots,n; \text{ and} \\
&S_3(i,j,m) \sim N\left\{ 0, \rho \, \sigma_c / m \right\}; \qquad j \neg \in C'; \; m=1,\ldots,p; \quad i,j=1,\ldots,n.
\end{aligned} \tag{10}
$$

Thus, in our eight-variable system, c_i equals 3, 4, 5, or 6 and the prior means for the first own lag equals $2\big/(c_i^{'}+1)$ and the first lags of the other important variables in each equation equal $1\big/(c_i^{'}+1)$. We also adopt the values for the hyperparameters used by Gupta and Miller (2009): $\sigma_c = 0.1, \eta = 8,$ and $\rho = 0.5.$ [14] Consequently, the weighting matrix becomes the following:

$$
C' = \begin{bmatrix}
0.286 & 0.143 & 0.143 & 0.143 & 0.0 & 0.143 & 0.0 & 0.143 \\
0.167 & 0.334 & 0.167 & 0.167 & 0.0 & 0.0 & 0.167 & 0.0 \\
0.167 & 0.167 & 0.334 & 0.0 & 0.0 & 0.167 & 0.0 & 0.167 \\
0.167 & 0.167 & 0.0 & 0.334 & 0.167 & 0.0 & 0.167 & 0.0 \\
0.0 & 0.0 & 0.0 & 0.25 & 0.5 & 0.0 & 0.25 & 0.0 \\
0.2 & 0.0 & 0.2 & 0.0 & 0.0 & 0.4 & 0.0 & 0.2 \\
0.0 & 0.2 & 0.0 & 0.2 & 0.2 & 0.0 & 0.4 & 0.0 \\
0.2 & 0.0 & 0.2 & 0.0 & 0.0 & 0.2 & 0.0 & 0.4
\end{bmatrix}. \tag{11}
$$

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.

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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.

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

Specifically, we denote a single 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:

$$\begin{bmatrix} r_{111} \\ r_{112} \\ . \\ . \\ . \\ r_{nnp} \end{bmatrix} = \begin{bmatrix} \sigma/\sigma_{111} & 0 & . & . & . & 0 \\ 0 & \sigma/\sigma_{112} & 0 & . & . & 0 \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ 0 & . & . & . & . & 0 \\ 0 & 0 & . & . & 0 & \sigma/\sigma_{nnp} \end{bmatrix} \begin{bmatrix} \beta_{111} \\ \beta_{112} \\ . \\ . \\ . \\ \beta_{nnp} \end{bmatrix} + \begin{bmatrix} u_{111} \\ u_{112} \\ . \\ . \\ . \\ u_{nnp} \end{bmatrix} \tag{12}$$

Note that $Var(u) = \sigma^2 I$, and the prior means r_{ijm} and the prior variance σ_{ijm} [15] take the forms shown in equations (3) and (4) for the Minnesota prior; in equations (3), (4) and (6) for the FOSC prior; in equations (2), (3), and (7) for the TC prior, in equation (9) for the RWA prior, and in equation (10) for the WRWA prior. With equation (12) written as follows:

$$r = \Sigma\beta + u , \tag{13}$$

we derive the estimates for a typical equation as follows:

$$\hat{\beta} = (X'X + \Sigma'\Sigma)^{-1}(X'y_1 + \Sigma'r) \tag{14}$$

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.

4. Model Estimation and Results

This section reports our econometric findings. First, we determine whether cointegration exists

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

between the variables in our model. Second, we select the optimal model for forecasting each market's housing price, using the minimum root mean square error (RMSE) for one- to four-quarter-ahead out-of-sample forecasts. Finally, we examine the ability of the optimal forecasting models to detect turning points in our-of-sample forecasts.

Evidence on Cointegration

The first step in our analysis tests for Granger temporal causality between the eight housing price series. Temporal causality tests emerge from VAR or VEC models. 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 six lags. Cointegration tests – the trace statistic and maximum eigen-value test – both indicate seven cointegrating vector. Table 2 tabulates the findings.

Running the VEC specification and using the block exogeneity test, we discover that housing prices in Los Angeles temporally cause housing prices 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 housing prices temporally cause Los Angeles prices. In other words, each coastal MSA housing price index temporally causes the Los Angeles index.[16]

The most isolated MSA in causality terms is Santa Barbara, where its hosing prices are

[16] 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.

temporally caused by Santa Ana's housing prices and housing prices in Los Angeles and Oxnard temporally lead housing price adjustments in Santa Barbara. The Oxnard MSA housing prices respond to the most other MSA housing prices – Bakersfield, Riverside, San Diego, San Luis Obispo, Santa Ana, and Santa Barbara. Further, the Santa Ana MSA housing prices temporally lead the most other MSA housing prices – Bakersfield, Los Angeles, Oxnard, Riverside, San Diego, and Santa Barbara.[17]

On a bivariate basis, we observe seven pairs of MSAs with no causality between their housing prices 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 housing prices and housing prices 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 housing prices with the housing prices of any other MSA. The Santa Ana, San Diego, and San Luis Obispo MSAs each exhibit two-way causality of their housing prices with the housing prices in three other MSAs, where housing prices in Santa Ana cause housing prices in the most other MSAs.

Examining the no bivariate causality findings, we see that unexpectedly four pairs of

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[17] The Santa Ana housing prices just fall short of significantly causing housing prices in San Luis Obispo at the 10-percent level.

MSAs that geographically share portions of their borders exhibit no causality between their housing prices in either direction -- Bakersfield-Riverside, Bakersfield-Santa Barbara, Riverside-San Diego, and San Luis Obispo-Santa Barbara.[18] 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.

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.[19] 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 (2007, 2008), who observe marked differences in housing price growth across U.S. regions since

[18] 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.

[19] 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.

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 housing 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 prices for the above mentioned eight MSAs. The nominal housing 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 housing price by the personal consumption expenditure (PCE) deflator from the Bureau of Economic Analysis (BEA) to generate our real housing price series. As Hamilton (1994, p. 362) notes, we seasonally adjust the data, since the Minnesota-type priors do not perform will with seasonal data.

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.[20] We calculate the root mean squared errors (RMSE)[21] 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 reports the average RMSEs across all eight MSAs. The last column looks at the average RMSE across the one-, two-, three-, and four-quarter-ahead forecast. 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

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

[21] 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: $\sqrt{\left[\sum_1^N \left({}_tF_{t+n} - A_{t+n}\right)^2 \big/ N\right]}$ where N equals the number of forecasts.

factor reduces the influence of lagged values more quickly. The optimal specifications for the one-, two-. three-, and four-quarter-ahead forecasts equal the BVAR with *w=0.1* and *d=1*.0, BVAR with *w=0.1* and *d=2*.0, BVAR and causality BVAR with *w=0.2* and *d=2*.0, respectively.

Tables 5 through 12 report 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. 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 (0.010004), San Diego (0.012190), San Luis Obispo (0.015627), Los Angeles (0.018092), Santa Ana (0.020822), Santa Barbara (0.026338), Riverside (0.038635), and Bakersfield (0.043258) 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 Turning Points

Figure 1 illustrates that each housing market experienced a marked reversal of real housing prices after the peaks in 2005 and 2006, depending on the MSA. We exposed our optimal forecast models to the acid test – predicting turning points. We estimated the optimal models based on the average RMSE from Tables 5 through 12, using data through the fourth quarter of 2004. Next we forecasted prices from the first quarter of 2005 through the end of the sample period in the second quarter of 2008. Then we updated the data by one quarter and repeated the forecasting exercise with a model estimated through the first quarter of 2006 and forecasting with this model from the second quarter of 2006 to the second quarter of 2008. We then continue the updating and forecasting process until the end of the sample in the second quarter of 2008. The results of this forecasting experiment appear in Tables 13 through 20.

The various forecasting models do a better or worse job of forecasting the turning point in each MSA. Overall, the performance is good with a few exceptions. First, Bakersfield, Los Angeles, Riverside, and San Diego all predict a turning point once we include data up to but not including the actual peak in the housing price. In addition, San Diego also predicted a turning point in the housing price after including the actual peak price. The other three MSAs each predict a falling housing price for all forecasting models that include more actual data, once the peak price is included in the sample used to estimate the forecasting model. Moreover, the first quarter forecast falls below its forecast value in the previous forecast period.

Second, the forecasting models for Santa Ana nearly match those just discussed, but with a longer delay. That is, the forecasting models continue to predict rising prices through the end of the forecasting period until the eighth forecasting period that uses data through 2006:Q3, one quarter after the actual housing price peaks. Then from the eighth forecasting period onward, the models all predict declining prices through the end of the sample period.

Third, the forecasting of the San Luis Obispo MSA housing prices provides the best performance. The first forecast effort that begins by predicting the 2005:Q1 housing price predicts a peak price in 2006:Q1, when the actual housing price does peak. The second and third forecasts also predict a peak price in the future, but now in 2005:Q1, one quarter too early. The fourth forecast predicts a peak price in 2006:Q2 and the fifth and sixth forecasts predict a peak in 2006Q3, two quarters too late. The seventh and all future forecasts predict a monotonically falling housing price.

Fourth, the forecasting models for Oxnard perform the worst of all the MSAs. Although the housing price actually peaks in 2006:Q2, the forecasting models continue to predict rising housing prices until the eleventh forecast that uses data through 2007:Q2 to estimate the forecasting model. The eleventh and twelfth forecasts each predict a peak in the second quarter of the forecasts. Then thirteenth forecast predicts declining prices to the end of the sample.

Finally, the Santa Barbara MSA forecasting models present the most complex picture. The second forecast predicts a peak in the housing price in 2007:Q2, using data to construct the model that ends in 2005:Q1. The actual peak in the housing price occurs in 2005:Q4. The next two forecasts, however, predict declining housing prices through the end of the sample. Then the fourth, fifth, and sixth forecasting models predict turning points. The eighth and all remaining forecast predict monotonically declining housing prices through the end of the sample.

5. Conclusion

Housing 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 housing 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 turning points in housing prices that occurred in 2006:Q4.

Los Angeles housing prices temporally cause housing prices 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 housing prices temporally cause Los Angeles prices. In other words, each coastal MSA housing price index temporally causes the Los Angeles index. Santa Barbara proved the most isolated MSA in causality terms. The Oxnard MSA housing prices respond to the most other MSA housing prices and the Santa Ana MSA housing prices temporally lead the most other MSA housing prices. More evidence exists of temporal causality occurring with non-adjacent MSAs than with adjacent MSAs, an unexpected result. Los Angeles and Oxnard each causally link to every other MSA in Southern California.

Different time-series models prove better at forecasting housing prices 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 experiences the lowest average RMSE across the one-, two-, and three-quarter-ahead forecast horizon. That is, the forecasting performance in all the coastal MSAs beat the performance in the two inland MSAs.

Forecasting turning points in housing prices proves a difficult task. When we estimate our model using data through 2004:Q4, forecasts generally continue to predict a rising trend in housing prices and do not signal any turning point except for the San Luis Obispo MSA. When we update the data for the estimated model as new data become available, then we do forecast turning points generally one quarter before the actual peak in the housing price and then we forecast declining prices in future forecast periods, except for Oxnard.

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Table 1: Lag-Length Selection Tests

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1473.603	NA	3.59e-30	-45.09548	-44.82786	-44.98989
1	1962.895	843.0880	7.56e-36	-58.18139	-55.77284	-57.23106
2	2090.049	187.7969	1.18e-36	-60.12460	-55.57511	-58.32953
3	2179.955	110.6525	6.72e-37	-60.92168	-54.23126	-58.28188
4	2290.222	108.5707	2.66e-37	-62.34528	-53.51392	-58.86074
5	2498.835	154.0526	8.11e-39	-66.79491	-55.82262	-62.46564
6	2687.379	92.82181*	1.13e-39*	-70.62704*	-57.51381*	-65.45303*

Note: 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).

Table 2: Johansen Cointegration Tests

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.948321	542.9606	159.5297	0.0000
At most 1 *	0.823094	350.3845	125.6154	0.0000
At most 2 *	0.710271	237.7955	95.75366	0.0000
At most 3 *	0.626334	157.2729	69.81889	0.0000
At most 4 *	0.509552	93.28736	47.85613	0.0000
At most 5 *	0.348198	46.97895	29.79707	0.0002
At most 6 *	0.245797	19.15801	15.49471	0.0134
At most 7	0.012565	0.821902	3.841466	0.3646
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.948321	192.5761	52.36261	0.0001
At most 1 *	0.823094	112.5890	46.23142	0.0000
At most 2 *	0.710271	80.52261	40.07757	0.0000
At most 3 *	0.626334	63.98553	33.87687	0.0000
At most 4 *	0.509552	46.30841	27.58434	0.0001
At most 5 *	0.348198	27.82095	21.13162	0.0049
At most 6 *	0.245797	18.33610	14.26460	0.0108
At most 7	0.012565	0.821902	3.841466	0.3646

Note: The trace and maximum eigen-value tests both indicate 7 cointegrating vectors at the 5-percent level.

* denotes rejection of the hypothesis at the 0.05 level
** 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*	

Note: 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 housing prices do not significantly affect housing prices in the Bakersfield MSA at the 5- and 10-percent levels.

* rejection of the null-hypothesis at 5-percent level.

** rejection of the null-hypothesis at the 10-percent level.

Table 4: Forecast Results for All Eight MSAs

Parameterization	Models	RMSEs 1	2	3	4	Average
	VAR	0.080942	0.126143	0.240683	0.346271	0.19851
	VEC	0.080696	0.191404	0.358172	0.538615	0.292222
w=0.3, d=0.5	**BVAR**	0.065956	0.108213	0.215062	0.27712	0.166588
	BVEC	0.07153	0.130146	0.232009	0.325186	0.189718
	Causality BVAR	0.053987	0.123166	0.256702	0.289006	0.180715
	Spatial BVAR	0.040968	0.079404	0.181547	0.24517	0.136772
	Causality BVEC	0.071399	0.120781	0.228494	0.312339	0.183253
	Spatial BVEC	0.047387	0.091118	0.186629	0.252942	0.144519
w=0.2, d=1	**BVAR**	0.039539	0.07829	0.173346	0.186551	0.119432
	BVEC	0.052079	0.088746	0.157391	0.204771	0.125747
	Causality BVAR	0.046515	0.092174	0.200975	0.22459	0.141064
	Spatial BVAR	0.047227	0.086561	0.18788	0.247707	0.142344
	Causality BVEC	0.068552	0.094571	0.164629	0.209873	0.134406
	Spatial BVEC	0.043917	0.100808	0.179006	0.238969	0.140675
w=0.1, d=1	**BVAR**	**0.035317**	0.049335	0.126794	0.118866	0.082578
	BVEC	0.040412	0.070014	0.112726	0.145979	0.092283
	Causality BVAR	0.03695	0.069036	0.141288	0.159988	0.101815
	Spatial BVAR	0.053974	0.087413	0.153998	0.197612	0.123249
	Causality BVEC	0.059594	0.061908	0.077585	0.095575	0.073665
	Spatial BVEC	0.048128	0.090642	0.133854	0.180043	0.113167
w=0.2, d=2	**BVAR**	0.045177	**0.044248**	0.098074	0.1065	0.0735
	BVEC	0.038224	0.084254	0.140296	0.185433	0.112052
	Causality BVAR	0.037346	0.057389	0.101926	0.108124	0.076196
	Spatial BVAR	0.062963	0.093693	0.1583	0.189729	0.126171
	Causality BVEC	0.048603	0.058534	0.092229	0.117084	0.079112
	Spatial BVEC	0.04641	0.091007	0.144945	0.1809	0.115816
w=0.1, d=2	**BVAR**	0.060534	0.064287	**0.067053**	0.092407	0.07107
	BVEC	0.039296	0.072925	0.125208	0.166128	0.100889
	Causality BVAR	0.046477	0.073562	0.082498	**0.089092**	0.072907
	Spatial BVAR	0.065141	0.08505	0.105803	0.14503	0.100256
	Causality BVEC	0.041374	0.056676	0.081271	0.101583	**0.070226**
	Spatial BVEC	0.057068	0.08626	0.124128	0.158378	0.106459
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.088071	0.084746	0.146872	0.172476	0.123041
	RBVAR Causality2	0.082801	0.08946	0.15063	0.175755	0.124662
	RBVAR Spatial1	0.077357	0.087919	0.183671	0.179352	0.132075
	RBVAR Spatial2	0.083549	0.082698	0.170235	0.182005	0.129622
	RBVEC Causality1	0.071244	0.254395	0.184218	0.183024	0.17322
	RBVEC Causality2	0.071244	0.254395	0.184218	0.183024	0.17322
	RBVEC Spatial1	0.080824	0.290871	0.323186	0.234723	0.232401
	RBVEC Spatial2	0.079189	0.276654	0.270396	0.210936	0.209294

Note: 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.

Table 5: Forecast Results for Bakersfield

Parameterization	Models	RMSEs				
		1	2	3	4	Average
	VAR	0.055025	0.057967	0.143001	0.088551	0.086136
	VEC	0.016500	0.029062	0.170797	0.179115	0.098868
w=0.3, d=0.5	**BVAR**	0.066336	0.047092	0.167823	0.105393	0.096661
	BVEC	0.023590	0.078523	0.253199	0.288952	0.161066
	Causality BVAR	0.044398	0.134031	0.363022	0.323425	0.216219
	Spatial BVAR	0.061439	0.009220	0.153415	0.193957	0.104508
	Causality BVEC	0.030896	0.139480	0.343697	0.457309	0.242846
	Spatial BVEC	**0.010408**	**0.002868**	0.109574	0.106279	0.057282
w=0.2, d=1	**BVAR**	0.068738	0.040972	0.210664	0.189994	0.127592
	BVEC	0.038345	0.080053	0.245034	0.273255	0.159172
	Causality BVAR	0.047769	0.097551	0.309303	0.295255	0.187470
	Spatial BVAR	0.116423	0.034904	0.173983	0.222131	0.136860
	Causality BVEC	0.037202	0.122558	0.303183	0.381359	0.211075
	Spatial BVEC	0.052514	0.045832	0.045170	0.029515	**0.043258**
w=0.1, d=1	**BVAR**	0.089704	0.013843	0.144885	0.127121	0.093888
	BVEC	0.053143	0.050303	0.174508	0.172277	0.112558
	Causality BVAR	0.080099	0.023619	0.205677	0.193380	0.125694
	Spatial BVAR	0.142038	0.089160	0.095800	0.107266	0.108566
	Causality BVEC	0.049043	0.076164	0.187635	0.176595	0.122359
	Spatial BVEC	0.106420	0.075926	**0.002381**	0.028032	0.053190
w=0.2, d=2	**BVAR**	0.093464	0.053834	0.078107	0.046613	0.068005
	BVEC	0.046229	0.058255	0.214111	0.225821	0.136104
	Causality BVAR	0.103108	0.044657	0.096801	0.060511	0.076269
	Spatial BVAR	0.154430	0.119174	0.054355	0.060508	0.097116
	Causality BVEC	0.031631	0.095688	0.236777	0.243915	0.152003
	Spatial BVEC	0.099409	0.063180	0.037630	0.011094	0.052828
w=0.1, d=2	**BVAR**	0.137000	0.141000	0.056480	0.127312	0.115448
	BVEC	0.058368	0.030153	0.158980	0.152909	0.100103
	Causality BVAR	0.165140	0.161459	0.074100	0.152894	0.138398
	Spatial BVAR	0.166268	0.172644	0.049805	0.083297	0.118003
	Causality BVEC	0.050257	0.027775	0.108125	0.050372	0.059132
	Spatial BVEC	0.118428	0.068345	0.033845	0.009551	0.057542
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.095711	0.062697	0.254129	0.247825	0.165090
	RBVAR Causality2	0.081154	0.072446	0.260185	0.261446	0.168807
	RBVAR Spatial1	0.168662	0.010138	0.155446	0.157675	0.122980
	RBVAR Spatial2	0.155025	0.007738	0.153893	0.156208	0.118216
	RBVEC Causality1	0.072810	0.303861	0.018852	0.078509	0.118508
	RBVEC Causality2	0.072810	0.303861	0.018852	0.078509	0.118508
	RBVEC Spatial1	0.120527	0.167964	0.060914	**0.002401**	0.087951
	RBVEC Spatial2	0.117675	0.205918	0.105261	0.042453	0.117827

Note: See Table 4.

Table 6: Forecast Results for Los Angeles

Parameterization	Models	RMSEs				
		1	2	3	4	Average
	VAR	0.081802	0.327154	0.655579	0.928672	0.498302
	VEC	0.091155	0.281502	0.597506	0.938820	0.477246
w=0.3, d=0.5	**BVAR**	0.064639	0.271955	0.537467	0.734121	0.402045
	BVEC	0.084609	0.210290	0.422984	0.610132	0.332004
	Causality BVAR	0.071690	0.255841	0.470013	0.603031	0.350144
	Spatial BVAR	0.027526	0.149027	0.322108	0.418028	0.229172
	Causality BVEC	0.098097	0.167451	0.293486	0.374339	0.233343
	Spatial BVEC	0.037842	0.069015	0.131947	0.108525	0.086832
w=0.2, d=1	**BVAR**	0.029286	0.169434	0.347830	0.427997	0.243637
	BVEC	0.068386	0.142963	0.287269	0.382136	0.220189
	Causality BVAR	0.050118	0.190663	0.364521	0.438864	0.261042
	Spatial BVAR	0.021293	0.051761	0.163010	0.184329	0.105098
	Causality BVEC	0.091182	0.134110	0.231520	0.269716	0.181632
	Spatial BVEC	0.019301	0.034084	0.080885	0.046782	0.045263
w=0.1, d=1	**BVAR**	0.002818	0.092346	0.212566	0.221072	0.132201
	BVEC	0.040207	0.061510	0.145830	0.164870	0.103104
	Causality BVAR	0.035105	0.147369	0.296743	0.344251	0.205867
	Spatial BVAR	0.045781	**0.000006**	0.080336	0.057389	0.045878
	Causality BVEC	0.067497	0.083417	0.154820	0.161940	0.116918
	Spatial BVEC	**0.001396**	0.006152	0.047601	0.018211	0.018340
w=0.2, d=2	**BVAR**	0.016099	0.047640	0.138078	0.110658	0.078119
	BVEC	0.037678	0.068101	0.163622	0.196471	0.116468
	Causality BVAR	0.009976	0.098720	0.226004	0.242940	0.144410
	Spatial BVAR	0.052760	0.010435	0.063652	0.025435	0.038071
	Causality BVEC	0.057658	0.081958	0.165716	0.182928	0.122065
	Spatial BVEC	0.002976	0.014829	0.070233	0.054808	0.035711
w=0.1, d=2	**BVAR**	0.042215	0.021199	0.021283	0.055769	0.035116
	BVEC	0.013086	0.015576	0.080416	0.074208	0.045821
	Causality BVAR	0.002488	0.064342	0.167689	0.160908	0.098857
	Spatial BVAR	0.059497	0.038493	**0.007456**	0.068231	0.043419
	Causality BVEC	0.032069	0.039404	0.107458	0.107518	0.071612
	Spatial BVEC	0.017541	0.021625	0.017873	**0.015329**	**0.018092**
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.109634	0.096958	0.209929	0.262315	0.169709
	RBVAR Causality2	0.090326	0.113081	0.234251	0.281885	0.179886
	RBVAR Spatial1	0.145943	0.069003	0.184614	0.273225	0.168196
	RBVAR Spatial2	0.132557	0.066301	0.179862	0.251062	0.157446
	RBVEC Causality1	0.002019	0.214690	0.188836	0.123455	0.132250
	RBVEC Causality2	0.002019	0.214690	0.188836	0.123455	0.132250
	RBVEC Spatial1	0.026912	0.354950	0.205635	0.075064	0.165640
	RBVEC Spatial2	0.025945	0.380385	0.195588	0.091964	0.173470

Note: See Table 4.

Table 7: Forecast Results for Oxnard

Parameterization	Models	RMSEs				
		1	2	3	4	Average
	VAR	0.115150	0.252746	0.507114	0.761972	0.409245
	VEC	0.126310	0.216132	0.557702	1.025562	0.481427
w=0.3, d=0.5	**BVAR**	0.069155	0.184779	0.377138	0.548993	0.295016
	BVEC	0.097909	0.096329	0.257540	0.445084	0.224215
	Causality BVAR	0.025297	0.106331	0.294484	0.372073	0.199546
	Spatial BVAR	0.052357	0.074530	0.118265	0.134998	0.095038
	Causality BVEC	0.032471	0.108670	0.279048	0.451324	0.217878
	Spatial BVEC	0.064684	0.129251	0.236039	0.390122	0.205024
w=0.2, d=1	**BVAR**	0.008457	0.073719	0.171977	0.213835	0.116997
	BVEC	0.038568	0.023576	0.029617	0.068528	0.040072
	Causality BVAR	0.044202	0.039487	0.160983	0.201701	0.111593
	Spatial BVAR	0.027495	0.075214	0.110392	0.191788	0.101222
	Causality BVEC	0.021428	0.056982	0.151692	0.222267	0.113093
	Spatial BVEC	0.020732	0.179819	0.277824	0.415763	0.223535
w=0.1, d=1	**BVAR**	0.017655	**0.004724**	0.037705	**0.005663**	0.016437
	BVEC	**0.006177**	0.106098	0.115442	0.152644	0.095090
	Causality BVAR	0.072944	0.055458	0.015049	0.030025	0.043369
	Spatial BVAR	0.048643	0.122346	0.173724	0.282750	0.156866
	Causality BVEC	0.011374	0.017384	**0.001608**	0.009651	**0.010004**
	Spatial BVEC	0.026046	0.196147	0.260178	0.353979	0.209087
w=0.2, d=2	**BVAR**	0.020834	0.032115	0.006814	0.069661	0.032356
	BVEC	0.018909	0.128483	0.134729	0.174989	0.114278
	Causality BVAR	0.048811	0.039243	0.003024	0.035449	0.031632
	Spatial BVAR	0.068431	0.147487	0.187177	0.298562	0.175415
	Causality BVEC	0.009244	0.033671	0.023859	0.045401	0.028044
	Spatial BVEC	0.038444	0.198919	0.257918	0.353192	0.212118
w=0.1, d=2	**BVAR**	0.060579	0.122725	0.140266	0.245484	0.142263
	BVEC	0.031376	0.152096	0.178362	0.246382	0.152054
	Causality BVAR	0.092731	0.144188	0.152487	0.227135	0.154135
	Spatial BVAR	0.066661	0.149213	0.184742	0.309088	0.177426
	Causality BVEC	0.008986	0.099114	0.114970	0.153334	0.094101
	Spatial BVEC	0.063640	0.214452	0.266881	0.360905	0.226469
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.182437	0.034981	0.020337	0.031270	0.067256
	RBVAR Causality2	0.183808	0.037769	0.017301	0.016269	0.063787
	RBVAR Spatial1	0.132648	0.076631	0.119133	0.041671	0.092521
	RBVAR Spatial2	0.157885	0.092028	0.146126	0.084776	0.120204
	RBVEC Causality1	0.082430	0.152383	0.354839	0.247116	0.209192
	RBVEC Causality2	0.082430	0.152383	0.354839	0.247116	0.209192
	RBVEC Spatial1	0.051474	0.265714	0.657952	0.683151	0.414573
	RBVEC Spatial2	0.071044	0.244668	0.634023	0.522665	0.368100

Note: See Table 4.

Table 8: Forecast Results for Riverside

Parameterization	Models	RMSEs				
		1	2	3	4	Average
	VAR	0.048250	0.014699	0.152299	0.191810	0.101764
	VEC	0.026229	0.157782	0.098093	0.154955	0.109265
w=0.3, d=0.5	**BVAR**	0.040950	0.022964	0.163094	0.180879	0.101972
	BVEC	0.023186	0.105291	0.024205	0.001856	**0.038635**
	Causality BVAR	0.023404	0.125192	0.335594	0.359388	0.210894
	Spatial BVAR	**0.001083**	0.113337	0.322361	0.426022	0.215701
	Causality BVEC	0.064049	0.070615	0.124141	0.164153	0.105739
	Spatial BVEC	0.011423	0.005494	0.167344	0.200228	0.096122
w=0.2, d=1	**BVAR**	0.020529	0.070855	0.248123	0.285587	0.156273
	BVEC	0.026007	0.072788	0.065984	0.055378	0.055039
	Causality BVAR	0.046081	0.071489	0.255528	0.285651	0.164687
	Spatial BVAR	0.025322	0.149721	0.376967	0.505147	0.264289
	Causality BVEC	0.076780	0.086224	0.079714	0.097003	0.084930
	Spatial BVEC	0.002980	0.002869	0.157613	0.185708	0.087292
w=0.1, d=1	**BVAR**	0.028641	0.059013	0.228857	0.258538	0.143762
	BVEC	0.034814	0.061516	0.069454	0.057173	0.055739
	Causality BVAR	0.044290	0.046576	0.213625	0.235417	0.134977
	Spatial BVAR	0.007846	0.113134	0.304029	0.373019	0.199507
	Causality BVEC	0.081794	0.105688	0.015244	0.011818	0.053636
	Spatial BVEC	0.010009	0.026482	0.114837	0.124967	0.069074
w=0.2, d=2	**BVAR**	0.064169	0.007495	0.159112	0.177180	0.101989
	BVEC	0.027121	0.049826	0.068824	0.062304	0.052019
	Causality BVAR	0.069873	0.001221	0.141684	0.150387	0.090791
	Spatial BVAR	0.022722	0.074224	0.257921	0.314941	0.167452
	Causality BVEC	0.069310	0.081419	0.046384	0.034208	0.057830
	Spatial BVEC	0.007144	0.025169	0.103816	0.112053	0.062046
w=0.1, d=2	**BVAR**	0.097632	0.072578	0.024700	0.013500	0.052103
	BVEC	0.047417	0.057393	0.058448	0.050103	0.053340
	Causality BVAR	0.072491	0.030210	0.076884	0.037913	0.054374
	Spatial BVAR	0.063618	**0.000462**	0.133630	0.132338	0.082512
	Causality BVEC	0.078908	0.103257	**0.013531**	0.058028	0.063431
	Spatial BVEC	0.028384	0.042183	0.078327	0.083278	0.058043
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.110328	0.047476	0.243835	0.261372	0.165753
	RBVAR Causality2	0.099990	0.062879	0.251513	0.268491	0.170718
	RBVAR Spatial1	0.018109	0.185350	0.391483	0.438508	0.258362
	RBVAR Spatial2	0.008656	0.198479	0.402759	0.438584	0.262119
	RBVEC Causality1	0.168743	0.404328	0.199462	0.014889	0.196855
	RBVEC Causality2	0.168743	0.404328	0.199462	0.014889	0.196855
	RBVEC Spatial1	0.131970	0.358721	0.133772	**0.000694**	0.156289
	RBVEC Spatial2	0.133987	0.370365	0.164469	0.051406	0.180057

Note: See Table 4.

Table 9: Forecast Results for San Diego

Parameterization	Models	RMSEs 1	2	3	4	Average
	VAR	0.009100	0.005308	0.004184	0.030170	**0.012190**
	VEC	0.031665	0.291746	0.537845	0.931422	0.448169
w=0.3, d=0.5	**BVAR**	0.011965	0.024363	0.035940	0.093844	0.041528
	BVEC	0.027426	0.197926	0.328421	0.575538	0.282328
	Causality BVAR	0.035566	0.120105	0.074147	0.050141	0.069990
	Spatial BVAR	0.039478	0.046371	0.013030	0.024248	0.030781
	Causality BVEC	0.035306	0.055509	0.177431	0.411596	0.169961
	Spatial BVEC	0.010804	0.187877	0.208320	0.201895	0.152224
w=0.2, d=1	**BVAR**	**0.000187**	0.032149	0.048548	**0.005239**	0.021531
	BVEC	0.006519	0.130010	0.173506	0.295500	0.151384
	Causality BVAR	0.034141	0.119803	0.115742	0.103780	0.093367
	Spatial BVAR	0.045548	0.022921	0.032126	0.032797	0.033348
	Causality BVEC	0.040741	0.020245	0.101112	0.259499	0.105399
	Spatial BVEC	0.030482	0.170679	0.164443	0.128750	0.123588
w=0.1, d=1	**BVAR**	0.001874	0.039949	0.076875	0.021881	0.035145
	BVEC	0.015818	0.043784	0.027613	0.061195	0.037103
	Causality BVAR	0.012748	0.085976	0.115208	0.097726	0.077914
	Spatial BVAR	0.053078	0.049205	0.023613	0.075499	0.050349
	Causality BVEC	0.048254	0.024191	0.003415	0.087465	0.040831
	Spatial BVEC	0.020317	0.081600	0.037885	0.014644	0.038611
w=0.2, d=2	**BVAR**	0.013364	0.031835	0.084140	0.043595	0.043234
	BVEC	0.018784	0.101982	0.094523	0.133957	0.087311
	Causality BVAR	0.002435	0.078040	0.128753	0.116317	0.081386
	Spatial BVAR	0.040987	**0.002022**	0.073902	0.057732	0.043661
	Causality BVEC	0.029629	0.004896	**0.003362**	0.076918	0.028701
	Spatial BVEC	0.033649	0.109572	0.081051	0.055492	0.069941
w=0.1, d=2	**BVAR**	0.029372	0.010214	0.019891	0.046312	0.026447
	BVEC	0.013088	0.058555	0.029965	0.040990	0.035649
	Causality BVAR	0.027613	0.025341	0.061672	0.007122	0.030437
	Spatial BVAR	0.044502	0.027468	0.011710	0.043916	0.031899
	Causality BVEC	0.031382	0.020212	0.029460	0.014728	0.023946
	Spatial BVEC	0.022309	0.044588	0.010918	0.048575	0.031598
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.006732	0.107565	0.112229	0.107678	0.083551
	RBVAR Causality2	0.005815	0.097696	0.102059	0.092186	0.074439
	RBVAR Spatial1	0.052854	0.057221	0.128082	0.090979	0.082284
	RBVAR Spatial2	0.093017	0.014722	0.030711	0.023951	0.040601
	RBVEC Causality1	0.010583	0.220292	0.398392	0.096319	0.181396
	RBVEC Causality2	0.010583	0.220292	0.398392	0.096319	0.181396
	RBVEC Spatial1	0.068673	0.479217	0.297497	0.094957	0.235086
	RBVEC Spatial2	0.044597	0.315998	0.262531	0.175886	0.199753

Note: See Table 4.

Table 10: Forecast Results for San Luis Obispo

Parameterization	Models	RMSEs				
		1	2	3	4	Average
	VAR	0.193574	0.125929	0.049781	0.120072	0.122339
	VEC	0.165042	0.263262	0.418691	0.468176	0.328793
w=0.3, d=0.5	**BVAR**	0.156269	0.126751	0.086422	0.035448	0.101223
	BVEC	0.132920	0.119109	0.204968	0.225480	0.170619
	Causality BVAR	0.126968	0.112904	0.270422	0.268431	0.194681
	Spatial BVAR	0.038255	0.069741	0.165881	0.275755	0.137408
	Causality BVEC	0.133798	0.214504	0.350089	0.388012	0.271601
	Spatial BVEC	0.051657	0.074758	0.039147	0.056746	0.055577
w=0.2, d=1	**BVAR**	0.083370	0.073640	0.060553	**0.000032**	0.054399
	BVEC	0.069552	0.032601	0.080484	0.077039	0.064919
	Causality BVAR	0.066990	0.045169	0.136037	0.131942	0.095035
	Spatial BVAR	0.015880	0.122445	0.180423	0.223949	0.135674
	Causality BVEC	0.113445	0.144465	0.214347	0.221068	0.173331
	Spatial BVEC	0.030700	0.067777	0.034409	0.072580	0.051366
w=0.1, d=1	**BVAR**	0.051005	0.035998	0.036418	0.000884	0.031076
	BVEC	0.013851	0.028527	0.011546	0.033894	0.021955
	Causality BVAR	0.014804	0.006066	0.053295	0.087465	0.040407
	Spatial BVAR	0.026466	0.116467	0.142439	0.157275	0.110662
	Causality BVEC	0.066016	0.045859	0.078691	0.084661	0.068807
	Spatial BVEC	0.020663	0.031406	**0.000906**	0.033182	0.021539
w=0.2, d=2	**BVAR**	0.050155	0.006434	0.009881	0.064591	0.032765
	BVEC	0.004870	0.032731	0.011589	0.041337	0.022632
	Causality BVAR	0.006960	0.045152	0.038646	0.062535	0.038323
	Spatial BVAR	0.031283	0.130907	0.157989	0.188553	0.127183
	Causality BVEC	0.041562	0.010494	0.030496	0.028910	0.027866
	Spatial BVEC	0.013278	0.019304	0.015325	0.014601	**0.015627**
w=0.1, d=2	**BVAR**	0.055253	0.035904	0.049352	0.018161	0.039667
	BVEC	0.006358	0.061469	0.067540	0.117162	0.063132
	Causality BVAR	0.005201	0.025240	0.032210	0.074694	0.034336
	Spatial BVAR	0.031216	0.116927	0.135568	0.169583	0.113324
	Causality BVEC	**0.001423**	0.053605	0.043416	0.055580	0.038506
	Spatial BVEC	0.016876	**0.005727**	0.035584	0.008289	0.016619
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.024262	0.011151	0.018329	0.117887	0.042907
	RBVAR Causality2	0.032771	0.012943	0.013099	0.108518	0.041833
	RBVAR Spatial1	0.014848	0.084800	0.102448	0.000115	0.050553
	RBVAR Spatial2	0.022458	0.056670	0.060607	0.042568	0.045576
	RBVEC Causality1	0.009732	0.185039	0.049050	0.335845	0.144916
	RBVEC Causality2	0.009732	0.185039	0.049050	0.335845	0.144916
	RBVEC Spatial1	0.025591	0.024626	0.612326	0.268608	0.232788
	RBVEC Spatial2	0.005786	0.042210	0.424891	0.099031	0.142979

Note: See Table 4.

Table 11: Forecast Results for Santa Ana

Parameterization	Models	RMSEs				
		1	2	3	4	Average
	VAR	0.017045	0.151326	0.285412	0.448223	0.225501
	VEC	0.032600	0.127259	0.237364	0.408985	0.201552
w=0.3, d=0.5	**BVAR**	0.006231	0.129495	0.235680	0.344475	0.178970
	BVEC	0.028883	0.093682	0.122344	0.167929	0.103209
	Causality BVAR	0.005547	0.130168	0.233911	0.315121	0.171187
	Spatial BVAR	0.025198	0.155381	0.258611	0.341559	0.195187
	Causality BVEC	0.031960	0.115006	0.128280	0.171101	0.111587
	Spatial BVEC	0.039626	0.127858	0.183226	0.230213	0.145231
w=0.2, d=1	**BVAR**	0.004479	0.112016	0.178155	0.216968	0.127904
	BVEC	0.017388	0.060622	0.048244	0.039451	0.041426
	Causality BVAR	0.014824	0.137510	0.238802	0.312823	0.175990
	Spatial BVAR	0.036724	0.171707	0.279751	0.344768	0.208237
	Causality BVEC	0.025578	0.088887	0.075829	0.074141	0.066109
	Spatial BVEC	0.031716	0.122501	0.177567	0.224209	0.138998
w=0.1, d=1	**BVAR**	0.006836	0.098483	0.140665	0.141251	0.096808
	BVEC	0.011740	0.037462	0.003613	0.030475	**0.020822**
	Causality BVAR	0.007479	0.107495	0.177235	0.216030	0.127059
	Spatial BVAR	0.040432	0.159989	0.240088	0.268878	0.177347
	Causality BVEC	0.018236	0.054401	0.013179	0.024142	0.027489
	Spatial BVEC	0.020198	0.094146	0.117866	0.136853	0.092266
w=0.2, d=2	**BVAR**	0.018145	0.107729	0.142780	0.123541	0.098049
	BVEC	0.009687	0.028263	**0.002668**	0.043027	0.020911
	Causality BVAR	0.018055	0.115310	0.169906	0.178411	0.120421
	Spatial BVAR	0.035893	0.139339	0.193358	0.189619	0.139552
	Causality BVEC	0.017573	0.046590	0.009592	0.031603	0.026339
	Spatial BVEC	0.015159	0.077243	0.095117	0.101760	0.072320
w=0.1, d=2	**BVAR**	**0.002830**	0.062998	0.060840	**0.001137**	0.031951
	BVEC	0.009415	**0.018172**	0.020814	0.071692	0.030023
	Causality BVAR	0.003883	0.054085	0.061017	0.022200	0.035296
	Spatial BVAR	0.030312	0.110407	0.126220	0.078064	0.086251
	Causality BVEC	0.015454	0.023381	0.024673	0.076532	0.035010
	Spatial BVEC	0.013635	0.055466	0.052137	0.033874	0.038778
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.065785	0.054911	0.100359	0.141774	0.090707
	RBVAR Causality2	0.065148	0.047752	0.094394	0.138320	0.086404
	RBVAR Spatial1	0.006636	0.154214	0.220001	0.269286	0.162534
	RBVAR Spatial2	0.007972	0.140015	0.202250	0.250378	0.150154
	RBVEC Causality1	0.005778	0.301415	0.200289	0.129102	0.159146
	RBVEC Causality2	0.005778	0.301415	0.200289	0.129102	0.159146
	RBVEC Spatial1	0.019940	0.272141	0.376706	0.201297	0.217521
	RBVEC Spatial2	0.014350	0.301839	0.358987	0.157570	0.208187

Note: See Table 4.

Table 12: Forecast Results for Santa Barbara

Parameterization	Models	RMSEs				
		1	2	3	4	Average
	VAR	0.127590	0.074013	0.128093	0.200702	0.132600
	VEC	0.156069	0.164485	0.247376	0.201886	0.192454
w=0.3, d=0.5	**BVAR**	0.112101	0.058306	0.116931	0.173806	0.115286
	BVEC	0.153721	0.140020	0.242411	0.286521	0.205668
	Causality BVAR	0.099023	**0.000759**	0.012026	0.020438	0.033062
	Spatial BVAR	0.082406	0.017626	0.098707	0.146788	0.086382
	Causality BVEC	0.144618	0.095013	0.131780	0.080875	0.113071
	Spatial BVEC	0.152651	0.131824	0.417431	0.729527	0.357858
w=0.2, d=1	**BVAR**	0.101268	0.053538	0.120919	0.152757	0.107121
	BVEC	0.151866	0.167358	0.328989	0.446880	0.273773
	Causality BVAR	0.067993	0.035723	0.026883	0.026705	0.039326
	Spatial BVAR	0.089131	0.063818	0.186385	0.276746	0.154020
	Causality BVEC	0.142056	0.103099	0.159631	0.153931	0.139679
	Spatial BVEC	0.162911	0.182902	0.494136	0.808442	0.412098
w=0.1, d=1	**BVAR**	0.084006	0.050326	0.136384	0.174516	0.111308
	BVEC	0.147544	0.170915	0.353801	0.495303	0.291891
	Causality BVAR	0.028131	0.079731	0.053470	0.075612	0.059236
	Spatial BVAR	0.067508	0.048999	0.171954	0.258819	0.136820
	Causality BVEC	0.134539	0.088156	0.166086	0.208331	0.149278
	Spatial BVEC	0.179978	0.213279	0.489178	0.730477	0.403228
w=0.2, d=2	**BVAR**	0.085183	0.066897	0.165682	0.216164	0.133481
	BVEC	0.142515	0.206394	0.432302	0.605562	0.346693
	Causality BVAR	0.039549	0.036771	**0.010590**	**0.018440**	**0.026338**
	Spatial BVAR	0.097197	0.125956	0.278043	0.382484	0.220920
	Causality BVEC	0.132215	0.113557	0.221647	0.292788	0.190052
	Spatial BVEC	0.161222	0.219841	0.498474	0.744196	0.405933
w=0.1, d=2	**BVAR**	0.059393	0.047679	0.163613	0.231581	0.125567
	BVEC	0.135261	0.189988	0.407136	0.575578	0.326991
	Causality BVAR	**0.002265**	0.083631	0.033929	0.029867	0.037423
	Spatial BVAR	0.059053	0.064790	0.197296	0.275725	0.149216
	Causality BVEC	0.112513	0.086660	0.208535	0.296575	0.176071
	Spatial BVEC	0.175734	0.237698	0.497457	0.707228	0.404529
sigma=0.1, tau=8, theta=0.5	**RBVAR Causality1**	0.109677	0.262227	0.215829	0.209685	0.199355
	RBVAR Causality2	0.103396	0.271118	0.232236	0.238924	0.211419
	RBVAR Spatial1	0.079156	0.065996	0.168161	0.163358	0.119168
	RBVAR Spatial2	0.090822	0.085632	0.185670	0.208515	0.142660
	RBVEC Causality1	0.217859	0.253152	0.064026	0.438956	0.243498
	RBVEC Causality2	0.217859	0.253152	0.064026	0.438956	0.243498
	RBVEC Spatial1	0.201505	0.403637	0.240689	0.551611	0.349361
	RBVEC Spatial2	0.220126	0.351846	0.017416	0.546515	0.283976

Note: See Table 4.

Table 13: Recursive Forecasts of the Real Housing Price Index: Bakersfield

Forecast	Actual	1	2	3	4	5	6	7	8	9	10	11	12	13	14
2005:Q1	226.1	220.0													
2005:Q2	239.5	247.6	242.5												
2005:Q3	253.5	282.6	269.3	257.8											
2005:Q4	268.1	327.7	301.9	285.6	271.7										
2006:Q1	278.4	381.5	342.7	317.6	300.4	288.5									
2006:Q2	282.6	452.3	390.5	355.7	334.3	318.7	301.0								
2006:Q3	283.9	540.3	450.7	399.7	375.1	351.3	327.8	300.0							
2006:Q4	**286.6**	659.8	524.2	452.2	421.4	387.2	356.3	317.8	294.8						
2007:Q1	283.5	815.1	618.7	514.9	477.3	427.3	387.2	334.6	299.0	**292.0**					
2007:Q2	275.3	1,034.9	738.2	590.5	542.1	471.3	421.1	350.8	**300.3**	288.9	**283.3**				
2007:Q3	265.8	1,335.4	895.8	683.3	620.4	521.3	457.7	368.0	299.3	284.0	278.7	**278.1**			
2007:Q4	251.3	1,783.6	1,102.8	796.5	713.2	576.0	498.5	384.2	298.8	278.0	273.5	274.3	**257.5**		
2008:Q1	228.7	2,432.8	1,384.5	939.7	825.7	638.9	542.0	402.0	295.9	272.3	267.9	270.0	250.0	**240.4**	
2008:Q2	207.6	**3,464.2**	**1,770.1**	**1,117.1**	**961.6**	**707.1**	**591.3**	**418.0**	294.2	265.5	262.6	265.1	243.2	231.8	**211.4**

Note: The Actual column gives the actual data. The Diagonal column gives the one-quarter-ahead forecast for Forecast 1, 2, …,, and 14. Forecast 1 estimates the model through 2004:Q4 and then forecasts one-, two-, ..,, and fourteen-quarters ahead. Forecast 2 estimates the model through 2005:Q1 and then forecasts one-, two-, …, and thirteen-quarters ahead, and so on. Finally, Forecast 14 estimates the model through 2008:Q1 and then forecasts one-quarter ahead. The bolded numbers equal the maximum prices in each column.

Table 14: Recursive Forecasts of the Real Housing Price Index: Los Angeles

Forecast	Actual	1	2	3	4	5	6	7	8	9	10	11	12	13	14
2005:Q1	325.7	330.2													
2005:Q2	342.5	346.8	344.5												
2005:Q3	357.5	367.0	360.3	364.1											
2005:Q4	377.5	391.7	378.5	381.0	373.4										
2006:Q1	391.0	418.7	400.0	399.9	387.1	401.6									
2006:Q2	398.2	451.4	423.2	421.6	402.6	418.7	409.9								
2006:Q3	403.5	488.3	450.1	444.8	420.2	436.9	423.4	410.3							
2006:Q4	**405.6**	533.1	479.8	471.2	438.6	456.5	437.3	418.4	411.4						
2007:Q1	401.5	584.8	514.5	500.1	459.5	476.9	451.9	426.1	414.1	**406.0**					
2007:Q2	398.3	648.0	553.6	532.8	481.3	498.8	466.9	433.3	**415.2**	403.6	**396.6**				
2007:Q3	391.1	722.8	599.0	569.1	505.9	521.8	482.4	440.6	415.1	400.2	394.4	**394.0**			
2007:Q4	376.8	815.3	651.0	610.1	531.9	546.3	498.3	447.4	415.2	395.8	391.7	388.9	**382.1**		
2008:Q1	350.7	927.5	711.5	656.6	561.0	572.1	514.8	454.3	414.0	391.7	388.8	382.6	377.5	**364.3**	
2008:Q2	321.5	**1,068.6**	**782.5**	**708.4**	**592.0**	**599.4**	**531.5**	**460.5**	413.1	386.5	386.1	375.5	373.3	357.9	**327.9**

Note: See Table 12.

Table 15: Recursive Forecasts of the Real Housing Price Index: Oxnard

Forecast	Actual	1	2	3	4	5	6	7	8	9	10	11	12	13	14
2005:Q1	336.8	352.2													
2005:Q2	347.7	373.0	358.3												
2005:Q3	360.4	397.0	376.1	359.1											
2005:Q4	374.6	425.5	396.0	373.9	371.4										
2006:Q1	382.5	457.1	418.8	390.8	391.4	391.0									
2006:Q2	**383.8**	494.5	443.4	410.1	413.6	413.1	398.7								
2006:Q3	379.8	537.3	471.5	430.7	438.9	437.7	419.4	394.2							
2006:Q4	373.6	587.6	502.5	454.3	466.1	465.6	442.1	410.0	384.8						
2007:Q1	364.3	647.0	537.4	479.7	496.8	495.7	467.7	427.4	392.8	370.8					
2007:Q2	356.6	717.1	576.6	508.6	530.3	529.8	495.3	446.8	402.9	374.2	357.4				
2007:Q3	346.0	802.0	620.6	540.4	567.8	567.4	526.4	467.3	415.2	378.3	359.6	350.4			
2007:Q4	331.5	902.2	671.0	576.0	609.7	609.8	560.3	490.0	428.3	383.2	361.2	**351.2**	333.2		
2008:Q1	307.8	1,027.5	726.8	616.0	655.7	657.8	598.0	514.4	443.7	388.2	362.6	350.8	**333.3**	**319.2**	
2008:Q2	284.2	**1,176.0**	**792.1**	**660.2**	**708.4**	**711.5**	**640.2**	**541.0**	**460.3**	**394.2**	**363.9**	349.8	332.7	317.8	**290.9**

Note: See Table 12.

Table 16: Recursive Forecasts of the Real Housing Price Index: Riverside

Forecast	Actual	1	2	3	4	5	6	7	8	9	10	11	12	13	14
2005:Q1	300.0	299.1													
2005:Q2	312.9	327.1	326.6												
2005:Q3	325.5	362.9	358.8	330.3											
2005:Q4	342.0	409.7	396.8	352.0	338.3										
2006:Q1	354.1	464.9	444.5	375.5	356.5	366.1									
2006:Q2	357.7	538.0	501.0	402.7	377.7	393.6	377.7								
2006:Q3	361.3	629.1	571.9	433.6	402.9	420.9	397.1	374.5							
2006:Q4	**363.7**	753.2	661.0	469.2	430.5	448.8	416.4	385.1	369.3						
2007:Q1	359.7	916.0	774.8	511.7	463.1	480.2	436.9	394.2	**371.0**	**364.6**					
2007:Q2	354.9	1,148.4	925.3	560.1	500.0	512.0	459.6	402.5	371.0	358.4	**352.9**				
2007:Q3	341.4	1,471.3	1,123.3	620.4	543.3	549.2	483.5	411.7	370.3	351.7	346.6	**351.6**			
2007:Q4	322.3	1,961.6	1,397.7	689.0	593.3	587.2	511.4	419.8	370.1	345.0	340.0	345.2	**332.1**		
2008:Q1	292.6	2,689.1	1,775.8	777.3	651.6	632.6	540.0	429.3	369.0	338.7	333.1	338.2	324.6	**311.0**	
2008:Q2	253.7	**3,886.0**	**2,324.9**	**878.0**	**721.1**	**679.5**	**575.0**	**437.1**	369.1	332.2	326.4	330.7	318.2	303.9	**270.0**

Note: See Table 12.

Table 17: Recursive Forecasts of the Real Housing Price Index: San Diego

Forecast	Actual	1	2	3	4	5	6	7	8	9	10	11	12	13	14
2005:Q1	383.5	376.2													
2005:Q2	391.8	406.3	399.4												
2005:Q3	396.2	415.3	405.1	405.4											
2005:Q4	401.7	421.6	417.3	409.4	395.6										
2006:Q1	**402.1**	444.8	429.2	425.4	411.1	420.0									
2006:Q2	398.4	460.6	435.4	437.0	426.4	435.7	421.7								
2006:Q3	395.4	474.8	444.0	447.8	431.0	447.9	424.7	**396.5**							
2006:Q4	391.4	490.1	452.6	456.8	436.0	455.1	431.9	391.0	**391.1**						
2007:Q1	383.2	511.7	456.9	467.3	440.9	463.0	**435.4**	386.0	375.3	**377.7**					
2007:Q2	373.9	526.3	463.1	477.3	445.6	466.4	435.3	378.3	362.9	357.8	**363.0**				
2007:Q3	361.8	548.3	468.0	485.1	445.1	466.8	427.6	365.7	351.0	344.9	346.4	**363.1**			
2007:Q4	347.9	569.4	471.8	494.1	448.1	**466.9**	421.1	351.1	336.0	330.3	330.4	346.3	**342.8**		
2008:Q1	329.1	594.3	475.1	502.9	449.9	465.8	413.5	335.0	315.9	310.5	311.8	333.3	330.1	**335.4**	
2008:Q2	302.8	**617.4**	**478.4**	**513.2**	**451.5**	462.2	402.2	317.9	296.5	288.9	291.8	316.4	316.6	323.7	**308.0**

Note: See Table 12.

Table 18: Recursive Forecasts of the Real Housing Price Index: San Luis Obispo

Forecast	Actual	1	2	3	4	5	6	7	8	9	10	11	12	13	14
2005:Q1	359.1	355.5													
2005:Q2	367.8	368.6	377.1												
2005:Q3	381.2	375.8	384.1	372.3											
2005:Q4	391.0	377.4	**385.7**	**372.5**	386.5										
2006:Q1	**392.0**	**379.5**	382.7	367.4	389.3	401.1									
2006:Q2	386.4	375.9	380.8	358.8	**389.9**	409.4	400.8								
2006:Q3	379.7	373.3	374.4	351.4	388.2	**411.1**	**401.1**	**393.6**							
2006:Q4	374.0	365.8	369.7	340.5	386.7	408.1	397.5	392.0	**378.1**						
2007:Q1	367.4	359.3	360.5	332.0	383.1	406.4	391.3	386.1	373.2	**366.0**					
2007:Q2	359.0	349.1	353.8	319.6	379.8	399.8	386.1	377.6	365.2	356.5	**358.3**				
2007:Q3	351.9	339.8	342.6	310.7	374.2	395.7	378.3	370.3	355.8	347.1	353.6	**345.2**			
2007:Q4	345.2	328.0	334.3	297.4	369.1	386.4	372.2	360.3	347.7	338.5	348.7	330.9	**344.3**		
2008:Q1	329.8	316.4	321.7	288.3	361.6	381.1	363.1	352.7	337.9	330.4	344.0	317.5	340.0	**337.8**	
2008:Q2	319.0	303.9	312.1	274.2	354.9	369.8	356.6	341.8	330.4	322.8	339.5	305.7	336.9	332.7	**320.0**

Note: See Table 12.

Table 19: Recursive Forecasts of the Real Housing Price Index: Santa Ana

Forecast	Actual	1	2	3	4	5	6	7	8	9	10	11	12	13	14
2005:Q1	343.5	357.4													
2005:Q2	360.2	380.5	364.3												
2005:Q3	371.9	409.1	381.9	377.5											
2005:Q4	386.9	444.9	402.9	395.3	385.4										
2006:Q1	400.0	485.3	428.1	416.0	398.8	406.8									
2006:Q2	**403.0**	535.8	455.1	440.1	413.7	419.7	416.8								
2006:Q3	402.3	594.8	487.3	465.8	430.2	433.9	427.6	412.4							
2006:Q4	400.1	668.8	522.8	495.6	447.5	449.5	439.3	415.8	**406.1**						
2007:Q1	392.2	758.4	564.8	527.4	466.7	465.5	451.6	419.6	403.1	**396.7**					
2007:Q2	385.6	871.8	611.9	564.4	486.6	482.9	464.2	423.4	400.3	391.0	**384.8**				
2007:Q3	372.8	1,014.1	667.7	604.5	508.9	500.5	477.5	427.0	397.5	385.4	379.3	**379.6**			
2007:Q4	358.8	1,197.3	731.5	651.2	532.1	519.9	490.8	430.6	394.5	379.5	374.0	371.5	**361.2**		
2008:Q1	331.0	1,435.8	807.2	702.1	558.0	539.1	505.0	433.7	391.7	373.6	368.6	363.3	353.8	**345.4**	
2008:Q2	306.8	**1,750.2**	**895.6**	**761.7**	**585.2**	**560.4**	**518.8**	**437.0**	388.6	367.6	363.3	354.8	347.3	337.0	**307.6**

Note: See Table 12.

Table 20: Recursive Forecasts of the Real Housing Price Index: Santa Barbara

Forecast	Actual	1	2	3	4	5	6	7	8	9	10	11	12	13	14
2005:Q1	393.5	396.1													
2005:Q2	408.1	418.6	409.1												
2005:Q3	412.8	435.9	413.5	417.5											
2005:Q4	**427.8**	454.2	419.1	431.5	426.2										
2006:Q1	424.3	478.3	427.4	443.2	434.2	436.0									
2006:Q2	422.5	499.8	432.0	456.1	444.4	447.4	433.1								
2006:Q3	417.1	524.8	435.8	466.9	454.3	457.9	444.2	424.7							
2006:Q4	405.7	551.1	439.4	478.0	462.0	466.7	447.0	**424.8**	**412.5**						
2007:Q1	396.6	578.9	441.4	489.0	468.1	472.7	450.3	416.8	405.8	**398.1**					
2007:Q2	376.4	608.8	**442.0**	499.9	473.8	477.6	**450.8**	409.9	391.8	385.5	**383.5**				
2007:Q3	357.6	641.4	441.7	510.2	478.3	480.7	449.6	399.6	377.4	368.6	367.8	**364.3**			
2007:Q4	334.3	676.6	439.9	520.2	482.1	**482.2**	446.9	387.7	360.5	350.7	350.3	349.4	**342.9**		
2008:Q1	318.8	714.7	436.8	529.9	484.8	481.8	443.0	374.5	342.8	330.8	331.7	331.4	323.9	**318.8**	
2008:Q2	296.0	**756.1**	432.1	**539.1**	**486.5**	479.6	437.0	360.0	324.4	310.4	311.7	314.1	305.7	301.9	**295.8**

Note: See Table 12.

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

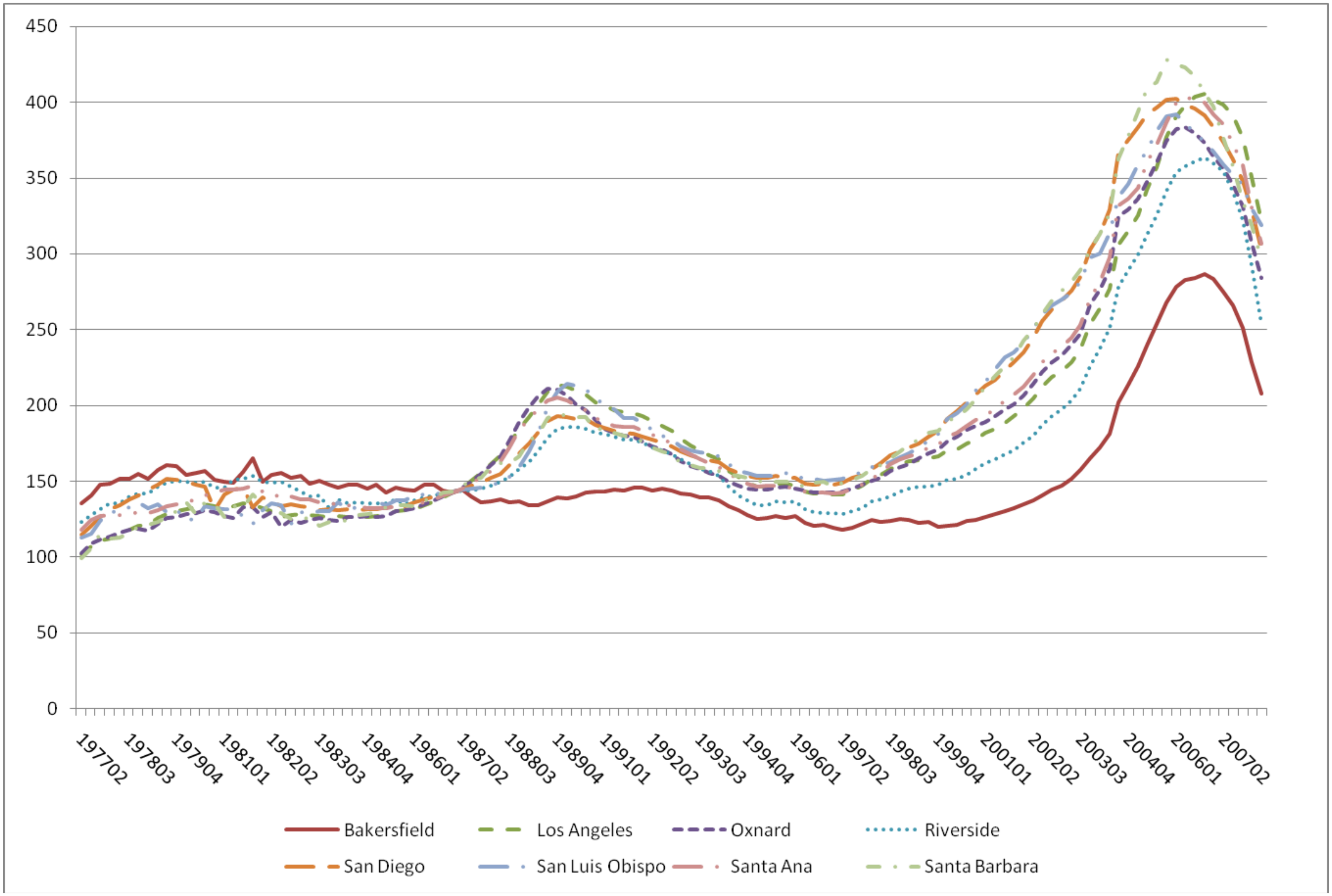

Figure 2: MSA Map: Bakersfield, Los Angeles, Oxnard, Riverside, San Luis Obispo, Santa Ana, and Santa Barbara