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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.

Journal of Economic Literature Classification: C32, R31

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1. 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 (Shiller2007), suggesting that the examination of the Southern California market may provide insights into other 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

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

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) provided some of the earliest tests of whether the housing market exhibited 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 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 that run-up and fall. The run-up and decline in the late 200s, 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

[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.

run-up and decline in the late 1980s and early 1990s and Riverside falls below the other six MSAs. But, in the late 2-000s, 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 thinking. Earlier, Case and Shiller (2003) a 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.

In sum, we argue that the run-up in house prices 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.

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

[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.

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 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.

We finally consider whether pure time-series models can predict the peak and decline of house prices in the Southern California market, no easy task. We do predict the decline in house prices generally one quarter before the actual peak in house prices and then we forecast declining prices in future forecast periods.

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.

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

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

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

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,

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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).

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]

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

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 (Estima 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 method imposes restrictions on the coefficients across different lag lengths, assuming that the coefficients of longer lags may approach more closely to

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[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.

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:

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

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, $\sigma^2_{\beta_i}$ 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 ($0 \leq k_{ij} \leq 1$), 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:

$$F = \begin{bmatrix} 1.0 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 1.0 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 1.0 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 1.0 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 1.0 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 1.0 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 1.0 & 0.5 \\ 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 1.0 \end{bmatrix}. \tag{5}$$

We order of the MSAs in matrix F and other matrices given below as follows: Bakersfield, Los Angeles, Oxnard, Riverside, San Diego, San Luis Obispo, Santa Ana, and Santa Barbara, an alphabetical order.

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

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 (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 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 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.

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.

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). 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. In sum, the weight matrix F in our application becomes as follows:

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

For example, in matrix F, Bakersfield and San Luis Obispo receive a weight of 1.0 (1^{st} row, 6^{th} column), because they share a common border (i.e., they are neighbors), while San Luis Obispo and San Diego receive a weight of 0.0 (5^{th} row, 6^{th} column) because they do not share a common border (i.e., they are not neighbors).

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

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

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).[8] They impose the condition that the first own-lagged variable proves twice as important as the other important variables.

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\begin{aligned}
&S_3(i,j,m) \sim N\left\{ 2/(c_i^{'}+1), \sigma_c \right\}; \;\; j \in C'; \quad m=1; \quad j=i \quad i,j=1,....,n; \\
&S_3(i,j,m) \sim N\left\{ 1/(c_i^{'}+1), \sigma_c \right\}; \;\; j \in C'; \quad m=1; \quad j \neq i \quad i,j=1,....,n; \\
&S_3(i,j,m) \sim N\left\{ 0, \eta \, \sigma_c/m \right\}; \qquad j \in C'; \quad m=2,....,p; \;\; i,j=1,....,n; \text{ and} \\
&S_3(i,j,m) \sim N\left\{ 0, \rho \, \sigma_c/m \right\}; \qquad j \neg \in C'; \;\; m=1,....,p; \quad i,j=1,....,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 $2/(c_i^{'}+1)$ and the first lags of the other important variables in each equation equal $1/(c_i^{'}+1)$. We also adopt the values for the hyperparameters used by Gupta and Miller (2009): $\sigma_c = 0.1, \eta = 8, \text{and } \rho = 0.5.$[9] Consequently, the weighting matrix becomes the following:

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

[8] 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.

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

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 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} [10] 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.

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

3. 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 one- to four-quarter-ahead out-of-sample forecasts. Finally, we examine the ability of the optimal forecasting models to detect the peak and decline in house prices 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. 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 six lags. 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 prices in Los Angeles temporally cause house 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 house prices temporally cause Los Angeles prices. In other words, each coastal MSA house price index temporally causes the Los Angeles index.[11]

The most isolated MSA in causality terms is Santa Barbara, where its house prices are temporally caused by Santa Ana’s house prices and house prices in Los Angeles and Oxnard temporally lead house price adjustments in Santa Barbara. The Oxnard MSA house prices respond to the most other MSA house prices – Bakersfield, Riverside, San Diego, San Luis

[11] 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.

Obispo, Santa Ana, and Santa Barbara. Further, the Santa Ana MSA house prices temporally lead the most other MSA house prices – Bakersfield, Los Angeles, Oxnard, Riverside, San Diego, and Santa Barbara.[12]

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

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

San Diego, and San Luis Obispo-Santa Barbara.[13] 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.[14] 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 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

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[13] 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.

[14] 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.

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. 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.[15] We calculate the root mean squared errors (RMSE)[16] 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

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

[16] 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.

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 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 House Price Peaks and Declines

Figure 1 illustrates that each housing market experienced a marked reversal of real house prices after the peaks in 2005 and 2006, depending on the MSA. That is, the house price peaked and then declined in the various MSAs. We exposed our optimal forecast models to the acid test – predicting the peaks and declines in house prices. 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 21. Table 13 reports the one-quarter ahead forecasts and actual data. Figures 3 to 10 illustrate these data. Tables 14 to 21 report the forecasts through the end of the sample in 2008:Q2 for each recursive forecasting models.

For the one-quarter-ahead recursive forecasts, the various models perform well when forecasting the peak and decline in house prices in each MSA. That is, overall the performance exceeds our prior expectations. 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 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.

Third, 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.

Finally, Figures 3 to 10 confirm the above results. The Figures, however, do show that the one-quarter-ahead recursive forecasts generally over-predict the actual data series shortly before the peak and then through the decline in the house price indexes.When we consider the forecasts through the end of the sample in 2008:Q2, the various models perform at different levels when forecasting the peak and decline in house prices in each MSA – some good and others not so good. Overall, however, the performance exceeds our prior expectations. First, Bakersfield, Los Angeles, Riverside, and San Diego all predict the peak and decline in house prices once we include data up to but not including the actual peak in the house price. In addition, San Diego also predicted a peak and decline of the house price after including the actual peak price. The other three MSAs each predict a falling house 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 house 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 house prices provides the best performance. The first forecast effort that begins by predicting the 2005:Q1 house price predicts a peak price in 2006:Q1, when the actual house 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 house price.

Fourth, the forecasting models for Oxnard perform the worst of all the MSAs. Although the house price actually peaks in 2006:Q2, the forecasting models continue to predict rising house 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 house price in 2007:Q2, using data to construct the model that ends in 2005:Q1. The actual peak in the house price occurs in 2005:Q4. The next two forecasts, however, predict declining house prices through the end of the sample. Then the fourth, fifth, and sixth forecasting models predict the peaks and declines in house prices. The eighth and all remaining forecast predict monotonically declining house prices through the end of the sample.

4. 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 prices that occurred in 2005 and 2006.

Los Angeles house prices temporally cause house 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 house prices temporally cause Los Angeles prices. In other words, each coastal MSA house price index temporally causes the Los Angeles index. Santa Barbara proved the most isolated MSA in causality terms. The Oxnard MSA house prices respond to the most other MSA house prices and the Santa Ana MSA house prices temporally lead the most other MSA house 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 house 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 the peaks and declines in house prices proves a difficult task. When we estimate our model using data through 2004:Q4, forecasts generally continue to predict a rising trend in house 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 the peaks in house prices generally one quarter before the actual peak in the house 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	1473.6	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*

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). See Estima (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

Note: 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
** 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 house prices do not significantly affect house prices in the Bakersfield MSA at the 5- and 10-percent levels. See Estima (2007, p. 350).

* 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	0.081	0.126	0.241	0.346	0.199
	VEC	0.081	0.191	0.358	0.539	0.292
w=0.3, d=0.5	**BVAR**	0.066	0.108	0.215	0.277	0.167
	BVEC	0.072	0.130	0.232	0.325	0.190
	Causality BVAR	0.054	0.123	0.257	0.289	0.181
	Spatial BVAR	0.041	0.079	0.182	0.245	0.137
	Causality BVEC	0.071	0.121	0.228	0.312	0.183
	Spatial BVEC	0.047	0.091	0.187	0.253	0.145
w=0.2, d=1	**BVAR**	0.040	0.078	0.173	0.187	0.119
	BVEC	0.052	0.089	0.157	0.205	0.126
	Causality BVAR	0.047	0.092	0.201	0.225	0.141
	Spatial BVAR	0.047	0.087	0.188	0.248	0.142
	Causality BVEC	0.069	0.095	0.165	0.210	0.134
	Spatial BVEC	0.044	0.101	0.179	0.239	0.141
w=0.1, d=1	**BVAR**	**0.035**	0.049	0.127	0.119	0.083
	BVEC	0.040	0.070	0.113	0.146	0.092
	Causality BVAR	0.037	0.069	0.141	0.160	0.102
	Spatial BVAR	0.054	0.087	0.154	0.198	0.123
	Causality BVEC	0.060	0.062	0.078	0.096	0.074
	Spatial BVEC	0.048	0.091	0.134	0.180	0.113
w=0.2, d=2	**BVAR**	0.045	**0.044**	0.098	0.107	0.073
	BVEC	0.038	0.084	0.140	0.185	0.112
	Causality BVAR	0.037	0.057	0.102	0.108	0.076
	Spatial BVAR	0.063	0.094	0.158	0.190	0.126
	Causality BVEC	0.049	0.059	0.092	0.117	0.079
	Spatial BVEC	0.046	0.091	0.145	0.181	0.116
w=0.1, d=2	**BVAR**	0.061	0.064	**0.067**	0.092	0.071
	BVEC	0.039	0.073	0.125	0.166	0.101
	Causality BVAR	0.046	0.074	0.082	**0.089**	0.073
	Spatial BVAR	0.065	0.085	0.106	0.145	0.100
	Causality BVEC	0.041	0.057	0.081	0.102	**0.070**
	Spatial BVEC	0.057	0.086	0.124	0.158	0.106
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.088	0.085	0.147	0.172	0.123
	RBVAR Causality2	0.083	0.089	0.151	0.176	0.125
	RBVAR Spatial1	0.077	0.088	0.184	0.179	0.132
	RBVAR Spatial2	0.084	0.083	0.170	0.182	0.130
	RBVEC Causality1	0.071	0.254	0.184	0.183	0.173
	RBVEC Causality2	0.071	0.254	0.184	0.183	0.173
	RBVEC Spatial1	0.081	0.291	0.323	0.235	0.232
	RBVEC Spatial2	0.079	0.277	0.270	0.211	0.209

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	0.055	0.058	0.143	0.089	0.086
	VEC	0.016	0.029	0.171	0.179	0.099
w=0.3, d=0.5	**BVAR**	0.066	0.047	0.168	0.105	0.097
	BVEC	0.024	0.079	0.253	0.289	0.161
	Causality BVAR	0.044	0.134	0.363	0.323	0.216
	Spatial BVAR	0.061	0.009	0.153	0.194	0.105
	Causality BVEC	0.031	0.139	0.344	0.457	0.243
	Spatial BVEC	**0.010**	**0.003**	0.110	0.106	0.057
w=0.2, d=1	**BVAR**	0.069	0.041	0.211	0.190	0.128
	BVEC	0.038	0.080	0.245	0.273	0.159
	Causality BVAR	0.048	0.098	0.309	0.295	0.187
	Spatial BVAR	0.116	0.035	0.174	0.222	0.137
	Causality BVEC	0.037	0.123	0.303	0.381	0.211
	Spatial BVEC	0.053	0.046	0.045	0.030	**0.043**
w=0.1, d=1	**BVAR**	0.090	0.014	0.145	0.127	0.094
	BVEC	0.053	0.050	0.175	0.172	0.113
	Causality BVAR	0.080	0.024	0.206	0.193	0.126
	Spatial BVAR	0.142	0.089	0.096	0.107	0.109
	Causality BVEC	0.049	0.076	0.188	0.177	0.122
	Spatial BVEC	0.106	0.076	**0.002**	0.028	0.053
w=0.2, d=2	**BVAR**	0.093	0.054	0.078	0.047	0.068
	BVEC	0.046	0.058	0.214	0.226	0.136
	Causality BVAR	0.103	0.045	0.097	0.061	0.076
	Spatial BVAR	0.154	0.119	0.054	0.061	0.097
	Causality BVEC	0.032	0.096	0.237	0.244	0.152
	Spatial BVEC	0.099	0.063	0.038	0.011	0.053
w=0.1, d=2	**BVAR**	0.137	0.141	0.056	0.127	0.115
	BVEC	0.058	0.030	0.159	0.153	0.100
	Causality BVAR	0.165	0.161	0.074	0.153	0.138
	Spatial BVAR	0.166	0.173	0.050	0.083	0.118
	Causality BVEC	0.050	0.028	0.108	0.050	0.059
	Spatial BVEC	0.118	0.068	0.034	0.010	0.058
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.096	0.063	0.254	0.248	0.165
	RBVAR Causality2	0.081	0.072	0.260	0.261	0.169
	RBVAR Spatial1	0.169	0.010	0.155	0.158	0.123
	RBVAR Spatial2	0.155	0.008	0.154	0.156	0.118
	RBVEC Causality1	0.073	0.304	0.019	0.079	0.119
	RBVEC Causality2	0.073	0.304	0.019	0.079	0.119
	RBVEC Spatial1	0.121	0.168	0.061	**0.002**	0.088
	RBVEC Spatial2	0.118	0.206	0.105	0.042	0.118

Note: See Table 4.

Table 6: Forecast Results for Los Angeles

Parameterization	Models	RMSEs 1	2	3	4	Average
	VAR	0.082	0.327	0.656	0.929	0.498
	VEC	0.091	0.282	0.598	0.939	0.477
w=0.3, d=0.5	**BVAR**	0.065	0.272	0.537	0.734	0.402
	BVEC	0.085	0.210	0.423	0.610	0.332
	Causality BVAR	0.072	0.256	0.470	0.603	0.350
	Spatial BVAR	0.028	0.149	0.322	0.418	0.229
	Causality BVEC	0.098	0.167	0.293	0.374	0.233
	Spatial BVEC	0.038	0.069	0.132	0.109	0.087
w=0.2, d=1	**BVAR**	0.029	0.169	0.348	0.428	0.244
	BVEC	0.068	0.143	0.287	0.382	0.220
	Causality BVAR	0.050	0.191	0.365	0.439	0.261
	Spatial BVAR	0.021	0.052	0.163	0.184	0.105
	Causality BVEC	0.091	0.134	0.232	0.270	0.182
	Spatial BVEC	0.019	0.034	0.081	0.047	0.045
w=0.1, d=1	**BVAR**	0.003	0.092	0.213	0.221	0.132
	BVEC	0.040	0.062	0.146	0.165	0.103
	Causality BVAR	0.035	0.147	0.297	0.344	0.206
	Spatial BVAR	0.046	**0.000**	0.080	0.057	0.046
	Causality BVEC	0.067	0.083	0.155	0.162	0.117
	Spatial BVEC	**0.001**	0.006	0.048	0.018	0.018
w=0.2, d=2	**BVAR**	0.016	0.048	0.138	0.111	0.078
	BVEC	0.038	0.068	0.164	0.196	0.116
	Causality BVAR	0.010	0.099	0.226	0.243	0.144
	Spatial BVAR	0.053	0.010	0.064	0.025	0.038
	Causality BVEC	0.058	0.082	0.166	0.183	0.122
	Spatial BVEC	0.003	0.015	0.070	0.055	0.036
w=0.1, d=2	**BVAR**	0.042	0.021	0.021	0.056	0.035
	BVEC	0.013	0.016	0.080	0.074	0.046
	Causality BVAR	0.002	0.064	0.168	0.161	0.099
	Spatial BVAR	0.059	0.038	**0.007**	0.068	0.043
	Causality BVEC	0.032	0.039	0.107	0.108	0.072
	Spatial BVEC	0.018	0.022	0.018	**0.015**	**0.018**
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.110	0.097	0.210	0.262	0.170
	RBVAR Causality2	0.090	0.113	0.234	0.282	0.180
	RBVAR Spatial1	0.146	0.069	0.185	0.273	0.168
	RBVAR Spatial2	0.133	0.066	0.180	0.251	0.157
	RBVEC Causality1	0.002	0.215	0.189	0.123	0.132
	RBVEC Causality2	0.002	0.215	0.189	0.123	0.132
	RBVEC Spatial1	0.027	0.355	0.206	0.075	0.166
	RBVEC Spatial2	0.026	0.380	0.196	0.092	0.173

Note: See Table 4.

Table 7: Forecast Results for Oxnard

Parameterization	Models	RMSEs 1	2	3	4	Average
	VAR	0.115	0.253	0.507	0.762	0.409
	VEC	0.126	0.216	0.558	1.026	0.481
w=0.3, d=0.5	**BVAR**	0.069	0.185	0.377	0.549	0.295
	BVEC	0.098	0.096	0.258	0.445	0.224
	Causality BVAR	0.025	0.106	0.294	0.372	0.200
	Spatial BVAR	0.052	0.075	0.118	0.135	0.095
	Causality BVEC	0.032	0.109	0.279	0.451	0.218
	Spatial BVEC	0.065	0.129	0.236	0.390	0.205
w=0.2, d=1	**BVAR**	0.008	0.074	0.172	0.214	0.117
	BVEC	0.039	0.024	0.030	0.069	0.040
	Causality BVAR	0.044	0.039	0.161	0.202	0.112
	Spatial BVAR	0.027	0.075	0.110	0.192	0.101
	Causality BVEC	0.021	0.057	0.152	0.222	0.113
	Spatial BVEC	0.021	0.180	0.278	0.416	0.224
w=0.1, d=1	**BVAR**	0.018	**0.005**	0.038	**0.006**	0.016
	BVEC	**0.006**	0.106	0.115	0.153	0.095
	Causality BVAR	0.073	0.055	0.015	0.030	0.043
	Spatial BVAR	0.049	0.122	0.174	0.283	0.157
	Causality BVEC	0.011	0.017	**0.002**	0.010	**0.010**
	Spatial BVEC	0.026	0.196	0.260	0.354	0.209
w=0.2, d=2	**BVAR**	0.021	0.032	0.007	0.070	0.032
	BVEC	0.019	0.128	0.135	0.175	0.114
	Causality BVAR	0.049	0.039	0.003	0.035	0.032
	Spatial BVAR	0.068	0.147	0.187	0.299	0.175
	Causality BVEC	0.009	0.034	0.024	0.045	0.028
	Spatial BVEC	0.038	0.199	0.258	0.353	0.212
w=0.1, d=2	**BVAR**	0.061	0.123	0.140	0.245	0.142
	BVEC	0.031	0.152	0.178	0.246	0.152
	Causality BVAR	0.093	0.144	0.152	0.227	0.154
	Spatial BVAR	0.067	0.149	0.185	0.309	0.177
	Causality BVEC	0.009	0.099	0.115	0.153	0.094
	Spatial BVEC	0.064	0.214	0.267	0.361	0.226
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.182	0.035	0.020	0.031	0.067
	RBVAR Causality2	0.184	0.038	0.017	0.016	0.064
	RBVAR Spatial1	0.133	0.077	0.119	0.042	0.093
	RBVAR Spatial2	0.158	0.092	0.146	0.085	0.120
	RBVEC Causality1	0.082	0.152	0.355	0.247	0.209
	RBVEC Causality2	0.082	0.152	0.355	0.247	0.209
	RBVEC Spatial1	0.051	0.266	0.658	0.683	0.415
	RBVEC Spatial2	0.071	0.245	0.634	0.523	0.368

Note: See Table 4.

Table 8: Forecast Results for Riverside

Parameterization	Models	RMSEs 1	2	3	4	Average
	VAR	0.048	0.015	0.152	0.192	0.102
	VEC	0.026	0.158	0.098	0.155	0.109
w=0.3, d=0.5	**BVAR**	0.041	0.023	0.163	0.181	0.102
	BVEC	0.023	0.105	0.024	0.002	**0.039**
	Causality BVAR	0.023	0.125	0.336	0.359	0.211
	Spatial BVAR	**0.001**	0.113	0.322	0.426	0.216
	Causality BVEC	0.064	0.071	0.124	0.164	0.106
	Spatial BVEC	0.011	0.005	0.167	0.200	0.096
w=0.2, d=1	**BVAR**	0.021	0.071	0.248	0.286	0.156
	BVEC	0.026	0.073	0.066	0.055	0.055
	Causality BVAR	0.046	0.071	0.256	0.286	0.165
	Spatial BVAR	0.025	0.150	0.377	0.505	0.264
	Causality BVEC	0.077	0.086	0.080	0.097	0.085
	Spatial BVEC	0.003	0.003	0.158	0.186	0.087
w=0.1, d=1	**BVAR**	0.029	0.059	0.229	0.259	0.144
	BVEC	0.035	0.062	0.069	0.057	0.056
	Causality BVAR	0.044	0.047	0.214	0.235	0.135
	Spatial BVAR	0.008	0.113	0.304	0.373	0.200
	Causality BVEC	0.082	0.106	0.015	0.012	0.054
	Spatial BVEC	0.010	0.026	0.115	0.125	0.069
w=0.2, d=2	**BVAR**	0.064	0.007	0.159	0.177	0.102
	BVEC	0.027	0.050	0.069	0.062	0.052
	Causality BVAR	0.070	0.001	0.142	0.150	0.091
	Spatial BVAR	0.023	0.074	0.258	0.315	0.167
	Causality BVEC	0.069	0.081	0.046	0.034	0.058
	Spatial BVEC	0.007	0.025	0.104	0.112	0.062
w=0.1, d=2	**BVAR**	0.098	0.073	0.025	0.013	0.052
	BVEC	0.047	0.057	0.058	0.050	0.053
	Causality BVAR	0.072	0.030	0.077	0.038	0.054
	Spatial BVAR	0.064	**0.000**	0.134	0.132	0.083
	Causality BVEC	0.079	0.103	**0.014**	0.058	0.063
	Spatial BVEC	0.028	0.042	0.078	0.083	0.058
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.110	0.047	0.244	0.261	0.166
	RBVAR Causality2	0.100	0.063	0.252	0.268	0.171
	RBVAR Spatial1	0.018	0.185	0.391	0.439	0.258
	RBVAR Spatial2	0.009	0.198	0.403	0.439	0.262
	RBVEC Causality1	0.169	0.404	0.199	0.015	0.197
	RBVEC Causality2	0.169	0.404	0.199	0.015	0.197
	RBVEC Spatial1	0.132	0.359	0.134	**0.001**	0.156
	RBVEC Spatial2	0.134	0.370	0.164	0.051	0.180

Note: See Table 4.

Table 9: Forecast Results for San Diego

Parameterization	Models	RMSEs 1	2	3	4	Average
	VAR	0.009	0.005	0.004	0.030	**0.012**
	VEC	0.032	0.292	0.538	0.931	0.448
w=0.3, d=0.5	**BVAR**	0.012	0.024	0.036	0.094	0.042
	BVEC	0.027	0.198	0.328	0.576	0.282
	Causality BVAR	0.036	0.120	0.074	0.050	0.070
	Spatial BVAR	0.039	0.046	0.013	0.024	0.031
	Causality BVEC	0.035	0.056	0.177	0.412	0.170
	Spatial BVEC	0.011	0.188	0.208	0.202	0.152
w=0.2, d=1	**BVAR**	**0.000**	0.032	0.049	**0.005**	0.022
	BVEC	0.007	0.130	0.174	0.295	0.151
	Causality BVAR	0.034	0.120	0.116	0.104	0.093
	Spatial BVAR	0.046	0.023	0.032	0.033	0.033
	Causality BVEC	0.041	0.020	0.101	0.259	0.105
	Spatial BVEC	0.030	0.171	0.164	0.129	0.124
w=0.1, d=1	**BVAR**	0.002	0.040	0.077	0.022	0.035
	BVEC	0.016	0.044	0.028	0.061	0.037
	Causality BVAR	0.013	0.086	0.115	0.098	0.078
	Spatial BVAR	0.053	0.049	0.024	0.075	0.050
	Causality BVEC	0.048	0.024	0.003	0.087	0.041
	Spatial BVEC	0.020	0.082	0.038	0.015	0.039
w=0.2, d=2	**BVAR**	0.013	0.032	0.084	0.044	0.043
	BVEC	0.019	0.102	0.095	0.134	0.087
	Causality BVAR	0.002	0.078	0.129	0.116	0.081
	Spatial BVAR	0.041	**0.002**	0.074	0.058	0.044
	Causality BVEC	0.030	0.005	**0.003**	0.077	0.029
	Spatial BVEC	0.034	0.110	0.081	0.055	0.070
w=0.1, d=2	**BVAR**	0.029	0.010	0.020	0.046	0.026
	BVEC	0.013	0.059	0.030	0.041	0.036
	Causality BVAR	0.028	0.025	0.062	0.007	0.030
	Spatial BVAR	0.045	0.027	0.012	0.044	0.032
	Causality BVEC	0.031	0.020	0.029	0.015	0.024
	Spatial BVEC	0.022	0.045	0.011	0.049	0.032
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.007	0.108	0.112	0.108	0.084
	RBVAR Causality2	0.006	0.098	0.102	0.092	0.074
	RBVAR Spatial1	0.053	0.057	0.128	0.091	0.082
	RBVAR Spatial2	0.093	0.015	0.031	0.024	0.041
	RBVEC Causality1	0.011	0.220	0.398	0.096	0.181
	RBVEC Causality2	0.011	0.220	0.398	0.096	0.181
	RBVEC Spatial1	0.069	0.479	0.297	0.095	0.235
	RBVEC Spatial2	0.045	0.316	0.263	0.176	0.200

Note: See Table 4.

Table 10: Forecast Results for San Luis Obispo

Parameterization	Models	RMSEs 1	2	3	4	Average
	VAR	0.194	0.126	0.050	0.120	0.122
	VEC	0.165	0.263	0.419	0.468	0.329
w=0.3, d=0.5	**BVAR**	0.156	0.127	0.086	0.035	0.101
	BVEC	0.133	0.119	0.205	0.225	0.171
	Causality BVAR	0.127	0.113	0.270	0.268	0.195
	Spatial BVAR	0.038	0.070	0.166	0.276	0.137
	Causality BVEC	0.134	0.215	0.350	0.388	0.272
	Spatial BVEC	0.052	0.075	0.039	0.057	0.056
w=0.2, d=1	**BVAR**	0.083	0.074	0.061	**0.000**	0.054
	BVEC	0.070	0.033	0.080	0.077	0.065
	Causality BVAR	0.067	0.045	0.136	0.132	0.095
	Spatial BVAR	0.016	0.122	0.180	0.224	0.136
	Causality BVEC	0.113	0.144	0.214	0.221	0.173
	Spatial BVEC	0.031	0.068	0.034	0.073	0.051
w=0.1, d=1	**BVAR**	0.051	0.036	0.036	0.001	0.031
	BVEC	0.014	0.029	0.012	0.034	0.022
	Causality BVAR	0.015	0.006	0.053	0.087	0.040
	Spatial BVAR	0.026	0.116	0.142	0.157	0.111
	Causality BVEC	0.066	0.046	0.079	0.085	0.069
	Spatial BVEC	0.021	0.031	**0.001**	0.033	0.022
w=0.2, d=2	**BVAR**	0.050	0.006	0.010	0.065	0.033
	BVEC	0.005	0.033	0.012	0.041	0.023
	Causality BVAR	0.007	0.045	0.039	0.063	0.038
	Spatial BVAR	0.031	0.131	0.158	0.189	0.127
	Causality BVEC	0.042	0.010	0.030	0.029	0.028
	Spatial BVEC	0.013	0.019	0.015	0.015	**0.016**
w=0.1, d=2	**BVAR**	0.055	0.036	0.049	0.018	0.040
	BVEC	0.006	0.061	0.068	0.117	0.063
	Causality BVAR	0.005	0.025	0.032	0.075	0.034
	Spatial BVAR	0.031	0.117	0.136	0.170	0.113
	Causality BVEC	**0.001**	0.054	0.043	0.056	0.039
	Spatial BVEC	0.017	**0.006**	0.036	0.008	0.017
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.024	0.011	0.018	0.118	0.043
	RBVAR Causality2	0.033	0.013	0.013	0.109	0.042
	RBVAR Spatial1	0.015	0.085	0.102	0.000	0.051
	RBVAR Spatial2	0.022	0.057	0.061	0.043	0.046
	RBVEC Causality1	0.010	0.185	0.049	0.336	0.145
	RBVEC Causality2	0.010	0.185	0.049	0.336	0.145
	RBVEC Spatial1	0.026	0.025	0.612	0.269	0.233
	RBVEC Spatial2	0.006	0.042	0.425	0.099	0.143

Note: See Table 4.

Table 11: Forecast Results for Santa Ana

Parameterization	Models	RMSEs 1	2	3	4	Average
	VAR	0.017	0.151	0.285	0.448	0.226
	VEC	0.033	0.127	0.237	0.409	0.202
w=0.3, d=0.5	**BVAR**	0.006	0.129	0.236	0.344	0.179
	BVEC	0.029	0.094	0.122	0.168	0.103
	Causality BVAR	0.006	0.130	0.234	0.315	0.171
	Spatial BVAR	0.025	0.155	0.259	0.342	0.195
	Causality BVEC	0.032	0.115	0.128	0.171	0.112
	Spatial BVEC	0.040	0.128	0.183	0.230	0.145
w=0.2, d=1	**BVAR**	0.004	0.112	0.178	0.217	0.128
	BVEC	0.017	0.061	0.048	0.039	0.041
	Causality BVAR	0.015	0.138	0.239	0.313	0.176
	Spatial BVAR	0.037	0.172	0.280	0.345	0.208
	Causality BVEC	0.026	0.089	0.076	0.074	0.066
	Spatial BVEC	0.032	0.123	0.178	0.224	0.139
w=0.1, d=1	**BVAR**	0.007	0.098	0.141	0.141	0.097
	BVEC	0.012	0.037	0.004	0.030	**0.021**
	Causality BVAR	0.007	0.107	0.177	0.216	0.127
	Spatial BVAR	0.040	0.160	0.240	0.269	0.177
	Causality BVEC	0.018	0.054	0.013	0.024	0.027
	Spatial BVEC	0.020	0.094	0.118	0.137	0.092
w=0.2, d=2	**BVAR**	0.018	0.108	0.143	0.124	0.098
	BVEC	0.010	0.028	**0.003**	0.043	0.021
	Causality BVAR	0.018	0.115	0.170	0.178	0.120
	Spatial BVAR	0.036	0.139	0.193	0.190	0.140
	Causality BVEC	0.018	0.047	0.010	0.032	0.026
	Spatial BVEC	0.015	0.077	0.095	0.102	0.072
w=0.1, d=2	**BVAR**	**0.003**	0.063	0.061	**0.001**	0.032
	BVEC	0.009	**0.018**	0.021	0.072	0.030
	Causality BVAR	0.004	0.054	0.061	0.022	0.035
	Spatial BVAR	0.030	0.110	0.126	0.078	0.086
	Causality BVEC	0.015	0.023	0.025	0.077	0.035
	Spatial BVEC	0.014	0.055	0.052	0.034	0.039
σ_c=0.1, η=8, θ=0.5	**RBVAR Causality1**	0.066	0.055	0.100	0.142	0.091
	RBVAR Causality2	0.065	0.048	0.094	0.138	0.086
	RBVAR Spatial1	0.007	0.154	0.220	0.269	0.163
	RBVAR Spatial2	0.008	0.140	0.202	0.250	0.150
	RBVEC Causality1	0.006	0.301	0.200	0.129	0.159
	RBVEC Causality2	0.006	0.301	0.200	0.129	0.159
	RBVEC Spatial1	0.020	0.272	0.377	0.201	0.218
	RBVEC Spatial2	0.014	0.302	0.359	0.158	0.208

Note: See Table 4.

Table 12: Forecast Results for Santa Barbara

Parameterization	Models	RMSEs 1	2	3	4	Average
	VAR	0.128	0.074	0.128	0.201	0.133
	VEC	0.156	0.164	0.247	0.202	0.192
w=0.3, d=0.5	**BVAR**	0.112	0.058	0.117	0.174	0.115
	BVEC	0.154	0.140	0.242	0.287	0.206
	Causality BVAR	0.099	**0.001**	0.012	0.020	0.033
	Spatial BVAR	0.082	0.018	0.099	0.147	0.086
	Causality BVEC	0.145	0.095	0.132	0.081	0.113
	Spatial BVEC	0.153	0.132	0.417	0.730	0.358
w=0.2, d=1	**BVAR**	0.101	0.054	0.121	0.153	0.107
	BVEC	0.152	0.167	0.329	0.447	0.274
	Causality BVAR	0.068	0.036	0.027	0.027	0.039
	Spatial BVAR	0.089	0.064	0.186	0.277	0.154
	Causality BVEC	0.142	0.103	0.160	0.154	0.140
	Spatial BVEC	0.163	0.183	0.494	0.808	0.412
w=0.1, d=1	**BVAR**	0.084	0.050	0.136	0.175	0.111
	BVEC	0.148	0.171	0.354	0.495	0.292
	Causality BVAR	0.028	0.080	0.053	0.076	0.059
	Spatial BVAR	0.068	0.049	0.172	0.259	0.137
	Causality BVEC	0.135	0.088	0.166	0.208	0.149
	Spatial BVEC	0.180	0.213	0.489	0.730	0.403
w=0.2, d=2	**BVAR**	0.085	0.067	0.166	0.216	0.133
	BVEC	0.143	0.206	0.432	0.606	0.347
	Causality BVAR	0.040	0.037	**0.011**	**0.018**	**0.026**
	Spatial BVAR	0.097	0.126	0.278	0.382	0.221
	Causality BVEC	0.132	0.114	0.222	0.293	0.190
	Spatial BVEC	0.161	0.220	0.498	0.744	0.406
w=0.1, d=2	**BVAR**	0.059	0.048	0.164	0.232	0.126
	BVEC	0.135	0.190	0.407	0.576	0.327
	Causality BVAR	**0.002**	0.084	0.034	0.030	0.037
	Spatial BVAR	0.059	0.065	0.197	0.276	0.149
	Causality BVEC	0.113	0.087	0.209	0.297	0.176
	Spatial BVEC	0.176	0.238	0.497	0.707	0.405
sigma=0.1, tau=8, theta=0.5	**RBVAR Causality1**	0.110	0.262	0.216	0.210	0.199
	RBVAR Causality2	0.103	0.271	0.232	0.239	0.211
	RBVAR Spatial1	0.079	0.066	0.168	0.163	0.119
	RBVAR Spatial2	0.091	0.086	0.186	0.209	0.143
	RBVEC Causality1	0.218	0.253	0.064	0.439	0.243
	RBVEC Causality2	0.218	0.253	0.064	0.439	0.243
	RBVEC Spatial1	0.202	0.404	0.241	0.552	0.349
	RBVEC Spatial2	0.220	0.352	0.017	0.547	0.284

Note: See Table 4.

Table 13: 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

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

Table 14: Recursive Forecasts of the Real House 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 15: Recursive Forecasts of the Real House 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 16: Recursive Forecasts of the Real House 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 17: Recursive Forecasts of the Real House 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 18: Recursive Forecasts of the Real House 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 19: Recursive Forecasts of the Real House 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 20: Recursive Forecasts of the Real House 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 21: Recursive Forecasts of the Real House 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: **House Price Indexes: Bakersfield, Los Angeles, Oxnard, Riverside, San Luis Obispo, Santa Ana, and Santa Barbara**

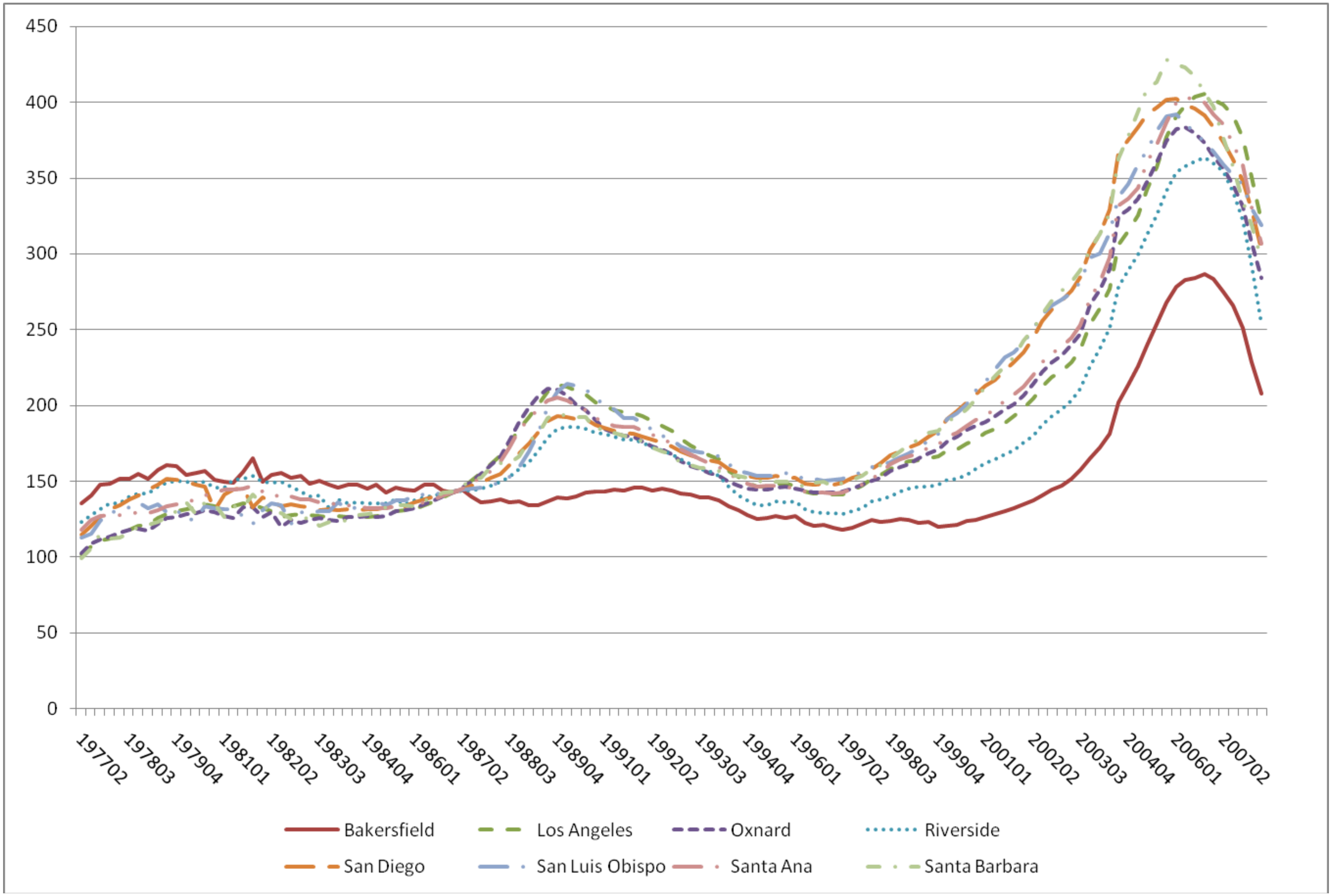

Figure 2: **MSA Map: Bakersfield, Los Angeles, Oxnard, Riverside, San Luis Obispo, Santa Ana, and Santa Barbara**

Figure 3: Recursive Forecasts for Bakersfield: 2005:Q1 to 2008:Q2

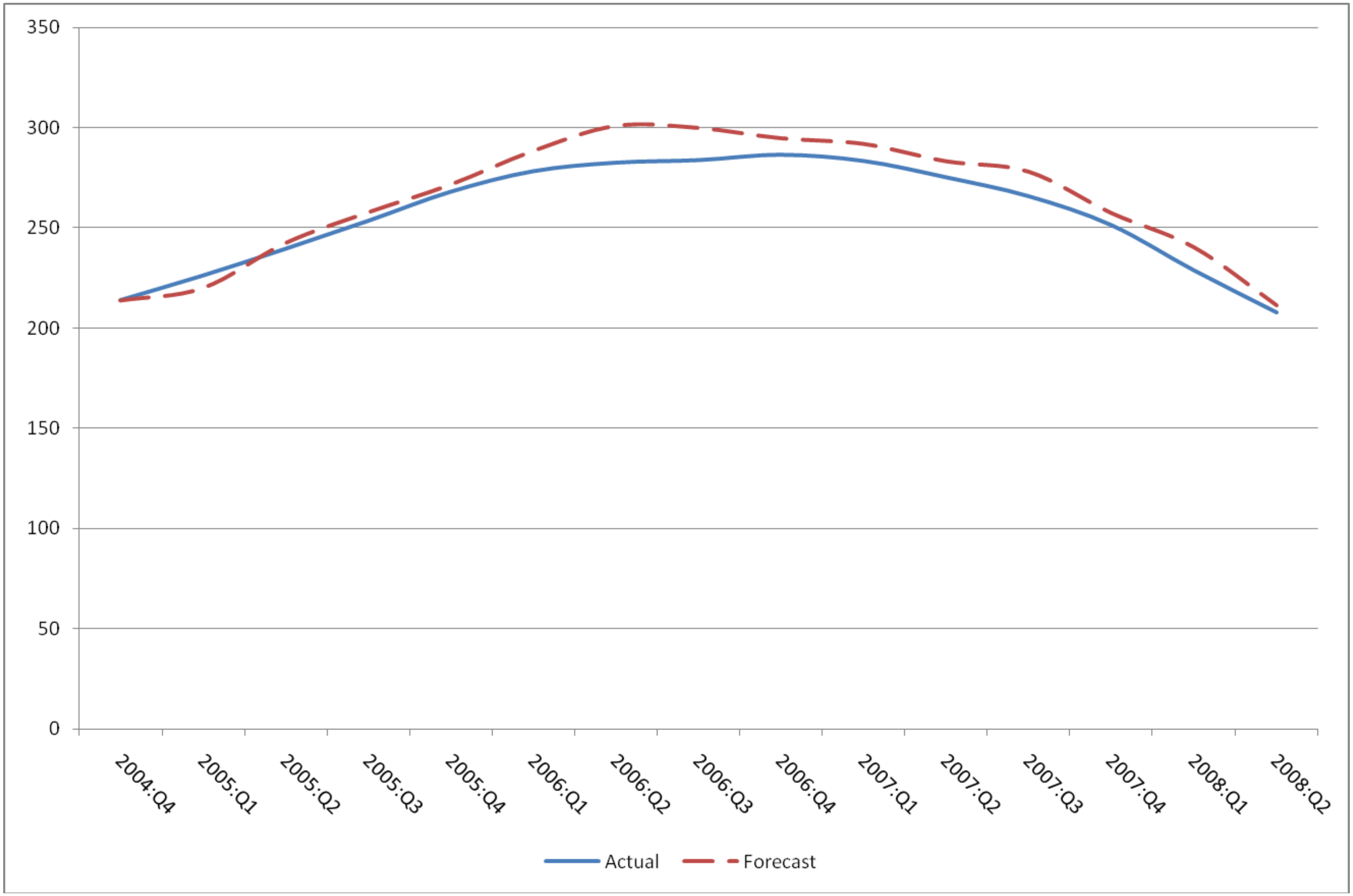

Figure 4: Recursive Forecasts for Los Angeles: 2005:Q1 to 2008:Q2

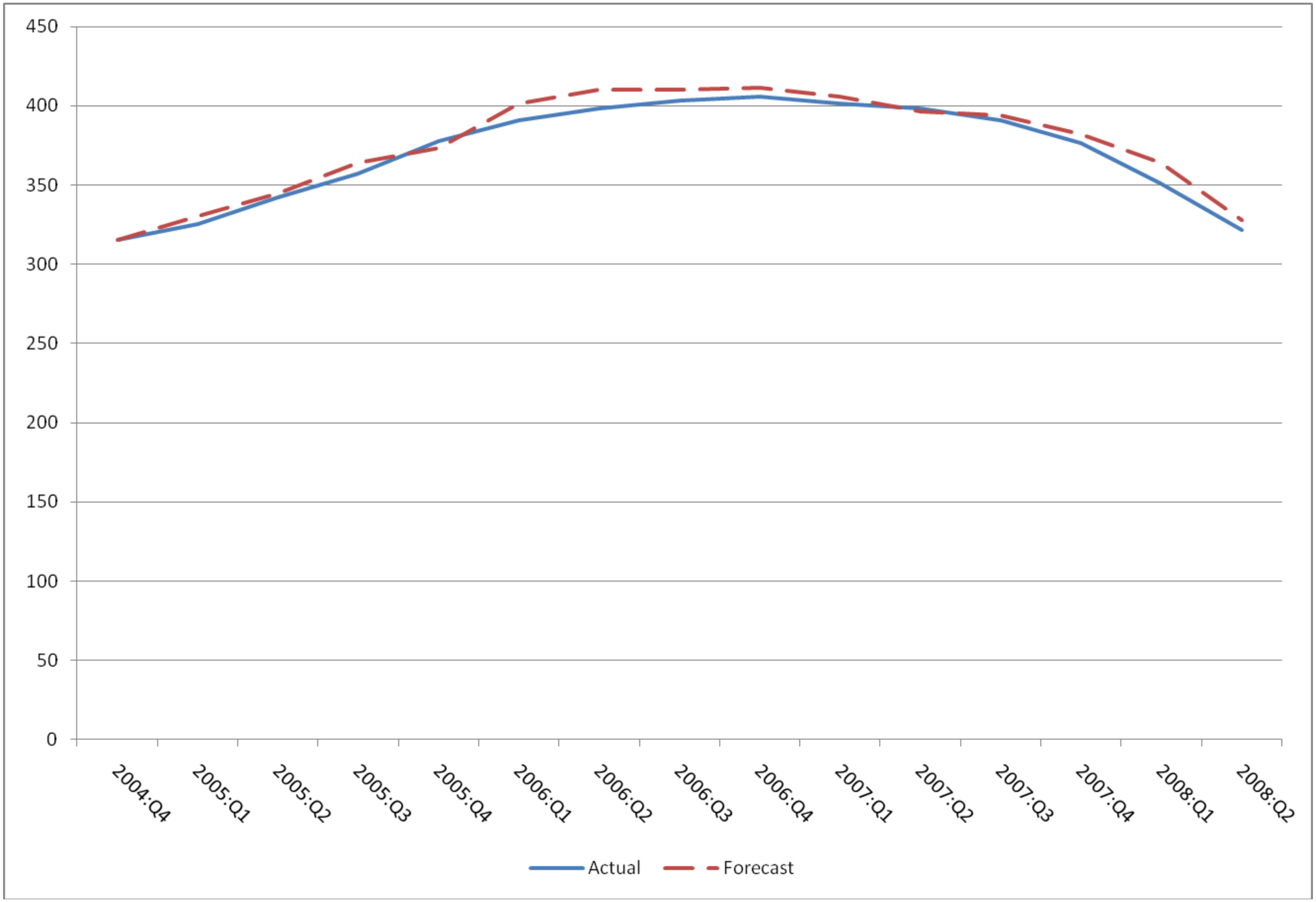

Figure 5: Recursive Forecasts for Oxnard: 2005:Q1 to 2008:Q2

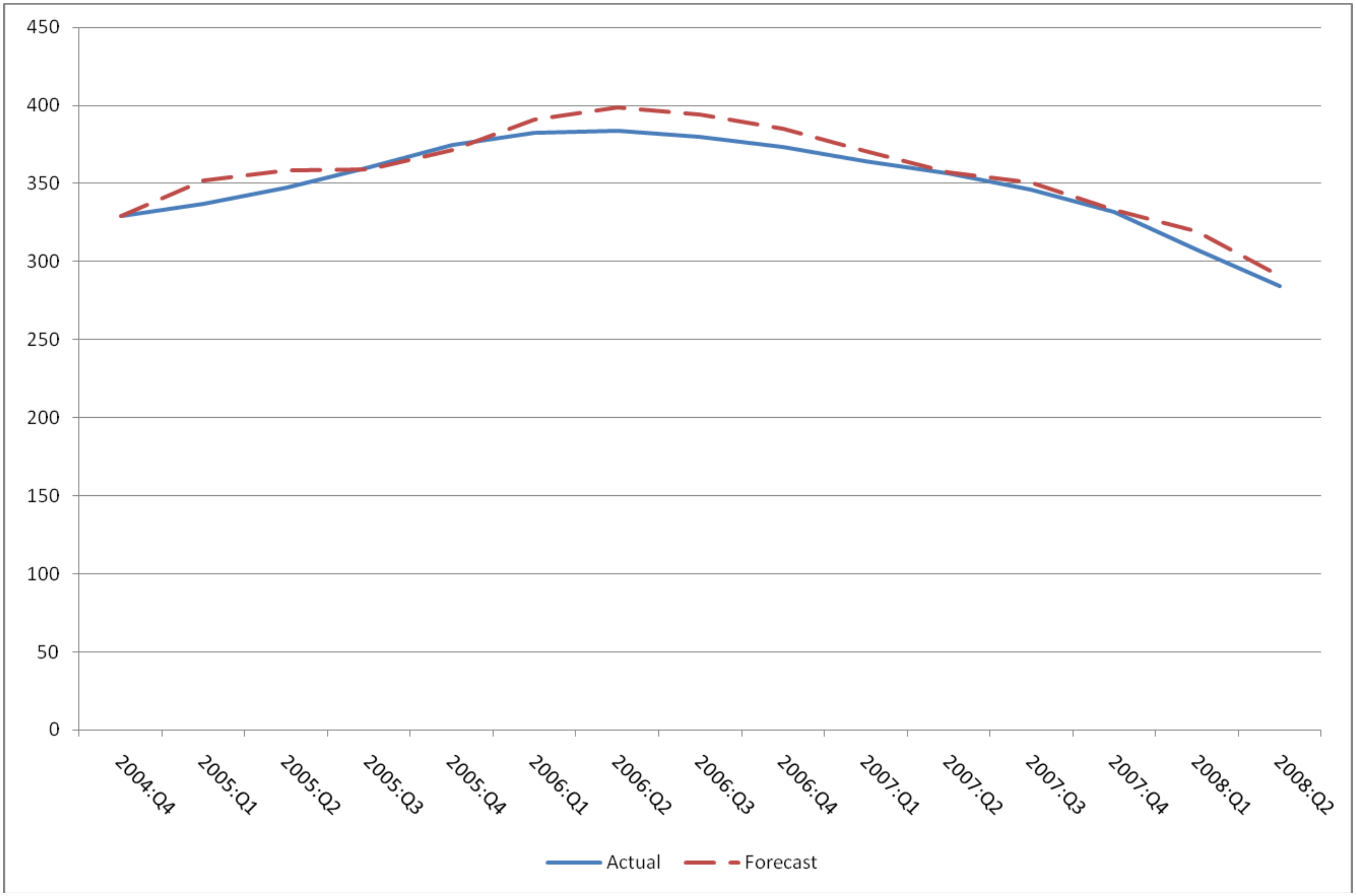

Figure 6: **Recursive Forecasts for Riverside: 2005:Q1 to 2008:Q2**

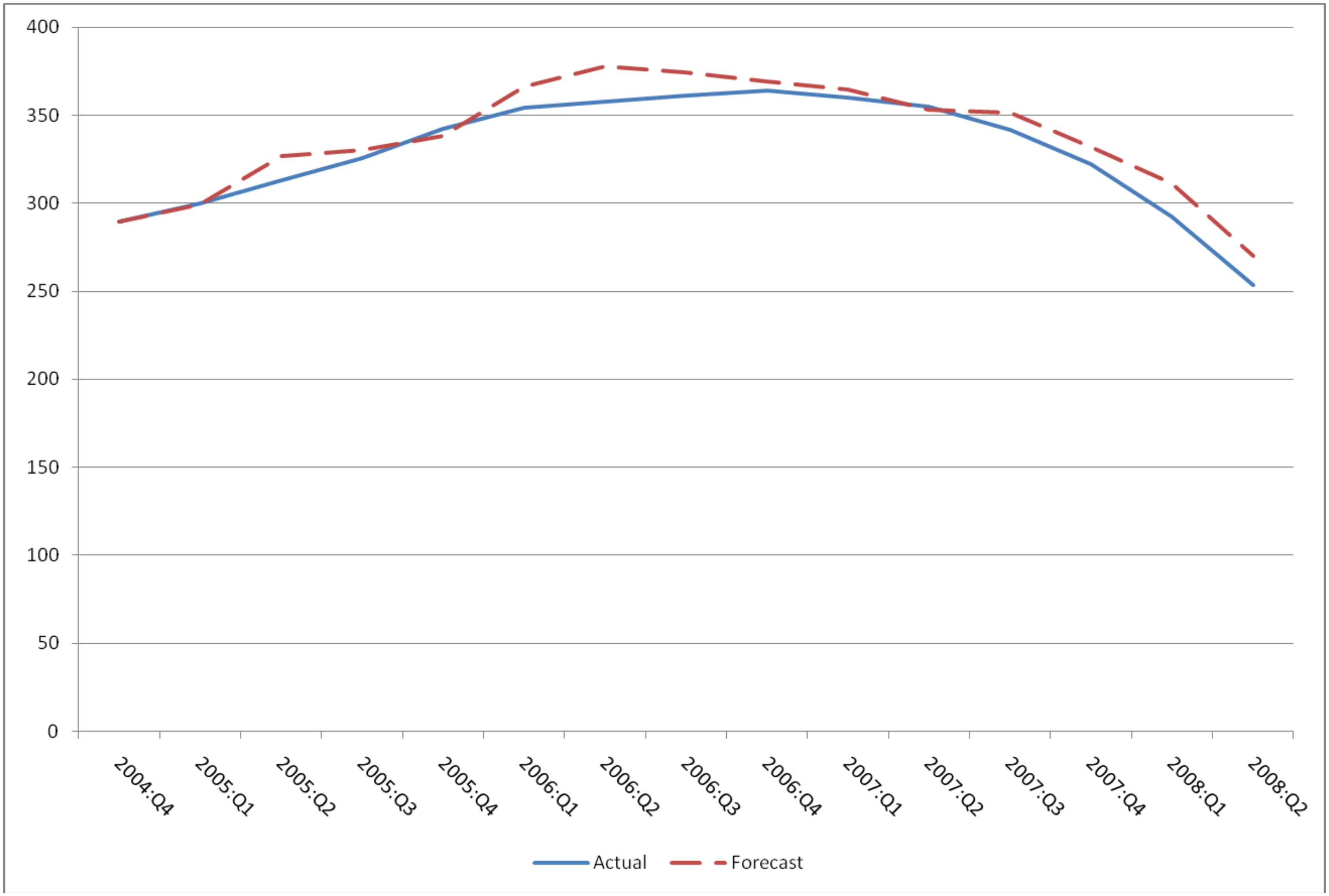

Figure 7: Recursive Forecasts for San Diego: 2005:Q1 to 2008:Q2

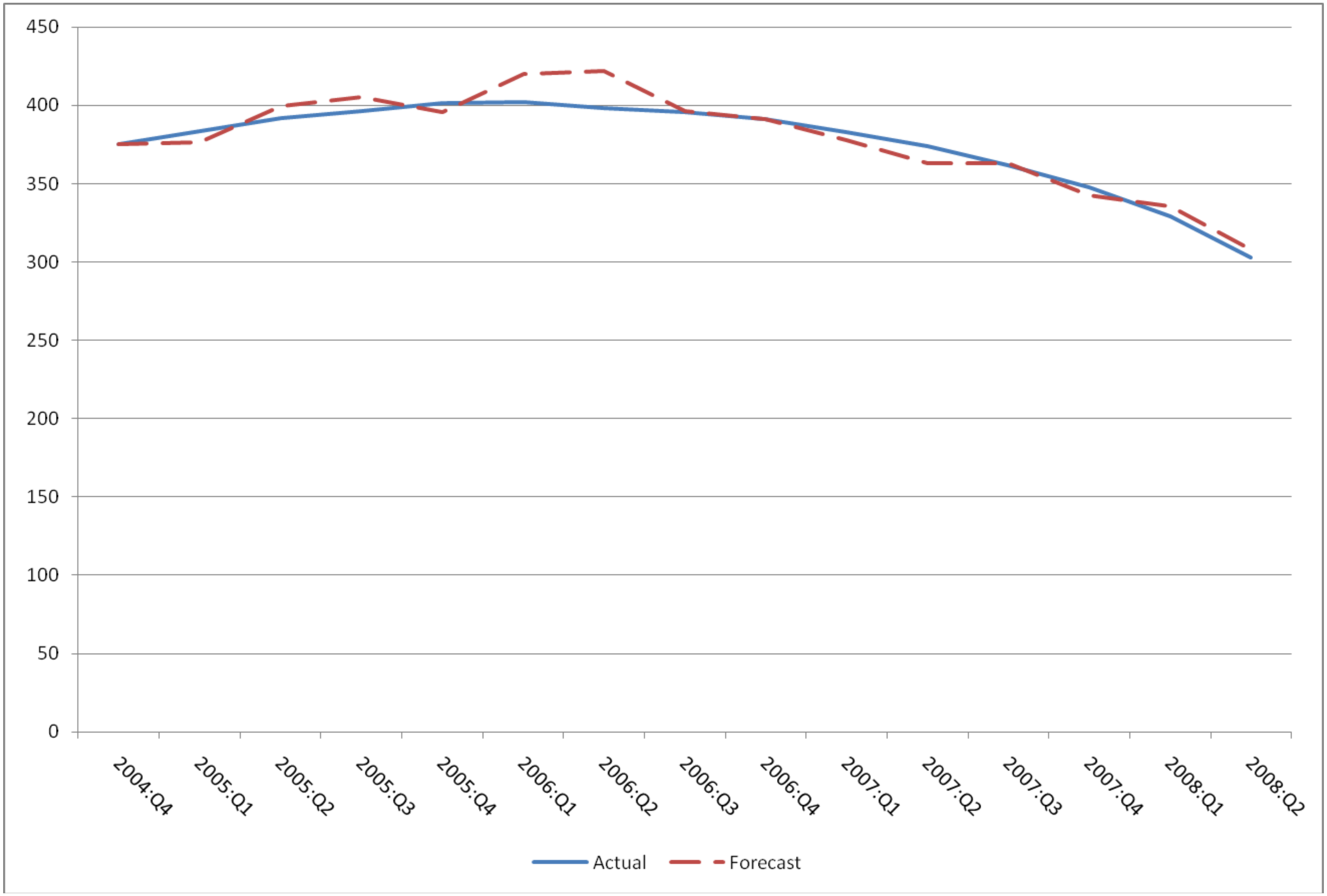

Figure 8: Recursive Forecasts for San Luis Obispo: 2005:Q1 to 2008:Q2

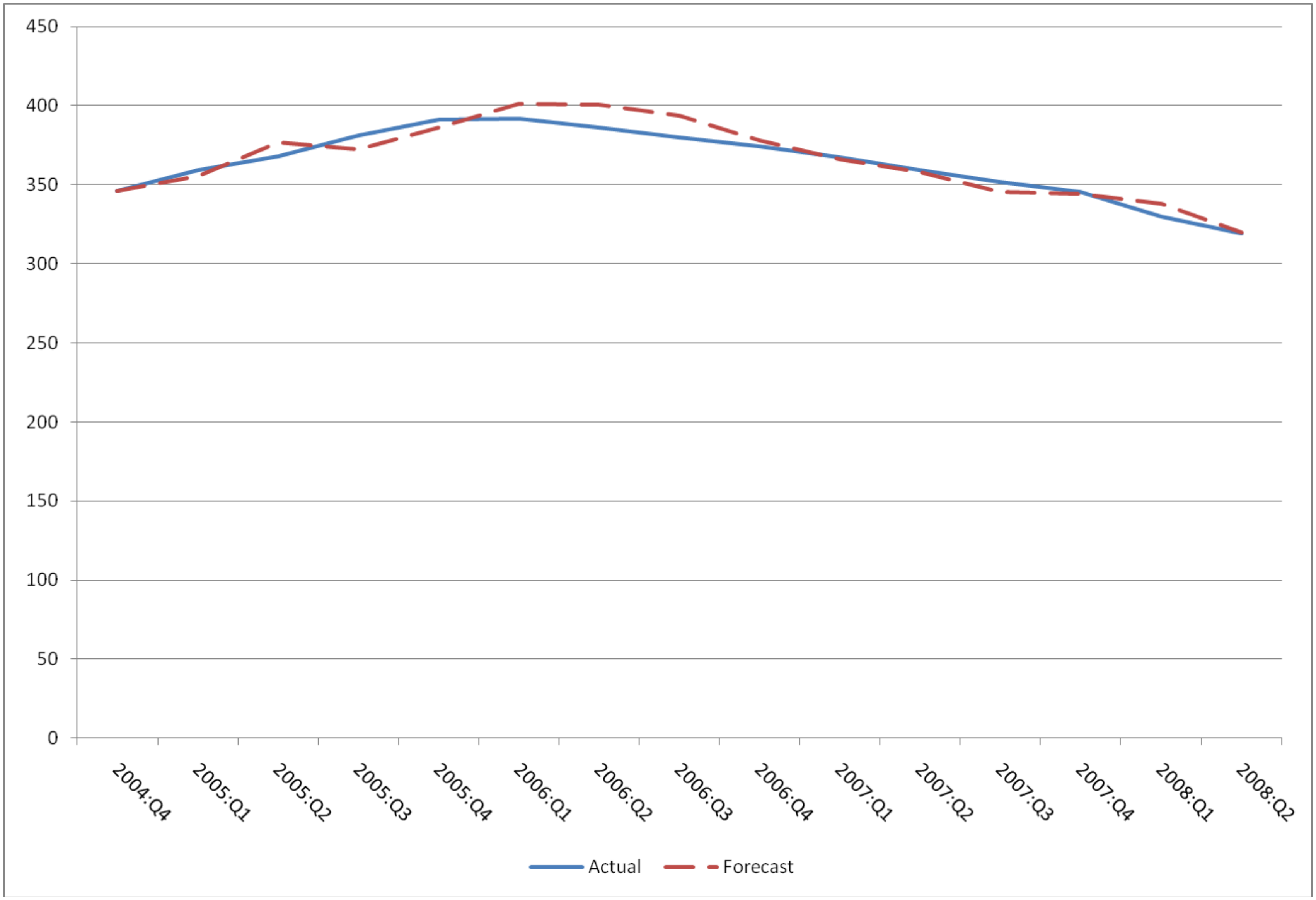

Figure 9: Recursive Forecasts for Santa Ana: 2005:Q1 to 2008:Q2

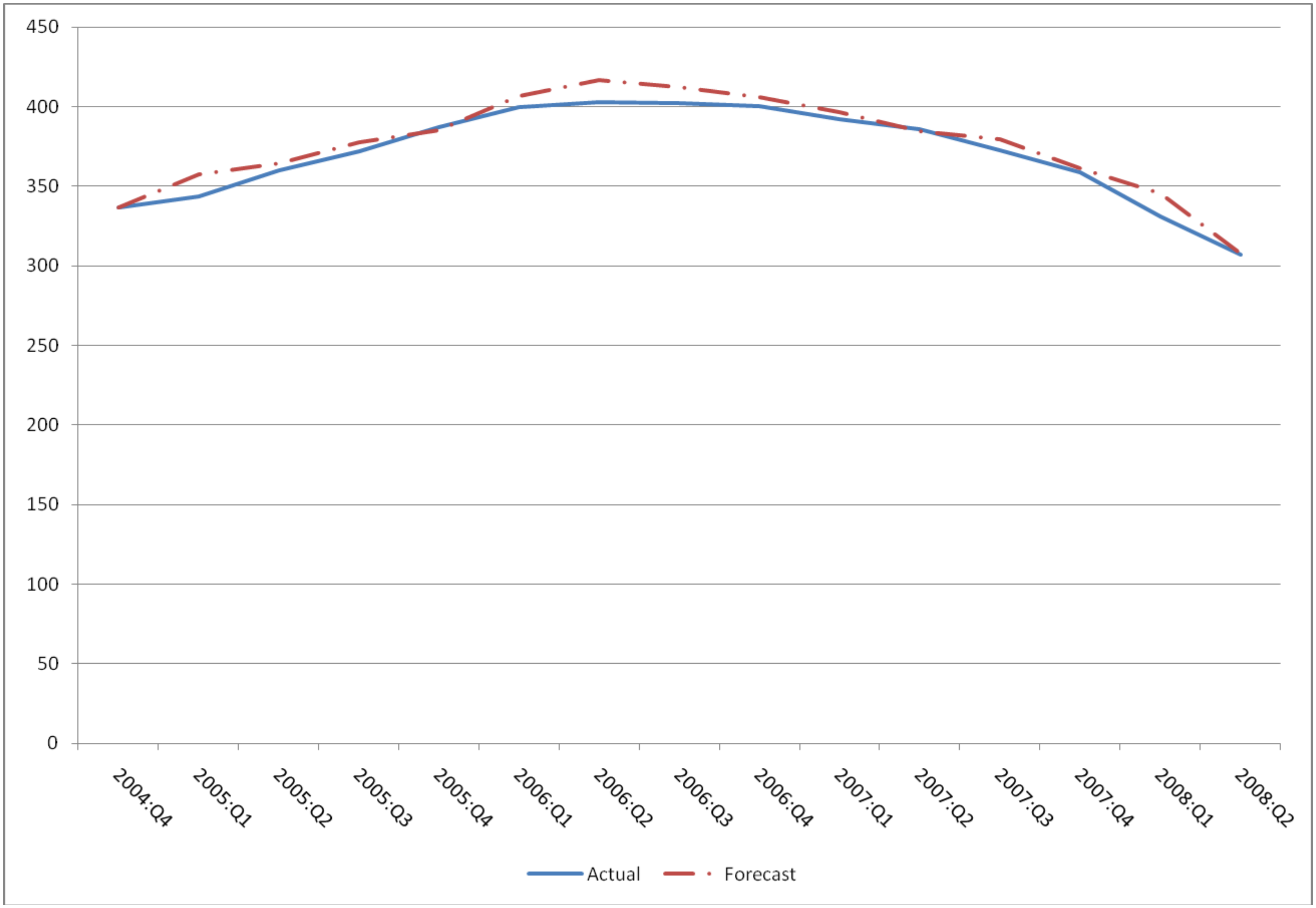

Figure 10: Recursive Forecasts for Santa Barbara: 2005:Q1 to 2008:Q2