“Ripple Effects” and Forecasting Home Prices In Los Angeles, Las Vegas, and Phoenix*

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Abstract

We examine the time-series relationship between house prices in Los Angeles, Las Vegas, and Phoenix. First, temporal Granger causality tests reveal that Los Angeles house prices cause house prices in Las Vegas (directly) and Phoenix (indirectly). In addition, Las Vegas house prices cause house prices in Phoenix. Los Angeles house prices prove exogenous in a temporal sense and Phoenix house prices do not cause prices in the other two markets. Second, we calculate out-of-sample forecasts in each market, using various vector autoregessive (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 cities.

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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 three Southwestern Metropolitan Statistical Areas (MSAs) – Los Angeles, Las Vegas, and Phoenix. Recent popular wisdom argues that residents of Southern California sell their local homes, cash out significant equities, and move (retire) to Las Vegas and Phoenix, where they significantly upgrade the quality of their homes.[1]

UK house experts identified a "ripple" effect of house prices that begins in the Southeast UK and proceeds toward the Northwest. Meen (1999) describes four different theories that may explain the ripple effect – migration, equity conversion, spatial arbitrage, and exogenous shocks with different timing of spatial effects. A ripple effect does not yet receive much support in the US economy. For example, most analysis relates to a given geographic housing market, such as a metropolitan area (Tirtiroglu 1992; Clapp and Tirtiroglu 1994; and Gupta and Miller 2010). Additional evidence across census regions also exists, which may reflect the fourth of Meen's explanations (Pollakowski and Ray, 1997; Meen 2002).

Visual evidence of house price movements in the Los Angeles, Las Vegas, and Phoenix MSAs reveal a consistent pattern. See Figure 1. All three markets exhibit a large run up in house prices in real terms, beginning at least by 2003 and peaking at the same time in late 2006. From the mid-1980s through early 1990s, Los Angeles experienced a smaller run up and decline in house prices, not followed by such movements in Las Vegas or Phoenix. In addition, the movement of people from Los Angeles to Las Vegas and Phoenix after retirement may link these three MSAs housing markets. Further, the purchase of houses in Las Vegas and Phoenix as second homes or as investments by Southern California residents also provides an important

[1] In fact, other Mountain Southwest MSAs may also respond to home prices in Los Angeles (and San Francisco). Recently, the Brookings Institution (2008) released a report on the rapid growth in the Mountain Southwest, identifying five megapolitan areas – Las Vegas, Phoenix, Denver, Salt Lake City and Albuquerque.

linkage. In sum, these three MSAs lie in contiguous states that experienced similar house price "bubbles" that "popped" at the beginning of the current worldwide financial crisis. We consider the econometric linkages between these three house price series and the ability of various forecasting models to predict house price movements. We use nominal house price data for the three MSAs, obtained from Freddie Mac's conventional mortgage home price index (CMHPI) database. These quarterly data encompass the fourth quarter of 1977 through the second quarter of 2008.

We begin by testing for the order of integration of the three house price indexes in logarithms. Since we find that all series are intergrated of order one, we then test for cointegration between real house prices in the three MSAs, using the Johansen technique (1991). Given that we find one cointegrating relationship between the real house prices, the block exogeneity tests on the vector error correction (VEC) model reveals that house prices in Los Angeles temporally cause prices in Las Vegas directly and Phoenix indirectly, and that house prices in Las Vegas temporally cause prices in Phoenix directly, but that Las Vegas and Phoenix house prices do not temporally cause prices in Los Angeles.

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 (LeSage 2004) and causality priors.[2] A spatial BVEC model performs the best across all three cities, although the forecasting performances in the individual cities do differ. That is, only Las Vegas performs the best in this spatial BVEC model that performs the best across all three cities.

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[2] One of our innovations includes the development of causality priors. See below.

We organize the rest of the paper as follows. Section 2 examines the relevant literature. Section 3 specifies the various time-series models estimated in Section 4. Section 5 concludes.

2. Literature Review

The literature review considers three different areas. First, we discuss housing dynamics and the various theories offered to explain those dynamics. Next, we describe the implications of housing dynamics on the time-series properties of house prices. Finally, we consider the differences between dynamic structural and time-series models in forecasting ability.

Housing Dynamics: Observations and Theory

Gupta and Miller (2010) adapt the Law of One Price from trade theory to facilitate the discussion of the possible geographic linkages between housing prices. Clearly, housing fails on at least two important assumptions in the theory of the Law of One Price – houses are not homogeneous or transportable between markets.

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 and so on. Typically, the geographic reach of the housing market reflects the commuting shed for the metropolitan area. That is, houses compete with each other within the same metropolitan area. 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. Gupta and Miller (2010) examine the eight MSAs in Southern California.

Does the fact that we cannot transport houses from one metropolitan market to another necessarily mean that the markets do not exhibit some linkage? Meen (1999) offers four different explanations of the “ripple” effect in the UK housing markets -- migration, equity conversion, spatial arbitrage, and exogenous shocks with different timing of spatial effects.[3] The life-cycle model of consumer choice used by Meen (1999), however, leaves out an important factor in the housing market, the supply side. 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.

Time-Series Implications for House Prices

To the extent that house prices follow a ripple effect between different geographic regions, then we should observe Granger temporal causality between regions. That is, price movements in one region should temporally precede price movements in another region. We can perform temporal causality tests using a vector autoregressive (VAR) specification. On the other hand, if house prices are *I(1)* series, exhibiting non-stationarity, then a long-run relationship between the house prices may exist, especially if the ripple effect holds. As such, then the house price series may exhibit cointegration and require the tests for Granger temporal causality to occur within a vector error-correction model (VEC).

Dynamic Structural Versus Time-Series Models

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[3] First, migration patterns between Los Angeles (Southern California) and Las Vegas or Phoenix could link Las Vegas and Phoenix prices to those in Los Angeles. That is, lower house prices in Las Vegas and Phoenix, significantly higher congestion in Los Angeles, enhanced employment possibilities in Las Vegas and Phoenix due to rapid economic growth, and so on may push or pull Los Angeles residents to Las Vegas and Phoenix. Second, longer-term residents of Southern California accumulate significant wealth in their home equity, cash out that equity by selling their home and moving to a lower cost region where a similar quality house costs much less, and pocket the liberated equity. Of course, such movements of home owners inflate prices at the margin in their new locations. Third, investors spatially arbitrage their funds to acquire properties in lower priced regions, where higher anticipated returns exist on housing investment. In this case, financial capital moves, rather than households, between regions to link house prices. Pollakowski and Ray (1997) find limited evidence of a spatial arbitrage (diffusion) effect across metropolitan regions in the US.

Two different approaches to modeling dynamic adjustment exist – dynamic structural and time-series models. Zellner and Palm (1974) demonstrate the theoretical equivalence between the two approaches. That is, any dynamic structural model implicitly reduces to a univariate time-series model for each endogenous variable. The dynamic structural model imposes restrictions of the coefficients in the reduced-form univariate time-series models.

Dynamic structural models prove most effective in performing policy analysis, albeit subject to the Lucas critique. Time-series models prove most effective at forecasting. That is, in both cases errors creep in whenever the researcher makes a decision about the specification. Clearly, more researcher decisions relate to a dynamic structural model than a univariate time-series model, suggesting that fewer errors enter the time-series model and allowing the model to produce better forecasts.

The "atheoretical" VAR and VEC models do not impose any exogeneity assumptions on the included variables. That is, lagged values of each variable may provide valuable information in forecasting each endogenous variable. VAR and VEC models, however, prove subject to over-parameterization, since the number of parameters to estimate increases dramatically with additional variables or additional lags in the system. Bayesian VAR or VEC models economize on the number of parameters estimated by using a small number of hyper-parameters in the specification.

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

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

$$y_t = A_0 + A(L) y_t + \varepsilon_t ,^{5} \tag{1}$$

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

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

where *y* equals a ($n \times 1$) vector of variables to forecast; *A(L)* equals an ($n \times n$) polynomial matrix in the backshift operator *L* with lag length *p*, and ε equals an ($n \times 1$) vector of error terms. In our case, we assume that $\varepsilon \sim N(0, \sigma^2 I_n)$, where I_n equals an ($n \times n$) identity matrix.

Additional restrictions on the standard VAR model lead to a VEC model, designed for use with cointegrated non-stationary series.[6] While allowing for short-run adjustment dynamics, the VEC model builds into the specification the cointegration relations so that it restricts the behavior of the endogenous variables to converge to their long-run relationships. The cointegration term, known as the error correction term, gradually corrects through a series of partial short-run adjustments.

VAR models typically use equal lag lengths for all variables in the specification, which implies that the researcher must estimate many parameters, some of which may prove statistically insignificant. This over-parameterization problem can result in multicollinearity and a loss of degrees of freedom, leading to inefficient estimates, and possibly large out-of-sample forecasting errors (Litterman, 1981; Doan *et al.*, 1984; Todd, 1984; Litterman, 1986; Spencer, 1993; Bikker, 1993). Often, researchers simply exclude lags with statistically insignificant coefficients (Hoehn, 1984; Hoehn *et al.*, 1984; Fackler and McMillin, 1984; Hafer and Sheehan, 1989; Keating, 1993; Ozcicek and McMillin, 1999). Alternatively, researchers use near VAR models, which specify unequal lag lengths for the variables and equations. Nevertheless, in our example with only three variables and, as we shall see below, only two lags, over parameterization does not present a serious problem. If the lag-length selection criteria had selected four lags, then the degrees-of-freedom problem would represent a concern to some extent.

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

Litterman (1981), Doan *et al.,* (1984), Todd (1984), Litterman (1986), and Spencer (1993), use Bayesian prior distributions for the coefficients of the VAR, producing a BVAR model, to address the over-parameterization problem.[7] The priors conform to a simple random-walk specification with uncertainty about the precise parameter values. That is, the model imposes a unity coefficient on the own first lag and zeros on all other lags, the Minnesota prior. The strategic aspect of the Minnesota prior involves the variance structure of the parameters as follows:

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

where β_i denotes 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 represents 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 $\bar{\beta}_i$ = 1, and $\bar{\beta}_j$ = 0, respectively.

Doan *et al.,* (1984) suggest a formula to generate standard deviations as a function of a small numbers of hyper-parameters: *w*, *d*, and a weighting matrix *f*(*i*, *j*) to address the over-parameterization in the VAR model as follows:

$$S_1(i,j,m)=[w\times g(m)\times f(i,j)]\left(\hat{\sigma}_i \big/ \hat{\sigma}_j\right), \qquad (3)$$

where $f(i, j) = 1$, if $i = j$ and k_{ij} otherwise, with ($0 \le k_{ij} \le 1$), and $g(m) = m^{-d}$, with $d > 0$. Note that $\hat{\sigma}_i$ equals the estimated standard error of the univariate autoregression for variable *i*. The

[7] For more details on the rest of this section, see the longer version of this paper posted at http://ideas.repec.org/p/uct/uconnp/2009-05.html.

ratio $\left(\hat{\sigma}_i \big/ \hat{\sigma}_j \right)$ 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 we reduce the value. 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 on increasing lags. The parameter $f(i, j)$ represents the tightness of variable *j* in equation *i* relative to variable *i*, and by increasing the interaction (i.e., the value of k_{ij}), we loosen the prior.[8]

The overall tightness (*w*) and the lag decay (*d*) hyper-parameters equal 0.1 and 1.0, respectively, in the standard Minnesota prior, while k_{ij} = 0.5, implying a weighting matrix (*F*) of with ones down the diagonal and 0.5 in the off-diagonal elements. In addition, we adopt several other combinations of tightness and decay parameters in our analysis below.

Alternatively, LeSage and Pan (1995) suggest constructing spatial BVAR (SBVAR) and BVEC (SBVEC) models. They propose the weight matrix based on the first-order spatial contiguity (FOSC) prior, which simply implies a non-symmetric *F* matrix that gives more importance to variables from neighboring states/cities than those from non-neighboring states/cities. They propose using unity both for the diagonal elements of the weight matrix, as in the Minnesota prior, as well as for place(s) that correspond to variable(s) from state(s)/city(ies) with which the specific state in consideration shares common border(s). For the elements in the *F* matrix that correspond to variable(s) from state(s)/city(ies) that are not immediate neighbor(s), Lesage and Pan (1995) adopt a weight of 0.1. In sum, some of the 0.5 weights in the Minnesota

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

specification become 1.0 for neighbors and 0.1 for non-neighbors.

In our specific example of Los Angeles, Las Vegas, and Phoenix, we could argue that each city neighbors the other cities or does not neighbor the other cities. Thus, the coefficients of 0.5 either change to 1.0 or to 0.1.

We also propose new specifications called causality BVAR (CBVAR) and BVEC (CBVEC) models, where the weight matrix depends on tests for Granger temporal causality –- the temporal causality (TC) prior. This modification of the LeSage and Pan (1995) first-order spatial-contiguity (FOSC) prior considers some neighbors as more important than other neighbors. In fact, non-neighbors may exert more influence than neighbors. If one city's home prices temporally cause another city's home prices, then we code the weight matrix for that off-diagonal entry at 1.0. If no temporal causality exists, then we code the off-diagonal entry as 0.1.

More recently, LeSage and Krivelyova (1999) develop an alternative approach to remedy the equal treatment nature of 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 model. Now the neighbors receive a weight on 1.0 and non-neighbors receive a weight of 0.0. Finally, the prior mean sums to one so that each important city receives a proportional weight. For example, if each city in our analysis proves important, then each city receives a weight of 0.33 in the mean equation.

We can interpret this standardized mean weight 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. LeSage and Krivelyova (1999) retain the distinction between important and unimportant variables in defining the prior variances. They use the following ideas: (i) Assign a smaller prior variance to parameters associated with unimportant variables, imposing the zero prior means with more certainty; (ii) Assign a small prior variance to the first own-lag of the important variables so that the 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 important variables, allowing those lags to exert some influence on the dependant variable; and (v) Finally, impose 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:

$$
\begin{aligned}
&S_2(i, j, m) \sim N(1/c_i, \sigma_c); \quad j \in C; \quad m = 1; \qquad i, j = 1, ..., n; \\
&S_2(i, j, m) \sim N(0, \eta\, \sigma_c/m); \quad j \in C; \quad m = 2, ..., p; \quad i, j = 1, ..., n; \text{ and} \\
&S_2(i, j, m) \sim N(0, \rho\, \sigma_c/m); \quad j \neg\in C; \quad m = 1, ..., p; \quad i, j = 1, ..., n;
\end{aligned}
\tag{4}
$$

where $0 < \sigma_c < 1$, $\eta > 1$, $0 < \rho \le 1$, and c_i equals the number of important variables in equation *i*. For the important variables in equation *i* (i.e., $j \in C$), the prior mean for the lag length of 1 equals the average of the number of important variables in equation *i*, and equals zero for the unimportant variables (i.e., $j \neg\in C$). With $0 < \sigma_c < 1$, the prior standard deviation for the first own lag imposes a tight prior mean to reflect averaging over important variables. For important variables at lags greater than one, the variance decreases as m increases, but the restriction that $\eta > 1$ allows for the loose imposition of the zero prior means on the coefficients of these variables. We use $\rho \sigma_c / m$ for lags on unimportant variables, with prior means of zero, to indicate that the variance decreases as m increases. In addition, since $0 < \rho \leq 1$, we impose the zero means on the unimportant variables with more certainty. In our model, however, we do not include any unimportant variables. That is, we only consider two cases – all cites are neighbors or all cities are non-neighbors.[9]

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

$$
\begin{aligned}
&S_3(i,j,m) \sim N\left\{ 2/(c_i+1), \sigma_c \right\}; \quad j \in C; \quad m=1; \quad j=i \quad i,j=1,....,n; \\
&S_3(i,j,m) \sim N\left\{ 1/(c_i+1), \sigma_c \right\}; \quad j \in C; \quad m=1; \quad j \neq i \quad i,j=1,....,n; \\
&S_3(i,j,m) \sim N\left\{ 0, \eta \sigma_c / m \right\}; \qquad j \in C; \quad m=2,....,p; \quad i,j=1,....,n; \text{ and} \\
&S_3(i,j,m) \sim N\left\{ 0, \rho \sigma_c / m \right\}; \qquad j \neg \in C; \quad m=1,....,p; \quad i,j=1,....,n.
\end{aligned} \tag{5}
$$

Thus, in our three-variable system, c_i equals 3 and the prior means for the first own lag equals one half (i.e., $2/(c_i+1) = 2/(3+1)$) and the first lags of the other two important variables in

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[9] When we assume that all cities are non-neighbors, then the weight matrix, C, reverts to the Minnesota random-walk prior on the means.

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

each equation equal one fourth (i.e., $1/(c_i+1)$ = $1/(3+1)$). We employ the following values for the hyperparameters: $\sigma_c = 0.1, \eta = 8,$ and $\rho = 0.5.$ [11]

We estimate the BVAR, BVEC, SBVAR, SBVEC, CBVAR, and CBVEC models, based on the FOSC, TC, RWA, and WRWA priors, using Theil's (1971) mixed estimation technique.[12] Essentially then, the method involves supplementing the data with prior information on the distribution of the coefficients – means and standard deviations. The number of observations and degrees of freedom increase artificially by one for each restriction imposed on the parameter estimates. Thus, the loss of degrees of freedom from over-parameterization in the classical VAR or VEC models does not emerge as a concern in the BVAR, BVEC, SBVAR, SBVEC, CBVAR, and CBVEC models.

4. Data Description, Model Estimation, and Results

This section reports our data sources and econometric findings. First, we describe the data. Second, we determine whether cointegration exists between the variables in our model. Finally, 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.

Data:

The models include house price indexes for the Los Angeles, Las Vegas, and Phoenix metropolitan areas. The nominal house price data for the three MSAs come from Freddie Mac's conventional mortgage home price index (CMHPI) database. Using matched transactions on the same property over time to account for quality changes, the Freddie Mac data consist of both purchase and refinance-appraisal transactions, and include over 33 million homes. We deflate the

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

[12] See Gupta and Miller (2010) for more details.

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. We employ quarterly data from the fourth quarter of 1977 through the second quarter of 2008. As Hamilton (1994, p. 362) notes, we seasonally adjust the data, since the Minnesota-type priors do not perform well without seasonally adjusted data.

Evidence on Cointegration

To test for Granger temporal causality between the three real house price series, we first consider whether the series contain a unit root (i.e., non-stationary data series). We run the augmented Dickey-Fuller (1979, ADF), the Phillips-Peron (1988, PP), the Kwiatkowski-Phillips-Schmidt-Shin (1992, KPSS), and the Elliott-Rothenberg-Stock (1996, DF-GLS) tests for unit roots, finding that the logarithm of each housing price series is nonstationary in levels but stationary in first differences.[13] We next 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 four lags, except the Schwarz information criterion that chooses two lags. Table 1 reports the results.

When we estimate the VAR model with four lags, stability does not occur, in the sense that not all the roots lie within the unit circle.[14] Sims (1987) states "Explosive parameter settings seem quite unlikely and produce bad long-range forecasts." (1987, p. 444). Thus, we adopt the SIC and estimate with two lags, where we find that the VAR model is stable. Cointegration tests

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[13] Results appear in the longer version of this paper posted at: http://ideas.repec.org/p/uct/uconnp/2009-05.html.

[14] The longer version of this paper posted at http://ideas.repec.org/p/uct/uconnp/2009-05.html includes the roots of the characteristic polynomial of the VAR models, showing an unstable VAR with four lags and a stable VAR with two lags.

– the trace statistic and maximum eigen-value test – both indicate one cointegrating vector. Table 2 tabulates the findings.

Running the VEC specification and using the block exogeneity test, we discover that house prices in Los Angeles temporally cause house prices in Las Vegas and that house prices in Las Vegas temporally cause house prices in Phoenix.[15] Further, house prices in Las Vegas or Phoenix do not temporally cause house prices in Los Angeles. In addition, house prices in Los Angeles do not directly cause house prices in Phoenix, but will exhibit an indirect effect through Las Vegas and Las Vegas's effect on house prices in Phoenix. Finally, house prices in Las Vegas do not cause house prices in Los Angeles. Table 3 reports the findings.[16] We did not expect to find that house prices in Los Angeles only directly cause house prices in Las Vegas and that only Las Vegas's house prices directly cause house prices in Phoenix. This result contradicted our prior beliefs, since we expected Los Angeles house prices to cause Phoenix house prices directly.

As a further test, we calculate the impulse response functions. Figure 2 illustrates the findings. We see that a one-standard deviation innovation to the Los Angeles house price produces significant increases in the Las Vegas and Phoenix house prices. The significant increases in house prices lasts for over 15 quarters in Los Angeles, for over 10 quarters in Las Vegas, and for over 20 quarters in Phoenix. In addition, a one-standard deviation innovation in Las Vegas house prices produces a significant increase in Phoenix house prices. Here, the significant increases in house prices last for just about 10 quarters in Las Vegas and for just about 10 quarters in Phoenix. In sum, although Los Angeles house prices do not directly Granger

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[15] Since the VEC specification constitutes the first differenced form of the three endogenous variables, and the optimal lag length used for the VAR is 2, we estimate all VEC models with 1 lag.

[16] We also perform Granger causality tests for the VAR in levels, which implicitly includes the cointegration relationship, but does not explicitly incorporate that cointegrating information. We find identical Granger causality results. The longer version of the paper posted at http://ideas.repec.org/p/uct/uconnp/2009-05.html includes this information.

cause Phoenix house prices, the indirect effects through Las Vegas house prices prove significant on Phoenix house prices as shown by the impulse response function. Moreover, because of these indirect effects, Los Angeles house price movements affect Phoenix house prices for a longer time span than Los Angeles house prices affect Las Vegas house prices and than Las Vegas house prices affect Phoenix house prices.

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 Los Angeles, Las Vegas, and Phoenix over the period 1978:Q1 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 2008:Q2, and compare the forecast accuracy relative to the forecasts generated by an unrestricted VAR and VEC models. 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, 2009) and does not include the dramatic run up in home prices at the end of the out-of-sample forecast period.[17]

Each equation of the various VAR (VEC) models includes 7 (5) parameters with the constant, given that we estimate the models with 2 (1) lag(s) of each variable.[18] We estimate the

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[17] The longer version of this paper posted at http://ideas.repec.org/p/uct/uconnp/2009-05.html ends this analysis of forecast accuracy in 2005:Q4. The results remain unchanged in qualitative terms. Then, the longer version performs ex ante and recursive forecasts from 2006:Q1 through 2008:Q2 to see if the models can forecast the turnings points. Ex ante forecasts do not update the data beyond the 2005:Q4 observations where as recursive forecasts update each quarter with the new observations. Forecasting turning points in house prices proves a difficult task. When we do ex ante forecasts, these forecasts predict rising trend in house prices and do not signal any turning point. The one-step-ahead, recursive forecasts do reasonably well, however. The forecast prices actually peak in Las Vegas and Phoenix in the second quarter of 2006, two quarters before the actual series peak. That is, in both Las Vegas and Phoenix, the forecasts begin to exceed the actual values sufficiently to cause the forecasts to attempt to close that overestimation. Less of a gap appears in Los Angeles and its forecasts do not peak until the fourth quarter of 2006, when the actual series itself peaks. Note that the recursive forecasts for the random-walk model would signal the peak two quarters after it occurs.

[18] As noted above, we initially chose 4 lags based on the unanimity of the sequential modified LR test statistic, the

three-variable models for a given prior for the period 1978:Q1 to 1994:Q4, and then forecast from 1995:Q1 through to 2008:Q2. Since we use two lags (one lag) for the VAR (VEC) model, the initial two (one) quarters (quarter) starting at 1978:Q1 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 44 quarters, with the first forecast beginning in 1995:Q1. This produced a total of 44 one-quarter-ahead forecasts, …, up to 44 four-quarters-ahead forecasts.[19] We calculate the root mean squared errors (RMSE)[20] for the 44 one-, two-, three-, and four-quarters-ahead model forecasts for the three home prices. We benchmark these results relative to the RMSE of the random-walk model, that is, we calculate the ratio of the RMSE of a given model relative to the RMSE of the random-walk model. We then examine the average of the relative RMSE statistics for one- through four-quarters ahead forecasts over 1995:Q1 to 2008:Q2. 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 (i.e., the Minnesota prior), and then increase the value to w = 0.2 to account for more influences from variables other than the first own lags of the dependant variables of the model. 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

final prediction error (FPE), Akaike information criterion (AIC), and the Hannan-Quinn information criterion (HQIC). The Schwarz information criterion (SIC) provided the exception of 2 lags. The VAR model using 4 lags, however, proved unstable. Thus, we opted for the 2 lags indicated by the SIC, which generated a stable VAR.

[19] For this, we used the algorithm in the Econometric Toolbox of MATLAB, version R2009b.

[20] 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: $\sqrt{\left[\frac{1}{N} \sum_1^N \left({}_tF_{t+n} - A_{t+n} \right)^2 \right]}$ where N equals the number of forecasts.

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.[21]

Table 4 reports the findings for Los Angeles. The last column looks at the average of RMSEs across the one- through four-quarter-ahead forecast RMSEs. The spatial BVEC1 model with the first (RWA) prior, $w=0.1$, and $d=2.0$ provides the lowest average RMSE, which we identify as the optimal specification.[22] This specification also minimizes the RMSE for the two-quarter-ahead forecasts as well. The BVAR model with $w=0.2$, and $d=1.0$ provides the optimal specification for the one-quarter-ahead forecast, while the spatial RBVEC1 and causality RBVEC1 models with the first (RWA) prior prove optimal for the three- and four-quarter-ahead-forecast horizon.

Table 5 reports the findings for Las Vegas. The spatial BVEC2 specification with $w=0.2$, and $d=2.0$ and the second (WRWA) prior provides the lowest average RMSE, as well as the lowest RMSE for the three- and four-quarter-ahead forecast horizon. The spatial BVEC1 model with the first (RWA) prior, $w=0.1$, and $d=1.0$ provides the optimal specification for the one-quarter-ahead forecast, while the spatial BVEC2 model with the second (WRWA) prior, $w=0.1$, and $d=2.0$ proves optimal for the two-quarter-ahead-forecast horizon.

Table 6 reports the findings for Phoenix. The spatial RBVAR2 model with the second (WRWA) prior provides the lowest average RMSE, as well as the lowest RMSE for the two- and

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[21] In addition, as in Dua and Ray (1995), Gupta and Sichei (2006), and Gupta (2006), we also estimate a BVAR model with w = 0.3 and d = 0.5. Since none of these models prove optimal, we do not report the findings. We will provide the results on request.

[22] The first (RWA) prior for the random walk models imposes equal weights on the coefficients of the first-lagged values of all variables in each equations (i.e., $1/3$).

four-quarter-ahead forecast horizon.[23] The causality RBVAR1 model with the first (RWA) prior provides the optimal specification for the one-quarter-ahead forecast, while the VAR model proves optimal for the three-quarter-ahead forecast horizon.

In sum, different specifications yield the lowest RMSE in different cities.[24] No common pattern emerges. Comparing the forecasting performance across cites, however, we see that Los Angeles experiences the lowest RMSE for the one-, two-, and three-quarter-ahead forecast horizon, while Las Vegas experiences the lowest RMSEs for the two- and four-quarter-ahead forecast horizon and for the average across all four forecast horizons.

5. Conclusion

The bloom is off the rose of the housing boom. House prices rose dramatically in Los Angeles, Las Vegas, and Phoenix in the early 2000s, peaking in real terms in 2006:Q4. This paper considers the time-series relationships between the house prices in these three MSAs, using Freddie Mac data from 1978:Q1 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.

Los Angeles house prices directly cause Las Vegas house prices and indirectly cause Phoenix house prices through their effect on Las Vegas house prices. That is, Las Vegas house prices directly cause Phoenix house prices. Las Vegas house prices do not cause Los Angeles house prices and Phoenix house prices do not cause house prices in Las Vegas or Los Angeles.

[23] The second (WRWA) prior for the random-walk models imposes twice the weight on the first own lag (i.e., $1/2$) as the coefficients on the first lags of other variables (i.e., $1/4$).

[24] We also considered the specifications that produce the lowest average RMSE across all three cities (not reported, results available on request). The spatial BVEC2 specification with the second (WRWA) prior, $w=0.2$, and $d=2.0$ provides the optimal specification for the average across all four horizons as well as for the three- and four-quarter-ahead forecast horizons. The VEC specification proves the optimal model for the one-quarter-ahead forecast horizon, while the spatial BVEC2 specification with the first (RWA) prior, $w=0.1$, and $d=2.0$ proves optimal for the two-quarter-ahead forecast horizon.

As a result, Los Angeles house prices prove temporally exogenous.

Different time-series models prove better at forecasting house prices in the different MSAs. For Los Angeles, a spatial BVEC1 model with the first (RWA) prior provides the best forecasts. For Las Vegas, another spatial BVEC2 specification with the second (WRWA) prior provides the best forecasts. Finally, for Phoenix, a spatial RBVAR2 model with the second (WRWA) prior provides the best forecasts.

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Table 1: Lag-Length Selection Tests

Lag	LogL	LR	FPE	AIC	SIC	HQIC
0	445.6276	NA	9.11e-08	-7.697871	-7.626264	-7.668806
1	1090.430	1244.749	1.44e-12	-18.75530	-18.46887	-18.63904
2	1174.314	157.5557	3.91e-13	-20.05763	-19.55638*	-19.85418
3	1184.930	19.38667	3.80e-13	-20.08574	-19.36967	-19.79509
4	1203.038	32.12151*	3.25e-13*	-20.24414*	-19.31325	-19.86629*
5	1209.859	11.74336	3.38e-13	-20.20624	-19.06053	-19.74120
6	1213.612	6.267124	3.72e-13	-20.11500	-18.75447	-19.56276
7	1218.061	7.195283	4.05e-13	-20.03584	-18.46049	-19.39642
8	1228.529	16.38470	3.97e-13	-20.06137	-18.27120	-19.33475

Note: Lag-length selection from a three variable VAR system of the three real house-price indexes. The star indicates lag order selected by the criterion. The criterion include the sequential modified likelihood ratio (LR) test statistic (each test at 5% level), the final prediction error (FPE), the Akaike information criterion (AIC), the Schwarz information criterion (SIC), and the Hannan-Quinn information criterion (HQIC).

Table 2: Johansen Cointegration Tests

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.191438	36.95976	29.79707	0.0063
At most 1	0.064056	11.46000	15.49471	0.1847
At most 2	0.028875	3.516001	3.841466	0.0608
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.191438	25.49976	21.13162	0.0114
At most 1	0.064056	7.943997	14.26460	0.3844
At most 2	0.028875	3.516001	3.841466	0.0608

Note: Johansen cointegration tests from a three variable system of the three real house-price indexes. The trace and maximum eigen-value tests both indicate one cointegrating vector at the 5-percent level.

* denotes rejection of the hypothesis at the 0.05 level
** MacKinnon-Haug-Michelis (1999) p-values

Table 3: Granger Temporal Causality Tests

Dependent variable: D(lnP$_{LA}$)			
Excluded	**χ^2**	**df**	**Prob.**
D(***lnP$_{LV}$***)	1.910253	1	0.1669
D(***lnP$_{PH}$***)	0.023862	1	0.8772
All	1.922211	2	0.3825
Dependent variable: D(lnP$_{LV}$)			
Excluded	**χ^2**	**df**	**Prob.**
D(***lnP$_{LA}$***)	8.442305	1	0.0037
D(***lnP$_{PH}$***)	0.009186	1	0.9236
All	10.88809	2	0.0043
Dependent variable: D(lnP$_{PH}$)			
Excluded	**χ^2**	**df**	**Prob.**
D(***lnP$_{LA}$***)	0.708430	1	0.4000
D(***lnP$_{LV}$***)	10.99597	1	0.0009
All	20.42951	2	0.0000

Note: Granger temporal-causality tests come from a three variable error-correction model of the three house-price indexes. Johansen cointegration tests from a three variable system of the three real house-price indexes. *D* equals the first difference operator, *ln* stands for the natural logarithm, and P_{LA}, P_{LV}, and P_{PH} equal the real home price indexes in Los Angeles, Las Vegas, and Phoenix, respectively. χ^2 equals the chi-squared statistic, *df* equals the number of degrees of freedom, and Prob. equals the probability of insignificance.

Table 4: Forecast Results for Los Angeles House-Price Index

Parameterization	Models	RMSEs 1	2	3	4	Average
	VAR	0.0171	0.2046	0.9062	0.8797	0.5019
	VEC	0.1556	0.0740	0.3776	0.2768	0.2210
w=0.2, d=1	**BVAR**	**0.0013**	0.1930	0.8717	0.8402	0.4766
	BVEC	0.1561	0.0717	0.3776	0.2525	0.2145
	Causality BVAR	0.0219	0.1793	0.8254	0.7809	0.4519
	Spatial BVAR1	0.0066	0.1966	0.8830	0.8536	0.4850
	Spatial BVAR2	0.0219	0.1794	0.8246	0.7806	0.4516
	Causality BVEC	0.1577	0.0741	0.4061	0.2972	0.2338
	Spatial BVEC1	0.1551	0.0717	0.3736	0.2475	0.2120
	Spatial BVEC2	0.1577	0.0752	0.4150	0.3054	0.2384
w=0.1, d=1	**BVAR**	0.0324	0.1692	0.8030	0.7636	0.4420
	BVEC	0.1562	0.0668	0.3757	0.2552	0.2135
	Causality BVAR	0.0123	0.1872	0.8454	0.8013	0.4616
	Spatial BVAR1	0.0209	0.1761	0.8246	0.7888	0.4526
	Spatial BVAR2	0.0123	0.1866	0.8421	0.7965	0.4594
	Causality BVEC	0.1478	0.0772	0.4299	0.3323	0.2468
	Spatial BVEC1	0.1540	0.0659	0.3639	0.2406	0.2061
	Spatial BVEC2	0.1478	0.0781	0.4349	0.3372	0.2495
w=0.2, d=2	**BVAR**	0.0291	0.1716	0.8103	0.7720	0.4458
	BVEC	0.1591	0.0658	0.3737	0.2520	0.2127
	Causality BVAR	0.0472	0.1614	0.7730	0.7207	0.4256
	Spatial BVAR1	0.0160	0.1798	0.8354	0.8011	0.4581
	Spatial BVAR2	0.0472	0.1612	0.7729	0.7224	0.4259
	Causality BVEC	0.1616	0.0689	0.4036	0.2992	0.2333
	Spatial BVEC1	0.1548	0.0665	0.3666	0.2426	0.2076
	Spatial BVEC2	0.1616	0.0694	0.4071	0.3027	0.2352
w=0.1, d=2	**BVAR**	0.0984	0.1258	0.6893	0.6456	0.3898
	BVEC	0.1602	0.0555	0.3627	0.2483	0.2067
	Causality BVAR	0.0673	0.1472	0.7352	0.6811	0.4077
	Spatial BVAR1	0.0849	0.1321	0.7076	0.6663	0.3977
	Spatial BVAR2	0.0673	0.1462	0.7312	0.6763	0.4052
	Causality BVEC	0.1448	0.0708	0.4203	0.3254	0.2403
	Spatial BVEC1	0.1535	**0.0536**	0.3477	0.2293	**0.1960**
	Spatial BVEC2	0.1448	0.0712	0.4223	0.3278	0.2415
σ_c=0.1, η=8, θ=0.5	**Causality RBVAR1**	0.4655	0.2650	1.1469	1.2210	0.7746
	Causality RBVAR2	0.4655	0.2663	1.1510	1.2243	0.7768
	Spatial RBVAR1	0.4655	0.2663	1.1510	1.2243	0.7768
	Spatial RBVAR2	0.9290	0.1271	0.8538	0.9494	0.7148
	Causality RBVEC1	0.3296	1.0721	0.4196	**0.2072**	0.5071
	Causality RBVEC2	0.3296	1.0746	0.4115	0.2077	0.5059
	Spatial RBVEC1	0.9956	0.4420	**0.0172**	0.5805	0.5088
	Spatial RBVEC2	0.8797	0.6114	0.0821	0.5137	0.5217

Table 4: Forecast Results for Los Angeles House-Price Index (continued)

Note: VAR and VEC refer to three-variable vector autoregressive and vector error-correction models in the three house-price indexes. BVAR and BVEC refer to Bayesian VAR and VEC models. The text identifies various priors and parameterizations. The causality BVAR and causality BVEC model adopt the *F* matrix in equation (7). The spatial BVAR1 and spatial BVAR2 models adopt the *F* matrix in equation (6a). The spatial BVEC1 and spatial BVEC2 models adopt the *F* matrix in equation (6b). The RBVAR and RBVEC with spatial1 or causality1 models adopt the mean specifications in equation (10). The RBVAR and RBVEC with spatial2 or causality2 models adopt the mean specifications in equation (11). 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 as well as the average RMSE across the individual forecasts.

Table 5: Forecast Results for Las Vegas House-Price Index

Parameterization	Models	RMSEs 1	2	3	4	Average
	VAR	0.5246	0.2297	0.1647	0.2138	0.2832
	VEC	0.0441	0.7322	0.8236	0.7605	0.5901
w=0.2, d=1	**BVAR**	0.5408	0.2513	0.1972	0.2475	0.3092
	BVEC	0.0538	0.6485	0.7392	0.5699	0.5029
	Causality BVAR	0.5902	0.3061	0.2778	0.3294	0.3759
	Spatial BVAR1	0.5298	0.2380	0.1764	0.2252	0.2923
	Spatial BVAR2	0.5901	0.3038	0.2822	0.3368	0.3782
	Causality BVEC	0.0517	0.6612	0.7272	0.5977	0.5094
	Spatial BVEC1	0.0428	0.7131	0.8048	0.6277	0.5471
	Spatial BVEC2	0.1641	0.2022	0.2878	0.1732	0.2068
w=0.1, d=1	**BVAR**	0.5668	0.2867	0.2495	0.3007	0.3509
	BVEC	0.0698	0.5060	0.5985	0.4564	0.4077
	Causality BVAR	0.5789	0.2972	0.2670	0.3154	0.3646
	Spatial BVAR1	0.5421	0.2580	0.2042	0.2521	0.3141
	Spatial BVAR2	0.5437	0.2508	0.2134	0.2636	0.3179
	Causality BVEC	0.0518	0.6212	0.7081	0.6063	0.4968
	Spatial BVEC1	**0.0388**	0.6679	0.7624	0.6031	0.5180
	Spatial BVEC2	0.2277	0.1067	0.2254	0.1577	0.1794
w=0.2, d=2	**BVAR**	0.5697	0.2908	0.2541	0.3067	0.3553
	BVEC	0.0774	0.4946	0.5833	0.4338	0.3973
	Causality BVAR	0.6084	0.3326	0.3128	0.3643	0.4045
	Spatial BVAR1	0.5440	0.2598	0.2061	0.2549	0.3162
	Spatial BVAR2	0.6059	0.3276	0.3142	0.3708	0.4047
	Causality BVEC	0.0596	0.6073	0.6735	0.5580	0.4746
	Spatial BVEC1	0.0478	0.6505	0.7447	0.5776	0.5051
	Spatial BVEC2	0.2024	0.0722	**0.1626**	**0.0635**	**0.1252**
w=0.1, d=2	**BVAR**	0.6054	0.3447	0.3294	0.3827	0.4156
	BVEC	0.1026	0.2947	0.3874	0.2697	0.2636
	Causality BVAR	0.5895	0.3202	0.2942	0.3405	0.3861
	Spatial BVAR1	0.5765	0.3107	0.2747	0.3217	0.3709
	Spatial BVAR2	0.5437	0.2636	0.2303	0.2809	0.3296
	Causality BVEC	0.0746	0.5118	0.6213	0.5322	0.4350
	Spatial BVEC1	0.0517	0.5150	0.6171	0.4812	0.4163
	Spatial BVEC2	0.2445	**0.0651**	0.1958	0.1428	0.1621
σ_c=0.1, η=8, θ=0.5	**Causality RBVAR1**	0.4388	1.0713	1.6507	1.7400	1.2252
	Causality RBVAR2	0.3781	1.0659	1.6648	1.7721	1.2202
	Spatial RBVAR1	0.4346	1.2043	1.7896	1.9317	1.3401
	Spatial RBVAR2	0.4468	1.2346	1.8602	1.9931	1.3837
	Causality RBVEC1	0.3978	0.4233	0.6440	0.8528	0.5795
	Causality RBVEC2	0.3770	0.1274	0.6934	0.9133	0.5278
	Spatial RBVEC1	0.3976	0.6716	0.5214	0.6815	0.5680
	Spatial RBVEC2	0.4182	0.6249	0.5643	0.7362	0.5859

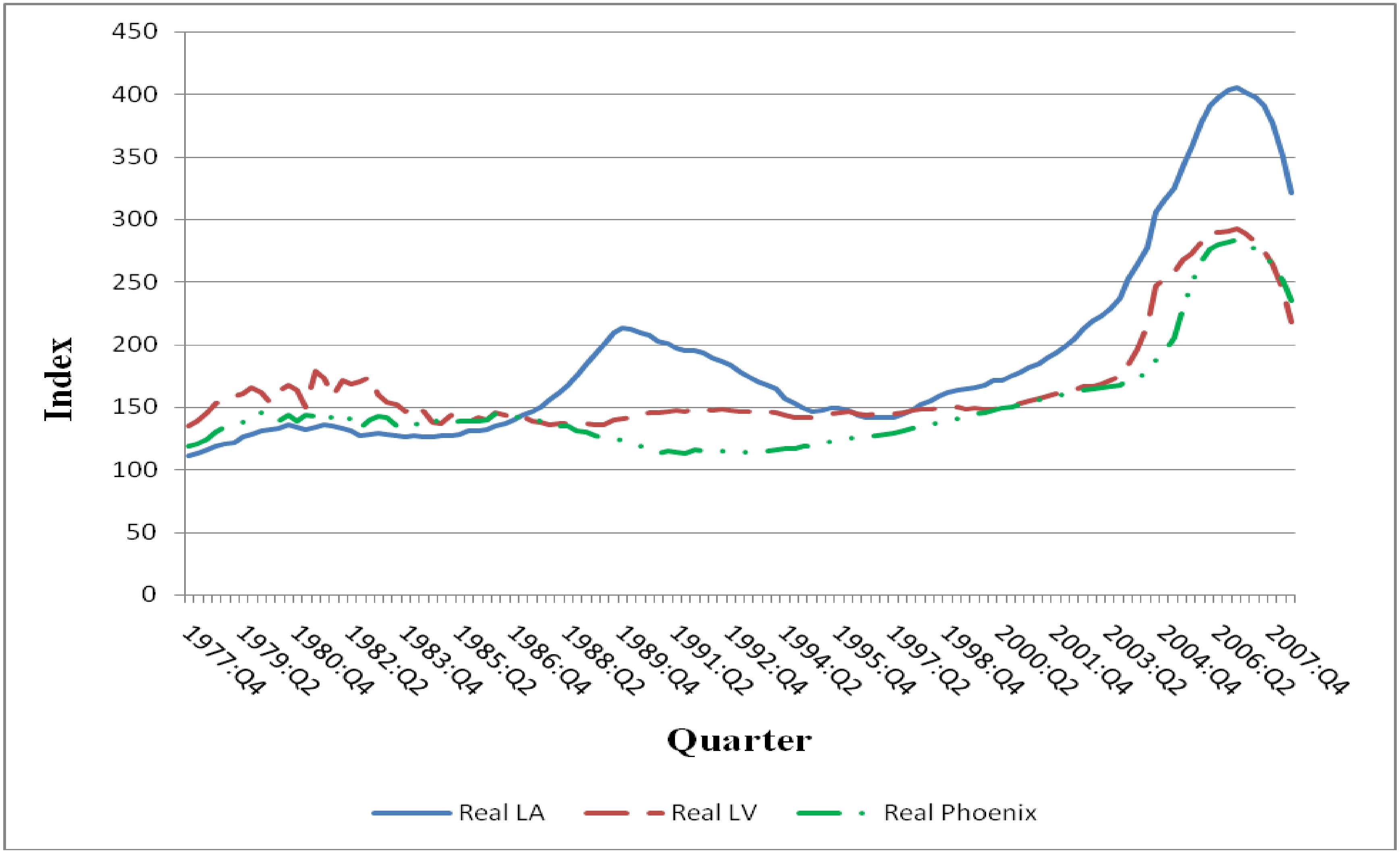
Note: See Table 4.

Table 6: Forecast Results for Phoenix House-Price Index

Parameterization	Models	RMSEs 1	2	3	4	Average
	VAR	0.5350	0.7499	**0.5081**	0.7181	0.6278
	VEC	0.5250	0.9671	0.7352	0.9294	0.7892
w=0.2, d=1	**BVAR**	0.5424	0.7508	0.5097	0.7182	0.6303
	BVEC	0.5321	0.9711	0.7385	1.1789	0.8551
	Causality BVAR	0.6030	0.8605	0.5923	0.8065	0.7156
	Spatial BVAR1	0.5402	0.7555	0.5140	0.7233	0.6332
	Spatial BVAR2	0.6303	0.7790	0.5240	0.7210	0.6636
	Causality BVEC	0.5533	0.9601	0.7122	1.1228	0.8371
	Spatial BVEC1	0.5299	0.9638	0.7344	1.1739	0.8505
	Spatial BVEC2	0.5800	1.0273	0.7719	1.2048	0.8960
w=0.1, d=1	**BVAR**	0.7461	0.7620	0.5200	0.7247	0.6882
	BVEC	0.8990	0.9785	0.7425	1.1728	0.9482
	Causality BVAR	0.6217	0.8731	0.6063	0.8207	0.7305
	Spatial BVAR1	0.5539	0.7696	0.5285	0.7360	0.6470
	Spatial BVAR2	0.6818	0.8185	0.5511	0.7443	0.6989
	Causality BVEC	0.5945	0.9219	0.6629	1.0198	0.7998
	Spatial BVEC1	0.5439	0.9557	0.7311	1.1589	0.8474
	Spatial BVEC2	0.6543	1.0298	0.7571	1.1442	0.8964
w=0.2, d=2	**BVAR**	0.5542	0.7491	0.5089	0.7130	0.6313
	BVEC	0.5344	0.9978	0.7530	1.1953	0.8701
	Causality BVAR	0.6340	0.8983	0.6216	0.8311	0.7462
	Spatial BVAR1	0.5485	0.7640	0.5230	0.7306	0.6415
	Spatial BVAR2	0.6636	0.7916	0.5243	0.7073	0.6717
	Causality BVEC	0.5602	0.9942	0.7290	1.1407	0.8560
	Spatial BVEC1	0.5313	0.9767	0.7417	1.1809	0.8576
	Spatial BVEC2	0.5867	1.0617	0.7921	1.2256	0.9166
w=0.1, d=2	**BVAR**	0.6106	0.7859	0.5351	0.7285	0.6650
	BVEC	0.5528	1.0176	0.7624	1.1933	0.8815
	Causality BVAR	0.6520	0.8868	0.6135	0.8132	0.7414
	Spatial BVAR1	0.5794	0.7937	0.5511	0.7530	0.6693
	Spatial BVAR2	0.6951	0.8251	0.5461	0.7232	0.6973
	Causality BVEC	0.5982	0.9361	0.6699	1.0228	0.8068
	Spatial BVEC1	0.5462	0.9888	0.7474	1.1748	0.8643
	Spatial BVEC2	0.6571	1.0453	0.7645	1.1478	0.9037
σ_c=0.1, η=8, θ=0.5	**Causality RBVAR1**	**0.0323**	0.6334	0.8412	0.7433	0.5625
	Causality RBVAR2	0.0339	0.5435	0.7700	0.6516	0.4998
	Spatial RBVAR1	0.0422	0.3130	0.6101	0.3915	0.3392
	Spatial RBVAR2	0.1041	**0.2893**	0.5531	**0.3456**	**0.3230**
	Causality RBVEC1	0.2018	0.7620	1.1047	0.8259	0.7236
	Causality RBVEC2	0.2553	0.9079	1.1092	0.8461	0.7796
	Spatial RBVEC1	0.0999	0.2982	0.9853	0.6803	0.5159
	Spatial RBVEC2	0.1581	0.5515	1.0057	0.7134	0.6072

Note: See Table 4.

Figure 1: House Price Indexes: Las Vegas, Los Angeles, and Phoenix [25]



[25] House-price indexes for the Los Angeles, Las Vegas, and Phoenix MSAs come from Freddie Mac's conventional mortgage home price index (CMHPI) database. We deflate the MSA-level nominal CMHPI house price by the personal consumption expenditure (PCE) deflator to generate our real house price series.

Figure 2: Impulse Response Functions