REGIONAL HOUSING PRICE CYCLES: A SPATIO-TEMPORAL ANALYSIS USING US STATE LEVEL DATA

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Abstract

We present a study of the effects of macroeconomic shocks on housing prices in the Western United States using quarterly state level data from 1988:1 – 2007:4. The study contributes to the existing literature by explicitly incorporating locational spillovers through a spatial econometric adaptation of vector autoregression (SpVAR). The results suggest these spillovers may Granger cause housing price movements in a large number of cases. SpVAR provides additional insights through impulse response functions that demonstrate the effects of macroeconomic events in different neighboring locations. In addition, we demonstrate that including spatial information leads to significantly lower mean square forecast errors.

Keywords: Housing prices, VAR, spatial econometrics

JEL Codes: C31, C32, R21

1 Introduction

The state of the current economy and recent events in the housing sector have lead to increased attention on the role of the housing sector in the economy as a whole. Policy makers, homeowners, and credit agencies are currently engaged in discussions to address what many are calling a "housing crisis." There is, therefore, a growing demand for economic research in this arena. Economists have studied the relationship between the housing sector and the macroeconomy since the 1970s, and one of the most active veins of literature address the long run and short run effects of unanticipated macroeconomic shocks in such measures as interest rates, mortgage rates, and housing supply. Previous studies have examined the housing sector at the national level (MCGIBANY and NOURZAD, 2004) and at subnational levels such as census region (BAFFOE-BONNIE, 1998; VARGAS-SILVA, 2007; GALLIN, 2006) and metropolitan statistical areas (MSA) (MILLER and PENG, 2006). Other studies have offered insights from other nations, such as Greece (APERGIS and REZITIS, 2003), Turkey (SARI et al., 2007), Canada (HOSSAIN, 2007), and the Netherlands (KAKES and END, 2004).

The most popular method to examine these relationships is vector autoregression analysis (VAR) (see SIMS, 1980). VAR is a generalized form of an autoregressive model in which the evolution of each variable is based on its previous values and previous observations of all other variables in the system. Therefore, the system is able to address the complete set of possible interactions in the data. This flexible method does not rely on a prior theoretical structure but, instead, allows the irregularities in the data to tell the story (LU, 2001). Alternatively, structural forms of VAR may contain additional constraints developed to model a prior theoretical structure.

The present study builds on the existing literature by modeling the housing sector at the state level through a spatial adaptation of the VAR. The spatial adaptation is motivated by VAR's inability to explicitly consider the potential impacts of economic events in neighboring states. In traditional VAR, an economic shock that occurs in a given location only affects the economic conditions in that location. All of the impacts remain within its borders, and there is no mechanism to model locational spillovers. In reality, a shock in a given location is likely to affect the economic conditions in neighboring locations as well. That is, the economic conditions in the spatially related regions are likely to exhibit co-movement over time (PAN and LESAGE, 1995).

We focus our attention on the housing sector in the Western United States for which we model the relationship between housing prices and the macroeconomy, using state level unemployment and per capita personal income. Our structural form of the spatial VAR (SpVAR) is shown to provide more accurate short-term forecasts when compared to aspatial alternatives. In addition, we are able to provide insights on the locational relationships not found in traditional VAR techniques. These include spatial complements to VAR impulse response functions and Granger causality.

A more thorough introduction to the traditional VAR model is presented in Section 2, followed by the spatial VAR model (SpVAR) in Section 3. In addition, we describe our data in Section 4 and model construction in Section 5. We then present a number of key insights obtained from the model in Section 6. Section 7 closes with a discussion of our findings and suggestions for future research.

2 Vector Autoregression

VAR is a set of symmetric equations in which each variable is described by a set of its own lags and the lags of all other variables in the system. A VAR with two random variables and p temporal lags can be expressed in the following form:

$$y_t = c_1 + a_{11}y_{t-1} + \cdots + a_{1p}y_{t-p} + b_{11}z_{t-1} + \cdots + b_{1p}z_{t-p} + \varepsilon_{1t} \tag{1a}$$

$$z_t = c_2 + a_{21}y_{t-1} + \cdots + a_{2p}y_{t-p} + b_{21}z_{t-1} + \cdots + b_{2p}z_{t-p} + \varepsilon_{2t} \tag{1b}$$

where y_t and z_t are series random variables observed over time $t = 1, ..., T$. Each i equation contains a constant term c_i, a set of unknown parameters a_{ij} for lag length $j = 1, .., p$, and an error term ε_{it}. In a VAR, the sequence of error terms are also called "innovations" because they contain information that determines y_t or z_t but is not contained in previous observations (y_{t-j} and z_{t-j}). These innovations are assumed to follow a number of standard conditions:

1. All error terms have an expected value of zero, $E(\varepsilon_t) = 0$.

2. All error terms are expected to have a constant variance, $E(\varepsilon_t\varepsilon_t') = \Omega$.

3. For any nonzero k, there is no serial correlation in the error terms, $E(\varepsilon_t\varepsilon_{t-k}') = 0$.

In addition, the error terms are assumed to be contemporaneously correlated due to common omitted variables which affect each equation in a similar fashion. As a result the system of equations is estimated using seemingly unrelated regressions (SUR). However, when the equations contain the same right hand side variables, as in the case presented in Equations (1a – 1b), there is no advantage over estimating each equation separately using ordinary least squares (OLS) (see GREENE, 1998, p. 343).

VAR analysis can be used to examine whether a variable is determined in part by the other variables in the system (GRANGER, 1969). A variable y_t is said to *Granger cause* z_t if the information contained in previous values of y_t are useful for forecasting z_t. If all variables in the VAR are free of a unit root, then Granger causality can be directly tested by a standard F-test of the restriction:

$$a_{21} = a_{22} = \cdots = a_{2p} = 0 \tag{2}$$

from Equation (1b). However, it should be noted that Granger causality is not *causality* per se, but Granger causality measures whether or not previous values of y_t help forecast future values of z_t.

In addition to the coefficient estimates, VAR analysis is able to gather additional insights from the information contained in the residual estimates. One of the most popular ways to interpret VAR results is the estimation of *impulse response functions* (IRF) (see ENDERS, 2004). An IRF is calculated by introducing a shock to a right hand side variable in the initial period, followed by an equal but opposite shock in the second period. Then, the difference between the initial residual estimates and the residual estimates from the series with the shocks can be plotted over time. This series then represents the cyclical behavior of the dependent variable following an exogenous shock. If the system of equations is stable, the effects should converge to zero as the system returns to the initial equilibrium. However, a shock to an unstable system could produce explosive or lasting effects.

3 Spatial VAR (SpVAR)

Advances in spatial econometric techniques have lead to an increase in the desire to incorporate locational information in a number of traditional econometric methods. VAR analysis has witnessed a limited number of studies that attempt to "spatialize" the technique. For example, PAN and LESAGE (1995) use spatial contiguity as an alternative prior in a Bayesian VAR model. Their analysis demonstrates that incorporating a spatial contiguity structure dramatically lowers forecast error. DI GIACINTO (2003) uses spatial relationships to derive parameter constraints in a structural VAR model. Structural VAR models are similar to the model presented in Equations (1a – 1b), but a number of coefficients are restricted (typically to zero) to follow prior theoretical beliefs. BEENSTOCK and FELSENSTEIN (2007) present a more thorough development of a flexible SpVAR model that builds on the spatial autoregressive model with a spatial error process. These techniques, however, have received limited attention in applied studies such as the one currently presented.

The model employed in our study most closely resembles a structural form of BEENSTOCK and FELSENSTEIN's SpVAR model. The model follows (1a)–(1b) but adds a set of s spatial crossregressive lags. Thus, the structural SpVAR(p,s) with N regions takes the following form:

$$\begin{aligned} y_{t1} =& c_{11} + a_{111}y_{t-1} + \cdots + a_{1p1}y_{t-p} + b_{111}z_{t-1} + \cdots + b_{1p1}z_{t-p} + \\ & \gamma_{111}Wy_{t-1} + \cdots + \gamma_{1s1}Wy_{t-s} + \delta_{111}Wz_{t-1} + \cdots + \delta_{1s1}Wz_{t-s} + \varepsilon_{1t1} \end{aligned} \tag{3}$$

$$\begin{aligned} z_{t1} =& c_{21} + a_{211}y_{t-1} + \cdots + a_{2p1}y_{t-p} + b_{211}z_{t-1} + \cdots + b_{2p1}z_{t-p} + \\ & \gamma_{211}Wy_{t-1} + \cdots + \gamma_{2s1}Wy_{t-s} + \delta_{211}Wz_{t-1} + \cdots + \delta_{2s1}Wz_{t-s} + \varepsilon_{2t1} \end{aligned} \tag{4}$$

$$\begin{aligned} y_{tN} =& c_{1N} + a_{11N}y_{t-1} + \cdots + a_{1pN}y_{t-p} + b_{11N}z_{t-1} + \cdots + b_{1pN}z_{t-p} + \\ & \gamma_{11N}Wy_{t-1} + \cdots + \gamma_{1sN}Wy_{t-s} + \delta_{11N}Wz_{t-1} + \cdots + \delta_{1sN}Wz_{t-s} + \varepsilon_{3tN} \end{aligned} \tag{5}$$

$$\begin{aligned} z_{tN} =& c_{2N} + a_{21N}y_{t-1} + \cdots + a_{2pN}y_{t-p} + b_{21N}z_{t-1} + \cdots + b_{2pN}z_{t-p} + \\ & \gamma_{21N}Wy_{t-1} + \cdots + \gamma_{2sN}Wy_{t-s} + \delta_{21N}Wz_{t-1} + \cdots + \delta_{2sN}Wz_{t-s} + \varepsilon_{4tN} \end{aligned} \tag{6}$$

The spatial crossregressive lags are obtained by premultiplying each temporal lag term by W, a spatial weight matrix. The spatial weight matrix essentially defines which locations are considered neighbors. In our analysis we adopt a binary first-order "queen" contiguity matrix. Matching a queen's movement on a chess board, two elements are considered neighbors if they share a common border, regardless of direction. It contains a row vector for each location, and the elements of this matrix take a value of 1 when two locations share a common border. All other elements, including the diagonal, are zero. Each row of the weight matrix is then standardized so that all elements sum to 1. Therefore the crossregressive lags represent the averages values at the neighbors in a previous period. The matrix only considers first order (immediate) neighbors but not higher order spatial relationships, such as neighbors of neighbors. Thus, shocks are not transmitted globally. However, it is important to note that previous studies have shown that the selection of the spatial weights matrix impacts coefficient estimates (BELL and BOCKSTAEL, 2000). These spatial crossregressive lags require the estimation of additional unknown parameters γ_{ijn} and δ_{ijn}.

Again, the error terms ε are expected to follow the properties listed, and the system of equations is estimated using SUR due to contemporaneous correlation. In the SpVAR model, each value of the spatially lagged variables is unique for each region n. Because the spatial weights matrix only considers neighboring observations and each observation has a unique set of neighbors, the crossregressive terms are not the same across all equations. As a result, the OLS estimates are no longer computationally equal to SUR results. We therefore estimate (3 – 6) by SUR. We also assume that the errors are not spatially autocorrelated.

Granger causality in an SpVAR context can again be examined with series of tests similar to Equation (2). This leads to additional Granger causality tests that are unique to SpVAR. It is possible to test locational spillovers as a determinant of each variable:

$$\gamma_{21n} = \cdots = \gamma_{2sn} = 0 \tag{7}$$

Alternatively, the locational and temporal values may jointly Granger cause z_{tn}:

$$a_{21n} = \cdots = a_{2pn} = \gamma_{21n} = \cdots = \gamma_{2sn} = 0 \tag{8}$$

The SpVAR lends itself to IRF analysis as well, but yet again, the spatial crossregressive lags lead to additional interpretations. In the traditional VAR construct, the effects of a given shock are assumed to only appear in the location in which it occurred. When the system follows the SpVAR construct, the shock is transmitted to neighboring regions via the spatial crossregressive terms. Thus the shock in one explanatory variable is transmitted to the neighboring locations in the following period, weighted by W.

4 Data

We model state level housing price as measured by the Conventional Mortgage Home Price Index (CMHPI) which is reported quarterly by Fannie Mae and Freddie Mac. The indices are constructed using repeated-sales data of over 4.5 million transactions nationwide. CMPHI is widely used in previous studies, and a more detailed description of the construction of the CMHPI index can be found in STEPHENS et al. (1995). The analysis examines the period beginning in the first quarter of 1988 and ending in the fourth quarter of 2007. The series were collected for each of the 11 states in the West Region defined by the United States Census Bureau: Arizona, California, Colorado, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington and Wyoming. Figure 1 shows the quarterly house price series for California, Arizona, Oregon, and Nevada.

FIGURE 1 ABOUT HERE

The CMPHI time series for California, Arizona, Oregon, and Nevada are shown in Figure 2. It appears that housing prices in each state follow a similar path with a gradual increase from 1988 – 2003 followed by a rapid increase. However, in the later quarters of 2005, housing prices began to fall in a number of states, most notably California. This rapid increase and decrease is commonly cited as evidence of a housing price bubble or attributed to the current housing "crisis."

FIGURE 2 ABOUT HERE

The other variables included in the analysis are state level unemployment obtained from the U.S. Department of Labor's Bureau of Labor Statistics, and per capita personal income obtained from the U.S. Department of Commerce's Bureau of Economic Analysis. Personal income and unemployment have both been used in previous studies as measures of the health of the economy, yet it is important to note that only a small number of time series data are published at the state level and, of these series, even fewer are reported at intervals less than one year.

It is also important to note that selecting a region for analysis can lead to undesirable edge effects. The selection imposes the assumption that spillovers only exist within the region, and events outside of the region do not affect the conditions within the region. For example, an economic event in Texas which borders the region will not affect the economic conditions within the region nor will events in Western states effect Texas' economic condition. However, we believe the selected scale is appropriate for state level analysis of housing price movements. There is limited economic spillover between the West and neighboring regions, the South and Midwest. However, migration patterns and economic stock flows are high within the region (CROMWELL, 1992).

4.1 Stationarity Tests

Stationarity in each series leads to straightforward interpretation of the results, especially in the case of IRFs. As a result, SIMS (1980) and SIMS et al. (1990) argue against first-differencing to obtain stationarity. We test for the presence of a unit root for all three variables in each of the 11 states and found stationarity in all series. As a result our SpVAR model examines each series in levels. The tests were conducted using three forms of the Augmented Dickey-Fuller (ADF) Test (DICKEY and FULLER, 1979):

$$\text{No intercept and no trend:}\quad \triangle y_t = \gamma y_{t-1} + \varepsilon_t \tag{9a}$$

$$\text{Intercept and no trend:}\quad \triangle y_t = a_0 + \gamma y_{t-1} + \varepsilon_t \tag{9b}$$

$$\text{Intercept and trend:}\quad \triangle y_t = a_0 + \gamma y_{t-1} + a_2 t + \varepsilon_t \tag{9c}$$

where $\triangle y_t$ is the first-difference of the variable of interest y_t, a_0 a deterministic drift and t a deterministic trend. The augmented ADF test determines whether to accept or reject the null hypothesis of $\gamma = 0$. The results of the augmented ADF tests for all three variables in each of the 11 states are presented in Table 1. For all series, we reject the presence of a unit root in levels and therefore conclude all series are stationary.

TABLE 1 ABOUT HERE

Further, we used the simple panel unit root test suggested by IM et al. (2003) for all series to examine the potential for non-stationarity across series. The results are reported in Table 2. The Z statistic is computed using the average value of the individual series for the tests reported in Equations (9a) – (9c):

$$\bar{t} = \frac{1}{n}\sum_{i=1}^{n} t_i \tag{10}$$

$$Z_{\bar{t}} = \frac{\sqrt{n}[\bar{t} - E(\bar{t})]}{\sqrt{var(\bar{t})}} \tag{11}$$

IM et al. (2003) provide Monte Carlo critical values for tests that include no intercept or trend, an intercept without a trend, and both an intercept and trend. Again, we determined the panel is stationary for all three variables in each of the 11 states.

TABLE 2 ABOUT HERE

4.2 Spatial Autocorrelation Tests

In addition to testing for stationarity across the series, we investigate whether each series follows a systematic pattern in its spatial distribution. That is, we test for the presence of spatial autocorrelation in each series to motivate the use of the spatial crossregressive lags. The test is conducted using the Moran's I statistic (MORAN, 1950):

$$I = \frac{N}{\sum_i \sum_j W_{i,j}} \frac{\sum_i \sum_j W_{i,j}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2} \tag{12}$$

where X is a random variable, $\bar{X}$ the mean value of X, N the number of observations, and W the spatial weights matrix. Generally speaking, Moran's I values range between -1 and 1.

The diagonal elements of Table 3 include the results of the Moran's I test for each variable in the first and last quarter observed. The test statistics were computed using a normalized first-order queen contiguity weights matrix, and statistical significance was determined through bootstrapping. The results suggest the presence of spatial autocorrelation in both housing prices and unemployment. However, personal income does not appear to be spatially autocorrelated in either period.

TABLE 3 ABOUT HERE

The off-diagonal elements of Table 3 include values of the bivariate Moran's I which measures the level of spatial correlation across two variables in the same region. The test statistic is computed using the following equation:

$$I_i = \frac{N(X_i - \bar{X}) \sum_j W_{ij}(Y_j - \bar{Y})}{\sum_i (X_i - \bar{X})^2} \tag{13}$$

The bivariate estimates provide evidence of spatial correlation across housing price and unemployment, as well as, unemployment and personal income. We therefore elect to include the spatial crossregressive lags in the estimation which is shown in the Section 5.

5 Estimation

The SpVAR(p,s) shown in Equations (3) – (6) consists of N equations, each with a constant term, p temporal lags, and s spatial lags for each variable. A system of k variables and N locations, would lead to the estimation of $(1 + pk + sk)N$ unknown parameters. To simplify estimation, we divide the system into three separate blocs, one for housing, one for income, and one for unemployment. Therefore, each variable is estimated in its own separate system. This simplification imposes an assumption that information regarding personal income and unemployment are only able to influence housing prices in the next period. For example, current observations of personal income and unemployment do not influence current housing prices (absolutely or through the error term), but predetermined observations of personal income and unemployment do affect current observations of housing prices.

The model includes 11 locations observed in total of 80 time periods. In order to preserve the necessary degrees of freedom, we incorporate a single temporal lag and a single spatial crossregressive lag of each variable – SpVAR(1,1). Thus, the housing price bloc contains a total of 11 equations that each take the following form:

$$h_{t,n} = c_n + a_{1,n} h_{t-1,n} + \gamma_{1,n} W h_{t-1,n} + a_{2,n} i_{t-1,n} + \gamma_{2,n} W i_{t-1,n} + a_{3,n} u_{t-1,n} + \gamma_{3,n} W u_{t-1,n} + \varepsilon_{t,n} \quad (14)$$

where $h_{t,n}$ is CMHPI at time t at location n, $i_{t,n}$ per capita personal income, and $u_{t,n}$ state level unemployment where $T = 80$ and $N = 11$. This yields a total of 77 coefficient estimates.

6 Results

To conserve space, we limit our discussion to the results of the housing price bloc. There is evidence that the inclusion of the spatial crossregressive lags leads to more desirable short-term forecasts. The model was estimated twice, once with the spatial crossregressive lags and again without. The SpVAR specification produced a statistically significant lower mean square forecast error, presented in Table 4.

TABLE 4 ABOUT HERE

6.1 Granger Causality

We find additional evidence that the spatial crossregressive terms add valuable information on the determination of housing prices. In several instances, we find that the locational variables Granger cause housing prices. The individual test results for each spatial crossregressive variable are reported in Table 5. The table indicates a statistically significant relationship at the 0.05-level, with a "1," and insignificant results are reported as "0." Housing prices in neighboring states provide useful forecasting information for in-state housing price forecasts in 64% of the Western states. However, the causality falls to 45% with respect to per capita personal income and 27% for unemployment. There is only a single state, California, in which all three locational variables Granger cause housing prices. This provides evidence that California acts as the region's economic leader, as suggested by CROMWELL (1992).

TABLE 5 ABOUT HERE

In addition, we examine the potential for Granger causality in a spatiotemporal sense for each variable by a joint significance test on the coefficients for both the temporal lag and spatial crossregressive lags. For example, to determine whether per capita personal income Granger causes housing prices in spatiotemporal sense, we test $a_{2,n} = \gamma_{2,n} = 0$ in Equation (14) for each state. The results are reported in Table 6.

TABLE 6 ABOUT HERE

The spatiotemporal Granger causality tests indicate that previous housing prices in space and time impact current housing prices in all of the 11 states examined. Again, the causality falls to 73% in the case of income and 36% for unemployment. There were only two instances for which all three spatiotemporal tests were significantly different from zero, California and Utah.

6.2 Impulse Response Functions

The Granger causality tests indicate that California is highly impacted by its neighbors, and as a result, we focus our discussion on the cyclical behavior of housing prices in California as modeled by three sets of IRFs. First, we discuss the response to a shock in per capita personal income in California and a separate shock in unemployment in California. Second, we present the IRFs that result from a shock in California's unemployment in its neighboring states of Arizona, Nevada, and Oregon. Finally, we show California's response to a shock in unemployment in each of the three neighboring states. The first set of IRFs are found in traditional VAR studies while the remaining sets are unique to SpVAR analysis.

The first set of IRFs are shown in Figure 3. Both lines represent the cyclical behavior in California housing prices, yet the solid line indicates a shock in per capita personal income while the dashed line shows the effects of a shock in state level unemployment. The response is plotted over the eight quarters following a one standard deviation shock in each variable. It appears that housing prices follow a more dynamic response after a shock in personal income. The cycle shows its most dramatic behavior in the first two periods, and the effect seems to dissipate near the fifth quarter. Unemployment appears to have more of a lagged effect that is also less pronounced. Again, the effect of the shock appears to die out in the fifth quarter. Further, in both series, the system appears to approach the initial equilibrium conditions at the end of the two years presented in Figure 3.

FIGURE 3 ABOUT HERE

In a similar fashion, Figure 4 maps the dynamic response in housing prices in Arizona, Nevada, and Oregon to a one standard deviation shock in California's unemployment. All three series follow the same general pattern, but the impact appears to be greater in Arizona (solid line) and Nevada (dashed line). Again, the system appears to stabilize after five periods, but housing prices in Arizona and Nevada may reach a lower equilibrium point than the initial condition.

FIGURE 4 ABOUT HERE

Conversely, SpVAR is able to show how housing prices in California may react differently when a shock occurs in each of its neighboring states. Figure 5 demonstrates the impact of a shock in unemployment in Arizona, Nevada, and Oregon on California's housing price. Again, the IRFs show a similar pattern which stabilizes after five quarters. However, in this example, Oregon appears to have a stronger effect on California than the two other neighboring states. The housing price also appears to settle below the initial equilibrium in each case.

FIGURE 5 ABOUT HERE

Overall, the IRF results suggest states are linked economically and geographically, and each state responds to it neighbor's economic conditions and events. Further, the state level responses follow a similar pattern in most cases, yet the estimates vary by magnitude. It is interesting to see that economic shocks appear to die out after 5 quarters. The cyclical patterns may provide useful information on the recent developments in the Western US economic, such as high levels of unemployment and suppressed housing prices.

7 Conclusion

In our analysis, we were able to demonstrate the cyclical behavior in housing prices in the wake of a macroeconomic shock in the Western United States using quarterly state level data. Our study contributes to the existing literature by introducing a framework which explicitly ties in neighboring locations so that economic events in one state are able to affect the economic conditions of its neighbors.

We motivate the study by exploring the degree of spatial autocorrelation in each series. The inclusion of spatial crossregressive lags appears to be warranted as our estimates produce lower mean square forecast error than the aspatial alternative. In addition, Granger causality tests show that these variables provide important forecasting information. The additional information garnered from the spatial vector autoregression analysis is highlighted by a discussion of California's housing prices. The state's recent housing price boom-and-bust has recently received a lot of attention. As a result, our results shed light on an area of growing interest to homeowners, industry professionals, and policy makers alike.

The study also suggests several avenues for future research. For example, we indicate the need for additional and more frequent macroeconomic measures reported at a state level. Access to longer and richer time series would provide the degrees of freedom required to expand the number of states considered by the model. In addition, it would allow researchers to study longer temporal lags, as well as higher order neighborhood relationships. Also the proposed structural SpVAR model may also be estimated assuming errors are both spatially and contemporaneously correlated.

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Table 1: Stationarity Test Results

	Housing price			**Personal income**			**Unemployment**		
State	No intercept	Intercept	Trend	No intercept	Intercept	Trend	No intercept	Intercept	Trend
Arizona	-0.01	-1.50	-3.21	16.66	5.90	-0.13	-0.96	-2.32	-2.90
California	-0.67	-1.87	-2.61	13.32	3.80	0.05	-0.17	-1.11	-1.70
Colorado	2.76	0.27	-2.70	12.74	2.92	-1.32	-1.44	-2.97	-2.82
Idaho	2.88	1.73	-1.81	13.84	3.67	0.72	-1.17	-5.06	-6.98
Montana	5.28	3.87	2.50	12.09	3.57	0.60	-1.40	-4.12	-11.91
New Mexico	2.69	1.53	-0.32	15.06	4.63	1.24	-1.51	-1.15	-2.74
Nevada	0.30	-1.19	-2.29	5.30	3.38	-0.07	-0.36	-1.45	-1.59
Oregon	1.72	0.29	-1.82	16.00	2.60	0.03	-0.62	-3.74	-3.75
Utah	1.75	0.21	-2.65	5.42	3.25	0.35	-1.15	-1.31	-1.37
Washington	1.80	0.46	-1.42	6.25	1.35	-1.43	-1.03	-3.62	-3.68
Wyoming	11.59	6.74	2.76	17.66	7.48	2.61	-1.58	-4.70	-11.20

Critical values for $\alpha = 0.05$: -2.90, -3.47, -1.94.

Table 2: Panel Stationarity Test Results

Test	Housing price	Personal income	Unemployment
No intercept	-2.36	10.36	-31.46
Intercpet	10.61	24.73	-21.70
Trend	-2.36	10.36	-31.46

Critical values for $\alpha = 0.05$: -3.90, -3.26, -2.94. Obtained from IM et al. (2003).

Table 3: Moran's I Test

	Housing price	Personal income	Unemployment
1988			
Housing Price	-0.18**		
Personal income	0.10	-0.04	
Unemployment	0.23*	-0.22	0.21**
2007			
Housing Price	0.36**		
Personal income	0.15	-0.04	
Unemployment	0.3**	0.34**	0.388**

Significance level: * 0.10, ** 0.05, *** 0.01

Table 4: Mean Square Forecast Error Results

	VAR	SpVAR
Mean	83.37	60.30
t-Statistic	-2.11	**

Significance level: * 0.10, ** 0.05, *** 0.01

Table 5: Granger Causality for Spatial Variables

State	Housing price	Personal income	Unemployment
Arizona	1	1	0
California	1	1	1
Colorado	1	1	0
Idaho	1	0	1
Montana	1	0	0
New Mexico	0	0	0
Nevada	1	1	0
Oregon	0	0	0
Utah	0	0	1
Washington	0	0	0
Wyoming	1	1	0

1 = Granger cause, 0 = Does not Granger cause

Table 6: Granger Causality for Spatial and Temporal Variables

State	Housing price	Personal income	Unemployment
Arizona	1	1	0
California	1	1	1
Colorado	1	1	0
Idaho	1	0	0
Montana	1	1	0
New Mexico	1	0	1
Nevada	1	1	0
Oregon	1	1	0
Utah	1	1	1
Washington	1	0	1
Wyoming	1	1	0

1 = Granger cause, 0 = Does not Granger cause

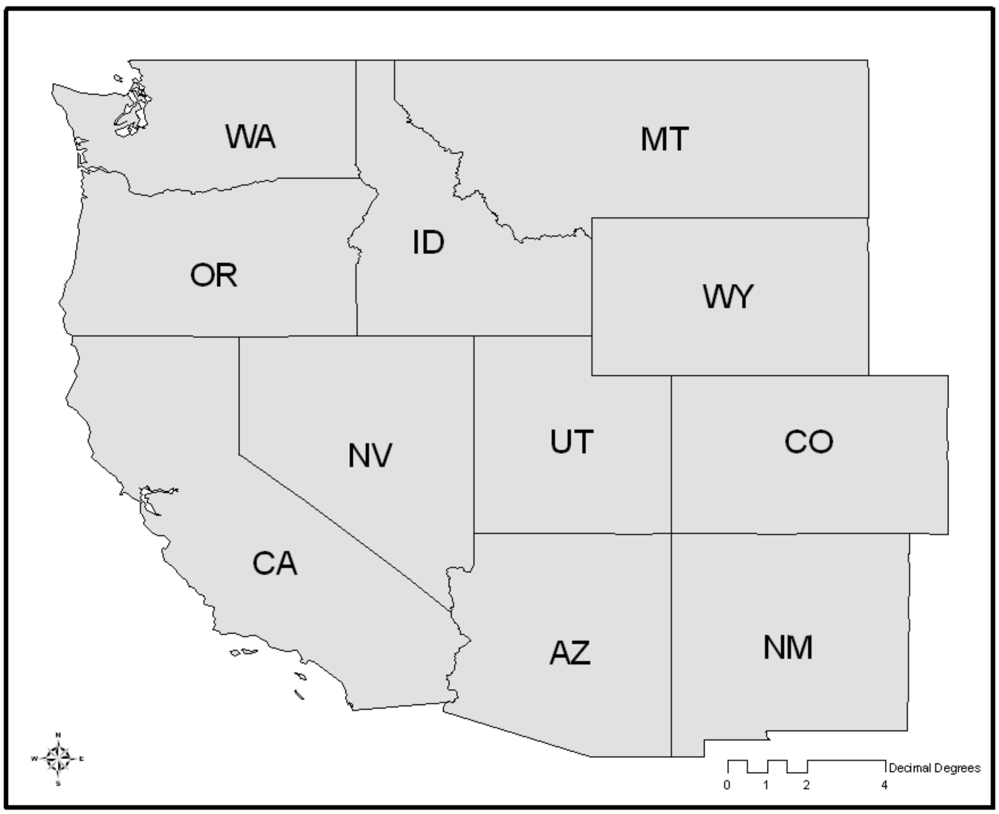

Figure 1: West Region

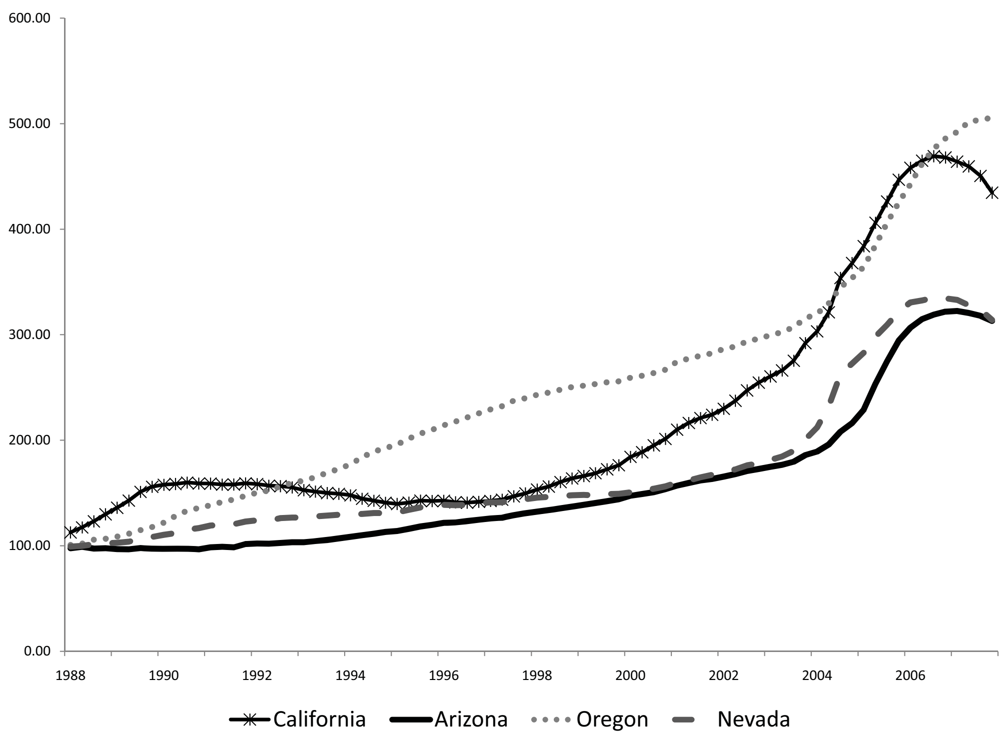

Figure 2: Housing Price Series

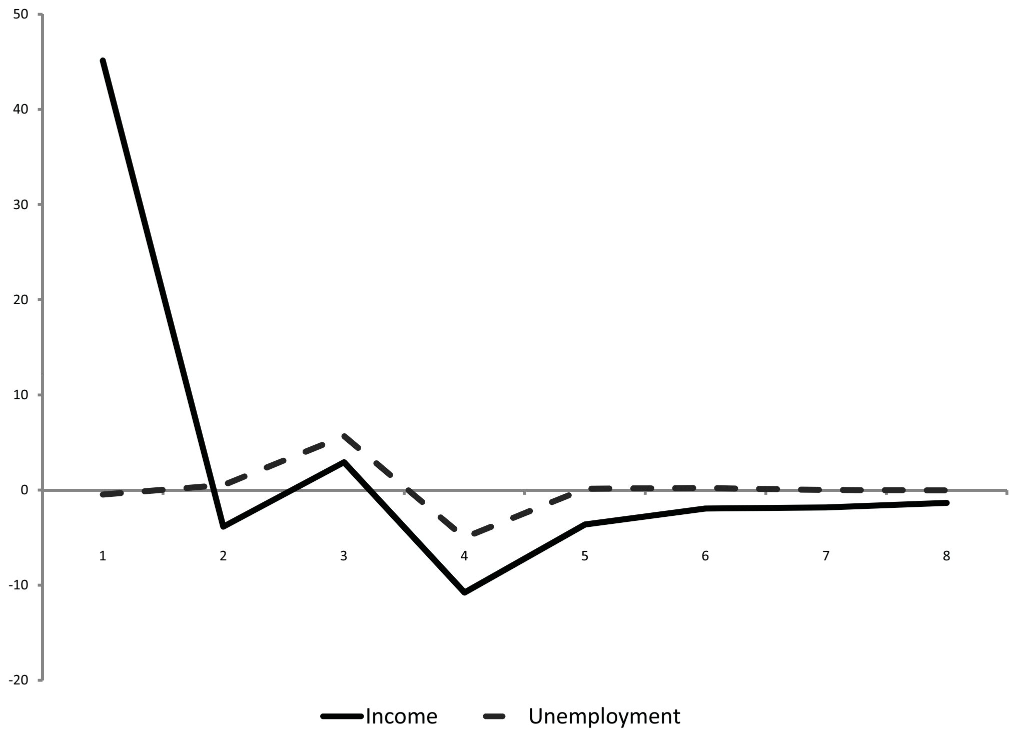

Figure 3: Housing price response in California to a one standard deviation shock to personal income and to unemployment in California

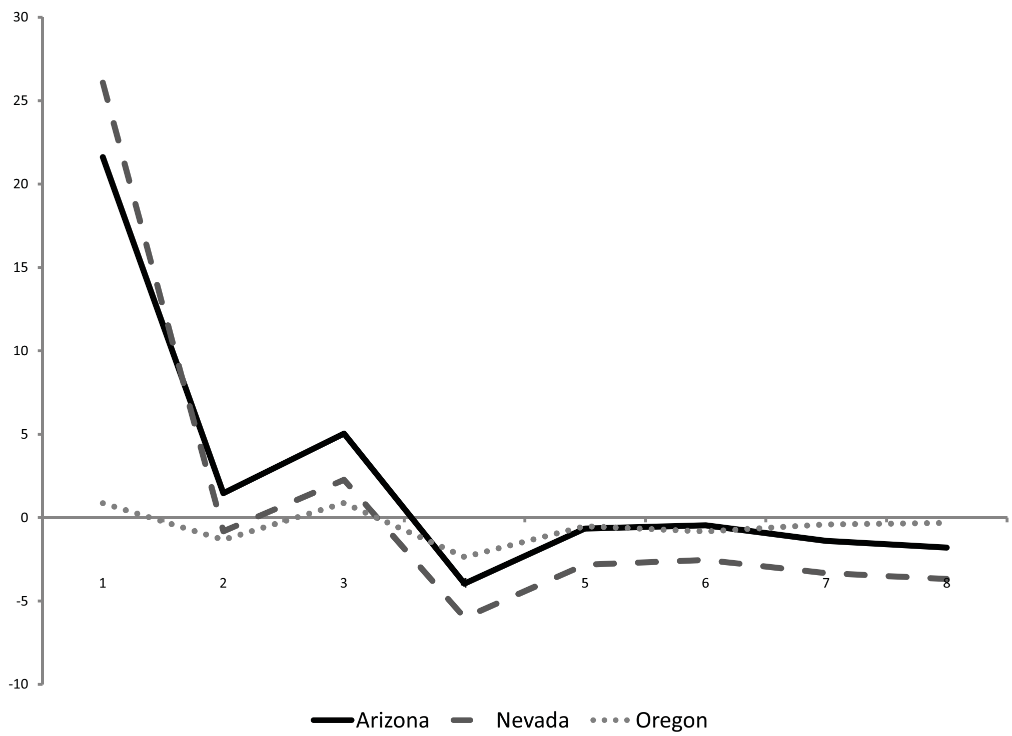

Figure 4: Housing price response in Arizona, Nevada, and Oregon to a one standard deviation shock to unemployment in California

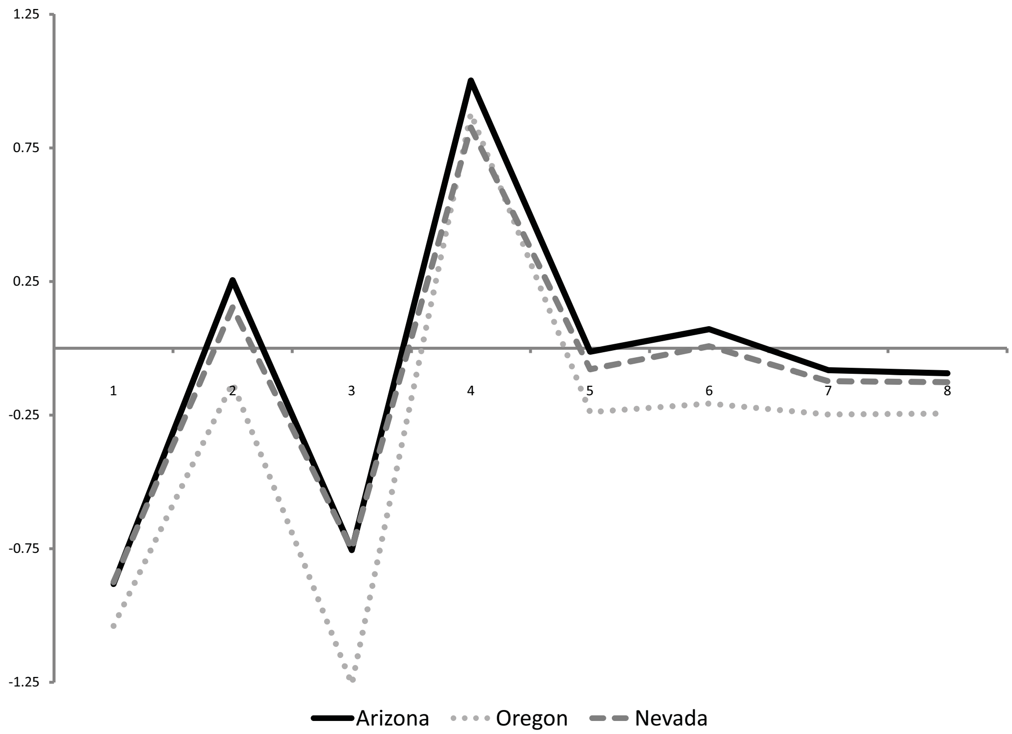

Figure 5: Housing price response in California to a one standard deviation shock to unemployment in Arizona, Nevada, and Oregon