Dynamic Interactions in the Western United States Electricity Spot Markets

Christine A. Jerko
Economic Research Analyst at Tractebel Electricity & Gas International, Houston, TX

James W. Mjelde
Professor, Dept. of Agricultural Economics at Texas A&M University, College Station, TX

David A. Bessler
Professor, Dept. of Agricultural Economics at Texas A&M University, College Station, TX

Abstract

Dynamic interactions between six electricity spot markets in the western United States are examined using time series analysis and directed graphs. Results show the western trading region to be highly integrated. The California market appears to be the driving force for prices in contemporaneous time. Seasonal analyses suggest there are seasonal differences in the short-run price discovery mechanisms. In the longer run, price dynamics appear to be similar between seasons. The mid-Columbia spot market appears to be the dominant market in the long run in both seasons.

Key words: electricity prices, directed graphs, vector autoregression, time series

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Corresponding Author: James W. Mjelde
Dept. Ag. Econ. MS 2124
Texas A&M University
College Station, TX 77843-2124
e-mail: j-mjelde@tamu.edu
Phone: (979) 845-1492
Fax: (979) 845-4582

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1. Introduction

The wholesale electricity industry in the western United States is characterized by a highly interconnected transmission system and established trading regime (De Vany and Walls, 1999b). The geographic scope of this market is quite wide under most market conditions, but narrow markets may arise when transmission congestion occurs (Bailey, 1998). The magnitude of trades between wholesale spot markets has been stimulated by the recent deregulation in the industry (U.S. Department of Energy, 1998). Deregulation of the electricity industry and its impact on electricity prices is a subject of considerable interest, especially given the recent electricity price spikes occurring in California and elsewhere. Weron (2000) notes deregulation is a global trend and is not limited to the United States. Further, Angelus (2001) states market structures appear to vary greatly between wholesale markets and the markets seem to be changing yearly, resulting in high and volatile prices.

Because electricity cannot be economically stored, demand and supply are balanced on a knife-edge with weather grid reliability, grid dynamics, transmission dynamics, and generation concentration paramount to determining price (Weron, 2000; Wagman, 2000). Weron and Przybylowicz (2000 p. 464) state, "The whole complex process of electricity price formulation results in a behavior not observed in the financial or even other commodity markets. It is extremely interesting to investigate this new world." Most studies of electricity pricing have investigated market structure and power, reasons for deregulation, or impact of deregulation on price (Joskow, 1997; White, 1996; Angelus, 2001; Deb et al., 2000), but few studies have examined the dynamic nature of empirical price evolution. Further, time series analysis has been used in only a handful of studies.

Weron (2000) and Weron and Przybylowicz (2000) using price data from California and Switzerland note the process underlying electricity prices is mean reverting. Because electricity prices are mean reverting, Weron (2000) suggests Black-Scholes type models must be questioned when modeling such prices. Weron and Przybylowicz (2000) suggest an appropriate modeling technique is the Hurst R/S approach. This approach attempts to distinguish "... completely random time series from correlated time series" (Weron and Przybylowicz, 2000 p. 463). Herguera (2000), in examining spot markets in England and Wales and the Nordic countries, notes there is significant differences in the evolution of prices and volume traded. He states the data supports the theoretical result of Allaz and Villa (1993) that the introduction of futures market leads to tougher price competition in spot markets. However, in the United States, prices may not be as transparent because must trades are bilateral and futures trading volume is limited.

DeVany and Walls (1999b) examined daily, peak and off-peak electricity spot prices during 1994 and 1996 using an error correction model on 11 regional markets in the western United States. They find spot markets are generally non-stationary and cointegrated. Peak prices at Palo Verde, however, are cointegrated with the off-peak price at only one other market, suggesting transfer capacities are limited during peak periods in this part of the western grid. DeVany and Walls (1999a) use a vector autoregressive model to obtain impulse response functions and variance decomposition. Their impulse responses indicate shocks to a market impact neighboring markets first and then more distant locations along the transmission network. Variance decompositions suggest the California-Oregon border as one of the most important spot market in determining prices throughout the network. Unlike De Vany and Walls (1999a, b), Woo et al. (1997) find the presence of stationarity within Pacific Northwest spot markets.

They infer the presence of pair-wise cointegration based on price difference tests of their stationary price series. The results of Woo et al. (1997) are questionable because cointegration refers to the linear combination of nonstationary variables (Engle and Granger, 1987).

Providing information on the dynamics of power prices in the western United States is the objective of this study. In achieving this objective, price discovery and communication between different spot markets are obtained. Dynamic relationships allow the degree of interaction between wholesale spot markets to be determined. Understanding how spot markets interact allows a better understanding of the direction and extent to which price innovations reverberate through the western trading region. To meet this objective, prices from six spot markets located in the western United States are used to estimate vector autoregression. Directed graphs are used to provide identification restrictions on causal information flows in contemporaneous time for impulse response functions and forecast error variance decompositions.

2. Data

The data consists of 643 observations of daily firm-peak spot market prices for day-ahead trades spanning the period of March 15, 1999 to August 24, 2001. The data are Platts power indices provided by Logical Information Machines, Inc. Chicago Illinois. Peak prices are sales with next day delivery for the hours between 6 a.m. and 10 p.m. Prices are, generally, for Monday through Friday. Starting in May 2001, peak prices for Saturday are included. Saturday peak prices are not included until May 2001, because of a high number of missing prices. Most national holidays are also excluded from the data set because of missing values. The prior day’s price is used to represent any remaining missing values for a particular day and market.

The six spot markets included are mid-Columbia (MC), California-Oregon border

(COB), North Path in California (NP), South Path in California (SP), Palo Verde (PV), and Four Corners (FC). The approximate locations of the markets (areas) are given in Fig. 1. Plots of the price series are provided in Fig. 2. The most striking features of the plots are the price spikes experienced in 2000 and 2001.

Typically, because of technical and economic reasons, gas-fired electricity is on the margin for peak prices. Of interest, however, is the capacity and main type of electricity generation near each spot market. The main source of electricity generation near mid-Columbia is hydro-generation (Ashton, 2001). Seven dams on midsection of the Columbia River have a generating nameplate capacity of 13,475 megawatts (U.S. Department of Energy, 2001). Fossil fuel generation is the primary source of power at Four Corners. This area (New Mexico and Arizona) has a collective nameplate capacity of approximately 7,962 megawatts (U.S. Department of Energy, 2001). Palo Verde is the site of the largest nuclear generating facility in the United States (U.S. Department of Energy, 2001). Three reactors have a combined nameplate capacity of 4,210 megawatts. North and South Path and the California-Oregon border are mainly transmission areas. While both the North and South Path areas have various types of electricity generating plates, the North Path is predominately hydro-generation, whereas the South Path has more oil and gas power plants (California Energy Commission, 2001b).

In addition to electricity prices, aggregate cooling and heating degree-days are used. Degree-days are units used to estimate heating and cooling requirements (Microsoft, 2001). One degree-day is defined as a difference of one degree between mean temperature ((maximum temperature + minimum temperature) / 2) and a reference temperature. For cooling degree-days the reference temperature is 75 degrees Fahrenheit (cooling degree-day = mean temperature - reference temperature), whereas for heating degree-days the reference temperature used is 65 degrees Fahrenheit (heating degree-day = reference temperature - mean temperature). If either degree-day is negative, it is set equal to zero. Daily cooling and heating degree-days are calculated for the following eight western cities: Seattle, Portland, San Francisco, Los Angeles, Salt Lake, Denver, Las Vegas, and Phoenix (Fig. 1). Daily degree-days for each city are then aggregated into daily total cooling and heating degree requirements for the western United States by calculating a weighted average. Population figures from 2000 for each city are used for the weights (U.S. Census Bureau, 2001). Temperature data is from the National Center for Environmental Prediction provided by Logical Information Machines, Inc.

3. Methods

Because the data are observed over time, it is expected they will show correlation patterns through time, such that pairs of observations located near one another will show higher correlation than observation pairs located at distant intervals. Further, because the data are prices, it is expected that unit root (non-stationary) patterns will characterize each price series (Samuelson, 1965).

3.1. Vector Autoregression

The basic engine of analysis is the vector autoregression (VAR), which allows regularities in the series to be studied without imposing many prior restrictions. For the historical electricity spot market price data, P_t, a six market VAR is:

$$P_t = \mu + \sum_{i=1}^{k} B_i P_{t-i} + CZ_{t-1} + e_t , \qquad (1)$$

where P_t and e_t are both (6 x 1) random vectors, Z_t is a (q x 1) vector of q non-stochastic (or strictly exogenous) variables, μ is a (6 x 1) vector of intercepts, B_i and C are appropriately dimensioned matrices of coefficients, k is the number of lags on P_t required to make the observed error ($\hat{e}_t$) white noise, and t is the particular observation from a sample of T observations. The innovation term e_t is assumed to be white noise, where $E(e_t) = 0$, $\Sigma_e = E(e_t\ e_t')$ is a (6x6) positive definite matrix. The innovations, e_t and e_s, are independent for $s \neq t$. Although serially uncorrelated, contemporaneous correlation among the elements of e_t is possible, such that the individual sources of error may move together (not orthogonal). Here, heating degree-days and cooling degrees-days in period t-1 are included in each equation of the VAR, as strictly exogenous variables.

Following Bernanke (1986), we can write the non-orthogonal innovations (e_t) as a function of more fundamental driving sources of variation, $,_t$, which are independent of other sources of variation:

$$e_t = A,_t, \qquad (2)$$

where A is a matrix which describe how each non-orthogonal innovation (e_t) is determined (or caused) by the orthogonal or driving sources of variation in each equation ($,_t$). Zero restrictions on A are investigated to obtain an identified "structural VAR". There are no easy rules for identifying A. For a VAR in six variables, if more than fifteen parameters are to be estimated, the model is not identified. Doan (1995, p. 8-10) suggests the following rule,

> *If there is no combination of i and j ($i \neq j$) for which both A_{ij} and A_{ji} are nonzero, the model is identified.*

Usual innovation accounting procedures (impulse response and forecast error decompositions) can be carried-out on the transformed VAR:

$$AP_t = A\mu + \sum_{i=1}^{k} AB_i\ P_{t-i} + ACZ_{t-1} + Ae_t\,. \qquad (3)$$

Directed acyclic graphs are used to provide identifying restriction on the matrix A. Before discussing model results, a brief overview of directed acyclic graphs is presented.

3.2. Directed Acyclic Graphs

A graph is an ordered triple <X, M, E> where X is a non-empty set of vertices (variables), M is a non-empty set of marks (symbols attached to the end of undirected edges), and E is a set of ordered pairs. Each member of E is called an edge, which are merely lines connecting variables (vertices). Vertices connected by an edge are said to be adjacent. Given a set of vertices {A, B, C, D, E} the following graphs can be obtained: (i) an undirected graph - contains only undirected edges (e.g., A — B); (ii) a directed graph - contains only directed edges (e.g., B $\rightarrow$ C); (iii) an inducing path graph - contains both directed edges and bi-directed edges (C $\leftrightarrow$ D); (iv) a partially oriented inducing path graph - contains directed edges, bi-directed edges, non-directed edges (o—o), and partially directed edges (o$\rightarrow$), where a "o" indicates the possibility fo an omitted latent variable at the vertex endpoint. Here, the arrow indicates causal flow. An undirected edge indicates causal flow, but the algorithm is unable to determine the direction of the flow, whereas a directed edge indicates the flow could be determined. Bi-directed edge indicates causal flow in both directions. Non-directed edges indicate no causal flow. Partially directed edges indicate the possibility of latent variables. A directed acyclic graph is a directed graph that contains no directed cyclic paths (an acyclic graph contains no vertex more than once). Only acyclic graphs are used here.

Directed acyclic graphs are designs for representing conditional independence as implied by the recursive product decomposition:

$$\Pr(x_1, x_2, x_3, \ldots x_n) = \prod_{i=1}^{n} \Pr(x_i \mid pa_i), \tag{4}$$

where Pr is the probability of vertices $x_1, x_2, x_3, \ldots x_n$ and pa_i the realization of some subset of the variables that precede (come before in a causal sense) x_i in order $(x_1, x_2, \ldots, x_n)$. Pearl (1995) proposes d-separation as a graphical characterization of conditional independence. That is, d-separation characterizes the conditional independence relations given by equation (4). If a directed acyclic graph is formulated in which the variables corresponding to pa_i are represented as the parents (direct causes) of x_i, then the independencies implied by equation (4) can be read off the graph using the notion of d-separation. Pearl (1995 p. 671) defines d-separation as,

> *Let X, Y and Z be three disjoint subsets of vertices in a directed acylic graph G, and let p be any path between a vertex in X and a vertex in Y, where by 'path' we mean any succession of edges, regardless of their directions. Z is said to block p if there is a vertex w on p satisfying one of the following: (i) w has converging arrows along p, and neither w nor any of its descendants are on Z, or, (ii) w does not have converging arrows along p, and w is in Z. Further, Z is said to d-separate X from Y on graph G, written (XμλY | Z) G, if and only if Z blocks every path from a vertex in X to a vertex in Y.*

Geiger et al. (1990) show that there is a one-to-one correspondence between the set of conditional independencies, X μλ Y | Z, implied by equation (4) and the set of triples (X, Y, Z) that satisfy the d-separation criterion in graph G. Essential for this connection is the following result: if G is a directed acyclic graph with vertex set X, A and B are in X, and H is also in X, then G linearly implies the correlation between A and B conditional on H is zero if and only if A and B are d-separated given H.

Spirtes et al. (1993) have incorporated the notion of d-separation into a program (TETRAD II) for building directed acyclic graphs, using the notion of sepset (defined below). TETRAD II is based on an algorithm, PC algorithm, that is an ordered set of commands that begins with a general unrestricted set of relationships among variables and proceeds step-wise to remove edges between variables and to direct "causal flow.” The algorithm is described in detail in Spirtes et al. (1993 p. 117). More advanced versions (refinements) are described as the Modified PC Algorithm (Spirtes et al., 1993 p. 166), the Causal Inference Algorithm (p. 183), and the Fast Causal Inference Algorithm (p. 188). Because the basic definition of a sepset is used in all algorithms and the PC algorithm is the most basic, the discussion is limited to the PC algorithm.

Briefly, one forms a complete undirected graph G on the vertex set X. The complete undirected graph shows an undirected edge between every variable of the system (every variable in X). Edges between variables are removed sequentially based on zero correlation or partial correlation (conditional correlation. The conditioning variable(s) on removed edges between two variables is called the sepset of the variables whose edge has been removed (for vanishing zero order conditioning information the sepset is the empty set). Edges are directed by considering triples X — Y — Z, such that X and Y are adjacent as are Y and Z, but X and Z are not adjacent. Direct edges between triples X — Y — Z as X $\rightarrow$ Y $\leftarrow$ Z, if Y is not in the sepset of X and Z. If X $\rightarrow$ Y, Y and Z are adjacent, X and Z are not adjacent, and there is no arrowhead at Y, then orient Y — Z as Y $\rightarrow$ Z. If there is a directed path from X to Y, and an edge between X and Y, then direct X — Y as X $\rightarrow$ Y.

In applications, Fisher's z (see Spirtes et al., 1993, p. 94) is used to test whether conditional correlations are significantly different from zero. Fisher's z can be applied to test for significance from zero. This statistic is:

$$z(\rho(i,j|k)n) = 1/2(n-|k|-3)^{1/2} \times \ln\{(|1 + \rho(i,j|k)|) \times (|1 - \rho(i,j|k)|)^{-1} \} \quad (5)$$

where n is the number of observations used to estimate the correlations, $\rho(i,j|k)$ is the population correlation between series i and j conditional on series k (removing the influence of series k on each i and j), and |k| is the number of variables in k (that are condition on). If i, j, and k are normally distributed and r(i,j|k) is the sample conditional correlation of i and j given k, then the distribution of $z(\rho(i,j|k)n) - z(r(i,j|k)n)$ is standard normal.

4. Results

The data is divided into two periods, spring - summer and fall - winter. The spring and autumn equinox dates are used as the dividing date for winter-spring and fall - winter. Over the data set period of March 15, 1999 – August 24, 2001, the following partial time series are obtained. For the fall - winter period the dates are March 15-19, 1999, September 21, 1999 - March 20, 2000, and September 21, 2000 - March 20, 2001. Dates for the spring - summer period are: March 22, 1999 - September 20, 1999, March 21, 2000 - September 20, 2000, and March 21, 2001 - August 24, 2001. The fall - winter series are spliced together using zero-one dummy variables (one for each period) for the second two periods (September 21, 1999 - March 20, 2000 and September 21, 2000 - March 20, 2001). Similarly, the spring - summer period is spliced together, using dummy variables for the periods March 21, 2000 - October 14, 2000 and March 21, 2001 - August 24, 2001. Three series are obtained the entire peak price data set, fall - winter peak prices, and spring - summer peak prices.

Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) tests of unit root behavior for each individual series are given in Table 1. The null hypothesis is peak prices in each market are generated by a non-stationary time series process. If the DF or ADF statistics are less than -2.89 the null hypothesis is rejected. The spring - summer peak prices appear to show non-stationary behavior, as the ADF test on each market is greater than -2.89. The DF test for each market in the spring - summer panel show autocorrelated residuals and should not be used for inference on unit root behavior. Residuals on the ADF tests for spring - summer are better behaved – closer to the white noise benchmark. The hypothesis that peak prices in the fall - winter series are non-stationary is rejected, under both the DF and the ADF tests (these tests are the same because the optimum lag length on the ADF test is zero lags for all markets).

Unit root tests become somewhat problematic when applied to “spliced” data as used here. The critical values were established using Monte Carlo methods on each form of the Dickey-Fuller tests (Fuller, 1976 p. 373). Here, the estimating regression is $)p_t = \exists_0 + \exists_1 p_{t-1} + *_1 D_1 + *_2 D_2$, where D_1 and D_2 are dummy variables set equal to one in periods two and three. Critical values from the standard DF tests were not originally derived using such dummy variables. Accordingly, DF and AF tests without these zero-one dummy variables in the regression were conducted. In this case, both the spring - summer and fall - winter series show non-stationary behavior. The ADF test statistics for COB, FC, MC, PV, SP, and NP (without the dummy variables) are: -1.99, -2.13, -1,92, -2.18, -2.10 and -2.00 (fall - winter) and -2.07, -1.76, -1.60, -1.89, -1.82, and -1.72 (spring - summer).[1]

Engle and Granger (1987) state a VAR in levels (non-differenced data) for a large number of observations will be equivalent to an error correction model (a time series model with first differences as the dependent variable). Following thier result, VARs in levels are estimated. Two tests for the appropriate number of lags in the VAR are given in Table 2. Tests are provided for both separate VARs fit to the spring - summer and the fall - winter data and to the entire sample. Under the separate data, dummy variables associated with the dates where splicing occurs, as described above, are included. In each seasonal VAR, both the Schwarz-loss and Hannan and Quinn’s M measure suggest one lag. In the VAR fit to the entire sample, Schwarz-loss again suggests a single lag VAR, while Hannan and Quinn’s loss suggests a two lag VAR. Given these tests, the remainder of this paper uses a single lag VAR.

Likelihood ratio tests of the equality of VAR coefficients in the spring - summer VAR versus the fall - winter VAR are conducted. The tests are based on the relative difference in residual variance-covariance, as measured by the log of the determinant of the error covariance matrix on a VAR fit to the entire data (with no seasonal dummy shifter) versus a VAR fit to the data, allowing coefficients to vary between spring - summer and fall - winter. This is a test of forty-two zero restrictions (six coefficients associated with fall - winter data in each of six equations (36), plus one intercept in each equation (6)). The likelihood ratio statistic is 96.25. Under the null hypothesis that these forty-two coefficients equal zero, the test statistic is distributed chi-squared with 42 degree of freedom. The null hypothesis is rejected at a very low level of significance (p-value < 0.000). Accordingly, throughout the remainder of the paper results for separate spring - summer and for fall - winter VARs are provided.

Because VARs in levels are fitted to the data, which possibly are non-stationary, tests of non-stationarity of residuals (innovations) are given in Table 3. It is important that the innovations from each VAR equation are stationary. The null hypothesis for each row of the table is that the innovations from that equation are non-stationary. DF and ADF tests are used, only now the critical value for the 5% level of significance is -3.40 because the tests are using estimated innovations rather than "true" innovations (Granger and Newbold, 1986). In all cases, the augmented tests indicate stationary innovations.

Provided in Table 4 are the p-values associated with lagged coefficients of each market price in the autoregressive equation of each market price. In the COB spring - summer equation, coefficients associated with lagged price from FC, MC and the NP are significant at the 5% level, whereas in the fall - winter data, only MC has a significant influence on the COB price. FC is significant in every spring - summer equation (except its own), but FC is not a significant variable in any fall - winter market, except its own. MC is significant in every spring - summer equation, while it is significant only for the northern markets (COB, MC, and NP) in the fall - winter equation. PV is significant in the PV, SP, and NP markets during spring - summer, but is significant only in the PV equation during fall - winter.

The estimated coefficients associated with aggregate heating degree-days and cooling degree-days are given in Table 5. Heating degree-days contribute negatively to price in the spring - summer data in all markets except MC. However, none of these heating-degree-days coefficients is significantly different from zero at the 5% level. On the other hand, cooling degree-days contribute positively and significantly (at a 5% level) to price in every market in the spring - summer data. The strongest effect on price is in the FC market (0.091), whereas the weakest effect is in the PV market (0.056). In the fall - winter data, heating degree-days contribute positively to price in all markets with the strongest effects being in PV (0.012) and SP (0.011). Using a 5% significance level, these effects are different from zero for all markets, except COB. Cooling degree-days in the fall - winter data show positive effects on price in every market, although not significantly different from zero at the 5% level.

Estimated correlation matrix on contemporaneous time innovations from each market for spring - summer VAR is:

$$corr\ (\hat{e}_{tss}) = \begin{bmatrix} 1.0 & & & & & \\ 0.88 & 1.0 & & & & \\ 0.96 & 0.85 & 1.0 & & & \\ 0.83 & 0.86 & 0.80 & 1.0 & & \\ 0.86 & 0.88 & 0.83 & 0.91 & 1.0 & \\ 0.90 & 0.85 & 0.87 & 0.86 & 0.94 & 1.0 \end{bmatrix} \qquad (6)$$

where $\hat{e}_{tSS}$ denotes innovations the spring - summer VAR and the listing order of the lower triangular elements of innovations from each market is COB, FC, MC, PV, SP, and NP. Innovations from the COB market show strongest correlations with contemporaneous innovations from the MC market (0.96) and weakest correlations with innovations from the PV market (0.83). The FC market innovations show strongest correlation with innovations in the SP market (0.88) and weakest correlations with innovations from NP and MC (0.85). MC shows the strongest correlations with innovations from COB (0.96) and weakest with innovations from PV (0.80). Innovations from PV shows the strongest correlation with innovations from SP (0.91) and weakest with innovations from MC (0.80). Innovations from the SP market show the strongest correlations with innovations from NP (0.93) and weakest correlations with innovations from MC (0.83). Finally, innovations from the NP market show the strongest correlation with innovations from SP (0.93) and weakest correlations with innovations from FC (0.85).

For the fall - winter VAR, the contemporaneous time error correlation matrix from the is:

$$corr\ (\hat{e}_{tFW}) = \begin{bmatrix} 1.0 & & & & & \\ 0.77 & 1.0 & & & & \\ 0.97 & 0.78 & 1.0 & & & \\ 0.72 & 0.85 & 0.73 & 1.0 & & \\ 0.74 & 0.85 & 0.75 & 0.92 & 1.0 & \\ 0.78 & 0.78 & 0.77 & 0.84 & 0.89 & 1.0 \end{bmatrix} \quad (7)$$

where $\hat{e}_{tFW}$ denotes innovations and the lower triangular elements are listed in order COB, FC, MC, PV, SP, and NP. The correlations in equation (7) are generally smaller (although not for all markets) than the correlations given in equation (6). There are just two correlations in equation (7), which exceed their corresponding elements in equation (6), albeit by a very small amount. The correlation between COB and MC in the fall - winter (0.97) exceeds its corresponding value in the spring - summer (0.96). Similarly, the correlation between PV and SP (0.92) exceeds its corresponding spring - summer entry (0.91). In all other cases, the fall - winter correlations are smaller than their corresponding spring - summer correlations.

Correlations from equations (6) and (7) are inputs for the directed graph analysis of the innovations from our spring - summer and fall - winter VARs. Based on vanishing correlations and partial correlation patterns derived from these two matrices, causal flow between contemporaneous innovations from each of these six markets is assigned. TETRAD II (Scheines et al., 1994) is used to obtain the causal flows (Fig. 3). Results are provided for each VAR (spring - summer and fall - winter) at three different levels of significance 1%, 5%, and 10%. Spirtes et al. (1993) recommend that one consider the graphical representation found using TETRAD II under several levels of significance. Further, they recommend applying an inverse relation between significance level used and the number of observations used to calculate correlations and partial correlations. Because each VAR is estimated using 310 observations, a modestly large number, the 5% panel is used in subsequent analysis. The term “Graphical Patterns” is used in Fig. 3, because several edges are not directed. These edges indicate possible information flow between their corresponding endpoints, however, the direction of flow is not clear.

The 5% panel of Fig. 3 shows a pattern with the PV market acts is an information “sink” in the spring - summer period. Arrows are directed into the PV node from FC and SP, but no arrows flow out. PV’s sink-like status does not hold in the 1% and 10% panels, because the edge between PV and SP is undirected in these alternative panels. The reason the edges are different between the various levels of significance is the addition or subtraction of edges between the markets. The SP market is a “link” in the causal chain running from NP to FC onto PV, via SP. Similarly, FC serves as an information link between COB and PV.

During the fall - winter period, NP is an information sink, because it receives information from SP and COB, passing nothing on to other markets (Fig. 3). All other edges in Fig. 3 are undirected, indicating interaction between COB and MC, MC and FC, FC and PV, and PV and SP, but no definitive direction of causal information flow.

Dynamic behavior of peak power prices using innovation accounting techniques is examined for each VAR model using the direction of causal flows defined in Fig. 3. Many researchers have modeled the information flow between markets in contemporaneous time by performing a Choleski factorization of the innovation covariance matrix, $\Gamma = H'H$, where Γ is the positive definite innovation covariance matrix. They then pre-multiplied contemporaneous price vector and each autoregressive coefficient matrix by the inverse of H to obtain a transformed VAR model with orthogonal residuals (innovations). This transformation of the VAR, while solving the problem of contemporaneous causality, has not been universally applauded, because the ordering of variables in the Choleski factorization is arbitrary. Researchers had little prior beliefs on which innovation came first in contemporaneous time (Cooley and LeRoy, 1985). Work by Bernanke (1986) and others has found other recursive orderings to address the arbitrariness of the Choleski form, while letting contemporaneous correlation to affect the dynamic model. Another way to "deal" with contemporaneous correlation would be to ignore it. The graphical patterns given in Fig. 3 allow the Bernanke procedure for dealing with contemporaneous correlation to be used, without having to resort to subjective or non-data based methods.

Forecasting to horizon t+h (h steps ahead) at time t, the error between what the VAR model predicts, based on information known up to period t and what actually happens, is a moving average (MA) process of order h-1 (Granger and Newbold, 1986). The coefficients associated with the moving average process are found by inverting the vector autoregression, writing it as an infinite sum of weighted past innovations. The standard error of the forecast at horizon k can be decomposed into shocks in each variable of the VAR. These forecast error decompositions are given for each VAR (spring - summer and fall - winter) in Tables 6 and 7 using the causal graphs in Fig. 3. Undirected edges are ignored. Alternative dynamic relationships assuming the undirected edges are directed one way or the other in Fig. 3 were studied. These alternative dynamic patterns are similar, but not identical, to the relationships reported here. They are available from the authors.

For spring - summer, in the long run (arbitrarily selected to be 15 days ahead), the MC market is clearly the dominant market. Over 55% (note from any panel in Table 6 at horizon 15, the percentage of the forecast uncertainty explained by innovations in MC is greater than 55%) of the forecast uncertainty at the 15-day horizon is explained by previous shocks in the MC price (Table 6). The other mover in long-run time is COB, as it explains over 20% of the uncertainty in all markets at the 15-day horizon.

In contemporaneous time (horizon zero), the sink-like behavior of price in the PV market is evident. PV peak electricity prices in contemporaneous time are explained predominately by innovations in the NP market. Innovations in the SP market price explain slightly over 9% of the variation in the PV price in contemporaneous time. The influence of price innovations from NP and SP on the PV price dampen with the influence of the MC price increasing over time, such that after 15 days the former two markets have less than a 10% combined contribution to price uncertainty in the PV market. MC explains over 57% of the uncertainty in the PV price at the long-run horizon.

For the spring - summer data, innovations from MC contribute very little or nothing to the uncertainty in price from all non-MC markets in the short-run (Table 6). To understand short-term price variation in FC, PV, NP, and SP, it is essential to understand innovations in the NP market. However, in the longer term (after two days and certainly after 15 days), price uncertainty during the spring - summer season is explained by innovations in the MC market.

This apparently reflects the short-run inability of western markets to move enough power around quickly (within the day or up to two days ahead) to offset regional price differentials. However, within two weeks, such movements appear to be possible and the markets adjust. It appears all other markets eventually move to the MC market. This may reflect MC's status as a low cost producer. Two issues help contribute to the inability to move power. First, Bonneville Power Association has a more complicated point-to-point transmission structure than the rest of the Western System Coordinating Council. Second, California electricity transmission has one of the premier power bottlenecks in the U.S., namely the electron pileup on Path 15 (Stouffer, 2001).

A similar set of panels for each market price from the fall - winter VAR is provided in Table 7. Again, the MC market price is the standard, accounting for over 55% of the price variation in all other markets at the 15-day horizon. In contemporaneous time, the fall - winter data are for the most part exogenous, as each market explains it's own contemporaneous time uncertainty. The one exception to this last point is NP; where over 55% of the movement in contemporaneous time uncertainty is explained by innovations in the SP price. An additional 12% of the variation in the NP price is accounted for by contemporaneous time innovations in the COB market.

Impulse response functions summarizing the dynamic response of each price series to a one time only shock in every series for the spring - summer and fall - winter VARs are given in Fig. 4 and 5. Again, the Bernanke ordering of contemporaneous correlation is used following the directed edges in Fig. 3. All responses from each VAR are provided in each figure to allow the reader to see the relative effects of each market. The horizontal axis on each sub-graph is the horizon or number of days following the shock, up to 60 days. The vertical axis is the standardized response to the one time shock in the market listed at the top of each column of graphs. This normalization is with respect to the historical standard deviation of innovations in the market listed on each row. The normalization keeps all responses within [–1, +1] range, allowing for comparisons of relative responses across markets.

The dynamic importance of a shock in the NP and the MC markets during the spring – summer period are shown in Fig. 4. Such shocks are transferred as a positive impulse to all other markets, damping to zero after several weeks. However, the response of all markets to an innovation in the NP market is immediate and dampens to zero thereafter; whereas a shock in the MC price takes a few days to be felt in all other markets, thereafter it too dampens to zero. No other market shows persistently strong influences on other markets; although an innovation is the COB price does show some lasting positive influence across other markets. Interesting is the response of all markets to an innovation in the price in the FC market. Here, the dominant effect is a negative response for several days following the jump in FC price. Such responses suggest the FC market is making-up for very short-run imbalances in other markets, which are quickly made-up in other markets in the following few days. Innovations in the price at the PV market are transferred to price in other markets, as small positive and damping effects - except for the MC market, were PV appears to have little effect.

The responses of each market to one time only innovations in fall - winter price from each market are given in Fig. 5. Again, the responses to MC are the most notable features in this set of responses. An innovation in MC has a relatively strong very short-run effect on each market in the fall - winter VAR, relative to its effect on the same markets in the spring - summer VAR (compare the column MC between Fig. 4 and 5). The negative delayed responses of each market to a shock in the COB market price is not unlike that observed in Fig. 4 for responses to shocks in the FC market price. FC, PV, and NP show no particularly strong effects on any other market price in the fall - winter period. SP shows some short-run positive effect on price in all markets, although this affects dampens to zero quickly.

5. Discussion

Results presented shows the western trading region is highly integrated, which is expected because of the highly liquid nature of the market. The importance of several markets is also established, along with seasonal differences. In contemporaneous time, directed graphs show the importance of the California market; SP and NP markets appear to be a driving force for electricity prices. This is especially true in the spring - summer period. The SP market includes the Los Angeles area, the largest metropolitan area in the west. Many directional flows (edges) between the markets are undirected, however, which indicates interaction between the markets, but no definitive direction of causal information flow. As noted by several previous studies (e.g. Bailey, 1998), narrow markets can arise because of more localized supply and demand conditions. Local weather conditions, plant outages, and transmission constraints contribute to these narrower markets. Narrower markets may help explain why some flows are undirected, as the information flow would vary based on the cause of the narrower markets.

Similar to Bailey (1998), we find contemporaneous correlations between prices are smaller in the fall - winter period than they are in the spring - summer period. Decrease in demand for electricity during the fall - winter period is the most likely reasons for the differences in correlations. This decrease also contributes to the changes in importance of the California market. It is interesting to note, the importance of the California market in the integration of the western trading region, even though California imports only 18% of its electricity over the year (California Energy Commission, 2001a). This 18%, however, is not a trivial amount.

Approximately 49,486 gWh of electricity are imported into California, in which 52% comes from the Pacific Northwest, 40% from the Southwest, and remaining 8% from Mexico (California Energy Commission, 2001a). Both the directed edges and larger error correlations occur between spot markets, which are adjacent in physical terms.

Forecast error variances and impulse response functions allow for analysis of information flows over time in contrast to the directed graph analysis which is only for contemporaneous time. Again, differences between the spring - summer and fall - winter periods are found. For short time frames (periods of two days or less), the California market remains an important driver of spring - summer prices. For all markets except COB and MC, NP in the largest spring - summer period acounts for the largest component of forecast error variance at the short time frames. COB and MC are relatively exogenous at these time frames, with there own decomposition explaining most of its forecasts error decomposition. Such exogeneity may be expected because MC is a winter peaking market and the close proximity of COB to MC. In the summer, demand is low and these markets have excess capacity depending on the snowpack year. During the fall - winter period, all markets are relatively exogenous (one except maybe COB) in the short-run. At longer time frames, for both periods, it is clear the major market is MC. MC's influence appears to be even stronger in the fall - winter than the spring - summer period. The increase in influence in fall - winter over spring - summer period may be caused by demand and supply conditions. In the fall - winter period, MC is demand driven with high winter demand, but in the spring - summer period, MC is supply driven with low demand and snowpack runoff giving cheap plentiful cheap hydropower.

During the data period of 2000 and 2001, limited snowpack may have also contributed to the demand driven fall - winter market. COB is the only other market at the longer time frame, which exerts a large influence on spring - summer prices. This influence, however, maybe related to transmission of electricity from the Pacific Northwest and not COB itself. During the fall - winter period, MC remains the dominant market in the long run with COB's influence still being strong, but generally smaller than in the spring - summer. Several markets, FC, PV, and SP, have some influence on their own price. The dominance of MC in the long run, maybe explained by this area being a low cost producer of electricity through hydropower. Further, coupling the dominance of MC area with the recent droughts in the Pacific Northwest helps explain some of the high electricity prices experienced in recent years. Pira Energy Group (2000a, 2000b, 2001) also suggests such a relationship.

Impulse response functions reinforce the discussion to this point. The importance of the California market is illustrated by the quick reaction of all spot market prices to a shock in the NP market in the spring - summer period. Responses to shocks to MC prices take several periods to be felt in the other markets, but all markets response positively to shocks in this market.

Results suggest short run price discovery varies between periods during this year. Electricity generally flows south during the summer months and north during the winter. Such changes in demand and supply conditions contribute to the differences in short run price discovery dynamics. In the longer run, price dynamics appear to be similar between periods, with an overwhelming reliance on the MC spot market. Such dynamics in price discovery or communication have not been reported by previous studies.

Results associated with cooling and heating degree-days are as expected. Aggregate cooling degree-days are significant in the spring - summer and contribute positively to electricity prices. Any cooler days represented by heating degree-days in the spring - summer period do not significantly increase electricity prices. Similarly, aggregate heating degree-days are significant and contribute positively to electricity prices in the fall - winter. Warmer days represented by cooling degree-days in the fall - winter period do not significantly increase electricity prices. Refinements would be to include northern and southern degree-days or individual degree-days for relevant cities. Although beyond the scope of this study, results indicate such refinements may help explain electricity prices.

6. Endnote

1) Other tests of unit root behavior were investigated, both with and without the splicing dummy variables. Sims' Bayesian test (see Doan (1995 pages 6-20)) gave probabilities of the null hypothesis of non-stationarity being true for COB, FC, MC, PV, SP and NP as follows .004. .001, .006, .005, .001, .001 (spring - summer with dummy variables) and .30, .192, .403, .131, .164, and .161 (spring - summer without dummy variables). Further, Sims Bayesian probabilities for COB, FC, MC, PV, SP and NP are: .000, .000, .000, .000, .000, .000 (fall - winter with dummy variables) and .588, .529, .648, .492, .565, and .530 (fall - winter without dummy variables). Finally, Phillips-Perron tests (Phillips and Perron, 1988) with six lags to account for covariance in residuals gave similar results. Robinson (2000) also found non-stationarity for pool electricity prices when using ADF tests.

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Table 1. Dickey-Fuller (DF), augmented Dickey-Fuller (ADF), and associated residual tests on the null hypothesis of non-stationarity of peak electricity prices from six western U.S. spot markets, spring - summer and fall - winter

Market	DF	Q (36)	p-value	ADF	k	Q (36)	p-value
			Spring - Summer				
COB	-3.37	108.19	0.00	-1.72	6	32.84	0.62
FC	-3.83	140.58	0.00	-2.14	6	48.29	0.08
MC	-3.27	110.44	0.00	-1.74	6	35.55	0.49
PV	-3.65	134.34	0.00	-2.13	6	48.30	0.08
SP	-3.93	124.93	0.00	-2.18	6	44.75	0.15
NP	-3.54	111.71	0.00	-1.42	7	34.42	0.54
			Fall - Winter				
COB	-3.76	21.65	0.97	-3.76	0	21.65	0.97
FC	-3.72	21.17	0.98	-3.72	0	21.17	0.98
MC	-3.53	19.05	0.99	-3.53	0	19.05	0.99
PV	-3.99	48.72	0.08	-3.99	0	48.72	0.08
SP	-3.70	38.53	0.35	-3.70	0	38.53	0.35
NP	-3.92	33.11	0.60	-3.92	0	33.11	0.60
			Entire Sample				
COB	-3.12	147.69	0.00	-1.97	6	40.06	0.29
FC	-3.34	159.49	0.00	-1.91	7	34.78	0.53
MC	-2.94	144.69	0.00	-1.97	6	36.25	0.46
PV	-3.29	148.46	0.00	-1.84	7	42.45	0.21
SP	-3.33	161.47	0.00	-1.82	7	42.12	0.22
NP	-3.20	146.15	0.00	-1.76	7	41.40	0.25

Notes: The column under the heading "DF" refers to the Dickey-Fuller test on the null hypothesis that the price data from the market listed in the far left-hand-most column are non-stationary in levels (non-differenced data). The test for each series of price data is based on an ordinary least squares regression of the first differences of prices from each market on a constant and one lag of the levels of prices (non-differenced prices) from each market. The t-statistic is associated with the estimated coefficient on the lagged levels variable from this regression. Under the null hypothesis, the statistic is distributed in a non-standard t. Critical values are given in Fuller (1976). The 5% critical value is -2.89. We reject the null for observed t values less than this critical value. The associated Q-statistic is the Lung-Box statistic on the estimated residuals from the above-described regression. Under the null hypothesis of white noise residuals Q is distributed chi-squared with 36 degrees of freedom. The p-value associated with this Q statistic is given in the column immediately to the left of the Q-statistic. We reject the null hypothesis for large values of Q or for low p-values (i.e. p-values less than .05).

The column under the heading "ADF" refers to the Augmented Dickey Fuller test associated with the null hypothesis that the series the null hypothesis that the price data from the market listed in the far left-hand-most column are non-stationary in levels (same null as above). Here, the test is of the same form as that described above, except that k lags of the dependent variable are added to the right-hand side of the DF regression. The value for k is determined by minimizing the Schwarz-loss metric on values of k ranging from 1 to 10. The ADF regression was run with lags of the dependent variable ranging from one lag to ten lags. The Schwarz loss metric was minimized at the value given in the column headed by the label "k". Again, the critical value of the t-statistic is -2.89 and we reject for values of the calculated statistic less than this critical value. Finally, as above, the Q-statistic is the Lung-Box statistic on the estimated residuals from the ADF regression. Under the null hypothesis of white noise residuals Q is distributed chi-squared with 36 degrees of freedom. The p-value associated with this Q statistic is given in the column immediately to the left of the Q-statistic.

Table 2. Schwarz loss and Hannan and Quinn loss on zero to 10 lags on levels vector autoregressions on daily peak electricity prices from six western U.S. spot markets, spring - summer and fall - winter

Number of Lags	Schwarz Loss	Hanan and Quinn Loss
	Spring - Summer	
0	-21.054	-21.188
1	-26.543 *	-26.917 *
2	-26.115	-26.738
3	-25.669	-26.541
4	-25.287	-26.408
5	-24.998	-26.368
6	-24.400	-26.019
7	-23.946	-25.814
8	-23.422	-25.540
9	-22.819	-25.186
10	-22.291	-24.907
	Fall - Winter	
0	-22.877	-23.011
1	-27.445 *	-27.818 *
2	-27.089	-27.712
3	-26.566	-27.438
4	-25.992	-27.113
5	-25.469	-26.839
6	-24.907	-26.527
7	-24.442	-26.310
8	-23.960	-26.078
9	-23.446	-25.813
10	-23.028	-25.644
	Entire Sample	
0	-20.212	-20.290
1	-26.476*	-26.694
2	-26.428	-26.793*
3	-26.156	-26.667
4	-25.919	-26.574
5	-25.751	-26.553
6	-25.442	-26.389
7	-25.219	-26.312
8	-24.929	-26.168
9	-24.628	-26.012
10	-24.391	-25.921

Notes. Tests are Schwarz-loss (SL), Hannan, and Quinn's M measure on lag length of a levels vector autoregression:

$$SL = \log (|\Gamma| + (6\ k)\ (\log T) / T, \text{ and}$$

$$M = \log (|\Gamma| + (2.01)\ (6k) \log (\log T)) / T$$

where Γ is the error covariance matrix estimated with k regressors in each equation, T is the total number of observations on each series, the symbol " | | " denotes the determinant operator, and log is the natural logarithm.

Table 3. Dickey-Fuller and augmented Dickey-Fuller tests and associated residual tests on the null hypothesis of non-stationarity of innovations (ê) in peak electricity prices from a levels VAR on six western U.S. spot markets, spring - summer and fall - winter

Market	DF	Q(36)	p-value	ADF	Number of Lags	Q(36)	p-value
			Spring - Summer				
COB	-15.84	107.12	0.00	-9.98	5	42.89	0.20
FC	-16.23	148.78	0.00	-9.35	5	55.44	0.02
MC	-15.83	104.30	0.00	-9.95	5	45.07	0.14
PV	-17.77	123.92	0.00	-8.47	5	51.35	0.05
SP	-16.57	127.08	0.00	-8.94	5	48.92	0.07
NP	-16.30	112.34	0.00	-9.41	5	42.33	0.21
			Fall - Winter				
COB	-18.74	21.02	0.98	-18.74	0	21.02	0.98
FC	-19.21	24.00	0.94	-19.21	0	24.00	0.94
MC	-18.68	21.20	0.98	-18.68	0	21.20	0.98
PV	-19.02	37.53	0.40	-19.02	0	37.53	0.40
SP	-19.14	31.46	0.68	-19.14	0	31.46	0.68
NP	-20.26	23.20	0.95	-20.26	0	23.20	0.95

Notes. The column under the heading “DF” refers to the Dickey-Fuller test on the null hypothesis that the price data from the market listed in the far left-hand-most column are non-stationary in levels (non-differenced data). The test for each series of price innovation data is based on an ordinary least squares regression of the first differences of prices from each market on a constant and one lag of the levels of prices (non-differenced prices). The t-statistic is associated with the estimated coefficient on the lagged levels variable from this regression. Under the null hypothesis, the statistic is distributed in a non-standard t. Critical values are given in Fuller (1976). The 5% critical value is –3.35. We reject the null for observed t values less than this critical value. The associated Q-statistic is the Lung-Box statistic on the estimated residuals from the above-described regression. Under the null hypothesis of white noise residuals, Q is distributed chi-squared with 36 degrees of freedom. The p-value associated with this Q statistic is given in the column immediately to the left of the Q-statistic. The null hypothesis is rejected for large values of Q or for low p-values (i.e. p-values less than .05).

The column under the heading “ADF” refers to the Augmented Dickey-Fuller test associated with the null hypothesis that the series the null hypothesis that the price data from the market listed in the far left-hand-most column are non-stationary in levels (same null as above). Here, the test is of the same form as that described above, except that k lags of the dependent variable are added to the right-hand side of the DF regression. Here, the value for k is determined by minimizing the Schwarz-loss metric on values of k ranging from 1 to 10. The ADF regression was run with lags of the dependent variable ranging from one lag to ten lags. The Schwarz loss metric was minimized at the value given in the column headed by the label “k”. Again, the critical value of the t-statistic is -3.35 and we reject for values of the calculated statistic less than this critical value. Finally, as above, the Q-statistic is the Lung-Box statistic on the estimated residuals from the ADF regression. Under the null hypothesis of white noise residuals, Q is distributed chi-squared with 36 degrees of freedom. The p-value associated with this Q statistic is given in the column immediately to the left of the Q-statistic.

Table 4. P-values on coefficients on lagged prices on each of six electricity spot markets in the vector autoregressive representation of daily peak market price by season

	Lagged Market					
Market	COB_{t-1}	FC_{t-1}	MC_{t-1}	PV_{t-1}	SP_{t-1}	NP_{t-1}
			Spring - Summer			
COB_t	0.08	0.01 *	0.00 *	0.09	0.70	0.03 *
FC_t	0.99	0.25	0.02 *	0.12	0.30	0.54
MC_t	0.08	0.00 *	0.00 *	0.06	0.72	0.09
PV_t	0.80	0.01 *	0.02 *	0.00 *	0.24	0.97
SP_t	0.66	0.04 *	0.02 *	0.00 *	0.02 *	0.90
NP_t	0.39	0.01 *	0.01 *	0.00 *	0.16	0.00 *
			Fall - Winter			
COB_t	0.15	0.38	0.00 *	0.75	0.78	0.14
FC_t	0.93	0.02 *	0.53	0.69	0.01 *	0.76
MC_t	0.01 *	0.37	0.00 *	0.88	0.65	0.22
PV_t	0.75	0.70	0.22	0.00 *	0.90	0.93
SP_t	0.61	0.94	0.10	0.97	0.00 *	0.92
NP_t	0.33	0.69	0.03 *	0.89	0.88	0.00 *

Notes. Table entries are p-values associated with the null hypothesis that the coefficient associated with the variable in the column heading in the equation associated with the variable in the row label is equal to zero. An asterisk (*) indicates rejection of the null hypothesis at a 5% significance level.

Table 5. Estimated coefficients on aggregate heating degree days and cooling degree days in each VAR market equation by season

	Heating Degree-Days		Cooling Degree-Days	
Market	Spring - Summer	Fall - Winter	Spring - Summer	Fall - Winter
COB	-0.001	0.007	0.065*	0.057
	(0.006)	(0.004)	(0.024)	(0.037)
FC	-0.005	0.008*	0.091*	0.046
	(0.006)	(0.003)	(0.024)	(0.032)
MC	0.001	0.007*	0.068*	0.052
	(0.006)	(0.003)	(0.025)	(0.038)
PV	-0.008	0.012*	0.056*	0.070
	(0.006)	(0.003)	(0.026)	(0.036)
SP	-0.008	0.011*	0.066*	0.046
	(0.006)	(0.003)	(0.024)	(0.031)
NP	-0.005	0.007*	0.068*	0.053
	(0.006)	(0.003)	(0.024)	(0.034)

Notes. Estimated standard errors are in parentheses. An asterisk (*) indicates significant at the 5% level.

Table 6. Forecast error decompositions from the VAR on daily peak electricity prices from six western U.S. spot markets, spring - summer

		Orthogonalized Market Innovations					
Step Ahead	Standard Error	COB	FC	MC	PV	SP	NP
			COB				
0	0.24	100.00	0.00	0.00	0.00	0.00	0.00
1	0.27	79.68	1.12	13.54	0.27	0.10	5.28
2	0.33	56.18	1.99	34.16	1.02	0.36	6.28
15	0.90	28.92	1.19	64.66	3.52	0.52	1.18
			FC				
0	0.18	35.77	27.40	0.00	0.00	4.47	32.36
1	0.22	24.73	18.94	9.73	0.31	4.58	41.71
2	0.27	18.51	13.47	27.49	1.18	3.41	35.93
15	0.74	23.93	2.57	63.46	3.93	0.68	5.40
			MC				
0	0.24	0.00	0.00	100.00	0.00	0.00	0.00
1	0.40	8.99	0.59	88.82	0.16	0.04	1.40
2	0.54	14.13	0.86	83.16	0.44	0.12	1.29
15	1.17	24.88	0.78	71.46	2.21	0.30	0.35
			PV				
0	0.23	1.83	1.40	0.00	19.75	9.33	67.66
1	0.29	1.19	0.95	6.73	25.67	7.88	57.55
2	0.35	1.99	1.04	19.09	27.00	5.87	45.00
15	0.87	20.13	0.88	57.54	12.49	1.08	7.88
			SP				
0	0.24	0.00	0.00	0.00	0.00	12.13	87.87
1	0.28	0.00	0.38	6.99	0.92	11.29	80.41
2	0.32	1.24	0.89	20.92	2.30	8.94	65.71
15	0.75	20.59	0.94	59.67	4.72	1.78	12.27
			NP				
0	0.23	0.00	0.00	0.00	0.00	0.00	100.00
1	0.27	0.31	0.66	7.90	1.02	0.21	89.89
2	0.31	0.89	1.42	23.88	2.51	0.51	70.79
15	0.80	20.67	1.12	62.03	4.63	0.56	10.98

Notes. Decompositions at each step are given for a “Bernanke” factorization of contemporaneous innovation covariance, following the flow of information summarized in Fig. 3. The decompositions sum to one hundred percent in any row within rounding error.

Table 7. Forecast error decompositions from the VAR on daily peak electricity prices from six western U.S. spot markets, fall - winter

		Orthogonalized Market Innovations					
Step Ahead	Standard Error	COB	FC	MC	PV	SP	NP
			COB				
0	0.22	100.00	0.00	0.00	0.00	0.00	0.00
1	0.34	47.85	0.44	50.48	0.20	0.83	0.20
2	0.46	34.37	0.52	63.67	0.15	1.02	0.27
15	0.78	25.58	0.59	72.27	0.06	1.13	0.37
			FC				
0	0.20	0.00	100.00	0.00	0.00	0.00	0.00
1	0.21	0.02	85.39	1.82	0.24	12.52	0.01
2	0.24	1.56	66.58	13.67	0.32	17.85	0.01
15	0.48	14.93	17.45	59.52	0.11	7.84	0.16
			MC				
0	0.23	0.00	0.00	100.00	0.00	0.00	0.00
1	0.42	11.68	0.32	87.19	0.05	0.67	0.10
2	0.55	15.27	0.41	83.27	0.04	0.88	0.15
15	0.88	18.86	0.53	79.23	0.02	1.08	0.28
			PV				
0	0.21	0.00	0.00	0.00	100.00	0.00	0.00
1	0.25	0.48	0.15	6.56	92.76	0.05	0.00
2	0.28	2.82	0.13	19.74	76.90	0.40	0.01
15	0.47	14.11	0.32	57.46	26.59	1.32	0.19
			SP				
0	0.19	0.00	0.00	0.00	0.00	100.00	0.00
1	0.23	1.22	0.00	10.33	0.00	88.43	0.00
2	0.27	4.65	0.02	26.35	0.00	68.96	0.00
15	0.49	15.37	0.23	60.47	0.00	23.66	0.16
			NP				
0	0.16	12.21	0.00	0.00	2.69	55.39	29.72
1	0.21	7.32	0.19	26.08	1.82	41.48	23.10
2	0.28	8.92	0.39	48.30	1.08	26.39	14.92
15	0.56	16.86	0.62	70.23	0.26	7.68	4.35

Notes. Decompositions at each step are given for a "Bernanke" factorization of contemporaneous innovation covariance, following the flow of information summarized in Fig 3. The decompositions sum to one hundred percent in any row (within rounding interval).

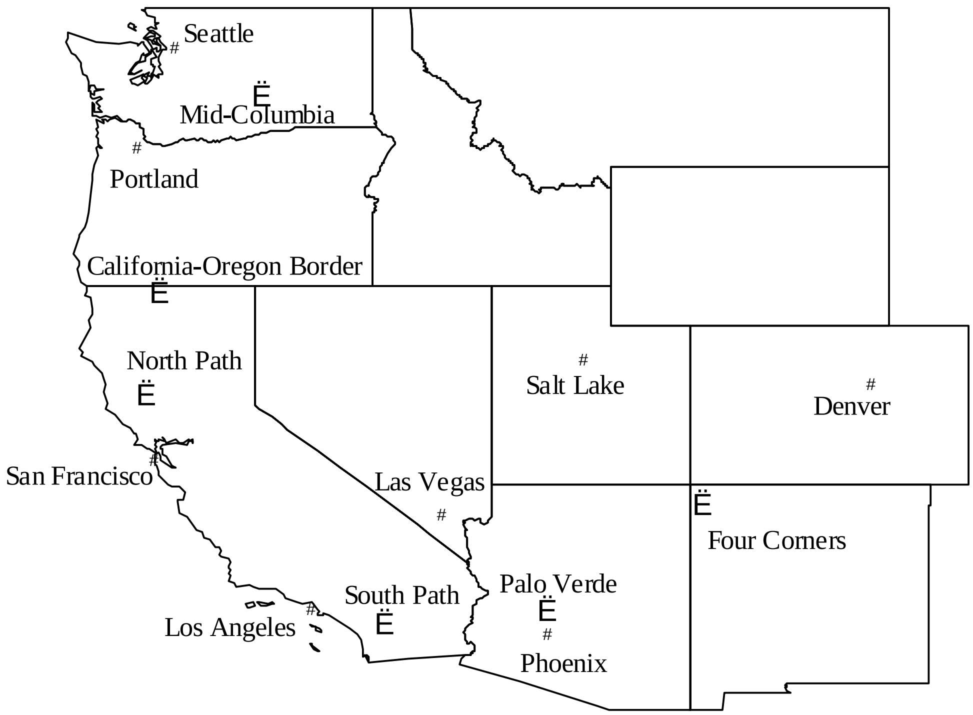


Figure 1. Approximate location of the spot markets (areas) and major cities in the western U.S. electricity region

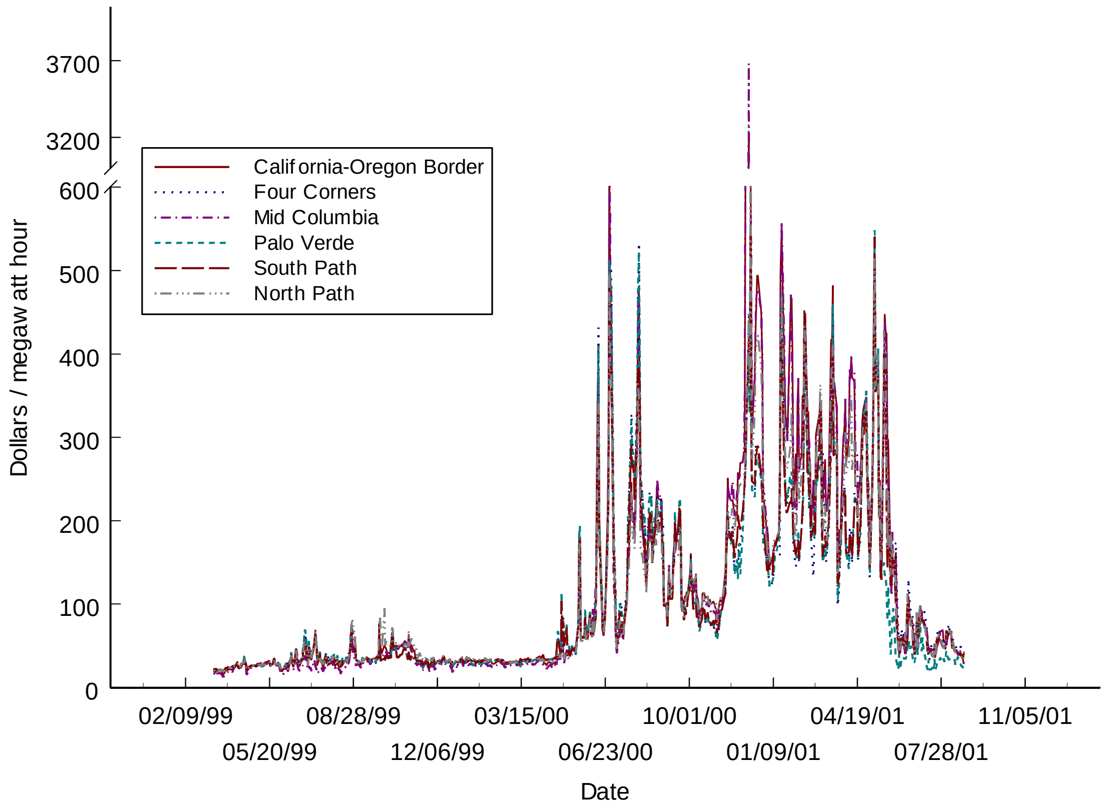
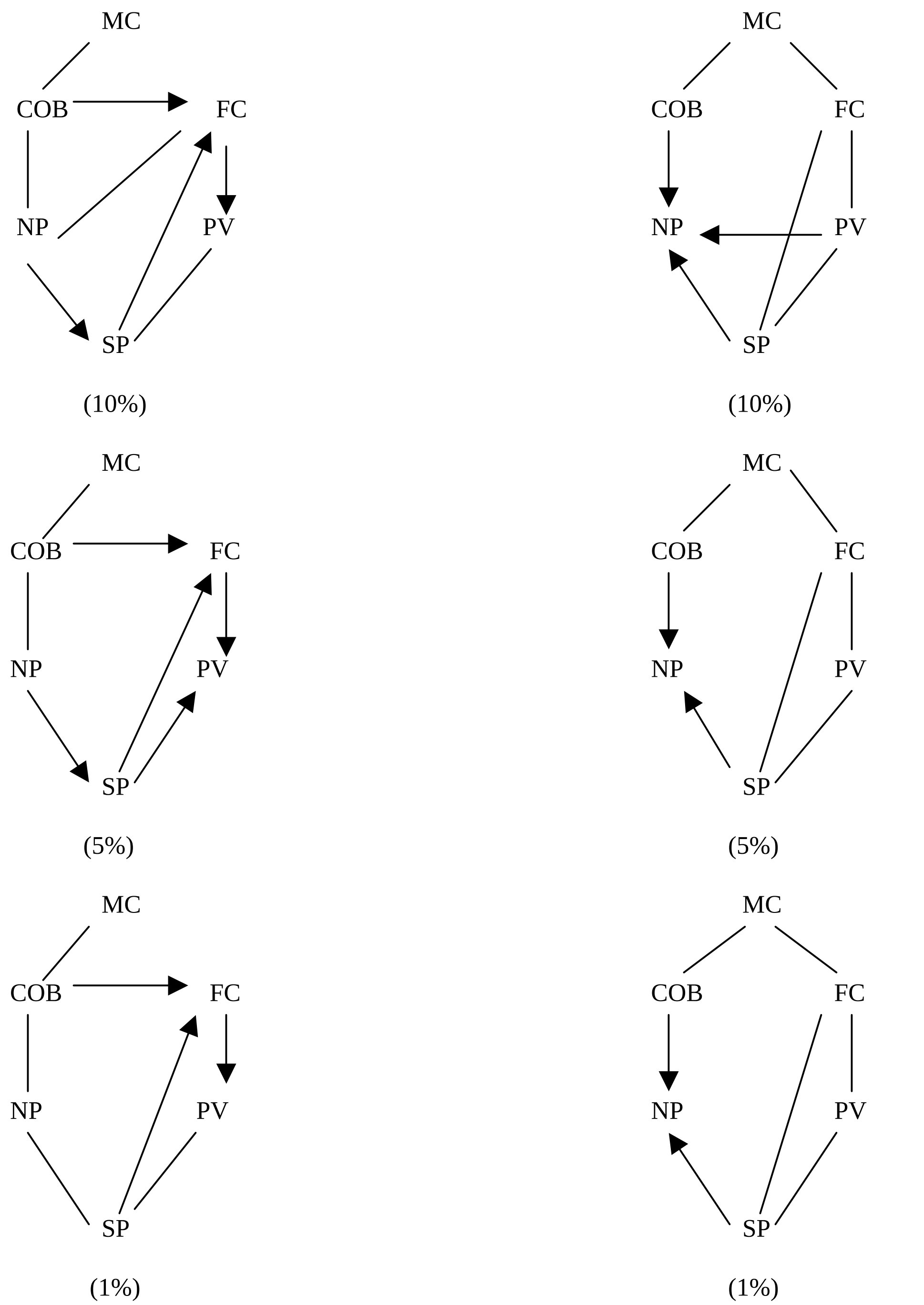


Figure 2. Dailey peak electricity prices for the six western U.S. spot markets



Spring - Summer 1999 - 2001 Fall - Winter 1999 - 2001

Figure 3. Graphical patterns at 1%, 5%, and 10% significance level on peak electricity price innovations from six western U.S. spot markets

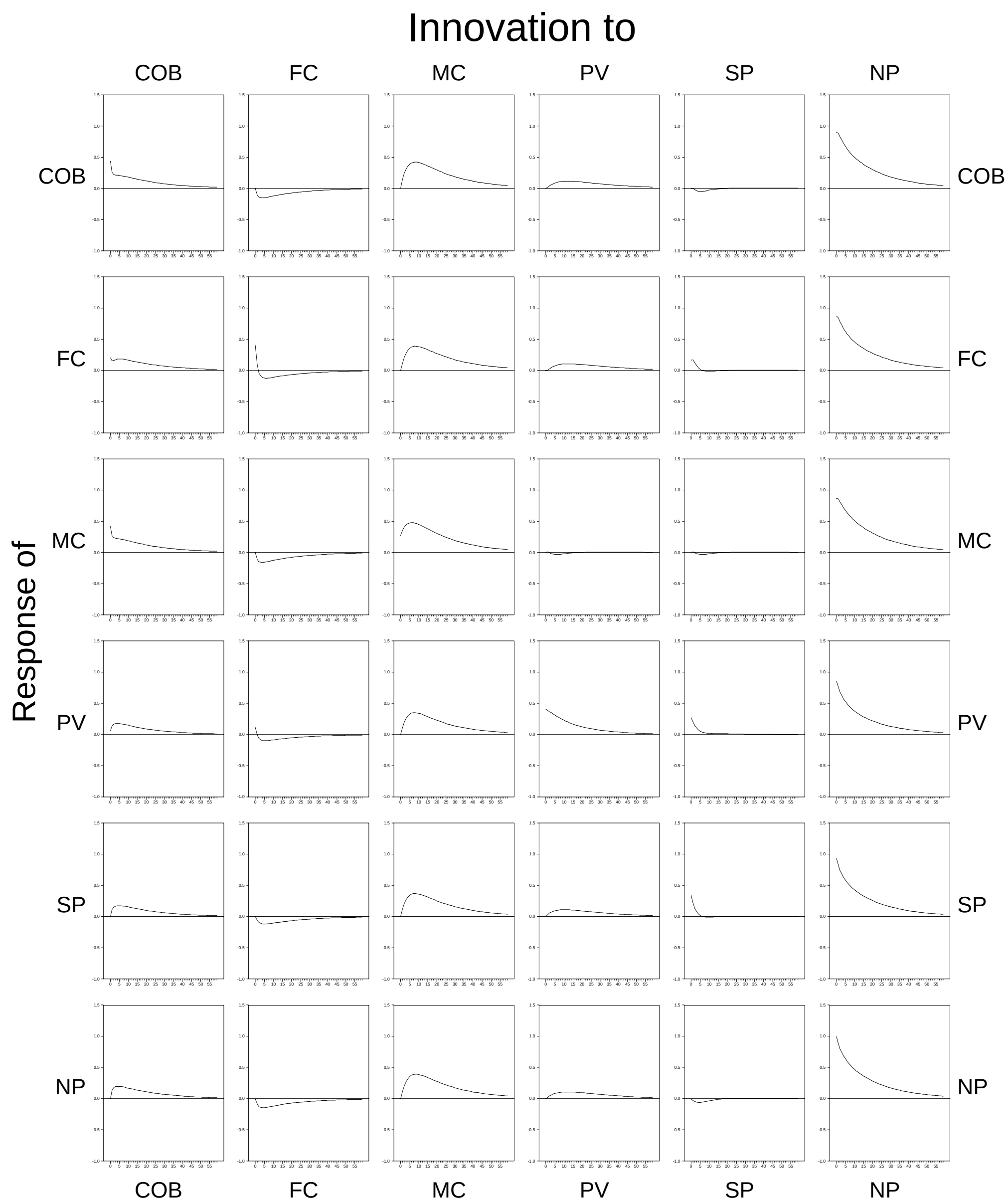


Figure 4. Normalized impulse response functions to one-time-only shocks in spring - summer peak prices from six western U.S. spot markets

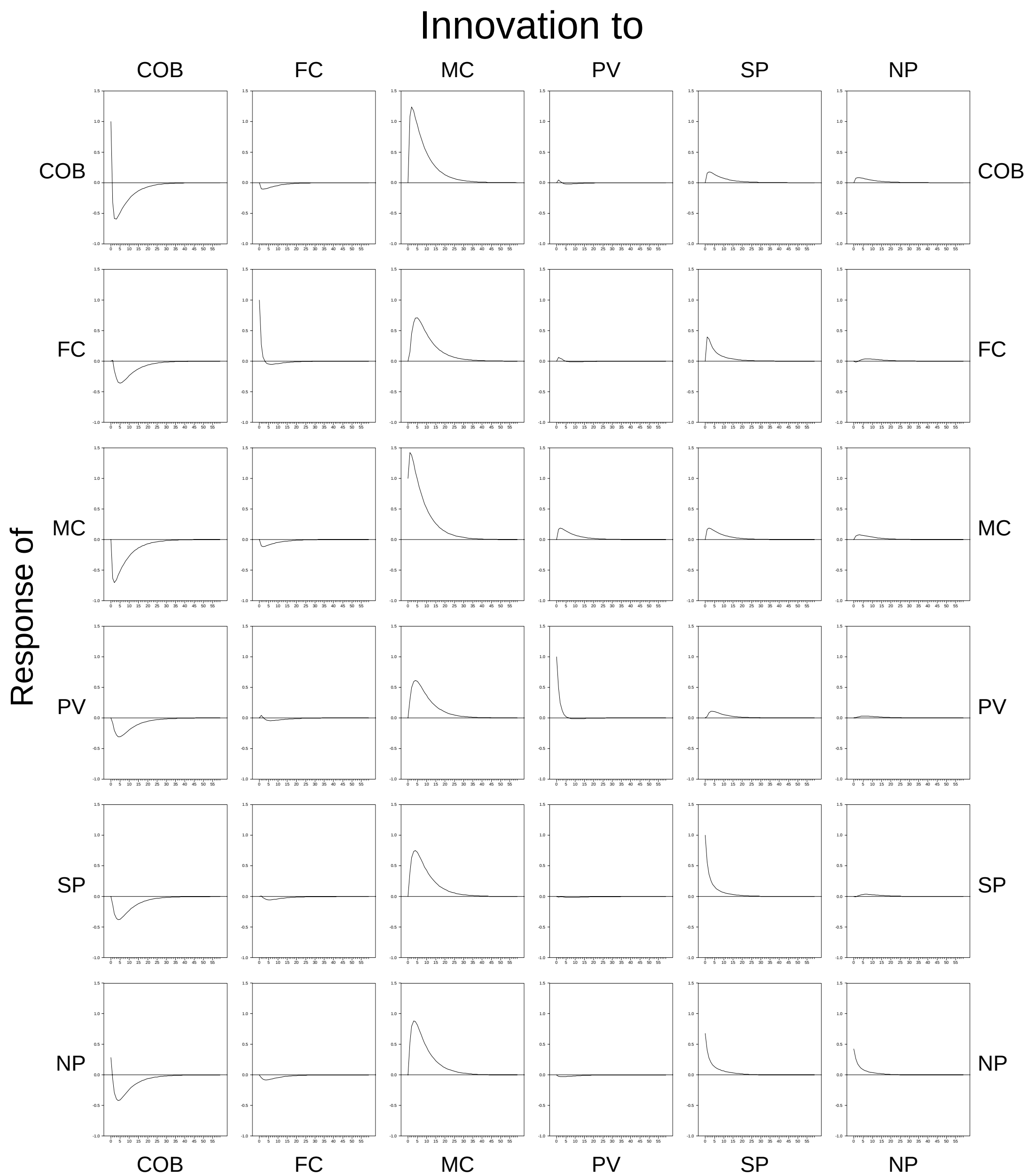


Figure 5. Normalized impulse response functions on one-time-only shocks in fall - winter peak prices from six western U.S. spot markets