ESSAYS ON PRICE DYNAMICS, DISCOVERY, AND DYNAMIC THRESHOLD EFFECTS AMONG ENERGY SPOT MARKETS IN NORTH AMERICA

A Dissertation

by

HAESUN PARK

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2005

Major Subject: Agricultural Economics

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Approved by:

Co-Chairs of Committee,	James W. Mjelde
	David A. Bessler
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	Diana M. Burton
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ABSTRACT

Essays on Price Dynamics, Discovery, and Dynamic Threshold Effects Among Energy Spot Markets in North America. (August 2005)

Haesun Park, B.A., Seoul National University, Korea

Co-Chairs of Advisory Committee: Dr. James W. Mjelde
Dr. David A. Bessler

Given the role electricity and natural gas sectors play in the North American economy, an understanding of how markets for these commodities interact is important. This dissertation independently characterizes the price dynamics of major electricity and natural gas spot markets in North America by combining directed acyclic graphs with time series analyses. Furthermore, the dissertation explores a generalization of price difference bands associated with the law of one price.

Interdependencies among 11 major electricity spot markets are examined in Chapter II using a vector autoregression model. Results suggest that the relationships between the markets vary by time. Western markets are separated from the eastern markets and the Electricity Reliability Council of Texas. At longer time horizons these separations disappear. Palo Verde is the important spot market in the west for price discovery. Southwest Power Pool is the dominant market in Eastern Interconnected System for price discovery.

Interdependencies among eight major natural gas spot markets are investigated using a vector error correction model and the Greedy Equivalence Search Algorithm in Chapter III. Findings suggest that the eight price series are tied together through six long-run cointegration relationships, supporting the argument that the natural gas market has developed into a single integrated market in North America since deregulation. Results indicate that price discovery tends to occur in the excess consuming regions and move to the excess producing regions. Across North America, the U.S. Midwest region, represented by the Chicago spot market, is the most important for price discovery. The Ellisburg-Leidy Hub in Pennsylvania and Malin Hub in Oregon are important for eastern and western markets.

In Chapter IV, a threshold vector error correction model is applied to the natural gas markets to examine nonlinearities in adjustments to the law of one price. Results show that there are nonlinear adjustments to the law of one price in seven pair-wise markets. Four alternative cases for the law of one price are presented as a theoretical background. A methodology is developed for finding a threshold cointegration model that accounts for seasonality in the threshold levels. Results indicate that dynamic threshold effects vary depending on geographical location and whether the markets are excess producing or excess consuming markets.

DEDICATION

To my family:

wife, Naeryung Kwon;

son, Hyungjun (June);

daughter, Jungwon (Jennifer).

To my mother and

mother-in-law.

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In his heart a man plans his course,

but the LORD determines his steps - Proverbs 16:9

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I deeply appreciate the support and patience of my family: my wife, Naeryung, and children, Hyungjun and Jungwon. Most of all, I would like to give deep appreciation to God who has led and will lead me. I firmly believe the gracious hand of God upon me enabled all these things to have been done.

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CHAPTER I

INTRODUCTION

Electricity and natural gas are important energy sources, accounting for over a third of the energy consumed in the United States. These industries have been some of the most highly regulated sectors of the economy because they have characteristics of a natural monopoly. Both electricity and natural gas markets, however, have been experiencing deregulation and restructuring to increase efficiency (Bailey, 1998; DeVany and Walls, 1994).

Electricity power grids and natural gas pipeline networks connect spot markets in each industry, making it possible to trade electricity and natural gas. As a result of deregulation and restructuring, a more competitive market environment is developing in both industries; the role of the spot markets has increased. Deregulation has also led to increasing interdependence in spot markets (Lucia and Schwartz, 2002). These market changes imply that price determination is more likely to be in the hands of the market than the regulators. Moreover, market participants are more likely to be exposed to the price risk that accompanies competitive markets.

Understanding the dynamics of spot market prices in electricity and natural gas is important for decision and policy makers in terms of price risk management. Further,

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This dissertation follows the style of *American Journal of Agricultural Economics.*

knowledge of the dynamics of price discovery and the transmission pattern of price shocks between markets may provide regulatory implications in addressing market efficiency and integration.

The overall objective is to characterize the price dynamics of major electricity and natural gas spot markets in North America. The dissertation is presented as three essays, Chapters II through IV. Specific objectives of these essays are:

- to characterize the dynamic interdependencies among 11 major electricity spot markets in North America and to examine each market's role in price discovery,
- to characterize the dynamic interdependencies among eight major natural gas spot markets in North America and to investigate each market's role in price discovery, and
- to examine the existence of threshold cointegration between natural gas spot markets and to develop a threshold cointegration model that accounts for seasonality in the threshold levels.

Chapters II through IV are self-contained, each with its own introduction, empirical methods, data, empirical results, and discussion.

Interdependencies in 11 major electricity spot markets in North America are examined in Chapter II. This chapter investigates each individual market's role in price discovery combining recent advances in causal flows with time series analysis. Directed acyclical graphs developed using PC (named after its authors, Peter and Clark)

Algorithm are used to find the contemporaneous causal flows among electricity spot markets in North America. Forecast error variance decompositions and impulse response functions with confidence intervals based on a vector autoregression model are utilized to find the dynamic interdependencies among markets. Daily peak firm price for the electricity of 11 spot markets from February 26, 1998 through December 20, 2002 are used in the empirical analysis. Because the demand for electricity is subject to weather effects, lagged U.S. aggregate cooling degree-days (CDD) and heating degree-days (HDD) are used to capture daily weather effects in electricity prices. No study has examined electricity price interdependencies over such an expansive geographical area, which includes three main power grids, ten different electricity reliability councils, and numerous smaller entities involved in generation, transmission, and distribution. Empirical results suggest that the western markets are separated from the eastern markets and the Electricity Reliability Council of Texas in contemporaneous time, but these separations disappear at longer time horizons.

Price dynamics among major natural gas spot markets in North America are investigated in Chapter III. To find the contemporaneous causal flows among markets, directed acyclical graphs are again used. I explore a new method, the Greedy Equivalence Search (GES) Algorithm, to find causal flows. This is one of the first applications of the GES Algorithm in economics. Empirical findings on the short-run interdependencies using a vector error correction model and associated forecast error variance decomposition and impulse response functions are presented. For empirical analysis, daily price for the natural gas of eight spot markets from January 12, 1998 through December 20, 2002 are used. As in Chapter II, lagged U.S. aggregate cooling degree-days (CDD) and heating degree-days (HDD) are used to capture daily weather effects in natural gas prices. No previous study has considered such a geographical dispersion and weather effects to analyze natural gas spot prices. Empirical findings suggest the natural gas market has developed into a single integrated market in North America since deregulation. Across North America, the U.S. Midwest region represented by the Chicago spot market is the most important market for price discovery. This result differs from previous studies that suggest the Henry Hub market in Louisiana is the important market.

The nonlinearity of price adjustment to the long-run equilibrium between natural gas spot market pairs is investigated in Chapter IV. In the presence of transaction costs, the threshold cointegration model may better explain nonlinear price adjustment behavior between spatially separated markets than nonthreshold models. Based on the empirical finding that the Chicago market is the important market for price discovery in North America, seven market pairs using Chicago as the benchmark, are considered in the analysis. The same data set used in Chapter III is used in this analysis. The nonlinearity of price adjustment between natural gas spot markets is tested and a bivariate three-regime threshold vector error correction model is estimated. Estimated transaction costs between Chicago and the other market show geographical differences along with differences between excess producing and excess consuming market regions.

Further, an important contribution of Chapter IV is the development of a threshold cointegration model that accounts for seasonality in the threshold levels. No previous study has developed such a model. A methodology is developed to estimate time-varying thresholds. Previous studies considered transaction costs in light of the law of one price are limited to the fixed thresholds under the assumption of time-invariant transaction costs and market conditions.

An overall summary is presented, a comparison of findings of Chapter II and III is provided, and areas for further study are proposed in Chapter V.

CHAPTER II

PRICE DYNAMICS AMONG ELECTRICITY SPOT MARKETS

Spot markets within the wholesale electricity industry are characterized by both price volatility and interdependencies among neighboring markets partially because of limited storability and transportability (Lucia and Schwartz, 2002). The limited storability may make the interdependencies of the electricity spot markets a factor in electricity price formulation and price volatility. Transmission constraints may make electricity contracts and prices highly local, because such constraints make it uneconomical to transmit electricity between certain regions (Lucia and Schwartz, 2002). Volatility and interdependency of wholesale electricity spot markets also results from highly interconnected transmission system, temporal demand-supply imbalance, and transmission congestion. Accordingly, the electricity prices may behave unlike other commodity markets (Weron and Przybylowicz, 2000).

With utility retail sales amounting to more than three percent of the U.S. gross domestic product (White, 1996), the electric power industry is vital to the economy. Historically one of the most highly regulated sectors of the U. S. economy, the electric power industry has undergone many structural changes, such as restructuring and deregulation over the past decade. As a result, a more competitive market environment is developing. These market changes imply that price determination is more likely to be placed in the hands of the market than regulators. Analyzing spot market price discovery is important for decision and policy makers because of the structural change the industry is undergoing and the importance of the industry. The objective of this study is to characterize the dynamic relationships among 11 major electricity spot markets in North America and to examine each individual market's role in price discovery. This study, therefore, focuses on spot prices rather than the factors affecting the prices. Providing information on the dynamics of electricity prices allows for a better understanding of how price innovations in one spot market affect the other markets and their interaction. In addition, this study addresses the following questions. Do certain markets have more influence on price than others? What markets play the role of price leadership? This study is the first attempt to describe the dynamic relationships at the national level among North America electricity spot markets. To this end, this study presents empirical findings on the contemporaneous and short-run interdependencies using a vector autoregressive model, causal flows based on directed acyclic graphs, and innovation accounting analysis.

To my knowledge, no study to date has examined electricity price interdependencies at the U.S. national level. Further, no study has examined electricity price interdependencies over such an expansive geographical area. The U.S. includes three main power grids, ten different electric reliability councils, and hundreds, if not thousands, of entities involved in generation, transmission, and distribution.

Brief Literature Review

Numerous studies on electricity pricing have been conducted. Most studies of electricity pricing behavior have focused on an industrial economics (market structure and market power), engineering (cost based pricing), or institutional aspects (impact of deregulation on price) (Joskow, 1997; Kleit, 2001; Angelus, 2001; Mansur, 2001; Puller, 2002). Few studies have investigated the dynamic behavior of empirical price using time series analysis. Studies examining electricity price dynamics have usually indicated the following stylized facts concerning electricity prices: high volatility, mean-reversion, seasonality, and frequent extreme jumps in prices (Huisman and Mahieu, 2003). See Bunn (2004) for more studies concerning modeling electricity prices.

De Vany and Walls (1999a) using daily peak and off-peak data from 1994 to 1996 investigated electricity spot price behavior and tested for market integration in western U.S. markets. They estimated vector error correction models using price data from eleven markets. They found all electricity spot price series except for one off-peak price series are non-stationary. Further, all of off-peak price series and most of peak price series are pair-wise cointegrated. De Vany and Walls (1999b) conducted impulse response function and variance decomposition analyses using an unrestricted vector autoregressive model for five western U.S. spot markets using daily peak and off-peak spot prices from 1994 to 1996. They found that electricity prices show relatively rapid (four or five trading days) convergence with respect to external shocks. Jerko, Mjelde, and Bessler (2004) using directed graphs to examine the contemporaneous causal flows among spot markets suggested electricity price information flows from north to south in the winter and from south to north in the summer differ between seasons in the western U.S.

Another avenue in empirical time series analysis of electricity prices is attempts to capture the volatility, seasonality, and mean reversion characteristics of electricity spot prices (Weron and Przybylowicz, 2000; Deng and Jiang, 2002; Huisman and Mahieu, 2003). Huisman and Mahieu (2003), Goto and Karolyi (2003), and Deng (1999) developed empirical models assuming the stationarity or mean reversion characteristic of electricity price. Huisman and Mahieu (2003) introduced a regime-switching model to address price spikes or volatility of prices. Using electricity price data from Dutch, German, and United Kingdom markets, they found a regime jump model is a better specification for both mean-reversion and spikes. Goto and Karolyi (2003) showed the conditionally autoregressive heteroskedasticity (ARCH) and time-dependent jumps are important features in modeling price volatility using four U.S. spot market prices, Nordic pool market prices, and Australia market price. Weron and Przybylowicz (2000) conducted Hurst rescaled range analysis for distinguishing random time series from correlated time series to capture the price volatility using the electricity prices from California and Central Europe. They found mean-reverting processes in both markets. De Vany and Walls (1999a), De Vany and Walls (1999b), and Jerko, Mjelde, and Bessler (2004) model the interactive behavior among the electricity spot markets; their studies, however, are limited to the western region of the U.S.

Empirical Methods

Vector Autoregression Model

A vector autoregression (VAR) model provides the basis for this analysis. A VAR model has the advantage that it allows regularities in the data to be studied without imposing as many prior restrictions as structural models impose. VAR models are often criticized because they are not economic theory based (Greene, 2000). However, a VAR model is appropriate for analyzing electricity price interdependences because economic theory does not suggest a prior structure for electricity price interdependences.

A VAR model is:

(1) $$P_t = \alpha + \sum_{i=1}^{k} \beta_i P_{t-i} + \gamma Z_t + e_t$$

where α is a (m x 1) vector of intercept terms, P_t is a (m x 1) vector of electricity prices, e_t is a (m x 1) vector of the residual terms (innovations), m is the number of price series, Z_t is a (q x 1) vector of strictly exogenous variables, β_i and γ are appropriately dimensioned matrices of coefficients, k represents the number of lags, and t is a specific observation from a sample of T observations. The innovation term e_t is assumed to be white noise, with $E(e_t) = 0$, and $\Sigma_e = E(e_t e_t')$ is a (m x m) positive definite matrix. Further, the innovations e_t and e_s are assumed to be independent for $s \neq t$. Although serially uncorrelated, contemporaneous correlations among the elements of e_t are possible, implying the contemporaneous correlation matrix may not an orthogonal matrix.

If no contemporaneous correlation among the elements of e_t exists, then innovation accounting procedures such as impulse response and forecast error variance decompositions are conducted using the moving average representation obtained from the estimated VAR. The moving average representation of a VAR expresses each series as a function of innovations (see Hamilton, 1994, p. 291). These procedures allow the dynamic properties of the VAR to be investigated. Impulse response functions describe the movement of each series in a VAR in response to a one-time shock in each series. Forecast error variance decompositions indicate whether the forecast error (the error between the VAR model prediction and actually observed) variance for each series at any horizon is due to its own innovations or other variables' innovations (Doan, 2000).

However, contemporaneous correlation among price series is the norm when using economic data. If innovations are contemporaneously correlated, it is misleading to examine a shock to a single variable in isolation (Doan, 2000). To address the contemporaneous correlation issue, the VAR model must be transformed such that the innovations are orthogonal. An ordering procedure suggested by Bernanke (1986) is used to obtain the transformed VAR.

Following Bernanke (1986), the innovations are written as a function of more fundamental driving sources of variation, ϵ_t, which are independent of other sources of variation:

(2) $$e_t = A^{-1}\epsilon t,$$

where A is a matrix representing how each non-orthogonal innovation is caused by the orthogonal variation in each equation. Usual innovation accounting procedures are carried-out on the moving average representation of the transformed VAR:

(3) $$AP_t = A\alpha + \sum_{i=1}^{k} A\beta_i P_{t-i} + A\gamma Z_t + Ae_t .$$

Because the VAR model has the same right hand side variables in each equation, the model is estimated using ordinary least squares equation by equation. There is no gain in efficiency using seemingly unrelated regression (Baltagi, 2002). Directed acyclic graphs are used to provide identifying restrictions on the matrix A. Hoover (2005) provides a discussion concerning the issue of contemporaneous causal order in VAR model including the application of directed graphs in dynamic models.

Directed Acyclic Graphs

A directed graph is an illustration using arrows and vertices to represent the causal flow among a set of vertices (or variables) (Pearl, 2000). Three elements, variables, marks representing the symbols attached to the end of edges, and edges between variables comprise a directed graph. A directed acyclic graph is a directed graph that contains no directed cyclic paths (Spirtes, Glymour, and Scheines, 2000). Only directed acyclic graphs are considered.

Directed acyclic graphs represent conditional independent relationships as implied by the recursive product decomposition:

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

where Pr is the joint probability of variables $x_1, x_2, x_3, \ldots, x_n$ and pa_i is a set of variables representing the minimal set of predecessors (the variables that come before in causal sense) of x_i that renders x_i independent of all its other predecessors (Pearl, 2000, p.14). It has been shown that there is a one-to-one correspondence between the set of conditional independencies among variables implied by equation (4) and the graphical expression of variables in directed graph (for details see Pearl, 2000). For example, consider four variables, x_1, x_2, x_3, and x_4. If there is causal relationship such as x_1 and x_2, cause x_3, and x_3 causes x_4, then the directed graph that represents this causal relationship is:

$$\begin{array}{ccccc} x_1 & & & & \\ & \searrow & & & \\ x_2 & \rightarrow & x_3 & \rightarrow & x_4. \end{array}$$

This directed graph is expressed as the following probability distribution product:

(5) $$\Pr(x_1, x_2, x_3, x_4) = \Pr(x_1)\Pr(x_2)\Pr(x_3 \mid x_1, x_2)\Pr(x_4 \mid x_3).$$

PC Algorithm, which finds causal flows from correlation relationships among the variables, is used in this study (Spirtes, Glymour, and Scheines, 2000). PC Algorithm begins with a general unrestricted set of relationships among the variables and proceeds step-wise to remove edges between the variables depending on correlation relationships. Finally, PC Algorithm directs causal flow using conditional independent relationships.

PC Algorithm makes three assumptions. First, causally sufficient sets of variables are included in the observational data set. This implies there are no omitted variables that cause any two of the included variables. Second, the casual Markov condition is assumed to be satisfied. This implies that if x_1 causes x_2 and x_2 causes x_3, then the underlying probability distribution on x_1, x_2 and x_3, $Pr(x_1, x_2, x_3)$, can be expressed as $Pr(x_1)Pr(x_2| x_1)Pr(x_3| x_2)$. In other words, this assumption means that one need only to condition on variables of direct cause to capture the probability distribution generating any variable. Finally, the faithfulness condition is assumed. The probabilities, $Pr(\cdot)$, are said to be faithful to the corresponding directed graph in the case that x_1 and x_2 are dependent if and only if there is an edge between x_1 and x_2 (Bessler and Lee, 2002). The first assumption, causal sufficiency may be too strong to be satisfied in applied studies, because such studies can only use a limited number of variables. Accordingly, it should be noted that PC Algorithm has some limitations because of this strong assumption.

Data

Eleven North America electricity spot markets are used to investigate markets' interdependency. Daily firm-peak spot market electricity prices for day-ahead trades covering the period of February 26, 1998 to December 20, 2002 are used. The data are Platts power indices provided by McGraw-Hill Companies, Inc., New York. Firm peak price is the price for next day guaranteed delivery for the hours between 6 a.m. and 10 p.m. Prices are for Monday through Friday. Each price series has 1257 observations. The total number of missing values in the 11 price series is 614. The missing values including holidays account for 4.4 percent of total observations. The prior day's price is used to represent any missing values for a particular day and market.

Regional dispersion and data availability are factors in determining which markets are included. The markets are mid-Columbia (MIDC), Palo Verde (PV), Four Corners (FC), Pennsylvania-New Jersey-Maryland (PJM), Northeast Power Pool (NEPL), Mid-Continent Area Power Pool (MAPP), Mid-America Interconnected Network (MAIN), East Central Area Reliability Coordination Agreement (ECAR), Southwest Power Pool (SPP), Entergy (ENT), and Electric Reliability Council of Texas (ERCOT). Approximate locations of the spot markets are shown in Figure 2.1. Plots of the price series for each market are provided in Figure 2.2.

One day lagged U.S. aggregate cooling degree-days (CDD) and heating degree-days (HDD) are used to capture daily weather effects in the electricity prices. Daily HDD are calculated as the difference between a reference temperature and the day's mean temperature (reference temperature – (maximum temperature + minimum temperature)/2), whereas CDD are computed as the difference mean temperature and a reference temperature ((maximum temperature + minimum temperature)/2 - reference temperature). The reference temperature used is 65 degrees Fahrenheit, the temperature used by U.S. National Oceanic and Atmospheric Administration (NOAA). HDD and CDD are set equal to be zero if the degree-day is negative. Daily degree-days for 23 cities are obtained (U.S. Department of Commerce, NOAA, 2003). The 23 cities are: Bismarck, Minneapolis, Kansas City, Chicago, Louisville, Pittsburg, New York, Billings, Seattle, San Francisco, Salt Lake, Denver, Boise, Dallas, Oklahoma City, Houston, New Orleans, Atlanta, Memphis, Los Angeles, Las Vegas, Phoenix, and

Albuquerque (Figure 2.1). Daily degree-days for each city are aggregated into a U.S. daily cooling and heating degree-days by computing a weighted average using each city's population as weights. Population data for each city in 2001 are obtained from the U.S Census Bureau. [1]

Empirical Results

Stationarity

Three tests are used to examine the stationarity of the 11 price series, Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and trace tests. As shown in Figure 2.2, each price series is highly volatility and potentially heteroscedastic. To help account for these two issues, all estimations are conducted using logarithmic transformed data using a robust estimator. The robust estimator computes a heteroscedasticity consistent estimate of the asymptotic covariance matrix of the estimated parameters (Greene, 2000).

DF and ADF test results are given in Table 2.1. The null hypothesis of both the DF and ADF tests is that the electricity price series is non-stationary. This null hypothesis is rejected if the DF or ADF statistic is less than –2.89 (-2.58) at a 5% (10%) level of significance (Fuller, 1976). The DF test statistics indicate NEPL, PJM, and ECAR spot markets are stationary at the 5% level. All markets except MIDC, MAPP and ERCOT are stationary at the 10% level. Using the ADF test, PJM, ECAR, and MAIN are stationary at the 5% level, while at the 10% level all series, but MIDC, PV, FC, MAPP, and ERCOT are stationary. Although these tests are not conclusive, the tests indicate at least three price series among eleven price series are stationary using both the DF and ADF tests at the 5% level.[2] At the 10% level, up to eight of the 11 series are stationary. Also presented in Table 2.1 are Q-statistics, which test if the residuals from the DF and ADF regressions are white noise. The null hypothesis of white noise residuals is rejected when the Q value is large or the p-value is small. Based on the Q-statistics and associated p-values, the residuals from DF and ADF tests regressions are not white noise for any of the series.

Results of the trace test (Table 2.2) indicate there are 11 cointegrating vectors among 11 price series, implying all series are stationary. This conclusion is similar to the conclusion from the DF test at the 10% level. With stationary data, it is appropriate to estimate a VAR in levels. Based on the three stationary tests, it appears most, if not all of the eleven series are stationary or close to stationary. Further, Engle and Granger (1987) suggest a VAR in levels is equivalent to estimating an error correction model when the number of observations is large. Accordingly, a VAR in logarithmic levels is estimated. When estimating the levels VAR, one lag of CDD and HDD are included as exogenous variables.[3]

Optimal Lag Length of Levels VAR

Schwarz loss, Akaike loss, Hannan and Quinn's phi measures are used to determine the optimal number of lags for the VAR model. Results of the three metrics for one to 12 lags are given in Table 2.3. The Schwarz loss and Hannan and Quinn loss metric are minimized at one lag and two lags. In contrast, the Akaike loss metric is minimized at ten lags.

Considering that the electricity spot market prices are the price for day-ahead trades it is reasonable to assume prices are affected by market conditions from the recent past and employing the parsimony principle, a smaller number of lags is more reasonable rather than the ten lags suggested by the Akaike loss metric. Further, the Schwarz loss metric may have a tendency to over-penalize additional regressors compared to the other metrics (Geweke and Meese, 1981). Given these considerations, a two lags VAR model suggested by Hannan and Quinn's phi measure is used.

Estimation Results of Two Lags VAR

The p-values of F-test associated with the null hypothesis "the coefficients for both one and two lagged prices are jointly equal to zero" are given in Table 2.4. In the following discussion, a 10% level of statistical significance is assumed. Coefficients associated with each market are significant in at least one market other than their own market equation. Only for MAPP are all of the coefficients associated with the other markets insignificant. The largest number of significant markets occurs in the NEPL equation, where seven markets have significant coefficients. In the majority of the equations, four or five markets have significant coefficients. The markets which are significant the most are PJM, NEPL, MAPP, ENT, and ERCOT. The western markets are only significant in the western markets and NEPL equations. Besides the western markets, only NEPL and PJM are significant in the western markets' equations. MAPP, ENT, and ERCOT tend to be significant in most of the non-western markets. It is surprising that the coefficients of NEPL and PJM are significant in three western markets. In contrast, the coefficients of western markets are not significant in most of the non-western market. One exception is that FC is significant in the NEPL market.

HDD variables are not statistically significant at the 10% level except in ECAR, MAIN, and MAPP markets (Table 2.5). CDD variables are statistically significant at the 10% level in seven of the 11 markets (Table 2.5). The four markets CDD are not significant are MIDC, PV, FC, and ERCOT. These results are consistent with the fact that electricity is not the main energy source for heating in most of the U.S., but electricity is the major energy source for cooling during the summer.

Identifying Contemporaneous Structure

Innovation accounting analysis is conducted to identify the contemporaneous structure among the eleven electricity markets. Using the innovations from the VAR model, the lower triangular of the contemporaneous innovation correlation matrix, C is :

$$
(6)\; C = \begin{array}{r}
\\ \text{MIDC} \\ \text{PV} \\ \text{FC} \\ \text{NEPL} \\ \text{PJM} \\ \text{ECAR} \\ \text{MAIN} \\ \text{MAPP} \\ \text{ENT} \\ \text{SPP} \\ \text{ERCOT}
\end{array}
\begin{array}{c}
\begin{array}{ccccccccccc}
\text{MIDC} & \text{PV} & \text{FC} & \text{NEPL} & \text{PJM} & \text{ECAR} & \text{MAIN} & \text{MAPP} & \text{ENT} & \text{SPP} & \text{ERCOT}
\end{array} \\
\begin{pmatrix}
1.00 & & & & & & & & & & \\
0.78 & 1.00 & & & & & & & & & \\
0.75 & 0.95 & 1.00 & & & & & & & & \\
0.03 & 0.01 & 0.02 & 1.00 & & & & & & & \\
0.06 & 0.07 & 0.07 & 0.65 & 1.00 & & & & & & \\
0.03 & 0.03 & 0.03 & 0.41 & 0.80 & 1.00 & & & & & \\
0.04 & 0.01 & 0.01 & 0.36 & 0.71 & 0.90 & 1.00 & & & & \\
0.03 & 0.02 & 0.02 & 0.38 & 0.59 & 0.69 & 0.71 & 1.00 & & & \\
0.04 & 0.03 & 0.03 & 0.36 & 0.71 & 0.89 & 0.85 & 0.69 & 1.00 & & \\
0.02 & 0.02 & 0.02 & 0.37 & 0.67 & 0.86 & 0.83 & 0.75 & 0.88 & 1.00 & \\
0.05 & 0.03 & 0.04 & 0.20 & 0.32 & 0.37 & 0.33 & 0.28 & 0.46 & 0.38 & 1.00
\end{pmatrix}
\end{array} .
$$

Innovations from the three western markets, MIDC, PV and FC, show strong correlations with each other and weak correlations with the markets from the rest of the U.S. Innovations from the markets in the central U.S., ECAR, MAIN, MAPP, ENT, and SPP, and the eastern market, PJM, generally have stronger correlations with each other. NEPL innovations correlations tend to be weaker than the correlation between the markets in the central U.S. Innovations from ERCOT have almost no correlations with the western markets and weaker correlations with the rest of the U.S. compared to correlation relationship among the other markets. These results are generally consistent with the three main power grids, Eastern Interconnected System, Western Interconnected System, and the Texas Interconnected System, in the U.S. (Figure 2.3).

Correlations from equation (6) are used in the directed graph analysis to identify the Bernanke ordering structure. Based on the correlation patterns derived from the correlation matrix, causal flows between contemporaneous innovations from each of 11 markets are assigned as in Figure 2.4 using TETRAD II, a computer software for PC Algorithm (Scheines et al., 1994). Similar results are obtained for significance levels of 1% and 0.1% (Figure 2.4). The direction between MAIN and ENT, the direction between MAPP and MAIN, and the edge between MIDC and FC are the only differences at the two significant levels. In the directed acyclic graph at the 1% significance level, there are bi-directed edges between MAPP and MAIN and between ECAR and ENT. There are bi-directed edges between MAIN and ENT and between ECAR and ENT in the directed acyclic graph at 0.1% significance level. These bi-directed edges indicate there are potentially omitted variables between these markets. The edges among three spot markets, MIDC, FC, and PV are not determined at either significance level. Further, there is no edge between MIDC and FC at the 0.1% significance level.

There are ten alternative directed acyclic graphs that are consistent with the three undirected edges in the western U.S.:

(D.1)
$$\begin{tikzcd} & \mathrm{MIDC} \arrow[dr] & \\ \mathrm{FC} & & \mathrm{PV} \arrow[ll] \end{tikzcd}$$

(D.2)
$$\begin{tikzcd} & \mathrm{MIDC} \arrow[dr] & \\ \mathrm{FC} \arrow[rr] & & \mathrm{PV} \end{tikzcd}$$

(D.3)
$$\begin{tikzcd} & \mathrm{MIDC} & \\ \mathrm{FC} \arrow[rr] & & \mathrm{PV} \arrow[ul] \end{tikzcd}$$

(D.4)
$$\begin{tikzcd} & \mathrm{MIDC} & \\ \mathrm{FC} & & \mathrm{PV} \arrow[ul] \arrow[ll] \end{tikzcd}$$

(D.5)
$$\begin{tikzcd} & \mathrm{MIDC} \arrow[dl] & \\ \mathrm{FC} & & \mathrm{PV} \arrow[ul] \arrow[ll] \end{tikzcd}$$

(D.6)
$$\begin{tikzcd} & \mathrm{MIDC} & \\ \mathrm{FC} \arrow[ur] & & \mathrm{PV} \arrow[ul] \arrow[ll] \end{tikzcd}$$

(D.7)
$$\begin{tikzcd} & \mathrm{MIDC} & \\ \mathrm{FC} \arrow[ur] \arrow[rr] & & \mathrm{PV} \arrow[ul] \end{tikzcd}$$

(D.8)
$$\begin{tikzcd} & \mathrm{MIDC} \arrow[dr] & \\ \mathrm{FC} \arrow[ur] \arrow[rr] & & \mathrm{PV} \end{tikzcd}$$

(D.9)
$$\begin{tikzcd} & \mathrm{MIDC} \arrow[dl] \arrow[dr] & \\ \mathrm{FC} & & \mathrm{PV} \arrow[ll] \end{tikzcd}$$

(D.10)
$$\begin{tikzcd} & \mathrm{MIDC} \arrow[dl] \arrow[dr] & \\ \mathrm{FC} \arrow[rr] & & \mathrm{PV}. \end{tikzcd}$$

Cycle paths such as following are not considered:

$$\begin{tikzcd} & \mathrm{MIDC} \arrow[dl] & \\ \mathrm{FC} \arrow[rr] & & \mathrm{PV}. \arrow[ul] \end{tikzcd}$$

For each of these ten alternative directed acyclic graphs, there are five alternative possibilities for the edges between MAIN-MAPP, MAIN-ENT, and ECAR-ENT markets:

(D.11)
$$\begin{tikzcd} \mathrm{MAIN} \arrow[d] \arrow[dr] & \mathrm{ECAR} \arrow[l] \arrow[d] \\ \mathrm{MAPP} & \mathrm{ENT} \end{tikzcd}$$

(D.12)
$$\begin{tikzcd} \mathrm{MAIN} \arrow[d] & \mathrm{ECAR} \arrow[l] \arrow[d] \\ \mathrm{MAPP} & \mathrm{ENT} \arrow[ul] \end{tikzcd}$$

(D.13)
$$\begin{tikzcd} \mathrm{MAIN} \arrow[d] & \mathrm{ECAR} \arrow[l] \\ \mathrm{MAPP} & \mathrm{ENT} \arrow[ul] \arrow[u] \end{tikzcd}$$

(D.14)
$$\begin{tikzcd} \mathrm{MAIN} & \mathrm{ECAR} \arrow[l] \\ \mathrm{MAPP} \arrow[u] & \mathrm{ENT} \arrow[ul] \arrow[u] \end{tikzcd}$$

(D.15)
$$\begin{tikzcd} \mathrm{MAIN} & \mathrm{ECAR} \arrow[l] \arrow[d] \\ \mathrm{MAPP} \arrow[u] & \mathrm{ENT}. \arrow[ul] \end{tikzcd}$$

There are 50 (10 x 5) possible alternative directed acyclic graphs that are consistent with the edges in Figure 2.4. A procedure is necessary to determine the direction of the MAPP-MAIN, MAIN-ENT, and ECAR-ENT edges and the undirected edges, MIDC-FC, MIDC-PV and FC-PV. A scoring method based on a modified version of the Schwarz loss metric is applied following Bessler and Yang (2003). Their procedure involves using the innovations from the VAR model. Each of the 50 alternative graphs is expressed as a set of 11 market regression equations, one for each market. To illustrate the procedure, 11 equations associated with each of the 11 markets' innovations are estimated using seemingly unrelated regression. For a given equation, the dependent variable is the innovations from the estimated VAR model associated with that market's equation. Independent variables are an intercept and innovations from the market(s) that causes the market in question. For example, consider the PJM and NEPL markets. The equation representing PJM has as independent variables the innovations from the NEPL and ECAR equations, whereas the equation representing NEPL has only an intercept term. These two equations do not change in the scoring method. Markets that have an undirected edge change in the scoring procedure.

For markets with undirected edges, the independent variables change according to the hypothesis as to which markets cause which markets. As an example, consider the first possible graph associated with the western market. The first possible alternative (D.1) is MIDC causes FC and PV and FC causes PV. In this case, the equation representing MIDC has only an intercept term, whereas the equation representing FC has as independent variables the innovations from the MIDC equation. The equation representing PV has the innovations from both MIDC and FC. For the second alternative (D.2) only changes in independent variables are necessary for the equations representing FC and PV, the other equations remain the same. In this way, 50 sets of regression equations are obtained. The 50 sets of seemingly unrelated regressions are scored using a modified Schwarz loss metric, $SL = \log(\mathrm{Trace}(\Sigma)) + k\log(T)/T$. Here, Σ represents the variance covariance matrix from each seemingly unrelated regression, and k represents the number of coefficients fit, and T is the number of observations. The Schwarz loss metrics associated with 50 alternatives are graphed in Figure 2.5. The set of equations that minimizes this Schwarz loss metric is considered the "best" directed acyclic graph. Only three Schwarz loss values are within 25% of the smallest value. The "best" directed acyclic graph is shown in Figure 2.6.

The directed acyclic graph shows clear market separation between the western markets and the rest of the U.S. Markets in the central part of the U.S., ECAR, MAPP, MAIN, SPP and ENT are strongly connected with each other. The information flow is ECAR causes MAIN, SPP and PJM. ENT causes SPP, MAIN, and ECAR. SPP and MAIN both cause MAPP. MAPP and PJM appear to be information sinks; they do not cause any other market. ERCOT causes ENT. Finally, in the northeastern markets NEPL causes PJM and ECAR. NEPL and ERCOT appear to be exogenous; there are no markets that cause these markets in contemporaneous time. For the western markets, PV causes both FC and MIDC.

Forecast Error Variance Decomposition

Based on the best directed acyclic graph, the forecast error variance decompositions are given in Table 2.6. Decompositions give the percentage of price variation in each market at time t+k that is due to innovations in each market (including itself) at time t. Listed are the results at horizons of zero (contemporaneous time), one day (short horizon), and 30 days ahead.

In contemporaneous time, the variation in MIDC is explained by innovations from MIDC (40.2%) and PV (59.8%). The variation in MIDC is explained by the innovations from MIDC (39.8%), PV (58.8%) at the short run, and MIDC (26.3%), PV (37.2%), PJM (11.7%), and SPP (10.2%) at 30-day horizon. PV appears to be exogenous at the shorter horizons, but is less exogenous at the longer horizon. At the 30-day horizon, PJM (16.3%), SPP (9.8%), and PV (48.9%) account for most of the variation in the PV. FC is nearly exogenous in contemporaneous time. The variation in FC is explained by innovations from PV (52.1%) and FC (45.3%) at the short run. At 30-day horizon, however, the variation in the FC is explained by PJM (17.3%), NEPL (8.6%), SPP (9.9%), FC (7.6%), and MIDC (6.1%). NEPL is exogenous in contemporaneous time and at the short run. At 30-day horizon, the variations in the NEPL are explained by NEPL (58.1%), PJM (12.4%), and nearly equal percentages from the other markets. PJM is exogenous in contemporaneous time and nearly so in the short run. At 30-day horizon, PJM (36.7%) and SPP (29.5%) account for the most of variation in PJM with contribution from MAIN (7.2%), MAPP (8.0%), and NEPL (6.3%).

ECAR is highly dominated by ENT (50.5%) in contemporaneous time. However, SPP accounts for over 50% variation of ECAR at the 30-day horizon. ENT (48.2%) dominates MAIN in contemporaneous time. At the 30-day horizon, SPP (34.9%), ENT (27.7%), and MAIN (16.5%) explain most of the variation in MAIN. MAPP is dominated by SPP at all horizons. The variation in the ENT is explained by itself (79.2%) and by ERCOT (20.8%) in contemporaneous time. In the short run, ENT (53.5%), SPP (25.7%) and ERCOT (13.8%) accounts for the variation in the ENT. SPP has considerable influence on ENT both in the short run and 30-day horizon. SPP is nearly exogenous in all time frames. ERCOT is highly exogenous at the shorter horizons. At 30-day horizon, however, SPP (29.5%) and PV (8.4%) account for some of variation in the ERCOT.

The importance of the SPP market on all markets except NEPL and itself increases over time. At the 30-day horizon, 30% or more of the decomposition in forecast error in seven of the 11 markets (PJM, ECAR, MAIN, MAPP, ENT, SPP, and ERCOT) is explained by innovations in SPP.

Impulse Response Functions

Impulse response functions are presented as a matrix of graphs with each element of the matrix corresponding to the response of one series to an one time only shock in another series (Figure 2.7). Horizontal axes on the sub-graphs represent the horizon or number of days after shock, here 30 days. Vertical axes indicate the standardized response to the one time shock in the each market labeled at the top of each column of graphs. Point estimates of impulse response alone, however, may give a misleading impression (Doan, 2000). In this study, confidence bands for impulse responses using Monte Carlo methods are provided based on the program given in Doan (2000). The point estimates plus or minus two times their standard errors estimated through 5,000 simulations are provided as the upper bound and lower bound of the confidence bands.

Shocks in western markets, MIDC, PV, and FC, are transferred as a positive impulse to the three western markets, but have a much smaller influence on the non-western markets than on the western markets. Specifically, the responses of three western markets to an innovation in the PV market are immediate and strong and dampen to zero thereafter. The responses of PV and FC to a shock in the MIDC market and the responses of MIDC and PV to a shock in the FC market show relatively small but long lasting positive impulses.

Considering almost no electricity transmission between NEPL and PJM and the western markets, it is surprising that the shocks in NEPL have relatively strong positive influences on the MIDC, PV, and FC market. However, the responses of non-western markets to an innovation in NEPL are generally small except PJM. In contrast, a shock in the PJM is transferred as a relatively strong and negative impulse to the three western markets and the NEPL market, whereas the shock is transferred as small negative impulse to the other markets except for its own market. These responses suggest PJM is maybe making-up for very short-run imbalances in the other markets. However, the responses of the western markets show the relatively larger and long lasting negative responses even though there is little to no electricity transmitted between the areas.

The responses of the western markets and non-western market such as ENT, SPP, and ERCOT to a shock in ECAR are small and negative. A shock in ECAR is transferred as an immediate and positive impulse to NEPL, and as relatively strong impulse to ECAR, PJM, and MAIN, dampening to zero quickly. Shocks in the ECAR market have a negative response in the ENT and ERCOT market, implying ECAR is making-up short-run imbalances in ENT and ERCOT. Imbalances in these three markets are quickly made-up. A shock in ECAR is transferred as an immediate and positive impulse to SPP.

A shock in MAIN has very little influence on the western markets. The response of MAIN to a shock in MAIN is strong and immediate, dampening to zero thereafter. A shock in MAIN is transferred as relatively small positive impulses to NEPL, PJM, ECAR, MAPP, and SPP, but small negative impulses to ENT and ERCOT. All markets dampen to zero quickly. The responses of the western markets to a shock in MAPP are long lasting and positive. A shock in MAPP is transferred as a quick and positive impulse to the non-western markets.

Shocks in ENT, SPP, and ERCOT are transferred as long lasting positive impulses to western markets. The response of NEPL to a shock in ENT is a mixture of positive and negative impulses. The responses of PJM, ECAR, MAIN, MAPP, ENT, and SPP to a shock in ENT are also a mixture of positive and negative impulses but are relatively strong and immediate. The response of ERCOT is small and positive. This mixed impulse behavior suggests the market price adjustment process associated with an innovation in ENT involves more active interaction among the markets than that associated with the other markets.

Similar to forecast error decomposition, innovations in the SPP market have relatively strong positive effects, at very short time lags in the non-western markets except for NEPL. Innovations in ERCOT are transferred as relatively little positive long lasting impulses to NEPL, whereas the responses of PJM, ECAR, MAIN, MAPP, ENT, and SPP are short and dampening to zero.

Discussion

The stationarity of electricity price series is addressed in previous papers analyzing electricity prices using time series methods. This study adds additional evidence that electricity prices have a mean reversion characteristic, indicating the price series of electricity are stationary. As suggested by other studies, electricity market may behave differently than other commodity markets.

In contemporaneous time, causal flow in the electricity markets as given by directed acyclic graphs reflects the three major power grids of U.S., Eastern Interconnected System, Western Interconnected System, and the Texas Interconnected System. Directed acyclic graphs suggest the Western Interconnect is separated from the other two grids. ERCOT in the Texas Interconnected System connects with the Eastern Interconnected System only through ENT.

In the Western Interconnected System, PV appears to be driving force for the other western markets for electricity price. ERCOT in the Texas Interconnected System and NEPL in the Eastern Interconnected System appear to be exogenous driving forces for electricity price through ENT and ECAR. The information flows from the directed graph analysis indicates that most of information flows occur between physically adjacent spot markets. This result is similar to findings by De Vany and Walls (1999b). It should be noted that the instantaneous price transmission pattern of western area in this study is not identical to the pattern given in Jerko, Mjelde, and Bessler (2004, Figure 3). In contrast to final directed acyclic graph (Figure 2.6), Jerko, Mjelde, and Bessler (2004) suggest that the FC influences PV and they show no edge between MIDC and PV in summer. In addition, there is undirected edge between MIDC and FC and between PV and FC in winter in their analysis. The dissimilarity is caused by including only three markets in this area in the current study instead of six markets used in their study, a different time frame, and they present both summer and winter models.

In contrast to the directed graph analysis, forecast error variance decomposition and impulse response functions allow for analysis of dynamic information flows over time. For the western markets, PV explains the price uncertainty in MIDC and FC. Further, PV appears to be exogenous at short run. Unlike De Vany and Walls (1999b) and Jerko, Mjelde and Bessler (2004), PV appears to be an important market in the western U.S. According to their studies, California-Oregon border (De Vany and Walls, 1999b) and South and North Path spot markets in California (Jerko, Mjelde, and Bessler, 2004) are the driving forces for the electricity prices in western U.S. This dissimilarity is partially caused by differences in the dates and markets included in the studies. COB and South and North Path spot markets in California are not included in this study because of data limitations. However, noting that PV is the spot market closest to the California; the importance of PV in western region is not inconsistent with previous studies.

SPP accounts for the large amount of forecast error variance at the longer periods in PJM, ECAR, MAIN, MAPP, ENT, and ERCOT; SPP is a dominant market in Eastern Interconnected System. Support for this result also comes from the impulse response functions. Innovations in SPP cause relatively large responses in non-western markets. Why SPP appears to be a dominant market is not entirely clear. One possible explanation is that the region within SPP relies more on natural gas as an energy source than the other markets. In states associated with SPP,[4] the percentage of natural gas as the primary energy source for generating electricity averages more than 28%. In contrast, the percentage for the entire U.S is less than 18% (U.S. Department of Energy, 2001). Natural gas is usually the energy source on the margin for peak power generation. Variation in natural gas prices may influence SPP first. The effects of gas price variations are then spread to the other markets.

The smaller influence of SPP in NEPL and the western markets may be because of the importance of hydroelectric generation in these regions. The above explanation cannot be the only answer. Although ERCOT and ENT are highly dependent on natural gas to generate electricity, they are not behaving as dominant markets. Reasons why ERCOT and ENT do not behave as dominant markets are as follows. First, most outgoing transmission lines from ERCOT are through ENT, therefore ERCOT may have limited influence on the other markets when compared to SPP. Second, ERCOT and ENT do not rely as heavily as SPP on coal as energy source. MAPP, MAIN, ECAR, and PJM markets may be influenced by SPP because they depend more on coal than the other markets. Accordingly, similarities between the higher dependency on coal in the SPP, MAPP, MAIN, ECAR, and PJM markets may provide another possible answer for the dominance of SPP.

Although there appears to be little contemporaneous time information flows between the western markets and non-western markets, PJM, SPP, NEPL, and ERCOT help explain the price uncertainty in the three western markets at longer horizons. Impulse response functions suggest that shocks in PJM and NEPL cause relatively large and long lasting responses in the western markets. Supporting these findings are the results that the coefficients of NEPL and PJM are statistically significant at 10% level in MIDC, PV, and FC markets implying NEPL and PJM “Granger cause” MIDC, PV, and FC. Such dynamic behavior cannot be explained by physical transmission connections because of the considerable distance between the two regions. There must be other factors that cause this dynamic relationship between the two regions. Although beyond the VAR analysis, several aspects of the regions may explain the dynamic behavior. First, PJM is the largest and oldest well-organized spot market in the U.S. (Deng and Jiang, 2002). PJM may be providing price discovery information through real-time price data. The western markets can obtain price information from the PJM market because of the time zone difference between the two regions (U.S. Department of Energy, 2002). Second, NEPL, PJM, and western markets are considerably more deregulated markets than the other markets (U.S. Department of Energy, 2003b). Further, PJM and California spot markets have a common three-tiered trading structure consisting of day-ahead, hour-ahead, and a real time markets. Finally for MIDC, PV, and PJM, there were future’s markets during the study period (U.S. Department of Energy, 2002). Considering these aspects, the relationship between PJM, NEPL, and the western markets may be explained not by physical assets, such as the transmission network, but by institutional arrangements such as the degree of deregulation, trading structure, and existence of futures markets.

Impulse response functions also show the innovations in SPP and ERCOT have relatively long lasting positive influence on western markets. Non-western markets generally have larger and quicker response to innovations, but they dampen toward zero. The different responses between western and non-western markets to the innovations in SPP and ERCOT also appear to be due to different institutional arrangements between the western and non-western markets.

As expected, the innovations in MIDC, PV, and FC have very little influence on almost every non-western markets, while they have long lasting influence on the western markets. This result is somewhat different than the results presented in De Vany and Walls (1999b) and Jerko, Mjelde, and Bessler (2004). According to their studies, the responses of western markets with respect to the shock of western markets are not as long lasting as found here. This dissimilarity also seems to be caused by the studies covering different time period. In contrast, the innovations in NEPL, PJM, ECAR, MAIN, MAPP, and ENT have relatively short influence on non-western markets. The different responses between western markets and non-western markets to its own innovations also indicate there may be certain different institutional aspects between two regions such as the degree of deregulation, the existence of futures markets, and market structure.

There are some practical questions suggested by the results that are not addressed explicitly but are important issues in the electricity industry. How is the price affected by the different market rules? What is the impact of continuing deregulation on prices? These questions should be topics of further study. In addition, temperature was only exogenous factor considered in the VAR model. Different factors such as variations in demand, congestion on the transmission system, and outages should be considered as factors affecting price in future studies.

End Notes

1. Regional HDD and CDD were investigated to determine how regional weather differences affect electricity prices. The U.S. was divided into four regions according to weather characteristics based on

Koeppen climate classification (Idaho State Climate Service, 2003). The degree-day indices for four regions were computed as a weighted average using population for the cities in each region as weights. There were serious multicollinearity problems between the eight regional degree-day indices. Accordingly, aggregate HDD and CDD are used in the analysis.

2. For completeness, the test results for the DF and ADF test for non-logarithmic and logarithmic transformed data both with and without using the robust estimation are given in Appendix C.

3. The VAR was estimated using eleven monthly dummies to capture the potential monthly effects in the electricity spot market price series. However, all the coefficients associated with the dummy variables were not statistically significant. Accordingly, the VAR model is estimated without the monthly dummies.

4. SPP currently covers all or part of the states of Arkansas, Kansas, Louisiana, Mississippi, Missouri, New Mexico, Oklahoma, and Texas. In these states, the percentage of natural gas as the primary energy source for generating electricity averages more than 28%. In contrast, the portion is less than 18% for the entire U.S (U.S. Department of Energy, 2001).

CHAPTER III

PRICE DYNAMICS AMONG NATURAL GAS SPOT MARKETS

Natural gas, an important energy source, accounted for more than 23% of total energy consumption of the U.S. in 2001. It is considered as one of the cleanest, safest, and most useful of all energy sources (Natural Gas Supply Association, 2004). Historically, the natural gas industry has been one of the most highly regulated sectors of the U.S. economy. However, starting in the late 1970s, the process of deregulating (elimination of price controls, deregulation of the production sector, and creating open access to pipelines) the industry began (De Vany and Walls 1994). By the early 1990s, the process of deregulation was completed (Cuddington and Wang 2004).

Natural gas is traded as a commodity, like corn, copper, and oil, because after processing natural gas is a similar product no matter where it is located. Two distinct markets trade natural gas: a spot market and a futures market. Market centers and hubs have resulted from restructuring and the execution of the Federal Energy Regulatory Commission's (FERC) Order 636[1] issued in 1992. These centers and hubs (henceforth centers and hubs are referred to jointly as centers) serve as natural gas spot markets. Natural gas futures are traded on the New York Mercantile Exchange (NYMEX). The market centers are located at the intersection of major pipeline systems and within major producing regions. There were 37 operational market centers in the U.S. and Canada in 2003 (U.S. Department of Energy, 2003c). These centers provide various types of services such as loaning, storage, electronic trading, and title transferring. The share of spot market volume of the total U.S. gas consumption was more than 70% in 1987-88 though their share has fallen to about 40% in 1995 (Dahl and Matson, 1998). Like most commodities, the price of natural gas is volatile. For example, natural gas prices are subject to variations in demand in response to changes in weather. Further, surge production is limited and expensive (U.S. Department of Energy, 2002).

The objective of this study is to characterize the dynamic interdependence relationships among eight major natural gas spot markets in North America and to investigate each individual market's role in price discovery. As such, the focus is on spot market price behavior and not the factors affecting prices. Analyzing spot market price discovery is important for industry decision makers and traders because price gaps across locations, called "price basis" in the natural gas industry, are monitored closely by market traders and become the foundation of gas trading by many firms (Cuddington and Wang, 2004). Providing information on the dynamics of natural gas spot market prices leads to a better understanding of how price innovations in market affects other markets. In obtaining this objective, the following questions are addressed. Do certain markets have more influence on price than others? Does one market play the role of price leader among a set of markets? Is there a dominant market?

This study is the first study to describe the dynamic interdependent structure among North American natural gas spot markets by combining recent advances in causal flows with time series analysis. A new method, Greedy Equivalence Search (GES) to find causal flows is used. This is one of the first applications of the GES Algorithm in economics. Empirical findings on the contemporaneous and short-run interdependencies using a vector error correction model (VECM), causal flows based on directed acyclic graphs, and innovation accounting analysis (forecast error variance decomposition and impulse response functions) are presented. The study provides a dynamic picture of daily information flow among eight North American natural gas spot markets for the recent past (1998-2002). The eight markets were chosen to provide geographical diversity, while accounting for data availability. Previous studies have not considered the geographical dispersion and weather effects in their analysis.

Brief Literature Review

Numerous studies on natural gas industry have been conducted because of the importance of this sector. Relatively few studies have investigated the dynamic behavior of empirical natural gas prices using time series analysis. Among those studies concerned with the dynamic behavior of natural gas prices using time series analysis, most studies focused on spot markets, however, a few studies (e.g. Lien and Root, 1999; Buchananan, Hodges, and Theis, 2001) focus on the natural gas futures market.

Serletis and Rangel-Ruiz (2004) investigated the strength of shared trends and cycles between North American natural gas and crude oil markets using cointegration tests. They showed there has been a decoupling of these two energy sources as a result of oil and gas deregulation in the U.S. They also examined the interconnectedness of North American natural gas markets using only two spot markets prices, U.S. Henry

Hub and AECO Alberta. From a high degree of similarity in the impulse responses of U.S. Henry Hub and AECO natural gas prices, they conclude that since deregulation North American natural gas prices are largely defined by Henry Hub price trends.

Serletis and Herbert (1999) explored the degree of shared trends among North American natural gas (Henry Hub natural gas price, Transco Zone 6 natural gas price), fuel oil (New York Harbor), and electricity prices (PJM electricity price). They found natural gas and fuel oil prices are nonstationary, but electricity price is stationary. Cointegration between the two natural gas spot markets prices and fuel oil price was found. The electricity spot market is not cointegrated with the other markets. Ewing, Malik, and Ozfidan (2002) examined changes in volatility in the oil and natural gas sectors over time and across markets using the multivariate generalized autoregressive conditional heteroscedasticity model. They note volatility is often interpreted as a proxy for information flow. Ewing, Malik, and Ozfidan (2002) found significant transmission of volatility from the natural gas sector to the oil sector. The previously mentioned studies dealt with the interrelationship among natural gas markets and other energy sector markets (oil and electricity). Interdependencies among natural gas markets are not addressed in these studies.

De Vany and Walls (1993) using daily price data from 1987 to 1991 investigated and tested for pair-wise market integration. Using Engle and Granger (1987) two-series cointegration, they found that most markets were not cointegrated in 1987 but more than 65% of the markets had become cointegrated in 1991. Based on their findings, De Vany and Walls (1993) argue the increased cointegration of prices is evidence that open access policy enacted by FERC in 1985 has made gas markets more competitive. De Vany and Walls (1994) also examined the policy impact of open access to the pipeline system which was enacted by FERC in 1985. They use Pearson correlation coefficients and price spreads between separate markets using monthly data from 1984 to 1989 for major five markets in U.S. They concluded that spot gas prices converged and became highly correlated after the enactment of the open access policy in 1985. Walls (1994) investigated cointegration between natural gas spot prices at various production fields, pipeline hubs, and city markets using daily data from 1990 to 1991 for 26 spot markets in the U.S. He showed the prices at certain locations, Chicago and to a lesser extent some California prices are cointegrated with field market prices.

King and Cuc (1996) investigated the degree of price convergence in North American natural gas spot markets using time-varying parameter (Kalman Filter) analysis and monthly price data from January 1986 to September 1995 for 17 markets across the U.S. and Canada. King and Cuc (1996) reported that price convergence in natural gas spot markets has increased significantly since the price deregulation of the mid-1980s. Further, they found an east-west split in North American natural gas markets.

Serletis (1997) examined North American natural gas spot markets using monthly data of eight price series for the U.S. and Canada from June 1990 to December 1995. To examine the robustness of King and Cuc's (1996) findings, Serletis (1997) adopted the Engle and Granger (1987) two-step procedure to model bivariate natural gas price relationships and tested for cointegration using Johansen's (1995) maximum likelihood approach. Serletis (1997) found the east-west split described by King and Cuc (1996) did not exist. Both of these studies focused on the price convergence and the dynamic interrelationship among spot market prices, but they did not explored dynamic interdependencies among natural gas markets in detail.

Cuddington and Wang (2004) investigated the degree and extent of market integration of natural gas spot markets in the U.S. using daily data for 76 geographically diverse pricing points over the period 1993 to 1997. They adopted the autoregressive (AR) model of price differentials across locations to estimate the speeds of adjustment toward equilibrium. Cuddington and Wang (2004) found that the half-lives of shocks to most price differentials range from a day to about two weeks.

Empirical Methods

Vector Error Correction Model

A vector error correction model (VECM) is used as the basic tool for this dynamic analysis. Economic theory does not suggest a prior structure for natural gas price interdependencies so VECM is an appropriate tool for analyzing natural gas price interdependencies.

Assuming first differencing makes the data stationary, the data generating process of P_t can be expressed in a VECM with k-1 lags as:

(7) $$\Delta P_t = \mu + \Pi P_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta P_{t-i} + \Psi Z_t + e_t\,, \qquad (t = 1,\ldots, T),$$

$$e_t \sim N\, iid\, (0,\Sigma),$$

where P_t denotes a vector that includes m non-stationary prices (m = 8 in the current study) at time t, ΔP_t is the first differences (P_t - P_{t-1}), Π is a matrix of coefficients relating lagged levels of prices to current changes in prices, Γ_i is a matrix of short-run dynamics coefficients relating lagged period *i* price changes to current changes in prices, μ is a constant term, Z_t represents a vector of exogenous variables (lagged heating and cooling "weather" variables), Ψ is a coefficient matrix associated with contemporaneous exogenous variables, Z_t, and e_t is a vector of innovations (Hansen and Juselius, 1995). As discussed later, Π may have reduced rank such that it can be re-expressed as $\alpha\beta'$ where α and β are m x r matrices of full rank and r is the number of cointegrating vectors (Hansen and Juselius, 1995). The parameters on the VECM provide information on the long-run, short-run, and contemporaneous structure. The long-run structure of market interdependencies can be identified by the cointegration space spanned by β and testing of hypotheses on β. Short-run structure can be identified through α and Γ_i (Johansen, 1995). The contemporaneous structure can be identified through the correlation matrix of observed innovations $\hat{e}_t$ using the directed acyclic graphs analysis (Spirtes, Glymour, and Scheines, 2000).

To examine the long-run structure of natural gas markets, determining the rank of Π, the number of cointegrating vectors, is necessary. In this study, two procedures are used to determine the lag order and cointegarting rank. The first procedure is the usual two-step procedure of determining the appropriate lag length first and then the cointegrating rank (Bessler and Yang, 2003). Here, loss metrics are used to determine the optimal lag length. Then a trace test is used to determine the number of cointegrating vectors.

The rank of Π is tested using the following hypothesis:

(8) $H(r): \Pi = \alpha\beta'$.

Trace tests on the eigenvalues of Π developed by Johansen (1991) are conducted to test the above hypothesis and to determine the rank of Π, the number of cointegrating vectors. In other words, trace tests confront the null hypothesis of r or less cointegrating vectors using test statistics from estimated eigenvalues. Accordingly, rejecting the null hypothesis indicates the number of cointegrating vectors is greater than r. The Π matrix can be factored as products of two matrices, α and β once the number of cointegrating vectors, *r* is determined: $\Pi = \alpha\beta'$. Before conducting trace tests, the lag order of VECM must be determined. Loss functions are used to determine the lag length.

In the second procedure, lag length and cointegrating rank are determined simultaneously using information criteria (Schwarz loss and Hannan and Quinn's Phi metrics) following the work of Phillips (1996) and Wang and Bessler (2005a). Both results are provided in this study for comparison purposes.

Testing hypotheses on β to identify the long-run structure include exclusivity tests. Exclusivity tests are conducted to determine whether some markets are excluded in all of the identified long-run relations. This exclusivity test uses the following hypothesis:

(9) $$H: R^{'}\beta = 0.$$

Here $R^{'}$ is a design matrix of zeros and ones placed to exclude variables from the cointegration space (Hansen and Juselius, 1995). The null hypothesis is that a particular market is not in the cointegrating space. Under the null, the likelihood ratio test is distributed Chi-squared with degrees of freedom equal to the number of cointegrating vectors (Hansen and Juselius 1995). Rejecting the null hypothesis indicates those variables (markets) are in the long-run relationships.

The short-run dynamic pattern of price interdependencies is related to two parts, α and Γ_i. The parameter α provides information about the short-run adjustment to perturbations in the long-run relations. Weak exogeneity tests on α are used to determine whether a market is unresponsive to deviation from the long-run relations in the short run (Johansen, 1991). To this end, the following hypothesis is used:

(10) $$H: B^{'}\alpha = 0,$$

where B is a design matrix of zeros and ones placed to express the particular hypothesis. The null hypothesis is that each market does not respond to perturbations in the cointegrating space. As with the exclusivity tests, under the null hypothesis, the likelihood ratio test is distributed Chi-squared with degrees of freedom equal to the number of cointegrating vectors. Another way to examine the short-run dynamics is through the parameters, Γ_i that define the short-run adjustment to the changes in the process (Johansen, 1995). However, the individual coefficients of the VECM, particularly Γ_i, are difficult to interpret individually as is the case with the standard vector autoregression (VAR) model. Accordingly, similar to VAR analysis, innovation accounting, impulse response functions and forecast error variance decomposition are used to describe the dynamic structure among price series (Swanson and Granger, 1997; Bessler and Davis, 2004).

The VECM in equation (7) is estimated using the maximum likelihood procedure suggested by Johansen (1995). The estimated VECM is re-expressed as a level VAR of equation (11) by algebraic manipulation of the parameters (Johansen and Juselius, 1990).

$$(11) \qquad P_t = \mu + (1 + \Pi + \Gamma_1)P_{t-1} - \sum_{i=1}^{k-2}(\Gamma_i - \Gamma_{i+1})P_{t-i-1} - \Gamma_{k-1}P_{t-k-1} + \Psi Z_t + e_t, \quad (t = 1,\ldots, T),$$

$$e_t \sim N\ iid\ (0,\Sigma).$$

Innovation accounting based on the equivalent levels VAR summarizes the short-run dynamic interactions among natural gas prices. Directed graph analysis, using the correlation matrix associated with the innovations, $\hat{e}_t$, from equation (7), is used to identify the contemporaneous structure.

Greedy Equivalence Search Algorithm

The GES Algorithm suggested by Meek (1997) and discussed by Chickering (2003) is used to identify the contemporaneous structure. In this study, GES Algorithm, as well as, PC (after its authors, Peter and Clark) Algorithm provided by TETRAD IV (TETRAD IV Manual, 2004) is used to identify the contemporaneous structure. Results are compared. GES Algorithm has several advantages over PC Algorithm. PC Algorithm requires three strong assumptions, causal sufficiency, Markov and faithfulness conditions. PC Algorithm may not work well when these conditions are not satisfied. Moreover, researchers have to select an appropriate significance level because it is based on standard Neyman-Pearson hypothesis testing. GES Algorithm does not require as strong assumptions as PC Algorithm (Wang and Bessler, 2005b). GES is also exempt from having to select an appropriate significance level; GES does not face the usual question of choice of significance level. However, the results from GES Algorithm are sensitive to Bayesian score values such that even small difference between two Bayesian scores may produce quite different results.

Because detailed discussions concerning directed graphs and PC Algorithm are provided in Chapter II, these topics are not discussed here. However, the GES Algorithm is described in detail because it is used to determine the contemporaneous structure, as an alternative to PC Algorithm used in Chapter II.

A directed graph is an illustration composed of arrows and vertices to represent the causal flow among a set of vertices (or variables) (Pearl, 2000). Only directed acyclic graphs, graphs contains no directed cyclic paths, are considered in this study. GES Algorithm provides a way to find causal flows from correlation relationships among the variables.

GES Algorithm is a two-phase greedy search algorithm that looks over equivalence classes (defined in Appendix D) of graphs starting from a graphical representation with no edges. A graph with no edges implies that all variables are independent of all the other variables. PC Algorithm, on the other hand, begins with a complete undirected graph that contains undirected edges to connect all variables, implying all variables are dependent on all the other variables. GES Algorithm proceeds stepwise searching over more complicated representations, scoring each using the Bayesian scoring criterion given in Appendix E. Through the addition and deletion of single edges and reversals of edges direction, GES scores each equivalence class of DAGs for every state (Chickering, 2003).

Consider the following case to illustrate equivalence classes and neighbors of states. DAG (D.16), (D.17), and (D.18) are in the same equivalence classes by the definition in Chickering's (2003) lemma 2, and they are in the same state, E:

$$
\text{(D.16)}\quad
\begin{tikzcd}[column sep=small] & A \\ B \arrow[ur] \arrow[r] & C \end{tikzcd}
\qquad
\text{(D.17)}\quad
\begin{tikzcd}[column sep=small] & A \\ B \arrow[ur] & C \arrow[l] \end{tikzcd}
\qquad
\text{(D.18)}\quad
\begin{tikzcd}[column sep=small] & A \arrow[dl] \\ B \arrow[r] & C. \end{tikzcd}
$$

From this state, the equivalence classes of neighboring states are obtained through the addition (or deletion) of a single edge, avoiding the cases that create a cycle when the single edge is added (or deleted). GES Algorithm only searches for acyclic graphs by definition. The neighbors of state E through adding single edges are:

(D.19)
$$\begin{tikzcd} & A \arrow[dr] & \\ B \arrow[ur] \arrow[rr] & & C \end{tikzcd}$$

(D.20)
$$\begin{tikzcd} & A & \\ B \arrow[ur] \arrow[rr] & & C \arrow[ul] \end{tikzcd}$$

(D.21)
$$\begin{tikzcd} & A & \\ B \arrow[ur] & & C \arrow[ul] \arrow[ll] \end{tikzcd}$$

(D.22)
$$\begin{tikzcd} & A \arrow[dl] \arrow[dr] & \\ B \arrow[rr] & & C. \end{tikzcd}$$

DAG (D.19), (D.20), (D.21), and (D.22) are neighbors of the equivalence class defined by (D.16), (D.17), and (D.18) (for details see Chickering, 2003, pages 511-523).

Using this example, the two phases of GES procedure can be illustrated. In the first phase, GES Algorithm begins with DAG (D.23) with no edges:

(D.23)
$$\begin{tikzcd} & A & \\ B & & C. \end{tikzcd}$$

Neighbors of this state are found by considering all possible single edge additions. The following DAGs show all possible neighbors of DAG (D.23):

(D.24)
$$\begin{tikzcd} & A & \\ B \arrow[ur] & & C \end{tikzcd}$$

(D.25)
$$\begin{tikzcd} & A \arrow[dl] & \\ B & & C \end{tikzcd}$$

(D.26)
$$\begin{tikzcd} & A & \\ B \arrow[rr] & & C \end{tikzcd}$$

(D.27)
$$\begin{tikzcd} & A & \\ B & & C \arrow[ll] \end{tikzcd}$$

(D.28)
$$\begin{tikzcd} & A & \\ B & & C \arrow[ul] \end{tikzcd}$$

(D.29)
$$\begin{tikzcd} & A \arrow[dr] & \\ B & & C, \end{tikzcd}$$

where DAG (D.24) and (D.25) are in an equivalence class, DAG (D.26) and (D.27) are in another equivalence class, and DAG (D.28) and (D.29) are in a third equivalence class. Accordingly, there are three different groups of equivalence classes as neighbors of DAG (D.23). All possible equivalence classes including DAG (D.23) are scored by Bayesian scoring criterion.

After score comparison, among all possible equivalence classes the one equivalence class that increases the score the most is chosen for the next step. Greedy search means that the algorithm always moves in the direction that increases the score the most. This procedure is repeatedly conducted until no such replacement increases the score. The causal pattern that generates the maximum Bayesian score is searched over equivalence classes through adding dependencies in the first phase.

Common scoring criteria (for example, Akaike Information Criterion and Bayesian Information Criterion) provide the same score to causal patterns in the same equivalence class (Chickering, 2002). TETRAD IV has adopted Bayesian Information Criterion as scoring criterion for continuous data. This criterion provides the same scores for causal patterns in the same equivalence class. For example, DAG (D.24) and (D.25) have the same score from GES Algorithm of TETRAD IV. At this point the edge between A and B is undirected. GES Algorithm can suggest either directed edges or undirected edges (TETRAD IV manual, 2004).

Once a local maximum is reached in the first phase, the second phase begins by deleting a single edge and comparing the scores of DAG in equivalence classes repeatedly until a local maximum is again reached. When the algorithm reaches a local maximum, it obtains the optimal solution (Chickering, 2003). Chickering (2003) provides a proof that GES Algorithm can identify the optimal solution in the limit of large sample size using these two phases.

Data

Considering regional dispersion and data availability, eight price series of natural gas trading hubs or spot market in the United States and Canada are included (Figure 3.1).

The trading hubs are Waha Hub, Texas (WAH), Henry Hub, Louisiana (HEN), Oklahoma (ONG), Opal Hub, Wyoming (OPA), Chicago Hub, Illinois (CHI), Ellisburg-Leidy Hub, Pennsylvania (ELL), Malin Hub, Oregon (MAL), and AECO Hub, Alberta, Canada (AEC). Although there are some important market centers that are not included in this study, the above eight trading hubs are considered in this study because of data availability. Daily prices of the trading hubs (from surveys of traders) provided by Bloomberg Energy Service from January 12, 1998 to December 20, 2002 are used. Spot prices are calculated as a volume-weighted average price for that location in dollars per MMBtu (a unit of heat equal to one million British thermal units) for gas delivered the next day. The prices are for Monday through Friday. Each price series has 1290 observations. The total number of missing values in the eight price series is 400. The missing values including holidays account for 3.8 percent of total observations. The prior day's price is used to represent any missing values for a particular day and market. Plots of the price series for each market are provided in Figure 3.2.

As in Chapter II, lagged U.S. aggregate cooling degree-days (CDD) and heating degree-days (HDD) are used to capture daily weather effects in natural gas prices. CDD and HDD are considered exogenous variables in the VECM.

Empirical Results

Stationarity

The stationarity of the eight price series is examined using Dickey-Fuller (DF) and augmented Dickey-Fuller (ADF) tests. All estimations use logarithmic transformed data (except HDD and CDD) and a robust estimator because each price series of natural gas is highly volatile and potentially heteroscedastic (Figure 3.2). The robust estimator computes a heteroscedasticity consistent estimate of the asymptotic covariance matrix of the estimated parameters (Greene, 2000). DF and ADF test results are provided in Table 3.1[2]. The null hypothesis of both the DF and ADF tests is that the natural gas price series is non-stationary. This null hypothesis is rejected if the DF or ADF statistic is less than –2.89 (-2.58) at a 5% (10%) level of significance (Fuller, 1976).

The DF test statistics indicate all natural gas spot prices except OPA are non-stationary at both the 5% and 10% levels. However, the ADF test statistics indicate all spot prices are non-stationary at the 5% level, while at the 10% level all markets except OPA are non-stationary. Q-statistics testing if the residuals from the DF and ADF regressions are white noise are also presented in Table 3.1. The null hypothesis of white noise residuals is rejected when the Q value is large or the p-value is small. Based on the Q-statistics and associated p-values, the residuals from DF tests regressions are not white noise for any of the series while the residuals from ADF are white noise in some cases, AEC and MAL (5% level), and AEC, MAL, HEN, and ELL (1% level).

In addition, the stationarity of the first difference of eight price series is examined using DF and ADF tests. DF tests show all the first differences of price series are stationary while ADF tests indicate that all the first differences are stationary except for CHI (Table 3.2). These results are consistent with previous studies, e.g. Serletis and Herbert (1999) and De Vany and Walls (1993).

Model Specification

As noted earlier, two procedures are used to determine the lag order and cointegarting rank using the logarithmic transformed data and considering one-day lags of CDD and HDD as exogenous variables. In the first procedure, Schwarz loss, Akaike loss, Hannan and Quinn's phi measures are used to determine the optimal length of lags for unrestricted VAR model. Results of the three metrics for one to 15 lags are presented in Table 3.3. Schwarz and Hannan and Quinn phi are minimized at one lag and three lags. In contrast, the Akaike loss metric is minimized at nine lags. One lag is selected as the lag order in a level VAR on the eight price series of natural gas spot market based on Schwarz loss metrics and the rule of parsimony. Trace tests are conducted using one lag VAR model as the second part of the first procedure (Table 3.4). Trace test results suggest seven long-run relations (cointegration) with constants in the cointegrating vectors.

The results of optimal lag order and cointegrating rank using the second procedure are given in Table 3.5. The second procedure suggests the appropriate model is one lag with a cointegrating rank of six as this model minimizes the Schwarz loss metric. In terms of a lag length, both procedures give the same length using Schwarz loss. Both procedures provide similar cointegrating ranks, but not exactly the same, which is consistent with the findings of Wang and Bessler (2005a).

Wang and Bessler (2005a) conducted Monte Carlo simulations to evaluate the possibility of using information criteria (Schwarz loss and Akaike loss) as an alternative for determining cointegrating rank in multivariate analysis. They provide comparison of the performances of two procedures through Monte Carlo simulations in determining the lag order and cointegrating rank. Wang and Bessler (2005a) found that when the sample is larger than 100, Schwarz loss metrics performs better than the trace test in determining cointegrating rank for all model specifications. Accordingly, an error correction model with a lag length of one and a cointegrating rank of six is used here.

Tests of Exclusion and Weak Exogeneity: Long-run Structure

After imposing six cointegrating vectors, the VECM of equation (7) is estimated. The estimated parameter matrices are provided in Appendix G. While six cointegrating vectors are found, there is the possibility that one and more price series are not part of any of the six long-run relationships. Using the exclusivity test described earlier, the null hypotheses that a particular series is not in the cointegration space are tested. The test results indicate the null hypotheses are rejected for all eight price series, implying all of the eight price series are in the cointegration space (Table 3.6). Further, the exogenous variables, HDD and CDD, are not also excluded from the long-run relationships.

The possibility that some markets do not respond to perturbations in the long-run equilibrium is investigated by weak exogeneity tests (Table 3.6). The null hypothesis is that the associated market does not make adjustments toward the estimated long-run equilibrium. All null hypotheses for each market are rejected at 1% level. Accordingly, all markets respond to perturbations in any of the six long-run equilibrium vectors.

Identifying Contemporaneous Structure

The lower triangular elements of the contemporaneous innovation correlation matrix, Σ, from the estimated VECM is:

$$
(12) \qquad \Sigma = \begin{array}{c} \\ \text{AEC} \\ \text{MAL} \\ \text{OPA} \\ \text{WAH} \\ \text{HEN} \\ \text{ONG} \\ \text{CHI} \\ \text{ELL} \end{array}
\begin{array}{c}
\begin{array}{cccccccc} \text{AEC} & \text{MAL} & \text{OPA} & \text{WAH} & \text{HEN} & \text{ONG} & \text{CHI} & \text{ELL} \end{array} \\
\left(\begin{array}{cccccccc}
1.00 & & & & & & & \\
0.32 & 1.00 & & & & & & \\
0.30 & 0.40 & 1.00 & & & & & \\
0.46 & 0.53 & 0.47 & 1.00 & & & & \\
0.48 & 0.46 & 0.41 & 0.89 & 1.00 & & & \\
0.46 & 0.49 & 0.42 & 0.92 & 0.90 & 1.00 & & \\
0.45 & 0.45 & 0.41 & 0.89 & 0.90 & 0.89 & 1.00 & \\
0.02 & 0.03 & 0.02 & 0.05 & 0.07 & 0.04 & 0.03 & 1.00
\end{array} \right)
\end{array}
$$

Innovations from the three southern markets, WAH, HEN and ONG, show strong correlations between each other and CHI, with relatively weaker correlations with the remaining markets in North America. Innovations from eastern market, ELL, have almost no correlation with the other seven markets. Innovations from AEC, MAL and OPA in the west have moderate correlations between each other and the other markets except ELL.

Correlations from equation (12) are used in the directed graph analysis to identify the Bernanke ordering structure. Based on the correlation patterns derived from the correlation matrix, causal flows between contemporaneous innovations from each of the eight markets are assigned as in Figures 3.3, 3.4 and 3.5 using TETRAD IV, a computer software that implements PC Algorithm (Scheines et al., 1994) and GES Algorithm (Chickering, 2003).

Somewhat similar results are obtained for significance levels of 1% and 0.1% (Figures 3.3 and 3.4) using PC Algorithm. No direction of causal flows among seven spot markets is determined at the 0.1% significance level. The edges between AEC and MAL, AEC and OPA, CHI and ONG, and CHI and HEN are different at the two significant levels (Figures 3.3 and 3.4). In the causal pattern at the 1% significance level, there is a bi-directed edge between AEC and OPA. Further, at the 1% level causal patterns are from MAL to AEC, from WAH to OPA, and from HEN to AEC. The bi-directed edge indicates there are potentially omitted variables between these markets. ELL has no edges (no causal flows) to connect with the other markets at either significance level.

GES Algorithm suggests a similar causal pattern for the eight natural gas spot markets, but it does not leave as many edges undetermined as PC Algorithm does and GES does not give bi-directed edges. The causal pattern from GES Algorithm includes the edges between AEC and MAL, AEC and OPA, and CHI and HEN that the causal pattern from PC Algorithm at 1% level includes, but the causal pattern from PC Algorithm at 0.1% level does not. In addition, the edge between CHI and ONG is included in the causal pattern from GES Algorithm while it is not included in the causal pattern from PC Algorithm at 1% level but is included in the causal pattern from PC Algorithm at 0.1% level. Moreover, the causal pattern from GES Algorithm includes the directed edge from ELL into HEN that is not presented in the causal pattern from PC Algorithm at either level. In the causal pattern from GES Algorithm, the directions of the edges that are not determined in the causal pattern from PC Algorithm at either level are suggested.

Wang and Bessler (2005b) assessed the overall appropriateness of the models generated by PC and GES Algorithm using a usual chi-squared test and found that the causal patterns suggested by the GES Algorithm fit data better than those from the PC Algorithm. Considering their arguments and the similar results from the two procedures, the causal pattern suggested by GES Algorithm is used as contemporaneous causal flows structure. This structure is imposed on the innovation accounting methods.

The information flows from the causal pattern suggested by GES Algorithm are as follows. WAH causes MAL and OPA. Both MAL and OPA cause AEC. AEC appears to be an information sink; it does not cause any other market. CHI causes WAH and HEN. ELL also causes HEN. ONG causes WAH and HEN. HEN causes WAH, as well as, AEC. Either CHI or ONG can be exogenous depending on the direction of undetermined edge between CHI and ONG. ELL is exogenous; there are no markets that cause ELL. These information flows appear plausible in light of natural gas delivery flows presented in Figure 3.6. Price information is likely to flow from potential excess consuming areas into excess producing areas.

Figure 3.7 more clearly shows gas transportation flows from major producing regions into major market regions (U.S. Department of Energy, 2004). The edge between HEN and WAH is not determined in the causal patterns suggested by PC Algorithm at both significance levels. GES Algorithm suggests the direction of the edge is HEN → WAH. This causal flow appears to be plausible in light of actual gas transportation flows between the two markets (Figure 3.8). With eight markets there are a possible 28 causal flows. The GES Algorithm directs 13 of the 28 flows to be nonzero (lines in Figure 3.5). A likelihood ratio test of the 15 zero restrictions gives a Chi-squared value of 13.105 (p-value = 0.59). At reasonable significance levels, the data does not reject the 15 zero restrictions.

However, GES Algorithm does not suggest the directions of edge between MAL and OPA and CHI and ONG. With respect to the undetermined edges, there are four possible cases, case I (OPA ← MAL, CHI ← ONG), case II (OPA ← MAL, CHI → ONG), case III (OPA → MAL, CHI ← ONG), and case IV (OPA → MAL, CHI → ONG). Because the number of possible cases is small, all four alternative DAGs are used in the innovation accounting analysis.

Forecast Error Variance Decompositions

Based on four cases, the forecast error variance decompositions are given in Tables 3.7, 3.8, 3.9, and 10. Decompositions give the percentage of price variation in each market at time t+k that is due to innovations in each market (including itself) at time t. Listed here are the results at horizons of zero (contemporaneous time), one day (short horizon), and 30 days ahead (longer horizon).

In case I (OPA ← MAL, CHI ← ONG), the uncertainty associated with contemporaneous price in AEC is explained by contemporaneous period shocks in its own price, AEC (75.0%), and shocks in ONG (19.6%). The variation in AEC is explained by the innovations from its own price, AEC (73.2%), and ONG (18.5%) at the short run, and AEC (33.9%), MAL (21.1%), WAH (6.4%), ONG (19.4%), and ELL (10.1%) at the 30-day horizon. MAL (72.2%) and ONG (23.4%) account for most of the variation in MAL in contemporaneous time. At short run, the variation in MAL is also explained by MAL (71.2%) and ONG (22.7%). However, at the 30-day horizon, the variation in MAL is explained by more markets, AEC (8.2%), MAL (50.6%), WAH (9.0%), ONG (20.6%), and ELL (5.3%), but MAL and ONG remain the most important markets.

In contemporaneous time, the variation in OPA is explained by OPA (75.0%) and ONG (18.3%). At the short run, the pattern is similar to that of contemporaneous time. However, AEC (11.3%), MAL (29.0%), OPA (40.0%), WAH (6.9%), and ONG (11.6%) account for the variation in OPA in the long run. The variation in WAH is explained mainly by ONG (84.0%) and WAH (12.7%) in contemporaneous time and ONG (84.8%) and WAH (11.0%) in the short run. At the 30-day horizon, however, HEN (7.0%), ONG (53.3%), and ELL (22.0%) account for the variation in WAH. The variation in HEN is explained by ONG (80.8%) and HEN (14.2%) in contemporaneous time and by ONG (80.0%) and HEN (13.9%) in the short run. OPA (5.1%), HEN (9.7%), ONG (50.8%), CHI (5.1%), and ELL (24.3%) explain the variation in HEN at the 30-day horizon.

ONG is exogenous at the shorter horizons, but is less exogenous at the longer horizon. At the 30-day horizon, HEN (7.1%), ONG (55.5%), and ELL (22.0%) account for most of the variation in the ONG. CHI is dominated by ONG (80.0%, 81.5%) at the shorter horizons as in WAH and HEN. At 30-day horizon, however, the variation in CHI is explained by HEN (6.8%), ONG (52.8%), CHI (6.7%), and ELL (22.9%). ELL is exogenous in contemporaneous time and nearly exogenous in the short run. The variation in ELL is explained by innovations from HEN (5.4%), ONG (30.4%), and ELL (49.7%) at the 30-day horizon.

ONG plays an important role as shown by ONG explaining 75% or more of the decomposition in forecast error in WAH, HEN, CHI, and ONG at the shorter horizons. ONG also account for 15% or more of the decomposition in forecast error in AEC, MAL, and OPA. The importance of the ONG market on WAH, HEN, CHI, and ONG decreases over time. At the 30-day horizon, however, ONG still accounts for 50% or more of the decomposition in forecast error in four markets (WAH, HEN, CHI, and ONG) and explains about 20% or more in three other markets (AEC, MAL, and ELL). Only in OPA does ONG explain less than 20%.

In case II (OPA ← MAL, CHI → ONG), the direction in the edge between CHI and ONG is switched from case I. As shown in Table 3.8, differences between Tables 3.7 and 3.8 appear in ONG and CHI columns. CHI now plays an important role in explaining the variation in the other markets. CHI is playing the role of ONG from in case I. Forecast error variance decompositions in case III (OPA → MAL, CHI ← ONG) are presented in Table 3.9. Case III is different from case I only in the direction of the edge between OPA and MAL. Accordingly, MAL and OPA columns are different than those columns in case I. The differences between forecast error variance decompositions of case I and of case III are very small. As in the case I, ONG is important market in case III, and the importance of ONG on all the other markets over time shows almost the same pattern as in case I. Forecast error variance decompositions for case IV (OPA → MAL, CHI →ONG) are presented in Table 3.10. These decompositions suggest the same pattern as in case III except ONG and CHI change roles. Switching the direction of edge between ONG and CHI changes the most important market between ONG or CHI, depending on direction of the edge. Reversal of the edge direction between MAL and OPA has little affect on the pattern of forecast error variance decompositions.

There are several patterns emerge from the forecast error variance decompositions in natural gas spot markets. First, either ONG or CHI is the most important market. One of these two markets account for approximately 20% of the variation in AEC, MAL, and OPA in west and this percentage remains constant over time for AEC and MAL. In OPA these markets are less important in the long run. On the other hand, ONG or CHI dominates WAH, HEN, and ONG or CHI in the shorter run (greater than 79%). At the 30-day horizon, the importance of ONG or CHI decreases, but they are still very important markets (more than 50%). Second, ELL is exogenous in the shorter horizons, but its variation is explained by ONG or CHI (more than 30%) at the 30-day horizon. Moreover, ELL does not account for the variations in all the other markets at the shorter runs. ELL, however, accounts for some of the variation in all markets at the 30-day horizon. ELL accounts for less than 10% of the variations of western markets while it accounts for more than 20% of the variations of non-western markets. Lastly, at the 30-day horizon, WAH accounts for more than 6% of the variations in the western markets, whereas it accounts for less than 5% of the variation in non-western markets. At the 30-day horizon of all four cases, HEN accounts for more than 5% of the variations of non-western markets while it accounts for less than 5% of variations of western markets. These results imply that WAH has more influence on western markets than non-western markets, whereas HEN has more influence on non-western markets than western markets in the long run.

Impulse Response Functions

Impulse response functions are presented as a matrix of graphs with each element of the matrix corresponding to the response of one series to a one time only shock in another series (Figures 3.9, 3.10, 3.11, and 3.12). Horizontal axes on the sub-graphs represent the horizon or number of days after the shock, here 1 to 30 days. Vertical axes indicate the standardized response to the one time shock in the each market labeled at the top of each column of graphs. Point estimates of impulse response alone, however, may give a misleading impression (Doan, 2000). In this study, confidence bands for impulse responses using Monte Carlo methods are provided based on the program given in Doan (2000). The point estimates plus or minus two times their standard errors estimated through 5,000 simulations are provided as upper bound and lower bound in confidence bands in Figures 3.9, 3.10, 3.11, and 3.12.

First, consider case I (Figure 3.9). Shocks in AEC western Canadian market are transferred as strong and lasting positive impulses to the two western markets (MAL and OPA). AEC shocks have less of an influence on the non-western markets than on the western markets. The responses of AEC and OPA to a shock in the MAL show immediate and long lasting positive impulses. Shocks in MAL are transferred as relatively weaker but lasting positive impulses to the non-western markets. The shocks in OPA have a very small influence on all the other markets.

The responses of all other markets to shocks in WAH and HEN show long lasting but generally weak positive impulses. Specifically, the responses of OPA to shocks in the HEN show very little negative impulses in the short run but are close to zero thereafter. These responses suggest OPA is maybe making-up for very short-run imbalances in the HEN markets. A shock in ONG has considerable influence on all the markets. The responses of all markets except ELL to a shock in ONG are strong, immediate, and long lasting. The response of ELL to a shock in ONG has also strong and long lasting, but is not immediate. A shock in CHI has relatively weak and long lasting influence on all markets. A shock in ELL has no immediate influence, but has long lasting positive influence on the other markets.

In case II, CHI plays an important role in explaining the price in each market instead of ONG (Figure 3.10). The responses of all eight markets to shocks in ONG and CHI are the main differences between cases I and II. Impulse response functions of case III show very similar results to those of case I. Further, impulse response functions of case IV are very similar to those of case II (Figure 3.12). If the DAG is modeled as CHI ← ONG, then ONG market is important in explaining the price in the other markets (cases I and II). On the other hand, if the DAG is modeled as CHI → ONG then CHI replaces the role of ONG as the dominant market (cases II and IV). The direction of the edge between MAL and OPA has little affect on the impulse response functions. As expected, the results of impulse response functions are consistent with the forecast error variance decompositions results.

Discussion

The stationarity of natural gas price series has been addressed in previous studies analyzing the natural gas prices using time series methods. Almost every study indicates the price series of natural gas after deregulation in the industry are non-stationary; however, a few studies (Serletis and Rangel-Ruiz, 2004; Cuddington and Wang, 2004) indicate some natural gas price series show stationary. This study adds additional evidence that natural gas prices have a unit root, indicating the price series of natural gas are non-stationary.

This study found eight price series in natural gas spot markets in North America are tied together with six long-run cointegration relationships. Exclusion and exogeneity tests show all eight markets are in the long-run relationship and respond to perturbation in any of the six long-run cointegration relationships. There appears to be seasonal differences in the long-run relationships because the exogenous variables, CDD and HDD, are also included in the cointegrating vectors. Besides industrial use, natural gas is used for heating and electricity generation in the winter and primarily for electricity generation in the summer, therefore, seasonality is plausible.

Based on results from contemporaneous causal patterns, two exogenous markets, CHI or ONG and ELL (depending on the case), appear to be driving forces for the other natural gas markets. Considering the result that ELL only causes HEN, CHI and/or ONG are more likely to be exogenous driving forces for natural gas prices. In case I (OPA ← MAL, CHI ← ONG) and case III (OPA → MAL, CHI ← ONG), ONG appears to be the exogenous driving force, while CHI is the driving force in case II (OPA ← MAL, CHI → ONG) and case IV (OPA → MAL, CHI → ONG).

Contemporaneous time causal flows reflect major natural gas transportation corridors in North America (Figure 3.7). Causal flows tend to originate from excess consuming regions to producing or supplying regions. In cases of edges such as MAL→AEC, OPA→AEC, CHI→WAH, CHI→HEN, and ELL→HEN, the causal or information flows match up to the reverse direction of major gas flows. Some edges do not exactly match up to this reverse price flow / gas flow direction. Price information is likely to flow from potential excess consuming areas into excess producing areas. This relationship provides evidence that the undirected edge between CHI and ONG is most likely directed CHI → ONG.

Another plausible reason to direct the edge CHI → ONG is as follows. The U.S. gas market is divided into six market areas: the Central (Montana, Wyoming, North Dakota, South Dakota, Nebraska, Colorado, Iowa, Missouri, Kansas, Utah), Midwest

(Minnesota, Wisconsin, Michigan, Illinois, Indiana, and Ohio), Northeast (Maine, New Hampshire, Vermont, Rhode Island, Connecticut, New York, New Jersey, Pennsylvania, Delaware, Maryland, West Virginia, Virginia), Southeast (Tennessee, North Carolina, South Carolina, Georgia, Alabama, Florida, Mississippi), Southwest (Arkansas, Louisiana, Oklahoma, Texas, New Mexico), and Western (Washington, Oregon, Idaho, Nevada, California, Arizona) (U.S. Department of Energy, 1998a). The Midwest area, which includes the CHI spot market, is the second largest market in U.S. next to Southwest and the second coldest region next to the Central. Further, the Midwest has the lowest ratio of natural gas production to consumption among the six market areas. This ratio implies the Midwest is dependent on the import of gas from the other areas to meet its demand (U.S. Department of Energy, 1998a). One possible explanation as to why CHI is the most important market in cases II and IV is the Midwest is the biggest importing market region. Further, natural gas supplies from southern Oklahoma along with western Texas tend to be the marginal supplies of both eastern and western markets because natural gas from these areas can easily be transported either east or west. Gas is sold in the market with the highest price (Serletis, 1997). This finding may support the argument that CHI rather than ONG is an important market in North America.

Forecast error variance decompositions and impulse response functions provide the analysis of dynamic information flows over time. Results vary depending on the contemporaneous casual structure assumed. In cases I and III, ONG accounts for a large amount of the forecast error variance at all time horizons in all eight markets except

ELL. The influence of ONG in ELL appears only in the long run. In cases II and IV, CHI, instead of ONG, accounts for the large amount of forecast error variance at all time horizons in all eight markets except ELL. The influence of ONG in ELL appears only in the long run. In all four cases it should be noted that the influence of a dominant market (ONG or CHI) in ELL appears only in the long run. Similarly, impulse response functions also show the innovation in either CHI or ONG have considerable positive influences on all eight markets. The response of ELL with respect to the innovations in either CHI or ONG is not immediate, but it increases over a short time period.

A possible explanation the influence on ELL occurring only in the longer run is that the ELL market area along with the Midwest region has relatively larger underground storage capacities than the other regions (Figure 3.13). Gas withdrawals from storage facility can help mitigate the price shocks in the other markets at the shorter time periods. This statement is supported by the observation that natural gas storage withdrawals account for a significant proportion of the supply necessary to meet total demand during the heating season, particularly in the East Consuming Region[3] (Herbert, Thompson, and Todaro, 1997).

Contemporaneous causal flows, forecast error variance decompositions, and impulse response functions indicate there is not an east-west split among North American natural gas spot markets unlike the findings of King and Cuc (1996). According to King and Cuc (1996), three gas producing regions, the Rocky Mountain basin (Wyoming, Utah, and Colorado), the San Juan basin (southwestern Colorado and northwestern New Mexico), and Western Canadian Sedimentary basin (Alberta and British Columbia) comprise western portion of east-west split. The Permian (western Texas) and Anadarko basin (southern Oklahoma) along with the South-Texas and Louisiana basins (the Gulf Coast) comprise the eastern portion of the east-west split.

As discussed earlier, the markets are tied together by six long-run cointegration relationships, implying that new price information in one market is transmitted to other markets through arbitrage activities in the long run. These results further suggest that there is no east-west split. Serletis (1997) also argues that an east-west split does not exist. A plausible explanation for the differences in the studies is the time frame of analyses. King and Cuc (1996) analyzed the period soon after the start of the major deregulation of the natural gas industry. Serletis (1997) and our analysis uses data farther removed from the start of deregulation. Taking these studies results into account, may indicate the natural gas market has developed into a single integrated market in North America since deregulation.

Henry Hub has attracted considerable attention in the literature. It is the most active and publicized market center in North America and has an extensive receipt and delivery capability (U.S. Department of Energy, 2003c). More than 180 customers regularly conduct business at Henry Hub through 14 pipeline systems and storage facilities. Henry Hub is also the delivery point for NYMEX futures (U.S. Department of Energy, 2003c). Further, Henry Hub accounts for large portion of gas transportation toward the East Consuming Region. In spite of the important position of Henry Hub in

North American natural gas industry, this study suggests Henry Hub does not play an important role in price discovery. Rather results suggest either ONG or CHI is the dominant market in North American natural gas spot markets in terms of price discovery. Southwest region, including Henry Hub, not only consumes the most natural gas but also produces the most (U.S. Department of Energy, 1998a). As such for gas to move from this region, the price must be bid up elsewhere. This observation may explain why Henry Hub does not play an important role in price discovery. Another reason for the importance of Henry Hub in previous studies is most studies only included one or two gas markets in which one was Henry Hub. As such, Henry Hub was representing the natural gas market.

There are many additional issues that are not addressed in this study but are important issues to the natural gas industry. The only exogenous factor consider in the VECM was temperature. Different factors such as variations in demand, storage capacity, future markets, and types of end use of natural gas should be considered in future studies. For example, Herbert, Thompson, and Todaro (1997) note the importance of storage on natural gas pricing. How is the price affected by storage capacity and amount of natural gas in storage? Another important issue is the role the futures market plays in price discovery. The futures market is very active in the natural gas industry. Inclusion of this market in future price discovery studies is an important extension. Considering electricity power plants accounted for about 27% of the U.S. natural gas consumption in 2002 (U.S. Department of Energy, 2004), spot markets from both electricity and natural gas industries should be included in future studies to examine the interdependencies of these two energy markets. Finally, contractual arrangements influence on spot market transactions and prices (applying the work of Love and Burton, 1999) may be a fruitful avenue of future research.

End Notes

1. Federal Energy Regulatory Commission's Order 636 (1992) mandated that pipelines must separate gas sales from transportation. Thus, this allows open access to pipeline transportation for gas producers and customers. This order completes a series of significant FERC actions starting in the 1980s that have resulted in a major reorganization of U.S. natural gas markets (see Doane and Spulber, 1994, p. 477 for details).

2. For completeness, the test results for the DF and ADF test for non-logarithmic and logarithmic transformed data both with and without using the robust estimation are given in Appendix F.

3. The East consuming region is all states east of the Mississippi River less Mississippi, plus Iowa, Nebraska, and Missouri (Herbert, Thompson, and Todaro, 1997).

CHAPTER IV

TIME-VARYING THRESHOLD COINTEGRATION AND THE LAW OF ONE PRICE

Production deregulation and open access to the pipelines in natural gas industry has caused market centers and hubs to develop which provide various services such as loaning, storage, electronic trading, and title transferring (U.S. Department of Energy, 2003c). Most major market centers and hubs (henceforth centers and hubs are referred to jointly as centers) in the U.S. serve as natural gas spot markets. These centers are located at the intersection of major pipeline systems and within major producing regions. Thirty-seven market centers in the U.S. and Canada were operating in 2003 (U.S. Department of Energy, 2003c).

At these market centers, natural gas is traded as a single commodity because after processing natural gas is a homogeneous product regardless of its location. Like most commodities, the price of natural gas is volatile. Natural gas prices are subject to price variations because of demand fluctuations caused, for example, by weather changes. Further, surge production is limited and expensive (U.S. Department of Energy, 2002). To meet the high demand of major consuming regions, natural gas is transported by pipelines from producing regions to consuming regions. Arbitrage behavior among natural gas spot markets in U.S may occur.

In Chapter III, it is shown that price series of major natural gas spot markets in North America are cointegrated; the price series move together in the long run. This result implies the law of one price holds in the long run between natural gas spot markets that are spatially separated in North America. Transactions costs, however, may lead to a neutral price differences band within which prices are not linked. This neutral band arises because transaction costs discourage trading when the possible profits are smaller than these costs. Arbitrage opportunities occur only when the deviation in prices is larger than the transaction costs. This neutral band feature associated with transactions costs has led to a new empirical approach, threshold cointegration, which explicitly recognizes the effect of transactions costs on spatial market linkages (Goodwin and Piggott, 2001). In the presence of transaction costs, the threshold cointegration model may explain the behavior of price adjustments in the long run better than the cointegration model. Cointegration assumes no band, but assumes prices always adjust in the long run. Previous studies (Lo and Zivot, 2001; Sephton, 2003; Goodwin and Piggott, 2001) use the threshold cointegration model to explain nonlinear price adjustment behavior in spatially separated markets in the presence of transaction costs.

The objective of this study is to examine the existence of threshold cointegration between natural gas spot markets. This study is the first attempt to apply the threshold cointegration model to natural gas spot markets in North America to investigate the nonlinear adjustment to the law of one price. Threshold cointegration models have been used in the analysis of financial and agricultural commodities (Tsay, 1998; Lo and Zivot, 2001; Goodwin and Piggott, 2001; Hansen and Seo, 2002).

The law of one price provides a theoretical background for the extent of market integration. This study develops a threshold cointegration model that accounts for seasonality in the threshold levels. No previous study has developed such a model. The extent of market integration has regulatory implications. Further, analyzing spot market price gaps provides information to industry traders. Price gaps across locations, called "price basis" in the natural gas industry, are monitored closely by market traders and are the foundation of gas trading by many firms (Cuddington and Wang, 2004).

The Law of One Price and Threshold Cointegration

The Law of One Price

For a given commodity, arbitrage ensures the commodity has a representative price adjusted for transaction costs across markets. This statement is referred to as the law of one price (Yang, Bessler, and Leatham, 2000; Ardeni, 1989). The law of one price provides a theoretical basis for international trade, exchange rate determination, and market integration studies for spatially separated markets.

Consider a simple two market example to illustrate the law of one price. The law of one price states the commodity will have the same price at the same time in both markets when transaction costs (all costs including trading and transportation costs) are small enough that profitable trade is not prohibited. Otherwise, there is an arbitrage opportunity. Traders would be able to profit by buying the commodity in one market and selling in the other market because of the price difference in the two markets. Such trading drives the prices in the two markets toward each other. Small deviation in prices of the commodity, however, may exist because of transaction costs. Transaction costs discourage traders from trading when the possible profits are smaller than these costs. Arbitrage opportunities occur only when the spread in prices between the two markets is larger than the transaction costs that link the markets (Goodwin and Piggott, 2001). The deviations from the law of one price have been defined in two different ways; absolute (price difference, $P_{1t} - P_{2t}$) difference or fixed transportation costs (O'Connell and Wei, 1997) and relative (log price difference, $\ln P_{1t} - \ln P_{2t}$) deviations or proportional transportation costs (O'Connell and Wei, 1997; Lo and Zivot, 2001). In this essay, the two types of deviations are considered, but the discussion in the text is limited to absolute deviations. Empirical results for relative deviations are provided in Appendix H.

In previous threshold cointegration literature, the upper and lower thresholds of price differences that determine if trading will occur are assumed to be constant over time. The assumption of constant threshold values, however, may not be appropriate in the real world. Four alternative cases for a neutral band associated with the law of one price can be developed. To develop the four alternatives, consider the two components that make up the price difference band. First is the difference between the upper and lower thresholds. This difference is the interval of the price difference band. Second is the mean (simple average) between the upper and lower thresholds. This average is referred to as the mean price differences. The four cases are illustrated in Figure 4.1. Previous cointegration studies are a special case of case I, in which the interval is assumed to be equal to zero. Whereas, previous threshold cointegration studies estimate the upper and lower thresholds for the interval but are limited to case I. In the first case, the interval of price difference band and the mean price differences are fixed over time. The interval of price difference band is fixed, but the mean price differences vary over time in case II. The third case consists of a variable interval, but a fixed mean price difference. In case IV, both the interval and the mean price differences vary over time.

The first case may be found in the financial markets in which local markets are well connected with low transaction costs and no significant seasonal effects, for example, exchange rate markets. The second case occurs when seasonal effects influence the supply and demand conditions in each local market but do not affect transaction costs significantly. Electricity with its seasonality in demand may be an example of case II. When the transaction costs between two markets varies over time, but the supply and demand conditions surrounding two markets do not vary, the third case is appropriate. Case III may occur because of differences in transportation rates caused by seasons. For example, because of winter weather conditions in the northern regions of U.S., transportation rates may be higher in the winter than in the summer. Case IV occurs when the transaction costs between two markets and the supply and demand conditions of the two markets vary over time. An agricultural product such as corn in two markets, one located in a major producing region and other being an excess consuming region may be an example of case IV. There are seasonal differences in the demand and supply conditions in the two markets. In addition, there are seasonal differences in transportation costs that are included in the transaction costs. In this study, the second case is examined. The other two cases are left for the future studies.

Threshold Cointegration

The law of one price has been tested in the context of long-run relationships rather than short-run relationships (Yang, Bessler, and Leatham, 2000). Ardeni (1989) first proposed cointegration as a method to test for the law of one price when considering nonstationarity of price data. Further, to address the nonlinear adjustment behavior in the presence of the transactions costs, the threshold autoregression (TAR) models or threshold vector error correction model (TVECM) has been used to test the law of one price (O'Connell and Wei, 1997; Tsay, 1998; Goodwin and Piggott, 2001; Lo and Zivot, 2001; Hansen and Seo, 2002; Sephton, 2003).

The TAR model has been applied in many fields including ecology, solar physics, finance, and hydrology (Tong, 1990). O'Connell and Wei (1997) test for transportation costs induced nonlinear price behavior for 48 final goods and services from 24 cities in the United States using a relative price panel data set. They tested three model specifications, autoregressive model of order one, equilibrium-TAR model, and band-TAR model, using likelihood ratio tests. O'Connell and Wei (1997) found that small deviations from price parity tend to be persistent, whereas large deviations revert towards an equilibrium. In addition, their findings imply that when adjustments in relative prices take place, they tend to eliminate, rather than reduce, price discrepancies. Whether there is any relationship between the estimated threshold values and explanatory variables such as distance remains an unanswered question.

Special attention has recently focused on bivariate threshold regime-switching models that extend the long-run linear equilibrium models of Granger (1981) to allow for different equilibrium adjustments mechanisms in different regimes. Combining threshold-nonlinearity and cointegration, Balke and Fomby (1997) first introduced the bivariate threshold cointegration model. They developed a methodology to test for the presence of the nonlinear effects for three types of threshold error correction models, eqilibrium-TAR, band-TAR, and random-TAR. Balke-Fomby type bivariate threshold cointegration model has attracted considerable attention from both applied and theoretical points of view (see Lo and Zivot, 2001 for a more detailed literature review).

Lo and Zivot (2001) used a bivariate TVECM with a known cointegrating vector using log price differences. They applied their methodology to 1,148 price series representing 41 goods and services in 28 cities. Following O'Connell and Wei (1997), they use New Orleans as the benchmark city to investigate the existence of pairwise threshold cointegration. They found threshold-type nonlinearity occurs mostly in goods that are tradable and relatively homogeneous. Further, they found prices adjust at different speeds for different cities.

Hansen and Seo (2002) propose a methodology to examine the case when the cointegrating vector is unknown. Their methodology uses maximum likelihood estimation of the threshold model to jointly search over the threshold values and the cointegrating vectors. A test called sup-LM is developed to test for the presence of a threshold effect. Goodwin and Piggott (2001) reported the existence of pair-wise threshold cointegration in daily corn and soybean prices in spatially separated markets in North Carolina. Sephton (2003) extends the work of Goodwin and Piggott (2001) in searching for thresholds by adopting the work of Hansen and Seo (2002) and Hansen (1999). He found the presence of one threshold in most of the bivariate commodity pairings using the same data as Goodwin and Piggott (2001).

Empirical Methods

Threshold Vector Error Correction Model

A bivariate three-regime TVECM is the basic tool used in this analysis. The general form of bivariate three-regime TVECM representation for price series, P_t (defined as $P_t = (P_{1t}, P_{2t})'$ where P_{nt} is the price of a good in location n, n =1, 2 at time t) with lag length k, threshold variable Z_t, and delay d is:

(13) $$\Delta P_t = \mu^{(j)} + \alpha^{(j)}\beta' P_{t-1} + \sum_{i=1}^{k-1} \Gamma_i^{(j)}\Delta P_{t-i} + e_t^{(j)}, \qquad \text{if } C^{(j-1)} \leq Z_{t-d} \leq C^{(j)},$$

where $t = 1,\ldots, T$, $j = 1, 2, 3$, $-\infty = C^{(0)} < C^{(1)} < C^{(2)} < C^{(3)} = \infty$, $C^{(1)}$ is the lower threshold value, $C^{(2)}$ is the upper threshold value, ΔP_t is the first differences (P_t - P_{t-1}), $\mu^{(j)}$ is a regime-specific constant term, $\Pi = \alpha^{(j)}\beta'$ is a regime-specific matrix of coefficients relating lagged levels of prices to current changes in prices, $\Gamma_i^{(j)}$ is a regime-specific matrix of coefficients, and $e_t^{(j)}$ is a serially uncorrelated regime-specific error term with mean zero and covariance matrix $\sum^{(j)}$. In the analysis presented here, the threshold variable Z_t, is assumed to be the price difference between two markets, whereas the delay variable *d*, lag length *k*, and threshold values $C^{(1)}$ and $C^{(2)}$ are unknown. The delay parameter *d* is assumed to be less than or equal to the lag length *k*. Most empirical studies investigating nonlinear adjustment to the law of one price based on the transaction cost theory used symmetric three regimes threshold cointegration model. Accordingly, only the three-regime model is considered.

The VECM with k-1 lags can be expressed as (see Chapter III):

(14) $$\Delta P_t = \mu + \alpha\beta' P_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta P_{t-i\,t} + e_t \qquad (t = 1,\ldots, T),$$

$$e_t \sim N\, iid\, (0,\Sigma),$$

where P_t denotes a vector that includes m non-stationary prices at time t, ΔP_t is the first differences (P_t - P_{t-1}), $\Pi = \alpha\beta'$ is a matrix of coefficients relating lagged levels of prices to current changes in prices, Γ_i is a matrix of short-run dynamics coefficients relating lagged period *i* price changes to current changes in prices, μ is a constant term, Ψ is a coefficient matrix, and e_t is a vector of innovations (Hansen and Juselius, 1995).

Comparing VECM with TVECM, the parameters on the TVECM may have different values depending on the regime. The VECM is a restricted version of the TVECM model; restrictions are $\mu^{(j)} = \mu$, $\alpha^{(j)} = \alpha$ **,** $\Gamma_i^{(j)} = \Gamma_i$, and $\Psi^{(j)} = \Psi$ for all regimes, j. In the TVECM the adjustment toward the long-run equilibrium relationship $\beta' P_{t-1}$ is regime-specific and nonlinear. The short-run structure identified through α and Γ_i can also differ between the TVECM and VECM. It is assumed in equation (13) that there is one common cointegrating vector β in all regimes. This assumption is often unnecessarily restrictive. Accordingly, it is more reasonable to allow the equilibrium error process to be different in each regime as in the regime-sensitive cointegration introduced by Siklos and Granger (1997). However, one common cointegrating vector, $\beta = (-1,1)'$ is assumed as it is appropriate for examining the law of one price between natural gas markets.

Multivariate threshold cointegration models beyond the bivariate cointegration model have been set up theoretically (Tsay, 1998). However, estimation of multivariate threshold cointegration models beyond the bivariate cointegration model leads to a dimensionality related to the computational burden. As such, to avoid these issues, the three-regime bivariate TVECM is used as the tool for empirical analysis.

Test of Nonlinearity

Balke and Fomby (1997) discuss problems related to testing for threshold cointegration. They indicate that one would like to test the no cointegration / linearity null hypothesis directly against the threshold cointegration alternative. However, several difficulties arise, including the presence of nuisance parameters (the thresholds) under the alternative hypothesis that are not present under the null (see Hansen, 1996 for a more detailed discussion). As a result, Balke and Fomby (1997) suggest a two-step procedure.

First, test for no cointegration versus cointegration using Johansen's trace test. Second, test for linear cointegration versus nonlinear or threshold cointegration. A similar two-step strategy for the threshold cointegration test is used here. For the first step, lag length and cointegrating rank are determined simultaneously using Schwarz loss measure following Wang and Bessler (2005a) and as used in Chapter III. If two series are cointegrated, the next step is to determine if the dynamics of the cointegrating relationship are linear or threshold nonlinear.

The basic idea of Balke and Fomby (1997) for testing linear versus nonlinear model is to make the existence of thresholds in the time-ordered data a structural change issue in a autoregression model. The model groups the data according to the value of the threshold variable instead of time. Balke and Fomby (1997) test for structural breaks in the reordered autoregression to test the linearity. Hansen (1996, 1999) suggests another method for testing the null hypothesis of linearity against the alternative of a TAR model based on nested hypothesis tests. Hansen tested the null hypothesis of TAR model with one regime versus the alternative of a TAR with m regime where some m > 1 using sup-F type tests. Hansen's method was extended to test linearity in multivariate TVECM by Lo and Zivot (2001). The test statistic in multivariate case is the sup-LR (likelihood ratio) statistic,

$$\text{(15)} \qquad \text{sup-LR} = T\,(\ln(\det(\hat{\Sigma})) - \ln(\det(\hat{\Sigma}_m(\hat{C}^{(j)}, \hat{d})))),$$

where $\hat{\Sigma}$, $\hat{\Sigma}_m(\hat{C}^{(j)}, \hat{d})$ denote the estimated residual covariance matrices from the linear VECM, and m-regime TVECM, $\hat{C}^{(j)}$ are the estimated threshold values, $\hat{d}$ is the estimated delay parameter, and det is the matrix determinant operator (Lo and Zivot, 2001). The test statistics are computed based on sequential conditional least square estimation as discussed later. Because the threshold values, $C^{(j)}$, are not known and are not identified under the null hypothesis of linear cointegration, a bootstrap procedure suggested by Hansen (1999) is used to compute p-values for the test. Tsay (1998) also extended his univariate test for threshold nonlinearity into a multivariate test. His work suggests another method to test threshold nonlinearity using predictive residuals for test statistics. In this study, the bootstrap procedure suggested by Hansen (1999) and generalized into multivariate model by Lo and Zivot (2001) is utilized to compute p-values for the linearity tests.

Estimation of Three-Regime TVECM

Lo and Zivot (2001) and Enders (2004) provide detailed descriptions concerning estimation of multivariate TVECM based on Hansen (1999) and estimation of threshold autoregressive model. Hansen type sup-LR in case of multivariate model uses the estimated residual covariance matrices from estimation of a linear TVECM and TVECM (m) for $m > 1$. As such, the nonlinearity test is closely related with the estimation of the threshold model. The estimation technique for multivariate TVECM is called sequential conditional least squares.

To describe the procedure of sequential conditional least squares estimation, consider general form of an unrestricted bivariate three-regime TVECM. An unrestricted bivariate three-regime TVECM of equation (13) can be expressed as:

$$\text{(16)} \qquad \Delta P_t = \begin{cases} \theta_1^{'} X_{t-1} + e_t^{(1)}, & \text{if } -\infty = C^{(0)} \leq Z_{t-d} < C^{(1)}, \\ \theta_2^{'} X_{t-1} + e_t^{(2)}, & \text{if } C^{(1)} \leq Z_{t-d} \leq C^{(2)}, \\ \theta_3^{'} X_{t-1} + e_t^{(3)}, & \text{if } C^{(2)} < Z_{t-d} \leq C^{(3)} = \infty, \end{cases}$$

where $X_{t-1} = (1, Z_{t-d}, \Delta P_{t-1}, \ldots, \Delta P_{t-k+1})$, $Z_{t-1} = \beta' P_{t-1}$, $\theta_j^{'}$ is a coefficient matrix (Lo and Zivot, 2001). Z_{t-d} is the threshold variable used to split the sample into three groups called regimes. Typically, it is assumed that the variances of the three error terms from each regime are equal, that is, $\text{Var}(e_t^{(1)}) = \text{Var}(e_t^{(2)}) = \text{Var}(e_t^{(3)})$ (Enders, 2004).

Defining indicator function, $I_t^{(j)}(C, d) = I_t^{(j)}(C^{(j-1)} \leq Z_{t-d} \leq C^{(j)})$ to take on the value of 1 if $C^{(j-1)} \leq Z_{t-d} \leq C^{(j)}$ is true and 0 otherwise allows equation (16) to be rewritten as a multivariate regression model:

$$\text{(17)} \qquad \Delta P_t = \theta_1^{'} X_{t-1} I_t^{(1)}(C, d) + \theta_2^{'} X_{t-1} I_t^{(2)}(C, d) + \theta_3^{'} X_{t-1} I_t^{(3)}(C, d) + e_t .$$

Here, $j = 1, 2, 3$, representing the three regimes (Lo and Zivot, 2001). If the threshold values are known, then equation (17) becomes a multivariate regression model with dummy variables. The estimation of this model is not complicated. However, in most cases, the threshold values are unknown. As such, the threshold values must be estimated along with the other parameters (Enders, 2004). The case of unknown threshold values is considered later in this discussion. For the threshold values to be meaningful, the data series must cross the thresholds. Accordingly, the threshold values, $C^{(1)}$ and $C^{(2)}$, should lie between the maximum and minimum values of the series (Enders, 2004). Hansen (1999) suggests using ten percent as a minimal percentage of data contained in each regime to constrain the threshold values. Adopting Hansen's suggestion, the threshold values should lie within the band containing no more than the middle 80 percent of the observations in case of three-regime model. Each observation within this initial 80 percent band is a candidate for a threshold value. In this study, the ten percent constraint Hansen (1999) suggested is adopted. In addition, the timing of the adjustment process may take more than one period, indicating d can take on values greater than one. The delay parameter must also be estimated.

The sequential conditional least squares estimation can be divided into two steps (Lo and Zivot, 2001). In the first step, conditional on potential candidates for the thresholds and delay parameter ($C^{(1)}, C^{(2)}, d$), the parameters ($\theta_1^{'}, \theta_2^{'}, \theta_3^{'}$) are estimated by multivariate least squares. From this estimation, the residual sum of squares of the three-regime model, $S_3(C^{(1)}, C^{(2)}, d)$, is obtained. For example, suppose observation, c_1, is chosen as a candidate for the lower threshold value and observation, c_2, is chosen as a candidate for the upper threshold value, and one as the assumed value of the delay parameter in three-regime model. Using these values, equation (17) is estimated. The residual sum of squares, $S_3(c_1, c_2, 1)$ is obtained from the estimation. The residual sum of squares from all possible combinations of ($C^{(1)}, C^{(2)}, d$), are obtained from the estimation. In the second step, the threshold values and delay parameter that minimize the residual sum of squares, $S_3\,(C^{(1)}, C^{(2)}, d)$ are found through a three dimensional grid search. Using the threshold values and delay parameter that minimize the residual sum of squares, the parameters $(\theta_1^{'}, \theta_2^{'}, \theta_3^{'})$ in TVECM are re-estimated. The delay parameter is assumed to be one in this study for simplicity.

Hansen (1999) notes the three dimensional grid search method is computationally burdensome. He suggests a shortcut to reduce computational burden utilizing sequential estimation of multiple breakpoints proposed by Bai (1997). This method suggests a sequential procedure to estimate the three-regime TVEM through estimating a two-regime TVECM first (see Bai, 1997 or Hansen, 1999 for more detailed discussions). In this study, the sequential estimation suggested by Hansen (1999) is utilized. To my knowledge, because of the dimensionality issue related to the computational burden, the estimation of the multivariate three-regime TVECM has been limited to bivariate three-regime TVECM.

Obtaining Time-Varying Threshold Values

Because of the importance of weather effects in the linear VECM presented in Chapter III, HDD and CDD are included in the bivariate three-regime TVECM. The Frisch Waugh Theorem is applied to filter the daily effect of weather from the price data. The Frisch Waugh Theorem allows one to obtain the partial regression coefficients by just using simple regression (see Baltagi, 2002 for more detailed discussion and proof of the Theorem). Using the Frisch Waugh Theorem, the filtered data are used in this study. To filter the data, each price series is regressed individually on lagged aggregate HDD and CDD using ordinary least squares:

(18) $$P_{it} = \gamma_i + \Phi_i HDD_{t-1} + \Psi_i CDD_{t-1} + e_{it} \qquad (t = 1,\ldots, T),$$

where γ_i is constant term, Φ_i and Ψ_i are coefficients associated with lagged HDD and CDD, and subscript *i* represents the eight markets. The filtered price series for the i^{th} market used in this study are the residuals, $\hat{e}_{it}$ from filtering regression for market *i*. Results from the estimation procedure using the filtered data provide thresholds that have a fixed interval and a fixed mean price difference. This is case I presented earlier. Time-varying thresholds (case II) based on CDD and HDD are obtained as follows. The fixed upper and lower threshold values, $C^{(1)}$ and $C^{(2)}$ for markets 1 and 2 are obtained from the estimation of the three-regime TVECM using filtered data, $\hat{e}_{1t}$ and $\hat{e}_{2t}$. This result implies the following relationship for the middle regime:

(19) $$C^{(1)} \leq \hat{e}_{1t} - \hat{e}_{2t} \leq C^{(2)},$$

where $\hat{e}_{1t} = P_{1t} - \hat{\gamma}_1 - \hat{\Phi}_1 HDD_{t-1} - \hat{\Psi}_1 CDD_{t-1}$ and in the same fashion, $\hat{e}_{2t}$ can be expressed as $\hat{e}_{2t} = P_{2t} - \hat{\gamma}_2 - \hat{\Phi}_2 HDD_{t-1} - \hat{\Psi}_2 CDD_{t-1}$. Through algebraic manipulation of equation (19), dynamic threshold values based on CDD and HDD are:

(20) $$C_t^{(1)} = C^{(1)} + (\hat{\gamma}_1 + \hat{\Phi}_1 HDD_{t-1} + \hat{\Psi}_1 CDD_{t-1} - \hat{\gamma}_2 - \hat{\Phi}_2 HDD_{t-1} - \hat{\Psi}_2 CDD_{t-1}),$$

(21) $$C_t^{(2)} = C^{(2)} + (\hat{\gamma}_1 + \hat{\Phi}_1 HDD_{t-1} + \hat{\Psi}_1 CDD_{t-1} - \hat{\gamma}_2 - \hat{\Phi}_2 HDD_{t-1} - \hat{\Psi}_2 CDD_{t-1}).$$

Using daily values of HDD and CDD in equation (20) and (21) provides time-varying thresholds.

Data

The data set used in Chapter III is used here. Considering regional dispersion and data availability, eight price series of natural gas market centers in the United States and Canada are included (Figure 3.1). The markets are Waha Hub, Texas (WAH), Henry Hub, Louisiana (HEN), Oklahoma (ONG), Opal Hub, Wyoming (OPA), Chicago Hub, Illinois (CHI), Ellisburg-Leidy Hub, Pennsylvania (ELL), Malin Hub, Oregon (MAL), and AECO Hub, Alberta, Canada (AEC). Although there are some important market centers that are not included, only the above eight market centers are considered because of data availability. Daily prices of the market centers (from surveys of traders) provided by Bloomberg Energy Service from January 12, 1998 to December 20, 2002 are used. Spot prices are calculated as a volume-weighted average price for that location in dollars per MMBtu (a unit of heat equal to one million British thermal units) for gas delivered the next day. The prices are for Monday through Friday. Each price series has 1290 observations. The total number of missing values in the eight price series is 400. The missing values, including holidays, account for 3.8 percent of the total observations. The prior day's price is used to represent any missing values for a particular day and market. Plots of the price series for each market are provided in Figure 4.2.

As in Chapter III, lagged U.S. aggregate cooling degree-days (CDD) and heating degree-days (HDD) are used to capture daily weather effects in natural gas prices. Daily

HDD are calculated as the difference between a reference temperature and the day's mean temperature (reference temperature – (maximum temperature + minimum temperature)/2), whereas CDD are computed as the difference mean temperature and a reference temperature ((maximum temperature + minimum temperature)/2 - reference temperature). The reference temperature used is 65 degrees Fahrenheit, the temperature used by U.S. National Oceanic and Atmospheric Administration (NOAA). HDD and CDD are set equal to be zero if the degree-day is negative. Daily degree-days for 23 cities are obtained (U.S. Department of Commerce, NOAA, 2003). The 23 cities are: Bismarck, Minneapolis, Kansas City, Chicago, Louisville, Pittsburg, New York, Billings, Seattle, San Francisco, Salt Lake, Denver, Boise, Dallas, Oklahoma City, Houston, New Orleans, Atlanta, Memphis, Los Angeles, Las Vegas, Phoenix, and Albuquerque (Figure 3.1). Daily degree-days for each city are aggregated into a U.S. daily cooling and heating degree-days by computing a weighted average using each city's population as weights. Population data for each city in 2001 are obtained from the U.S Census Bureau (2003).

Empirical Results

The stationarity of the eight price series is examined using Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) tests in Chapter III. The DF test statistics indicate all natural gas spot prices except OPA are non-stationary at both the 5% and 10% levels. However, the ADF test statistics indicate all spot prices are non-stationary at the 5% level, whereas all markets except OPA are non-stationary at the 10% level. DF tests show the first differences of all price series are stationary. ADF tests indicate the first differences of six of the eight series are stationary.

Given the result from Chapter III that CHI is the dominant market for price discovery in North American natural gas spot markets, CHI is used as the benchmark spot market for the bivariate linear VECM and bivariate three-regime TVECM. Seven bivariate models (AEC-CHI, MAL-CHI, OPA-CHI, WAH-CHI, HEN-CHI, ONG-CHI, ELL-CHI) are estimated. Nonlinearity tests that examine the existence of threshold effect using the null hypothesis of linear VECM versus the alternative of three-regime TVECM are conducted.

Before estimation, all data series were filtered using HDD and CDD. In the filtering regressions, all estimated coefficients associated with HDD and CDD except the coefficient associated with CDD in AEC are statistically significant at the 5% level (Table 4.1). All coefficients are positive, indicating an increase in either HDD or CDD tends to increase natural gas prices. Because aggregate U.S. HDD and CDD change slowly from day to day, the filtering regressions indicate seasonality in natural gas prices. The filtered price series, the residuals from filtering regressions, are graphed in Figure 4.2. As expected, the filtered data have the same general pattern as the original price series in each market, but the levels of the filtered price series are lower than the original price series.

In this analysis, the discussions about the empirical results are made based on non-logarithmic data to examine the price differences rather than price ratios between the two markets. However, the empirical results using filtered / unfiltered and logarithmic price data under the assumption that the loss of value from transportation is proportional are provided in the Appendix H[1].

Cointegration and Lag length

The first step for testing for the threshold cointegration is to conduct the cointegration tests for each pair of two markets using the filtered data. Lag length and cointegrating rank are determined simultaneously (Table 4.2). Results suggest each of the seven market pairs have a cointegrating rank of one because the Schwarz loss metric is minimized at one cointegrating rank. A rank of one indicates the markets are pairwise cointegrated. Cointegrating rank of one is consistent with the findings in Chapter III that the eight markets are cointegrated with six cointegrating vectors.

Regarding the lag length, however, the results do not suggest one appropriate model. For the pairs of AEC-CHI and MAL-CHI, the Schwarz loss metric is minimized at five lags. In the OPA-CHI, WAH-CHI, HEN-CHI, ONG-CHI, and ELL-CHI models, however, the Schwarz loss metric is minimized at four lags. Because the Schwarz loss metric suggests four lags as the appropriate model in five out of seven market pairs, four lags are assumed when estimating the VECM and TVECM. Four lags imply that there might be a day of week effect in natural gas markets, because a VECM with four lags is equivalent to a levels VAR with five lags. Day of week effects are detected in other financial markets (Aggarwal and Rivoli, 1989).

Tests of Nonlinearity and Estimation Results

Based on the results that the seven market pairs are cointegrated, nonlinearity tests are conducted using the sup-LR (likelihood ratio) test. The bootstrap p-values presented in Table 4.3 are defined as the percentage of bootstrapped LR statistics, which exceed the observed LR statistics (Hansen, 1999). The bootstrap p-values indicate that three-regime TVECM is significantly better than VECM in all seven pairs at the 5% level. Test results of using the unfiltered and logarithmic data and the filtered and logarithmic data are provided in Appendix H. In all seven pairs, the three-regime TVECM is significantly better than a VECM at the 10% level (see Appendix H). The estimated coefficients of parameters in seven pairs of bivariate three-regime TVECM are provided in Appendix I.

Schwarz loss metric can also be used as a model selection criterion to select the appropriate model from three-regime TVECM and VECM (Pena and Rodriguez, 2005). Using Monte Carlo experiments, Pena and Rodriguez (2005) suggest Schwarz loss metric can be a criterion for detecting non-linearity in large sample sizes. The Schwarz loss metrics of three-regime TVECM and VECM in each of seven pairs are obtained from the estimation procedure. Unlike the bootstrap p-value results, however, the Schwarz loss metrics are minimized using a linear model in all seven pairs (Table 4.4). Using the Schwarz loss metric as a criterion for detecting non-linearity remains a topic for the future study.

Time-varying patterns for the upper and lower threshold values in seven pairs are provided in Figure 4.3. These threshold values are the recovered values using equations (20) and (21). The recovered upper and lower threshold values show that threshold values based on daily HDD and CDD show seasonality. In MAL-CHI, OPA-CHI, and ELL-CHI, the means of price differences are lower in summer than in winter. The means of price differences of WAH-CHI, HEN-CHI, and ONG-CHI are higher in summer than in winter. In the winter when the demand of natural gas in the Chicago market is high, the level of mean of price differences between these three markets and CHI tend to be higher than in summer. The widths of the price differences bands defined as $C^{(2)} - C^{(1)}$, in the four pairs, AEC-CHI ($0.2153 per MMBtu), WAH-CHI ($0.1007 per MMBtu), HEN-CHI ($0.1912 per MMBtu), and ONG-CHI ($0.1547 per MMBtu) are narrower than those of the other markets (Table 4.5). The width of the price difference is largest in MAL-CHI ($1.4915 per MMBtu).

Discussion

Results indicate that there are non-linear adjustments to the law of one price in seven pair-wise natural gas markets. This result is similar to previous studies in that homogeneous and tradable goods between geographically separated markets may exhibit threshold cointegration relationships (Lo and Zivot, 2001; Goodwin and Piggott, 2001).

A methodology is developed that allows for seasonality in the mean price differences in threshold cointegration models. Markets (WAH, HEN, and ONG) that can be characterized as excess producing markets tend to have a higher mean price differences relative to Chicago in summer. AEC, another excess producing market, shows more complicated seasonal cycles. Excess consuming markets tend to have an opposite seasonal pattern; mean price differences are higher in winter. These results may be because the prices in excess producing markets are less sensitive to demand shifting conditions such as weather than excess consuming markets. Major excess consuming markets, MAL, OPA, and ELL, respond more to changes in weather.

The half of the widths of the price difference bands, $C^{(2)} - C^{(1)}$ can be considered as transaction costs including transportation costs between two markets. Estimated transaction costs between natural gas spot markets against CHI range from $0.05 per MMBtu (WAH-CHI) to $0.75 per MMBtu (MAL-CHI). Estimated transaction costs are approximately $0.10 per MMBtu in the three pairs, AEC-CHI, HEN-CHI, and ONG-CHI. Between WAH-CHI the estimated transaction cost is $0.05 per MMBtu. These four pairs represent the major supply regions with large pipeline capacity going into the Chicago market (Figures 4.4 and 3.7). Estimated transaction costs between OPA and CHI are nearly three times higher than between the previous four excess producing markets and CHI. This is indicative of the smaller capacity leaving OPA (Figure 3.7). Smaller capacity indicates less released capacity (see discussion below on the importance of release capacity). Estimated transaction costs are $0.35 between the two excess consuming markets ELL-CHI. Between two excess consuming markets it is expected price differences must be larger than between excess producing and excess consuming markets before trade occurs. Finally, transaction costs between MAL and

CHI are the largest because of geographical separation, pipeline capacity, and pipeline routes (Figure 3.7).

Kleit (1998) estimated the transaction costs following an estimation procedure suggested by Spiller and Huang (1986) to examine the effect of deregulation of natural gas pipeline contracts on the transaction costs. Kleit (1998) used price data in five gas producing regions, the Rocky Mountains, Oklahoma, Texas, Louisiana, and the Appalachians from 1984 to 1993. Among the statistically significant results, estimated transaction costs between Texas and the Appalachians were about \$0.62 per MMBtu in 1984 and \$0.34 per MMBtu in 1993. Direct comparison of the results in the present study with those of Kleit (1998) is not appropriate because the data sets are different in terms of time period and location. Nevertheless, estimated transaction costs in this study are generally less than those in Kleit (1998).

Further, the estimated transaction costs in both Kleit (1998) and in this analysis are less than the long-term transportation costs. Transaction costs being less than the long-term transportation costs may be explained as follows. First, in the pipeline transportation market where the long-term contracts were dominant, shippers tended not to renew long-term contracts after pipeline deregulation which provides the open access to pipelines (U.S. Department of Energy, 1998b). Turned back capacity has been remarketed to the other shippers at lower rates (U.S. Department of Energy, 1998b). This causes transaction costs to decrease. Second, a considerable amount of natural gas is still transported from the producing regions to consuming regions based upon long-term contracts, in spite of growing turned back capacity. In general, excess supplies and demands for natural gas are cleared at the spot markets. Thus, the transaction costs associated with spot markets may not reflect the long-term transportation costs. Third, the existence of released capacity also causes transaction costs to decrease. Shippers with excess capacity release their unused capacity, which is called released capacity, to the other shippers to recover some of their fixed costs (U.S. Department of Energy, 1998b). The released capacity market has grown steadily. This implies more shippers are using the release market as source for transportation of natural gas. The amount of released capacity has accounted for about 20 percent of total reserved firm transportation capacity (U.S. Department of Energy, 1998b). The transportation rate of natural gas is broken into two parts, demand and commodity charges (ICF Inc., 1997). " The monthly demand charge recovers the cost of the capacity. This is a fixed monthly cost regardless of the amount of gas that is shipped. The commodity charge covers the variable costs of transportation, usually a few cents per MMBtu plus the fuel charge " (ICF Inc., 1997, p. 20). " The cost of released capacity is expressed as a one part rate that recovers for the primary shipper some portion of his demand charges and all of the variable costs " (ICF Inc., 1997, p. 22). The variable costs of pipeline transportation, the commodity charge, range from $0.01 per MMBtu to $0.25 per MMBtu (GLJ Energy Publication Inc., 2003). These estimates indicate that the costs of released capacity are lower than the long-term transportation costs. Estimated transactions costs here are similar to previous estimates of the variable cost of pipeline transportation.

Although the assumption of constant threshold values may not be appropriate for real world, previous threshold cointegration literature assumed both the interval and mean price differences remain constant over time. Mean price differences allow for seasonal supply and demand differences to impact the linkages between spatially separated markets as related to the law of one price. This study explores time-varying mean price differences using data filtered for weather effects. The time-varying mean price differences imply there are different arbitrage behaviors depending on the season. For example, if the price difference between OPA and CHI is $-1.50 per MMBtu in the winter indicating the price difference is outside of the band, then the arbitrage trading occurs. However, if the price difference between OPA and CHI is $-1.50 per MMBtu in summer, the price difference is inside of the band, arbitrage trading between two markets does not appear to be present. The next step is to develop a methodology that allows the interval to vary over time and ultimately the most general case of both interval and mean differences to vary. In the natural gas sector, different rates for released pipeline capacity may be charged during the summer and winter (ICF Inc., 1997). Thus, more the generalized case of time-varying interval with time-varying mean may be more relevant.

End Notes

1. When using non-logarithmic and unfiltered price data, the estimation procedure did not converge. Thus, the case of using non-logarithmic and unfiltered price data is not presented in Appendix H.

CHAPTER V

CONCLUSIONS

Given the important role of electricity and natural gas in the North American economy, understanding of how markets for these commodities interact is important. As such, this dissertation independently characterizes the price dynamics of major electricity and natural gas spot markets in North America. Advances in causal flows are combined with time series analysis to study these two sectors. Vector autoregression (VAR) model is applied to the electricity sector because of stationarity in electricity prices. Natural gas prices are nonstationary, as such a vector error correction model (VECM) is applied to the natural gas sector. Directed acyclic graphs (DAGs) are used to analyze the contemporaneous time causal flows in both the electricity and natural gas sectors. Finally, threshold vector error correction model (TVECM) is applied to the natural gas sector to examine if there are nonlinearities in adjustments to price differentials in these markets. A generalization of price difference band associated with the law of one price is explored in this study.

Electricity Markets

Interdependencies among 11 major electricity spot markets in North America are examined in Chapter II. Dickey-Fuller (DF), augmented Dickey-Fuller (ADF), and trace tests indicate the electricity price series are generally stationary, adding additional evidence to the previous literature that electricity prices have a mean reversion characteristic. Estimation results of the VAR model indicate that U.S. aggregate heating degree-days variable (HDD) are not statistically significant in most of the markets at the 10% significance level, but U.S. aggregate cooling degree-days (CDD) are statistically significant in seven of the 11 markets at the 10% significance level. These results indicate the electricity prices are characterized by seasonality, particularly during the summer months where electricity is the major energy source used for cooling.

DAG results suggest that contemporaneous causal flows in electricity markets reflect the three major power grids of U.S., Eastern Interconnected System, Western Interconnected System, and the Texas Interconnected System. Western markets are separated from the eastern markets and the Electricity Reliability Council of Texas. In western markets, Palo Verde (PV) appears to be the driving force for the other western markets. The Electric Reliability Council of Texas (ERCOT) and the Northeast Power Pool (NEPL) are exogenous driving forces for electricity price through Entergy (ENT) and East Central Area Reliability Coordination Agreement (ECAR) in the eastern markets. The information flows from DAG indicate that most of information flows occur between physically adjacent spot markets.

The relationships between the markets, however, vary by time frame. In contrast to the contemporaneous time, at longer time frames separations between the western and non-western markets disappear, even though electricity transmission between the regions is limited. An interesting finding is that shocks in Pennsylvania-New Jersey-Maryland (PJM) and NEPL cause relatively large responses in the western markets in spite of considerable distance between the two regions. The relationships between markets are not only a function of physical assets such as transmissions lines between the markets, but are also a function of similar and dissimilar institutional arrangements including the degree of deregulation, market trading structure, and existence of futures markets between the markets. At longer time horizons, PV is still the important spot market in the west. The importance of PV is most likely because PV is the closest market to California included in the analysis. Southwest Power Pool (SPP) is the dominant market in Eastern Interconnected System. A likely reason for the importance of the SPP is because of the higher dependency on natural gas and coal as energy source for power generation in SPP.

Natural Gas Markets

Price dynamics among eight major natural gas spot markets in North America are investigated in Chapter III. DF and ADF tests indicate eight natural gas prices are nonstationary, which is consistent with most previous studies. Empirical findings suggest that the eight price series in natural gas spot markets in North America are tied together through six long-run cointegration relationships. All eight markets are in the long-run relationships and respond to perturbation in any of the six long-run cointegration relationships. Seasonal differences in the long-run relationships exist because HDD and CDD cannot be excluded from the cointegration space. Seasonality in prices may be because natural gas is used for heating and electricity generation in winter and mainly for electricity generation in the summer besides industrial uses.

Greedy Equivalence Search (GES) Algorithm and PC (after its authors, Peter and Clark) Algorithm were both used to provide contemporaneous causal flows in the eight natural gas spot markets. GES Algorithm did not leave as many edges undetermined as PC Algorithm did. Further, GES did not provide bi-directed edges. Therefore, the GES Algorithm appears to perform better than PC Algorithm, at least in terms of providing causal information. In contemporaneous time, causal flows tend to originate from excess consuming regions and point toward excess producing regions. Causal flows directions tend to be the reverse of the directions of the flows of natural gas. This indicates that price discovery tends to occur in the excess consuming regions and move to the excess producing regions. Across North America, the U.S. Midwest region represented by the Chicago spot market is the most important market for price discovery. This result differs from previous studies that suggest the Henry Hub market in Louisiana is important. The Ellisburg-Leidy Hub in Pennsylvania is also an important market for price discovery, especially for markets in the eastern two-thirds of the U.S. Malin Hub in Oregon is important for the western markets which include the AECO Hub in Alberta, Canada. The importance of Malin Hub may be because it is the closest market to California included in the analysis.

Contemporaneous causal flows, forecast error variance decompositions, and impulse response functions all indicate there is not an east-west split among natural gas spot markets in North America unlike an earlier study (King and Cuc, 1996). Results support Serletis (1997) argument that an east-west split does not exist. King and Cuc

(1996) study used data that was from a period soon after deregulation. Both Serletis (1997) and the present study include prices removed from the start of deregulation. These findings together suggest the natural gas market has developed into a single integrated market in North America since deregulation.

Natural Gas and Threshold Cointegration

Previous threshold cointegration literature assumes the law of one price includes a band of price differences between two markets in which trading does not occur because transaction costs are larger than the price difference. These previous studies assumed the price difference band between the markets is constant over time. In Chapter IV, a generalization of price difference band associated with the law of one price is explored. Four alternative cases for the neutral band associated with the law of one price are presented as a theoretical background to develop a threshold cointegration model that accounts for seasonality in threshold levels. As such, this is the first study to relax the assumption of a constant price difference band.

The nonlinearity of price adjustment to the long-run equilibrium between natural gas spot market pairs and dynamic threshold effects are investigated using bivariate three-regime TVECMs. Given the results from Chapter III, the estimations of seven bivariate three-regime TVECMs are conducted using price data filtered by CDD and HDD. Chicago is used as the benchmark market in seven market pairs. The filtering regressions indicate the existence of seasonality in natural gas prices because all estimated coefficients except one associated with CDD and HDD are statistically significant at the 5% level. Results show that there are nonlinear adjustments to the law of one price in seven pair-wise natural gas markets.

The recovered upper and lower threshold values from the estimation results of filtered data indicate that the threshold values vary based on daily CDD and HDD; seasonality in the thresholds exists. Dynamic threshold effects vary depending on geographical location and whether the market is a excess producing or excess consuming markets. Mean price differences between Chicago (CHI) and excess producing markets such as Waha (WAH), Henry (HEN), and Oklahoma (ONG) tend to be higher in the summer than the winter, whereas, mean price differences between Chicago and excess consuming markets are higher in the winter than the summer. These differences in thresholds are likely because the prices in excess producing markets are less sensitive to demand shifters, such as weather, than the prices in excess consuming markets. Major excess consuming markets respond more to changes in weather.

The estimated upper and lower threshold values provide information about transaction costs between Chicago and the other markets. Estimated transaction costs are smaller in the four pairs, AECO (AEC)-CHI, HEN-CHI, ONG-CHI, and WAH-CHI, than for the other market pairs. These four pairs represent the major excess producing regions with large pipeline capacity going into the Chicago market. The estimated transaction costs in this study are lower than long-term transportation costs presented in previous studies. However, the estimated transaction costs from this study are close to estimated variable costs of pipeline estimated in previous studies. It appears spot market transactions only consider the variable costs of transportation.

Comparisons of Electricity and Natural Gas Markets

The average value of the elements of contemporaneous innovation correlation matrix from the electricity spot markets is 0.36 while corresponding average value from the natural gas spot markets is 0.47. DAG results from Chapters II and III indicate that there is not a strong east-west split among natural gas spot markets in North America in contemporaneous time but such a split is present in the electricity spot markets. Any separation among the electricity markets, however, disappears at longer time horizons. These results imply that natural gas spot markets are more highly integrated than electricity spot markets in North America. Postulated reasons for more highly integrated markets in natural gas include 1) the fact that the deregulation of the natural gas industry is several years ahead of the electricity industry in North America, and 2) the natural gas markets have less physical infrastructure separation than electricity spot markets have.

Differences in the regions of price discovery exist between electricity and natural gas sectors. In electricity spot markets, SPP, which has a high marginal cost for generating electricity, is a dominant market for price discovery. However, CHI, which is a major excess consuming region, is the dominant market for price discovery in natural gas spot markets. These differences may be caused by differences in storability of the commodity, natural gas being an input for generation of electricity, and different transportation structures between the two sectors.

Limitations and Future Research

Anomalies in the price data attributed to the extended California energy shortage in 2000 and natural gas price spike in 2000 winter are not explicitly accounted for in this analysis. Further, accounting for anomalies that appear in the electricity spot markets, ECAR, Mid-Area Interconnected Network (MAIN), Mid-Continent Area Power Pool (MAPP), ENT, and SPP in 1998 summer and 1999 summer are not considered. Not accounting for these and other anomalies may bias the findings that the western electricity markets are separated from the rest of U.S. markets because of the characteristic of limited deliverability of electricity. Future studies may want to examine how these anomalies impact the price discovery process. Causes of the anomalies are starting to be published. Price anomalies in natural gas prices are also not explicitly accounted for in the analysis.

In this study, only eight markets in electricity and 11 markets in natural gas are included for the analysis. Particularly, in light of the importance of California market in two industries, markets from California should be included. Data limitations precluded inclusion of California markets in this study. Palo Verde in electricity and Malin Hub in natural gas that are physically close to California, however, are included in this study. Analysis including more markets with more recent data should be conducted in future studies. Another limitation of this study is that discussion concerning price discovery assumes Chicago (CHI) causes Oklahoma (ONG) even though the GES Algorithm did not suggest a clear causal direction between CHI and ONG markets. In Chapter IV, the cointegrating vector is assumed to be known and delay parameter is assumed to be equal to one in the TVECM. Future studies should relax these assumptions.

Results suggest other important issues need addressing. How is the electricity price affected by different market institutions? What are the impacts of continuing deregulation and piecemeal deregulation in the electricity industry on prices? These questions are topics of further study. In Chapters II and III, temperature is only exogenous variable considered in the models. Different factors such as variations in demand, congestion on the transmission system, and outages in electricity markets should be considered in electricity spot market analysis. Factors such as variations in demand, storage capacity, futures markets, and types of end use of natural gas should be considered in future studies of natural gas spot market analysis. In contrast to the electricity industry, the futures market is very active in the natural gas industry. Spot market prices from both electricity and natural gas industries should be investigated together to examine the interdependencies of these two energy markets because electricity power plants are important consumers of natural gas. Further, the influence of captive supply of electricity and natural gas based on contractual arrangements in spot market transactions and prices may be a fruitful avenue of future research. A methodology to estimate time-varying thresholds with fixed mean price difference and varying interval is developed. Methodologies to address more general cases await development. Examining threshold effects between spot market price and futures market price in the two sectors would contribute to the understanding of market behavior. Future research on these two energy markets will continue to provide interesting results on market behavior and price discovery.

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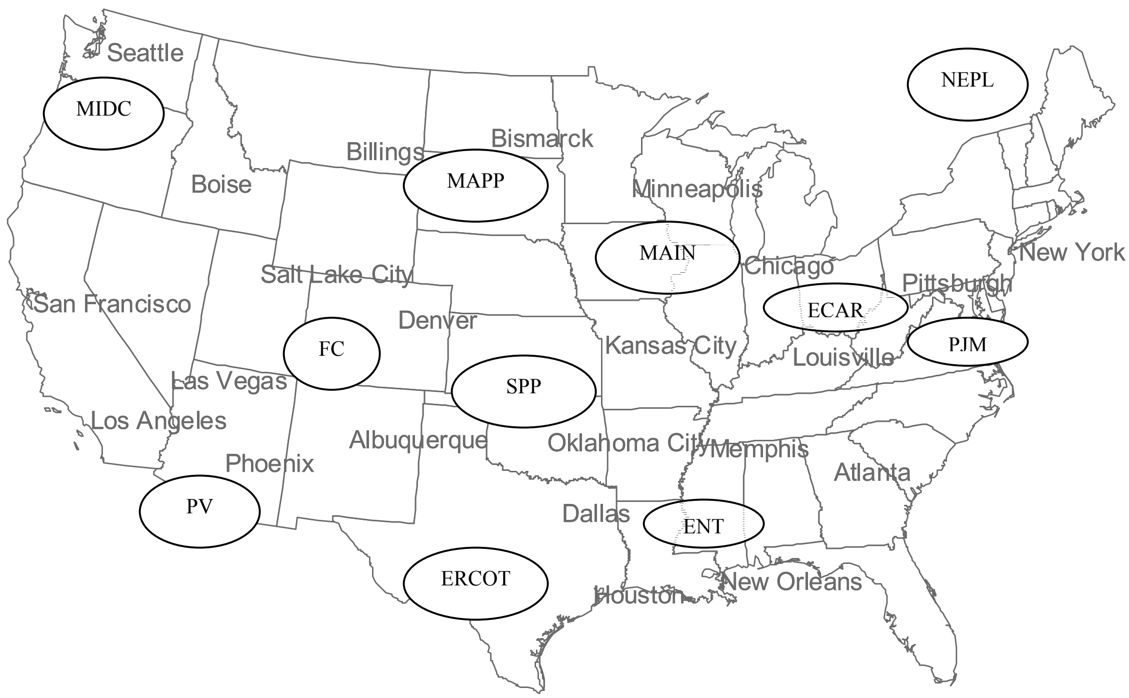
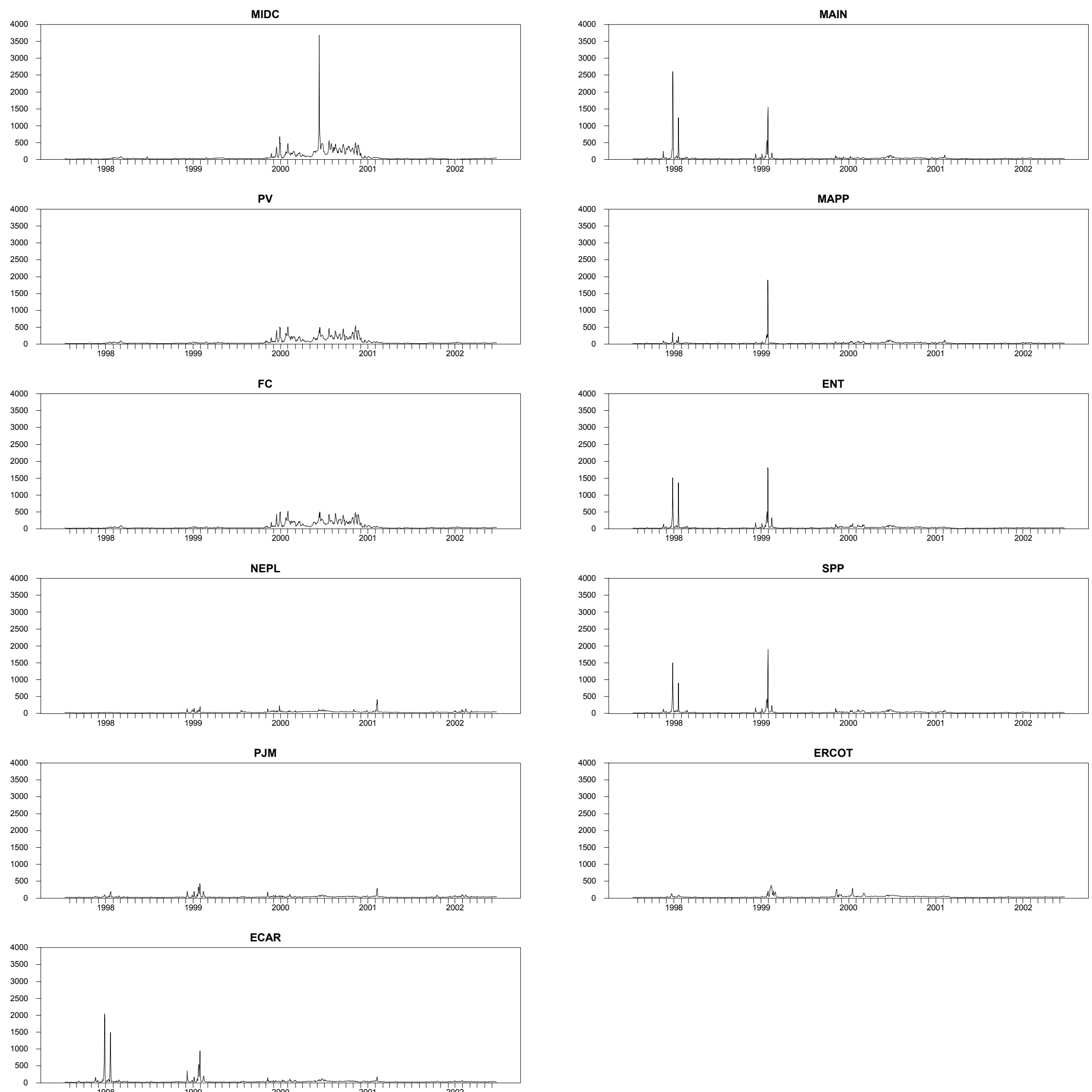
APPENDIX A

FIGURES



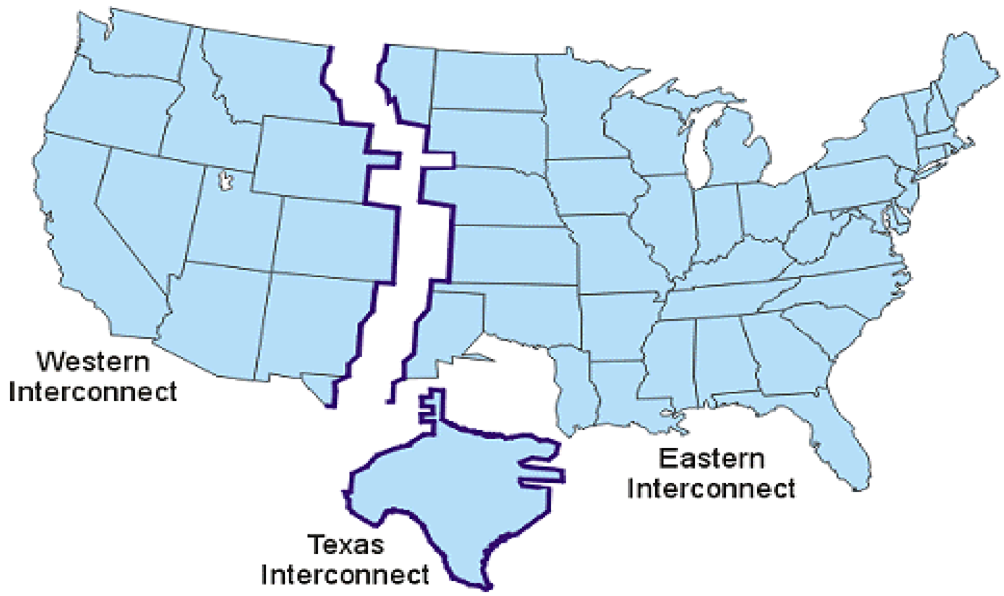
Note: See list of acronyms in Appendix J for definitions of spot markets.

Figure 2.1. Approximate Locations of 11 Electricity Spot Markets in North America and 23 Cities Included in the Analysis



Note: See list of acronyms in Appendix J for definitions of spot markets.

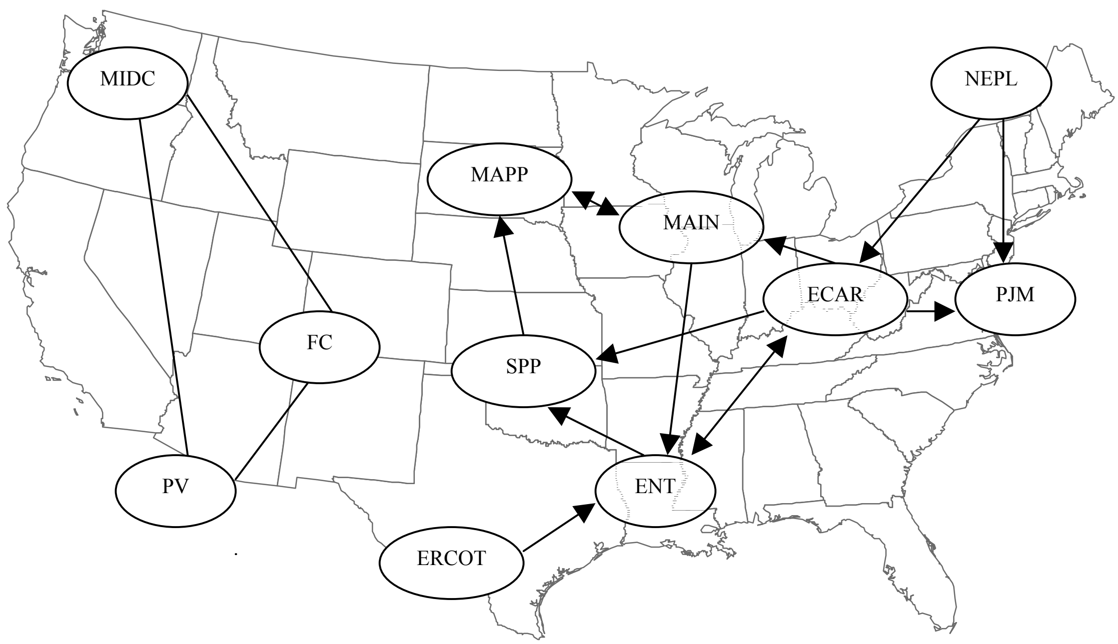
Figure 2.2. Daily Peak Electricity Prices for 11 North American Spot Markets in Dollars per Megawatt Hour (Feb. 26, 1998 – Dec. 20, 2002)



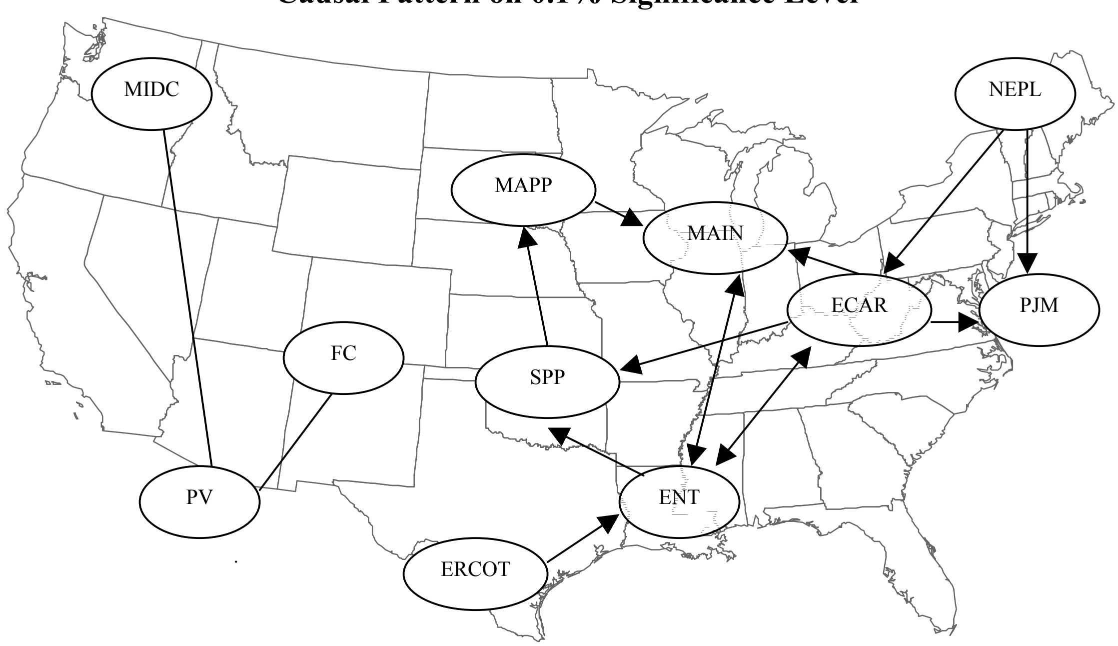
Source: U.S. Department of Energy, 2003a

Figure 2.3. North American Electric Power Grids

Causal Pattern at the 1% Significance Level

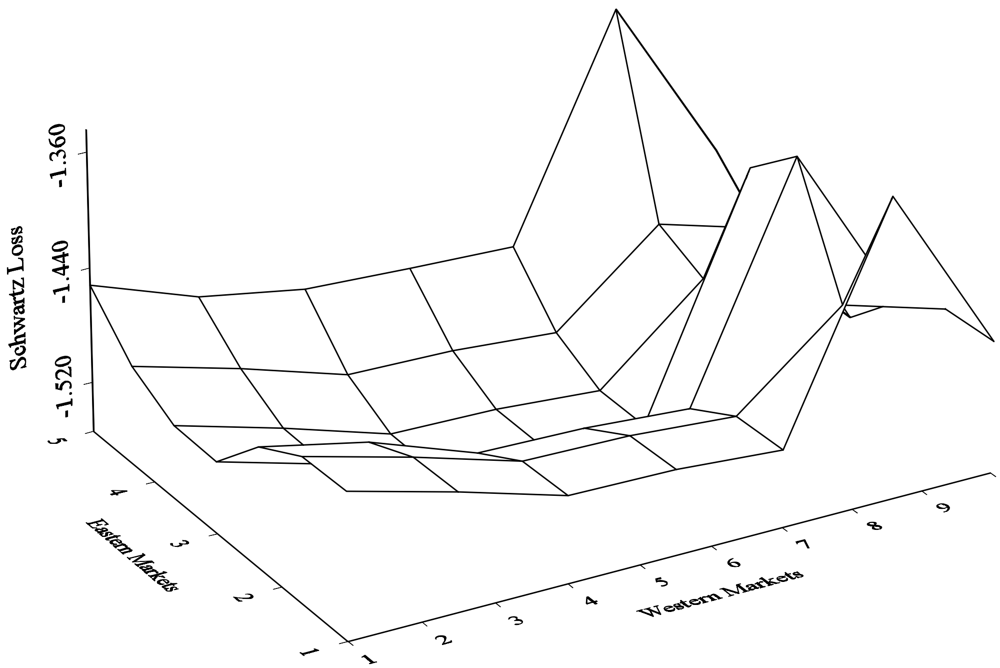


Causal Pattern on 0.1% Significance Level



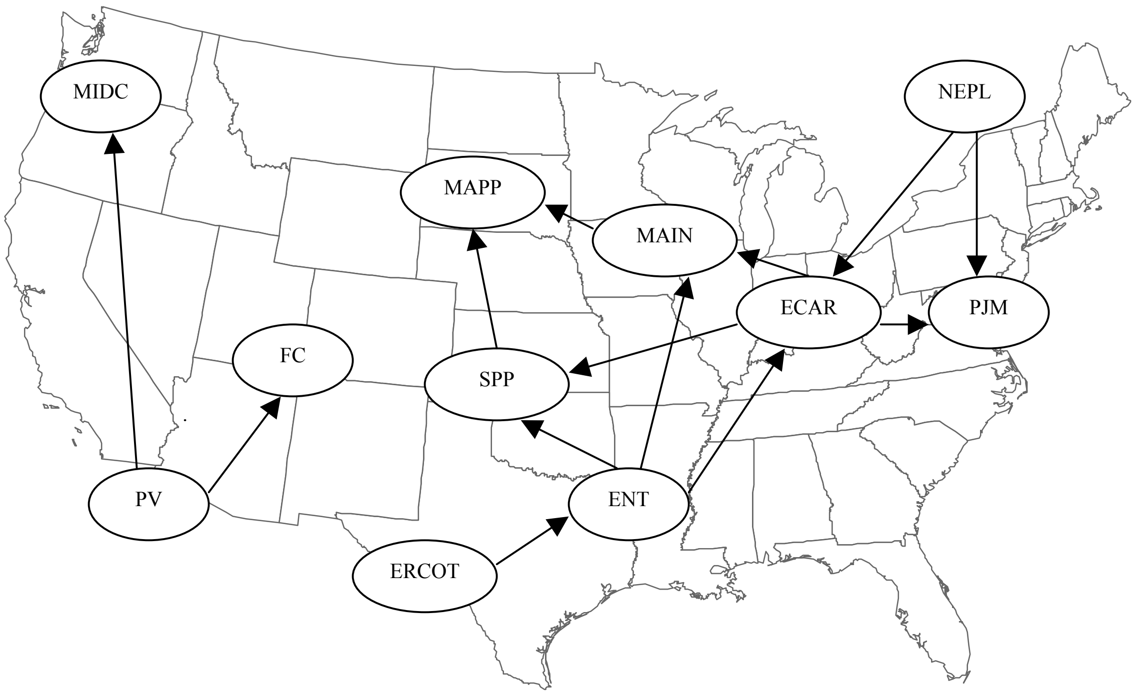
Note: See list of acronyms in Appendix J for definitions of spot markets.

Figure 2.4. Casual Patterns at the 1% and 0.1% Significance Level Obtained Using TETRAD II



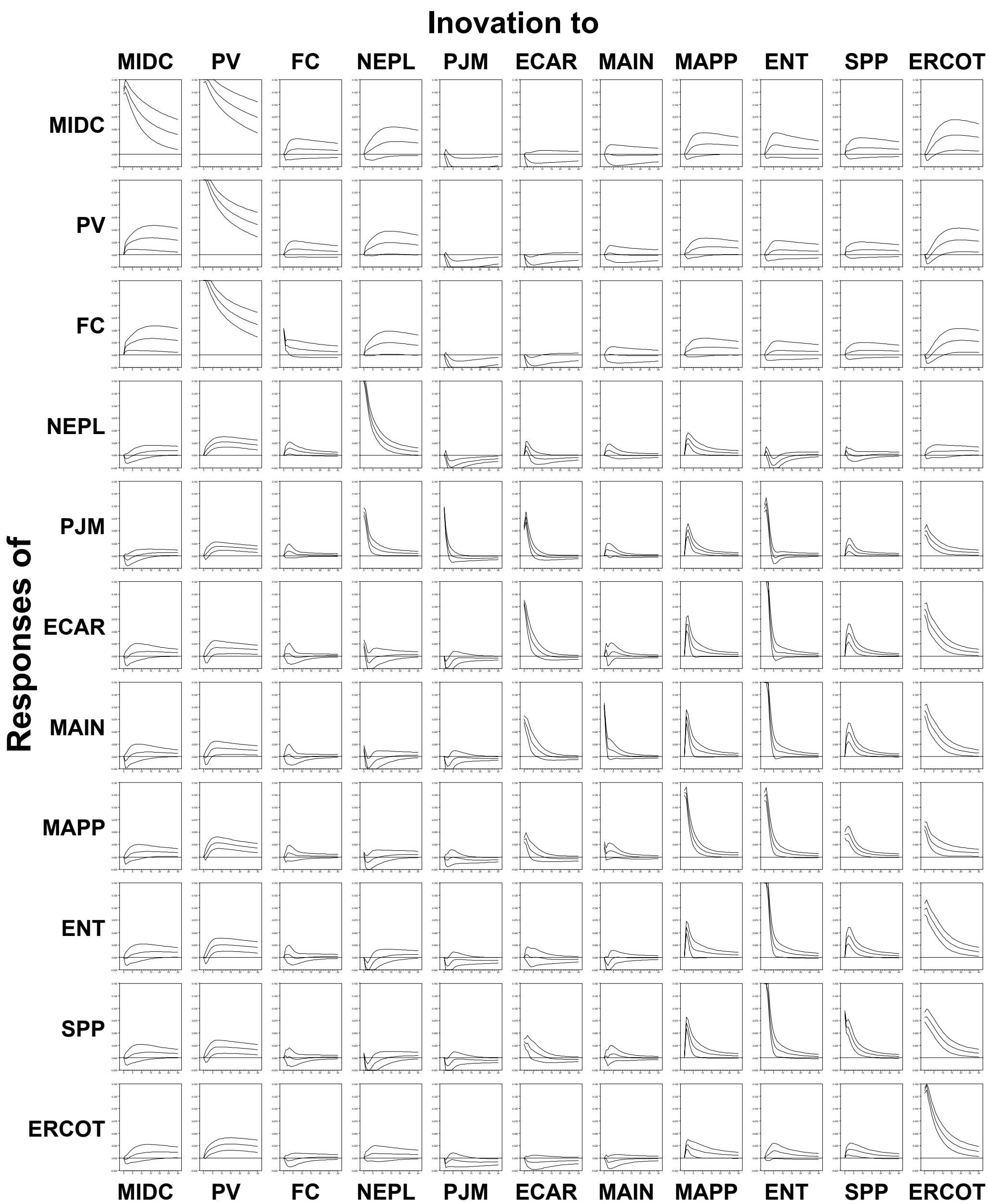
Note: The axis labeled "Western Markets" indicates ten alternative sets of directed acyclic graph from (D.1) to (D.10). The axis labeled "Eastern Markets" indicates the five possible alternative sets of directed acyclic graph from (D.11) to (D.15). The above three-dimensional graph shows the Schwarz loss value is minimized at the pair of (D.7) and (D.13).

Figure 2.5. Three-Dimensional Graph for the Schwarz Loss Metrics



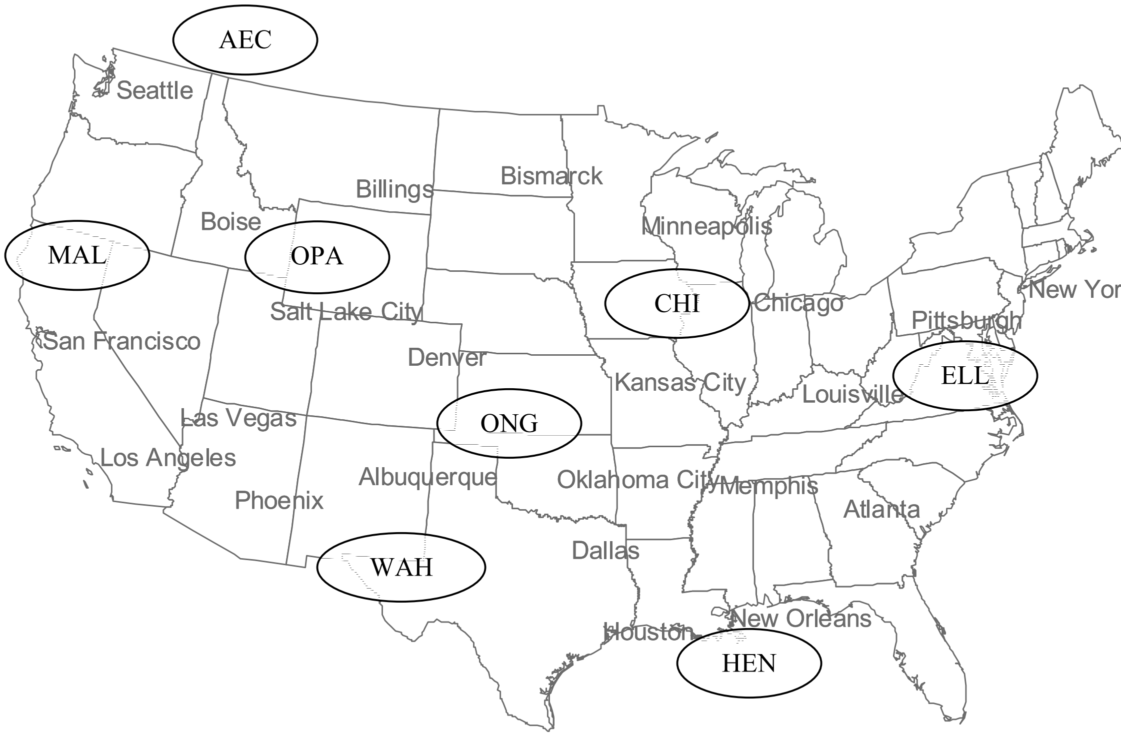
Note: See list of acronyms in Appendix J for definitions of spot markets.

Figure 2.6. Final Directed Acyclic Graph



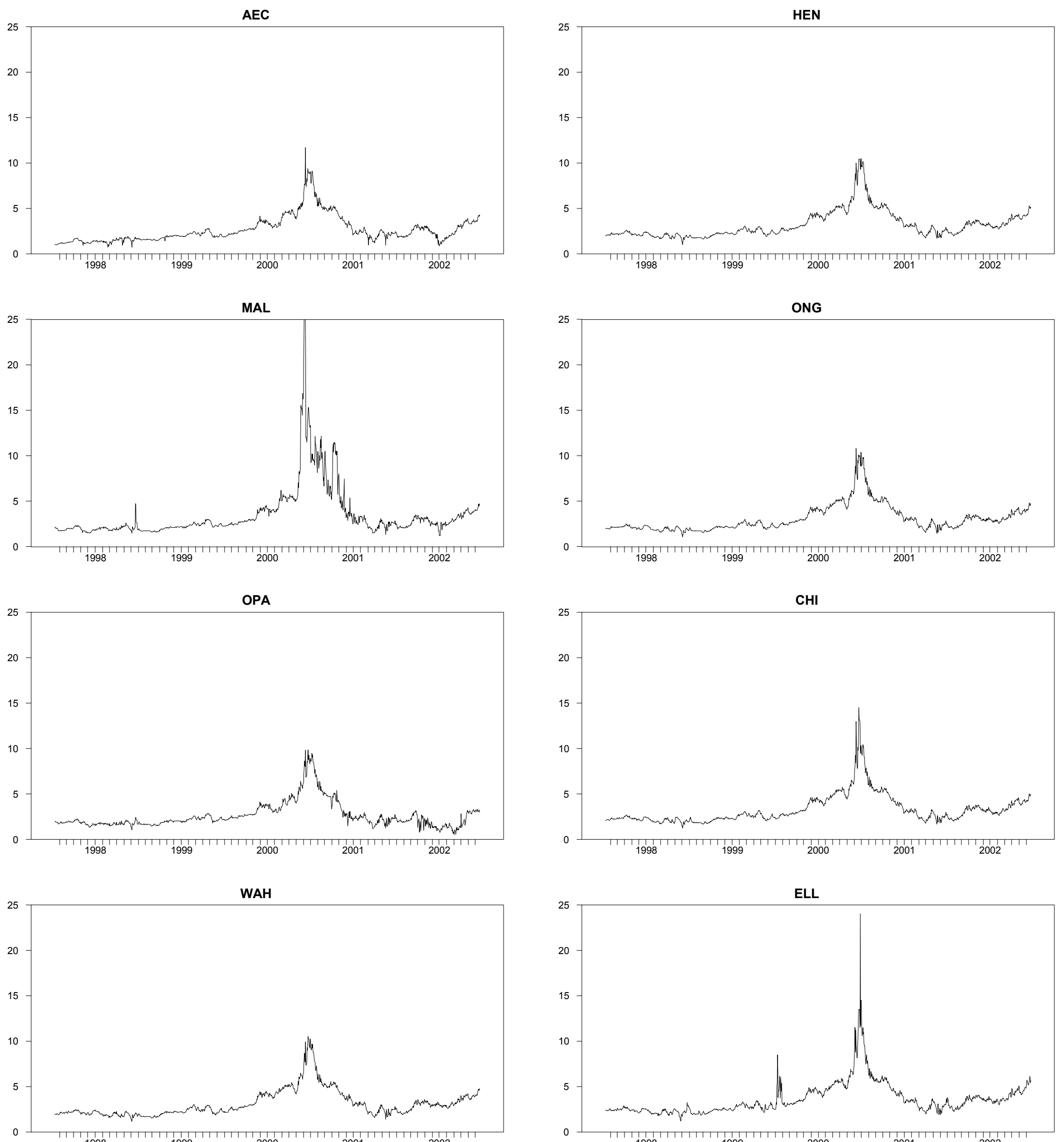
Note: See list of acronyms in Appendix J for definitions of spot markets.

Figure 2.7. Impulse Response Functions from Innovation of Two-Lag VAR



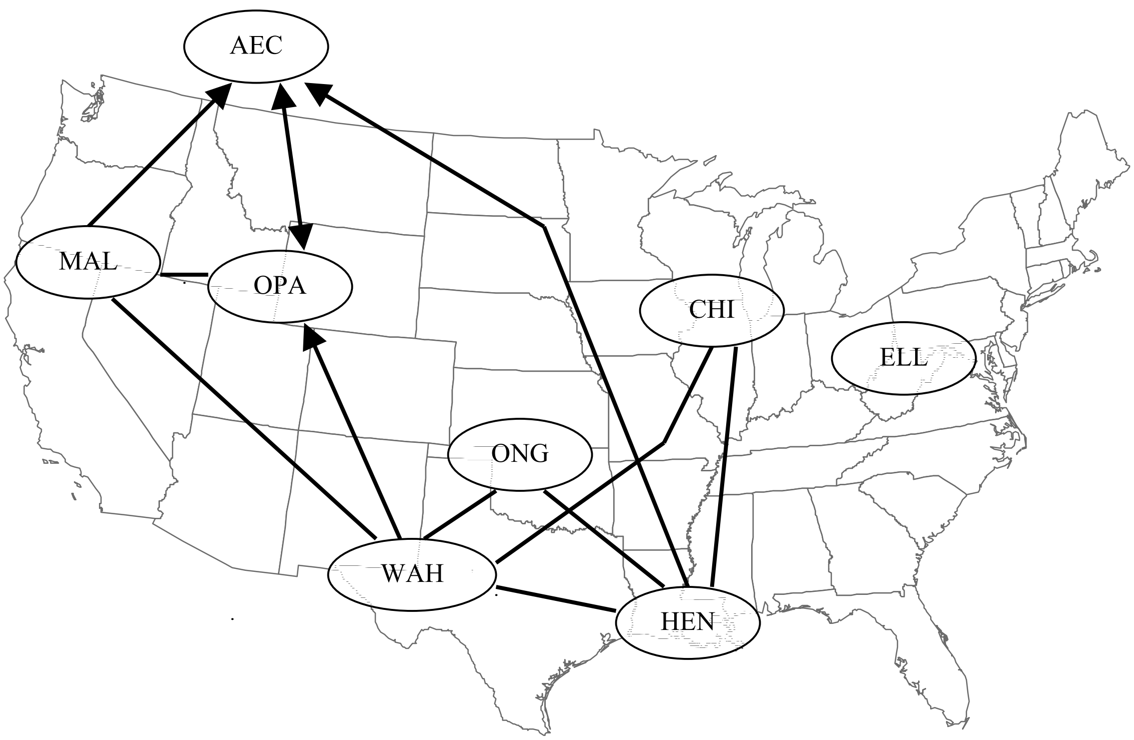
Note: See list of acronyms in Appendix J for definitions of spot markets.

Figure 3.1. Approximate Locations of Eight Natural Gas Spot Markets in North America and 23 Cities Included in the Analysis



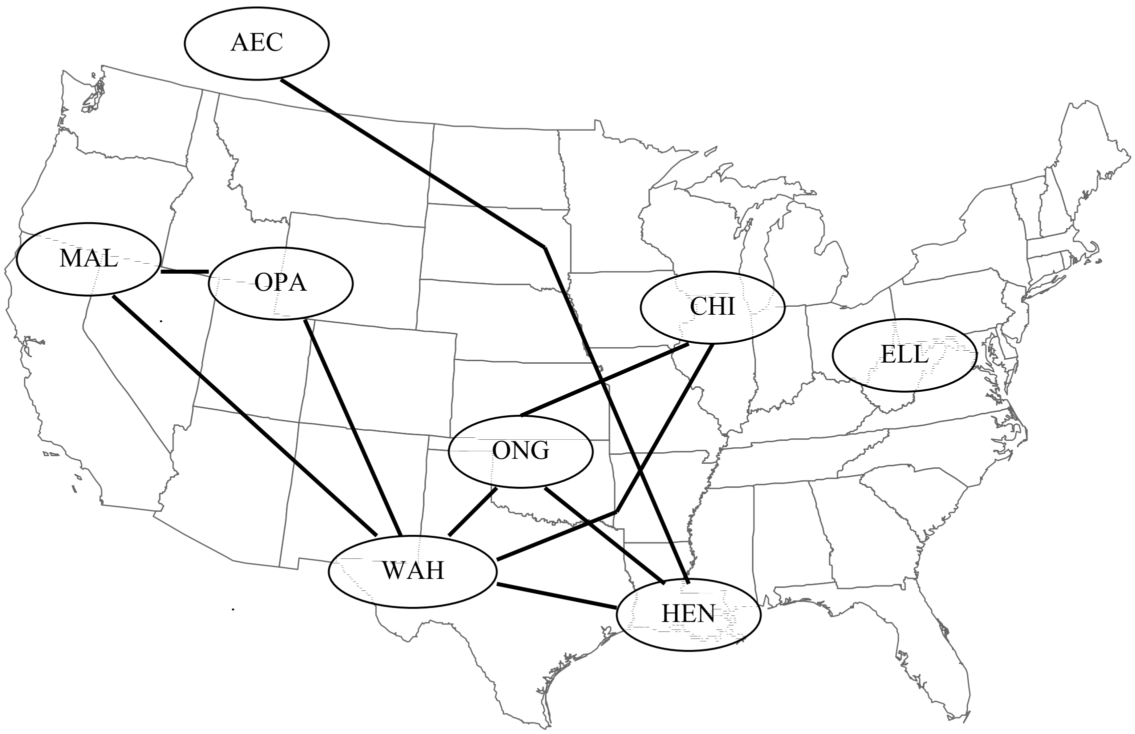
Note: See list of acronyms in Appendix J for definitions of spot markets.

Figure 3.2. Daily Natural Gas Prices ($/MMBtu) for the Eight North American Spot Markets (Jan. 12, 1998 – Dec. 20, 2002)



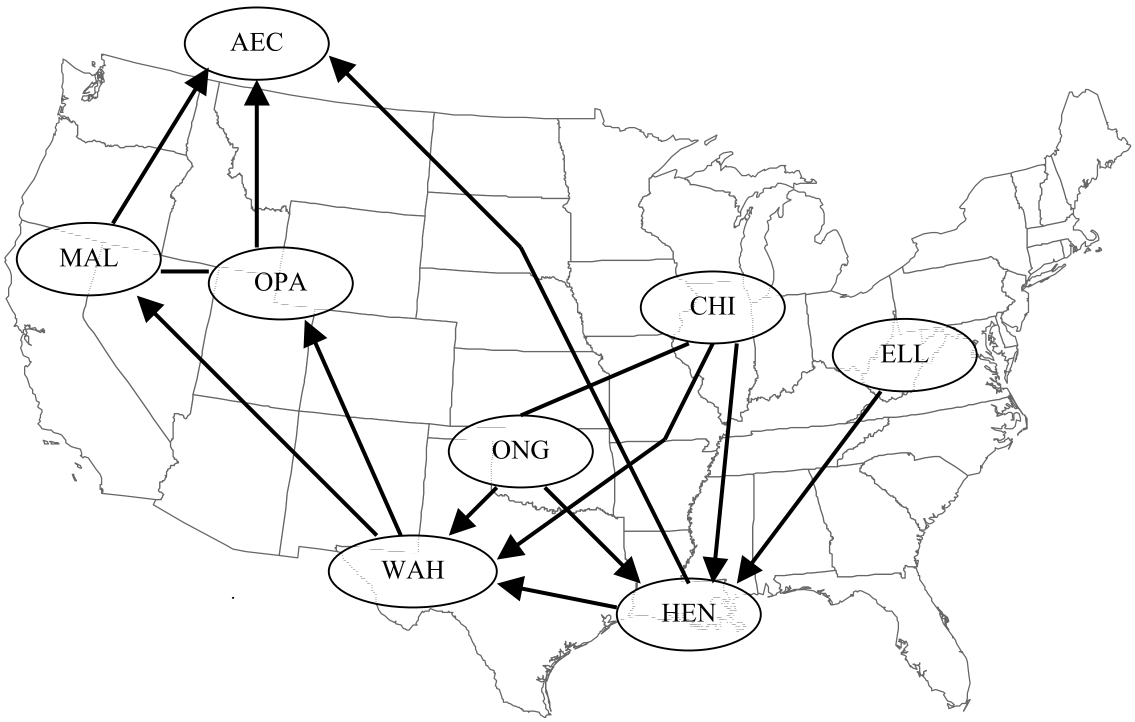
Note: See list of acronyms in Appendix J for definitions of spot markets.

Figure 3.3. Causal Pattern at the 1% Significance Level Obtained Using TETRAD IV with PC Algorithm



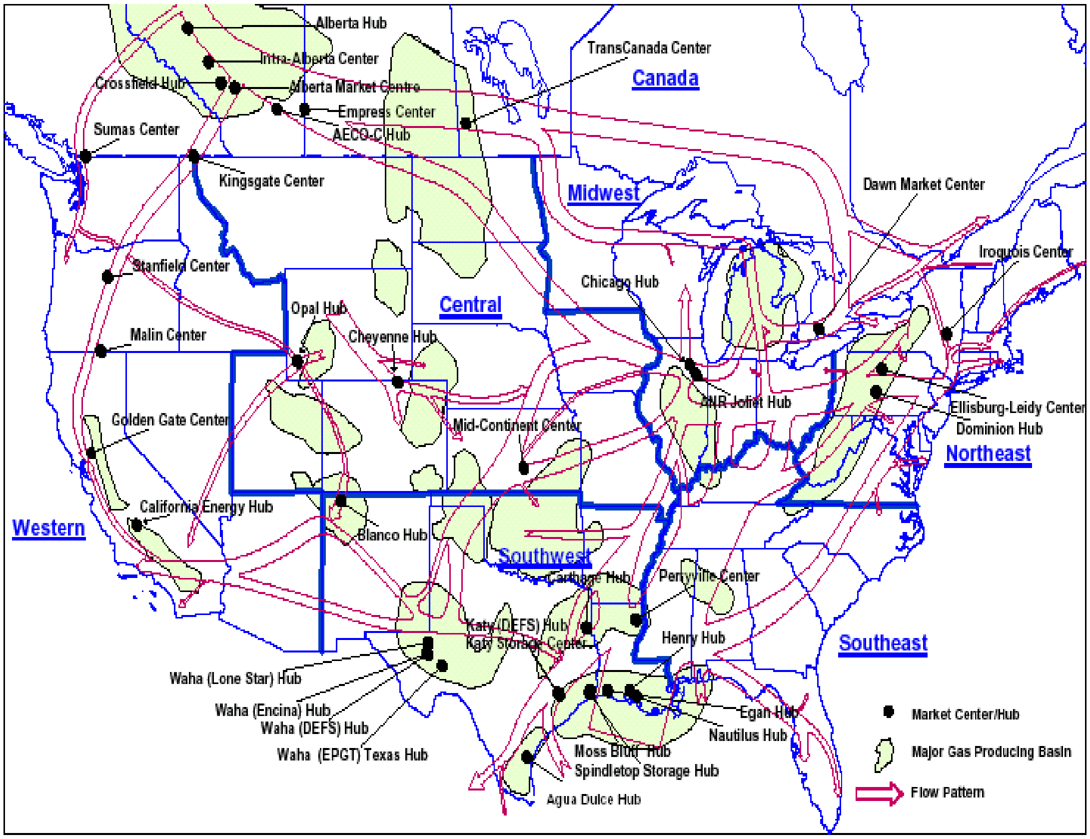
Note: See list of acronyms in Appendix J for definitions of spot markets.

Figure 3.4. Causal Pattern at the 0.1% Significance Level Obtained Using TETRAD IV with PC Algorithm



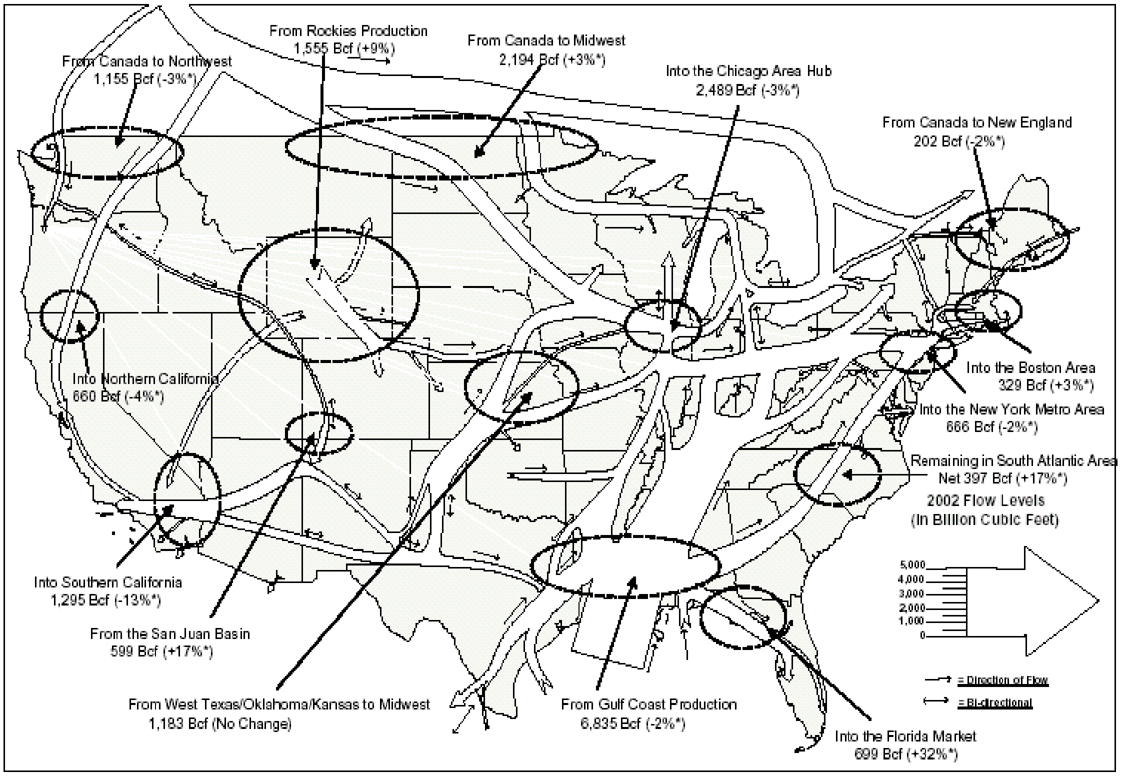
Note: See list of acronyms in Appendix J for definitions of spot markets.

Figure 3.5. Causal Pattern Obtained Using TETRAD IV with GES Algorithm



Source: U.S. Department of Energy. Energy Information Agency. 2003c.

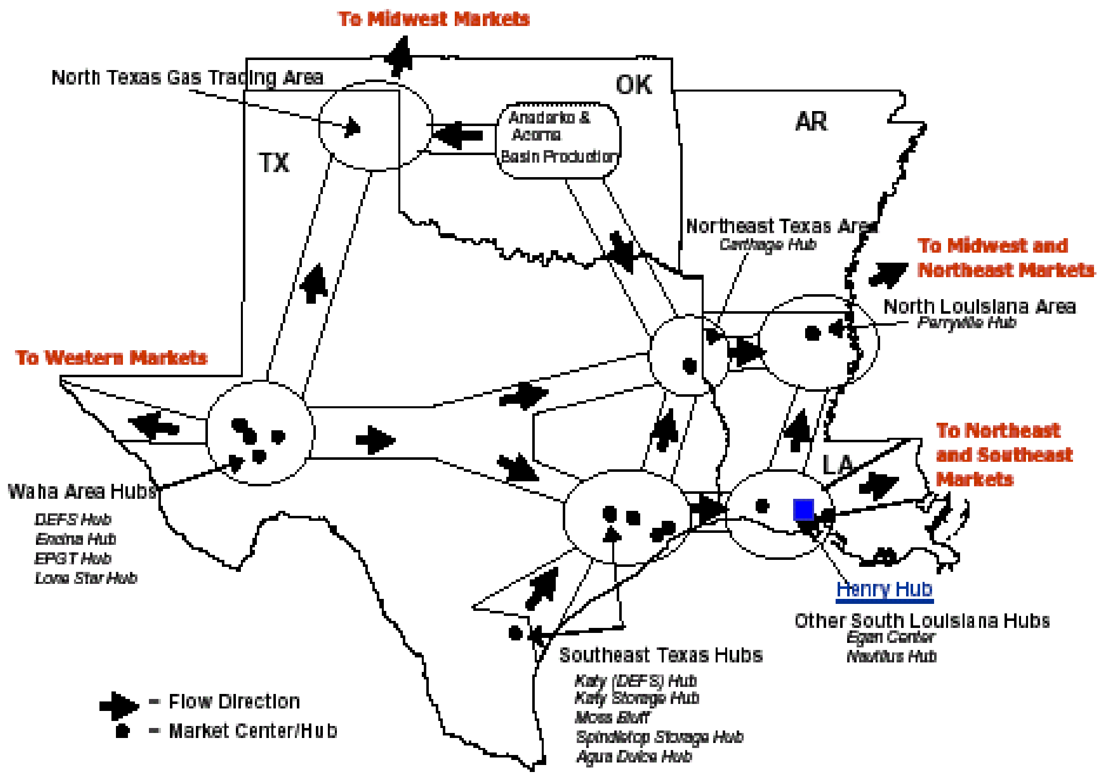
Figure 3.6. Major Natural Gas Producing Basins, Pipeline Transportation Routes, and Interstate Flow Levels at Selected Key Locations as of 2003



*Percent change in flow from 2001. Bcf = Billion cubic feet

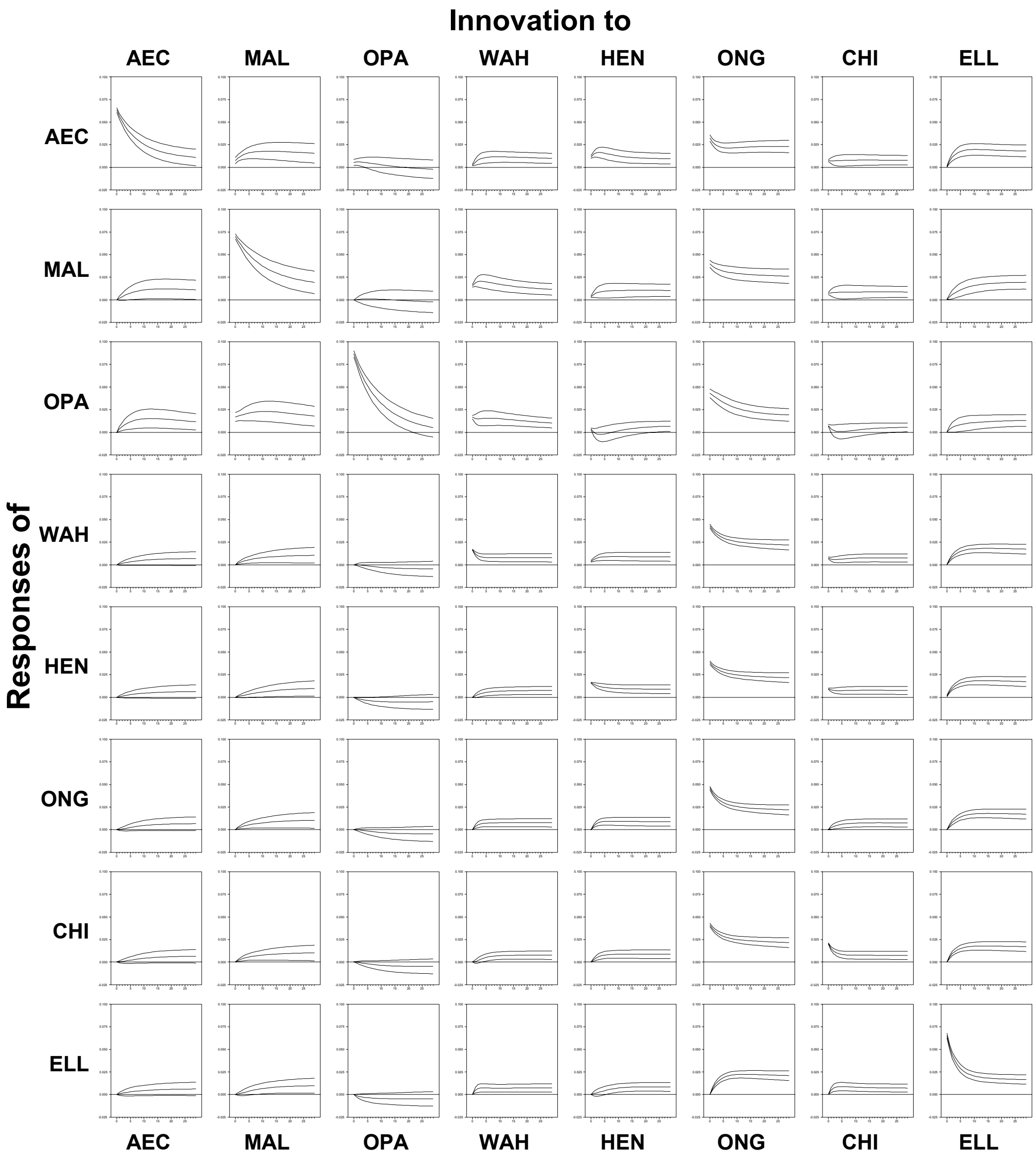
Source: U.S. Department of Energy. Energy Information Agency. 2004

Figure 3.7. Major Natural Gas Pipeline Transportation Routes and 2002 Flow Levels at Selected Key Locations



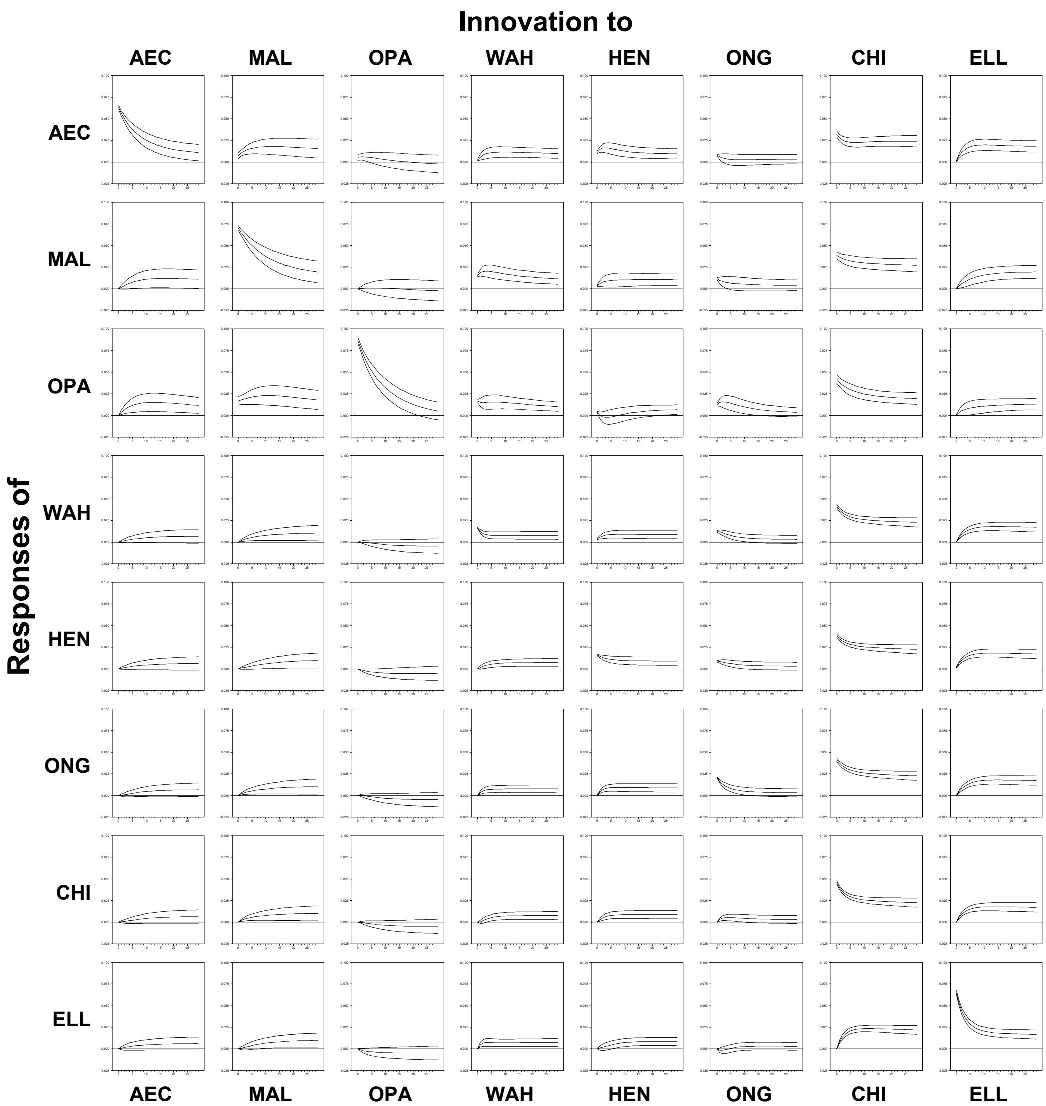
Note: DEFS = Duke Energy Field Services Co; EPGT Texas Pipeline Co.
Source: U.S. Department of Energy. Energy Information Agency. 2003c.

Figure 3.8. Natural Gas Pipeline Transportation Routes and Flow Levels Around Texas and Louisiana



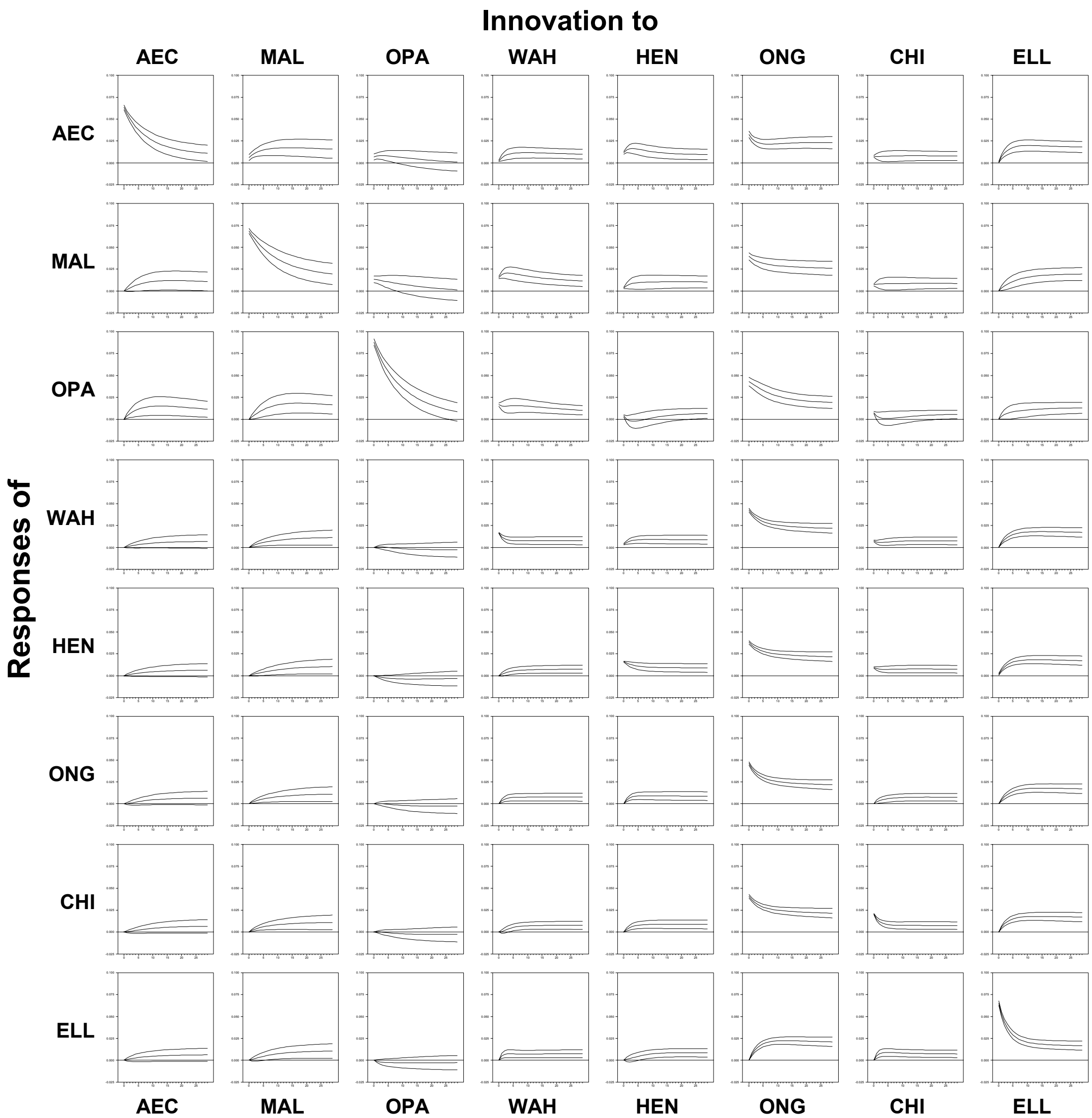
Note: See list of acronyms in Appendix J for definitions of spot markets.

Figure 3.9. Impulse Response Functions from Innovation of VECM of Case I (OPA ← MAL, CHI ←ONG)



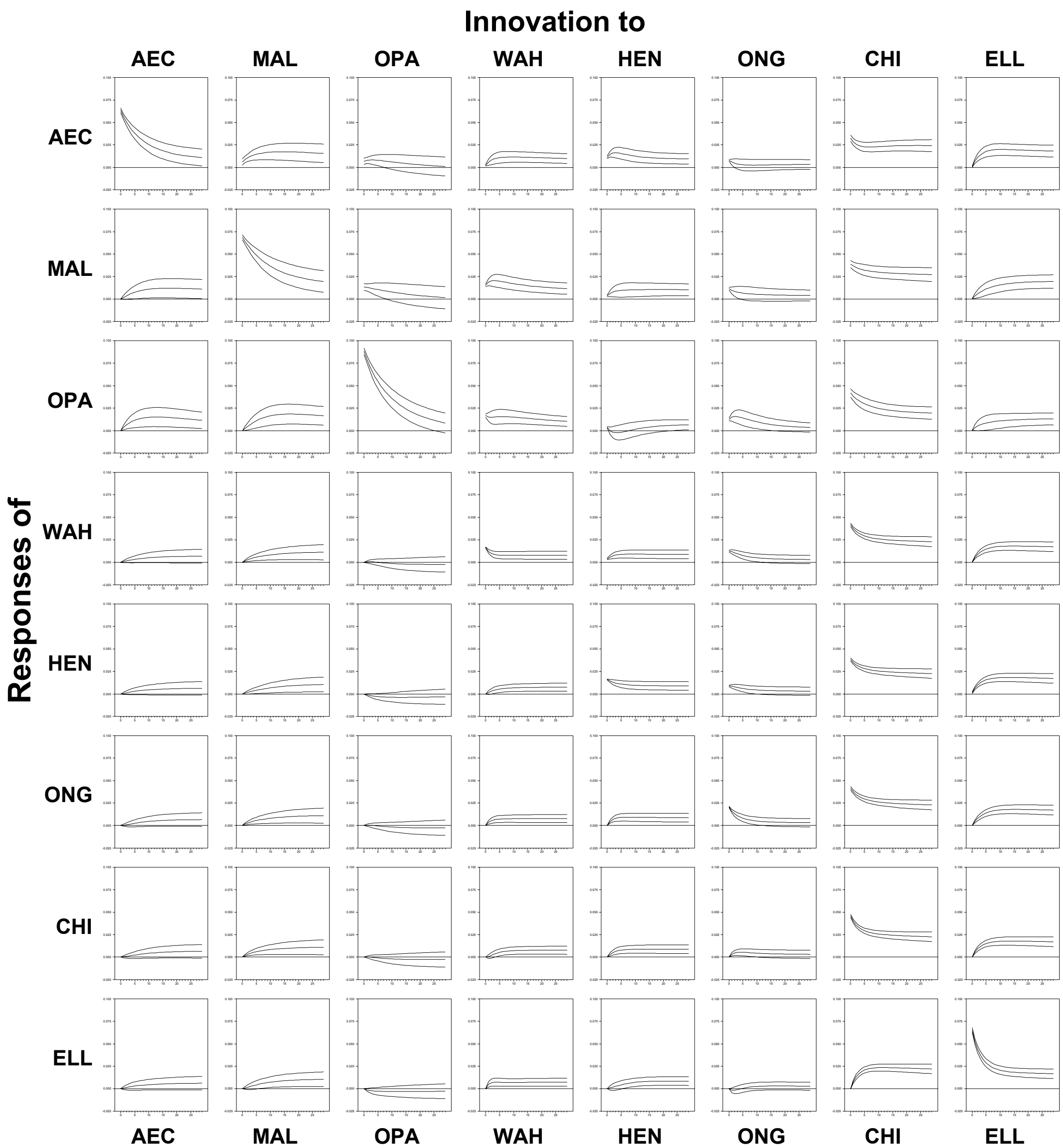
Note: See list of acronyms in Appendix J for definitions of spot markets.

Figure 3.10. Impulse Response Functions from Innovation of VECM of Case II (OPA ← MAL, CHI →ONG)



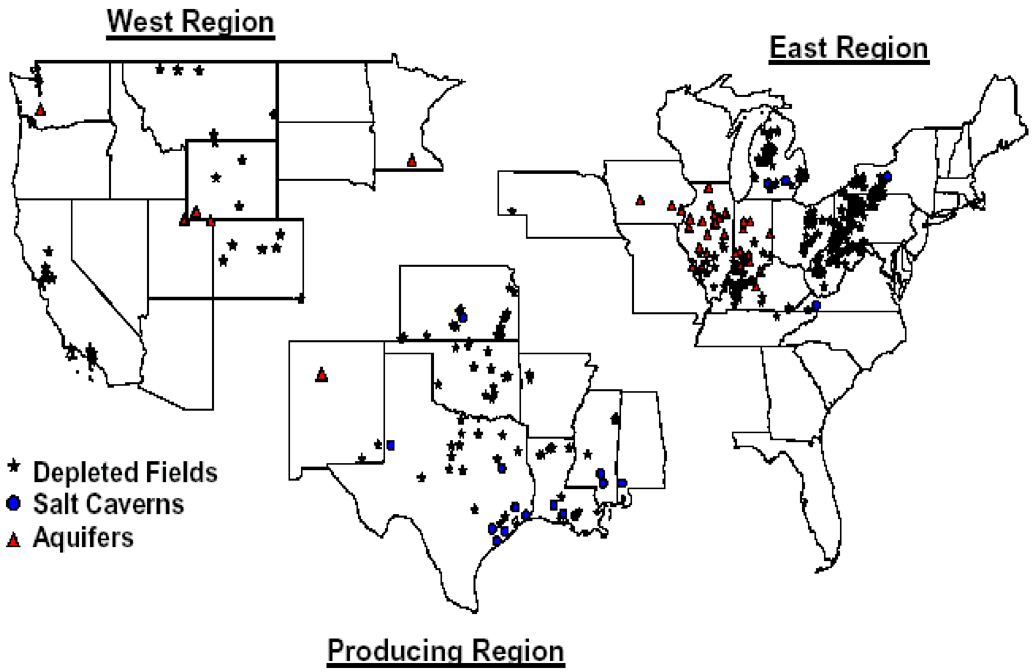
Note: See list of acronyms in Appendix J for definitions of spot markets.

Figure 3.11. Impulse Response Functions from Innovation of VECM of Case III (OPA → MAL, CHI ←ONG)



Note: See list of acronyms in Appendix J for definitions of spot markets.

Figure 3.12. Impulse Response Functions from Innovation of VECM of Case IV (OPA → MAL, CHI →ONG)



Source: U.S. Department of Energy. Energy Information Agency. 2004

Figure 3.13. Underground Natural Gas Storage Facilities in the U.S.

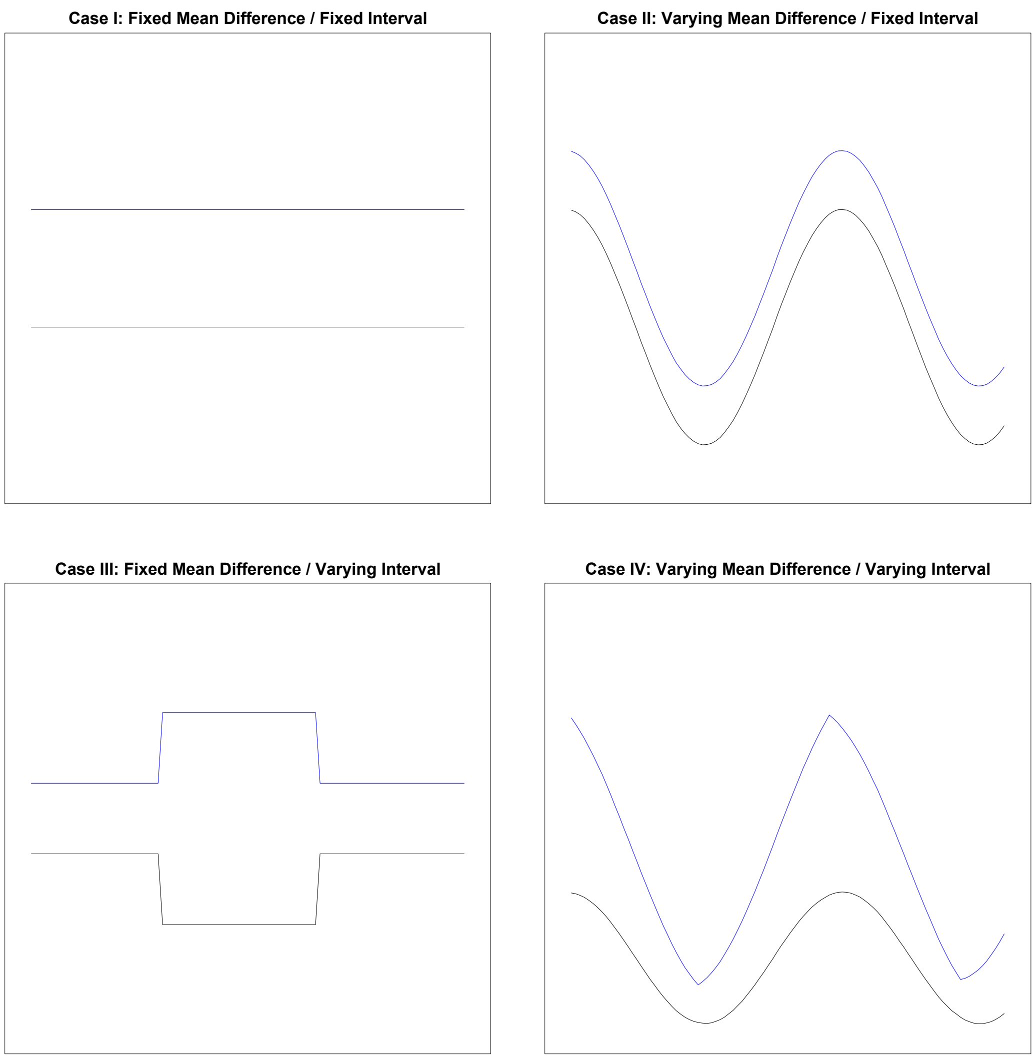
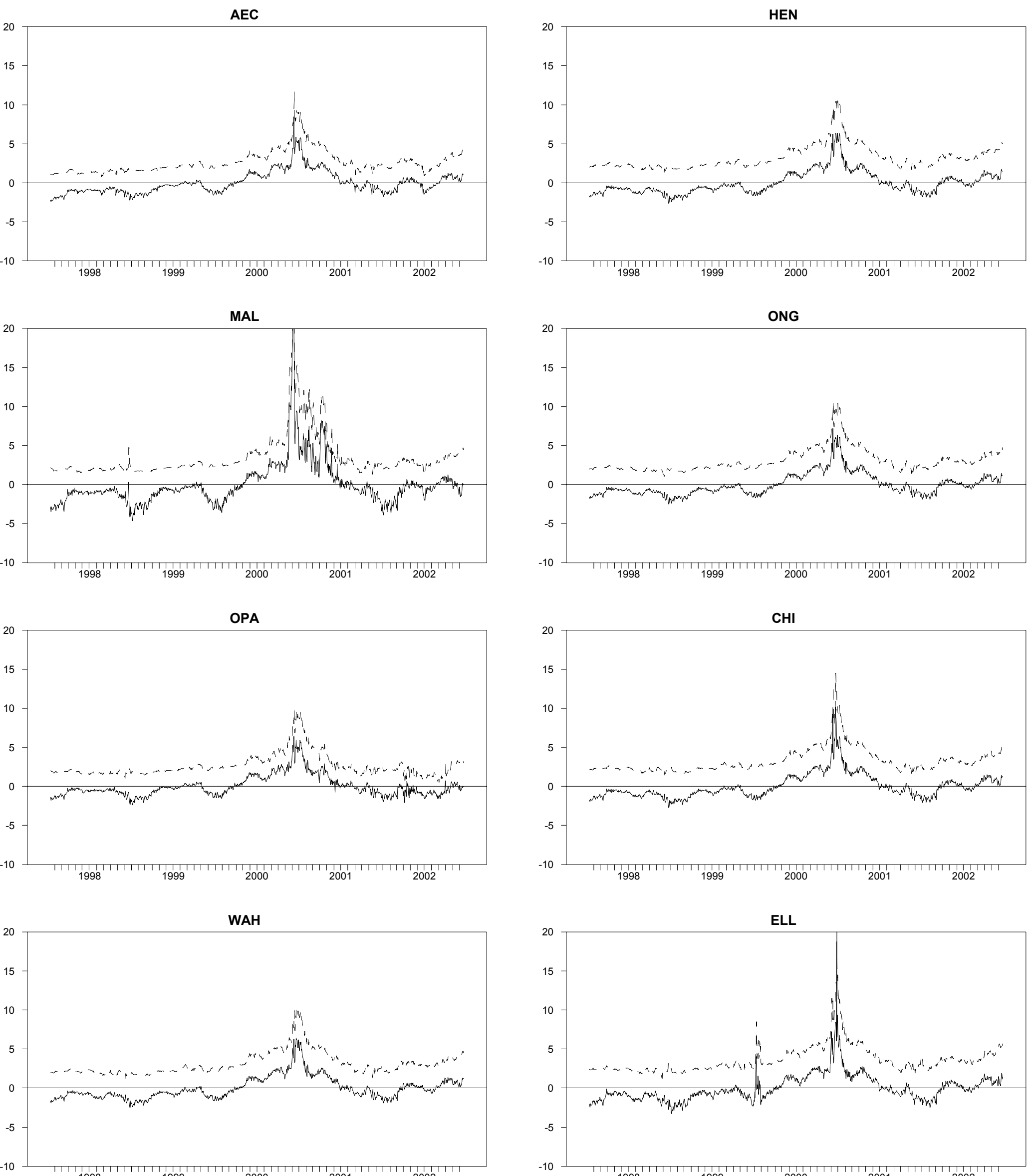
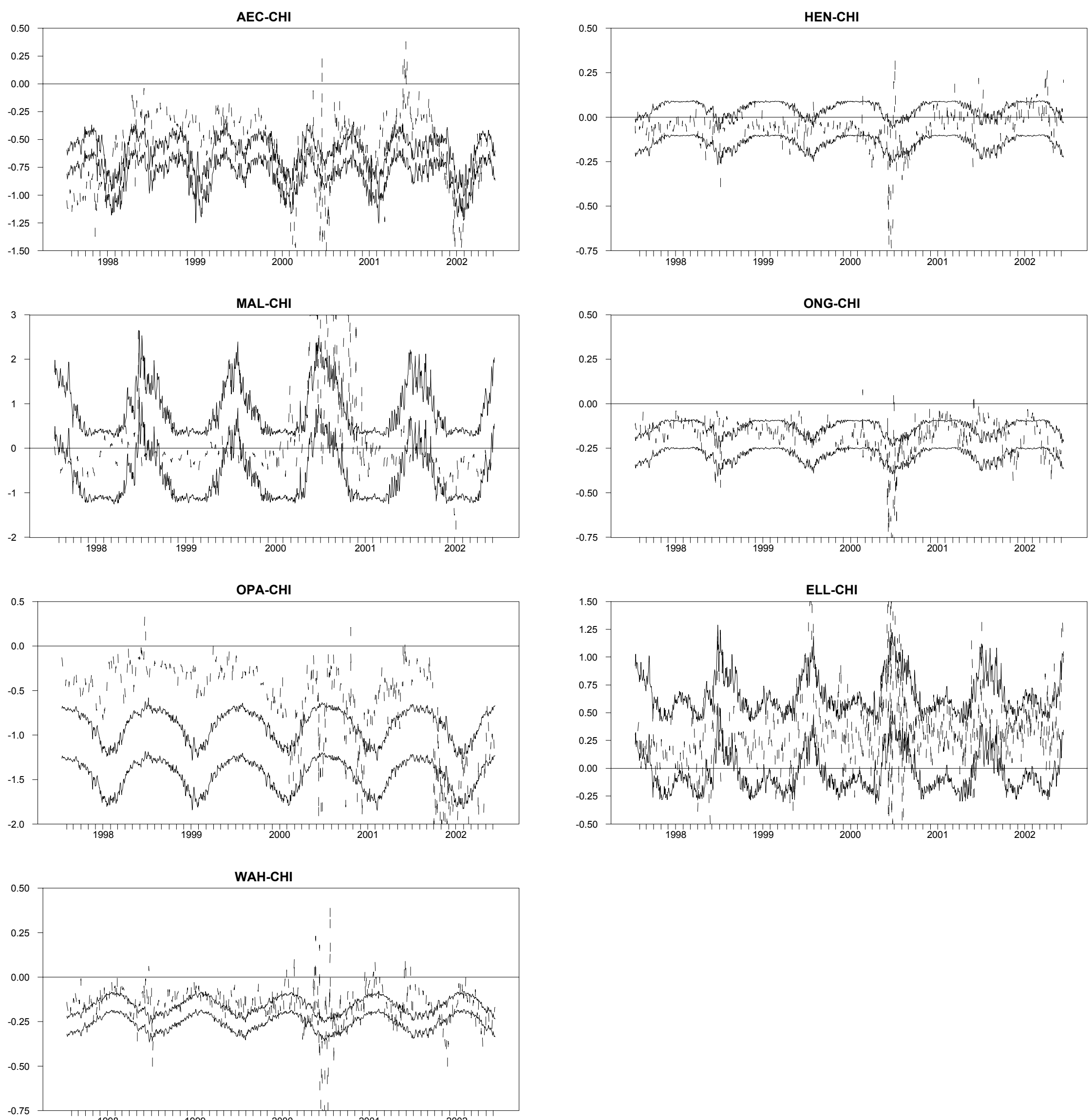


Figure 4.1. Four Alternative Cases of the Deviations in the Neutral Band Associated with the Law of One Price



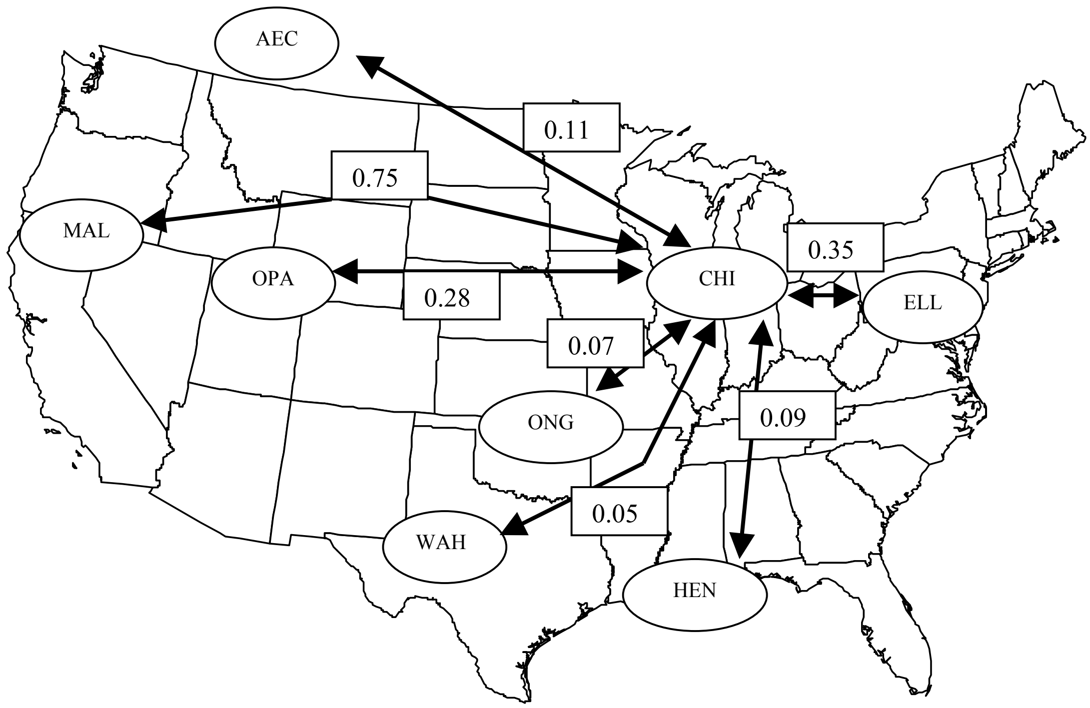
Note: See list of acronyms in Appendix J for definitions of spot markets.

Figure 4.2. Daily Natural Gas Prices (solid lines) and Filtered Natural Gas Prices (dotted lines) for the Eight North American Spot Markets (Jan. 12, 1998 – Dec. 20, 2002)



Note: The vertical scales for each graph are different. See list of acronyms in Appendix J for definitions of spot markets.

Figure 4.3. Time-Varying Upper and Lower Threshold Values (solid lines) and Daily Price Differences (dotted lines) Between the Seven Markets and CHI



Note: See list of acronyms in Appendix J for definitions of spot markets.

Figure 4.4. Estimated Transaction Costs Between the Seven Market Pairs ($/MMBtu)

APPENDIX B

TABLES

Table 2.1. Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and Associated Residual Tests of Non-Stationarity of 11 North American Electricity Spot Markets Using Logarithmic Transformed Data and Robust Estimator

	Dickey-Fuller			Augmented Dickey-Fuller			
Market	Test[1]	Q(15)[2]	Q(30)[3]	Test[4]	K[5]	Q(15)[6]	Q(30)[7]
MIDC	-2.11	228.14(0.00)	335.47(0.00)	-1.49	7	42.64(0.00)	105.17(0.00)
PV	-2.70	220.18(0.00)	388.26(0.00)	-1.92	10	25.29(0.05)	81.83(0.00)
FC	-2.72	176.84(0.00)	276.28(0.00)	-1.69	7	41.82(0.00)	92.33(0.00)
NEPL	-3.41	124.90(0.00)	176.47(0.00)	-2.76	7	18.79(0.22)	50.48(0.01)
PJM	-5.46	175.27(0.00)	218.98(0.00)	-4.42	3	44.20(0.00)	95.16(0.00)
ECAR	-3.33	176.12(0.00)	230.91(0.00)	-3.19	3	29.07(0.02)	94.49(0.00)
MAIN	-2.78	97.27(0.00)	177.33(0.00)	-3.02	2	25.26(0.05)	111.47(0.00)
MAPP	-2.27	68.21(0.00)	119.84(0.00)	-2.27	2	16.37(0.36)	60.68(0.00)
ENT	-2.68	139.69(0.00)	227.05(0.00)	-2.78	2	31.09(0.01)	119.15(0.00)
SPP	-2.66	105.15(0.00)	200.72(0.00)	-2.96	2	33.94(0.00)	125.81(0.00)
ERCOT	-2.29	110.75(0.00)	141.61(0.00)	-1.98	6	29.95(0.01)	55.03(0.00)

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. This column gives DF test statistics for the null hypothesis that price data for each spot market is non-stationary in levels. The DF test 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 from each market (Greene, 2000). The DF test statistics are the t-statistics of the estimated coefficient on the lagged levels variable from the test regression. This t-statistic is not distributed as a standard t-distribution under the null hypothesis. However, the 5% and 10% critical values (-2.89, -2.58) are given in Fuller (1976). The null hypothesis is rejected when the observed t-statistics are less than this critical value.

2. 3. These columns indicate associated Q-statistics with 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom. This Q-statistics is the Lung-Box statistics on the estimated residuals from the test regression. The p-value associated with this Q-statistic is given in parenthesis. The Q statistic is distributed chi-squared with maximum 36 degrees of freedom under the null in this case. The null hypothesis of white noise residuals is rejected when the Q value is large or the p-value is small.

4. 5. ADF column refers to Augmented Dickey-Fuller test. In this test, the null hypothesis is same as DF test, but the regression form is modified from the DF test. K lags of the dependent variable are included in the ADF regression. ADF test statistics are the t-statistics of the estimated coefficient on the lagged level variable. The critical value of the t-statistic is same as in DF test. After the ADF regression is run using different K values ranging from 1 to 10, the lag number of K is determined by minimizing the Schwarz loss metric on values of K. The ADF test statistics are reported using the value at K where Schwarz loss metric is minimized.

6. 7. These columns indicate associated Q-statistics of 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom.

Table 2.2. Trace Tests on Number of Cointegrating Vectors in 11 North American Electricity Spot Markets[1]

r	With constant			Without constant		
	T*	C(5%)*	Decision	T	C(5%)	Decision
= 0	1579.172	289.71	R	1653.087	276.37	R
≤ 1	1253.638	244.56	R	1327.525	232.6	R
≤ 2	1001.966	203.34	R	1072.926	192.3	R
≤ 3	769.368	165.73	R	824.698	155.75	R
≤ 4	571.560	132	R	616.754	123.04	R
≤ 5	437.896	101.84	R	478.710	93.92	R
≤ 6	317.521	75.74	R	356.715	68.68	R
≤ 7	210.694	53.42	R	237.558	47.21	R
≤ 8	134.962	34.8	R	152.069	29.38	R
≤ 9	67.265	19.99	R	77.259	15.34	R
≤ 10	10.196	9.13	R	10.721	3.841	R

1. The trace test with and without constant indicates the number of cointegrating vectors (r). The critical values (c) at $\alpha = 5\%$ are given in Hansen and Juselius (1995). The decision column indicates whether the null hypothesis is rejected (R) or failed to reject (F). The null hypothesis is the number of cointegrating vectors, given in the r column. As explained in Johansen and Juselius (1992), to find the number of cointegrating vectors, we start at left-top decision column in the column of "with constant", and go to right-top decision column in the column of "without constant," and move to next row sequentially until we find the F (fail to reject). In this table, however, there is no F (fail to reject). This means there are 11 cointgrating vectors from 11 series, implying 11 stationary series.

Table 2.3. Schwarz Loss, Akaike Loss, and Hannan and Quinn's Phi Measures on One to Twelve Lags for the VAR on Daily Peak Electricity Prices from 11 North American Electricity Spot Markets[1]

Number of lag	Schwarz	Akaike	HQ
1	-45.9441*	-46.8185	-46.3345
2	-45.7893	-47.3506	-46.4864*
3	-45.4028	-47.6511	-46.4066
4	-44.9488	-47.8840	-46.2593
5	-44.5054	-47.1276	-46.1227
6	-44.0595	-47.3687	-45.9835
7	-43.6095	-47.6056	-45.8402
8	-43.1151	-47.7981	-45.6525
9	-42.5933	-47.9633	-45.4375
10	-42.1030	-48.1600*	-45.2539
11	-41.6590	-47.4030	-45.1167
12	-41.1648	-47.5958	-44.9292

1. Schwarz loss, Akaike loss and Hannan and Quinn's phi metric are

$$SL = \ln(\det(\sum)) + ((k)*11)*\ln(T)/T,$$
$$Akaike = \ln(\det(\sum)) + 2*((k)*11)/T, \text{ and}$$
$$HQ = \ln(\det(\sum)) + ((k)*11)*(2.01)*\ln(\ln(T))/T,$$

where $\sum$ is the residual covariance matrix estimated with k regressors in each equation, T is the total number of observations in each series, $\det(\sum)$ is the determinant of residual covariance matrix, and ln is natural logarithm. * denotes minimum value for the particular loss function.

Table 2.4. p-values Associated with F-tests for the Null Hypothesis the Coefficients on One and Two Lagged Prices on Each of 11 North American Electricity Spot Markets Are Equal to Zero in the Two-Lag VAR[1]

	One-lag and Two-lag Market Price										
Market	MIDC	PV	FC	NEPL	PJM	ECAR	MAIN	MAPP	ENT	SPP	ERCOT
MIDC	0.00	0.81	0.58	0.00	0.03	0.45	0.98	0.92	0.69	0.52	0.77
PV	0.02	0.00	0.63	0.00	0.00	0.38	0.75	0.81	0.71	0.60	0.42
FC	0.02	0.00	0.00	0.00	0.01	0.63	0.91	0.36	0.39	0.92	0.55
NEPL	0.46	0.09	0.03	0.00	0.00	0.39	0.92	0.00	0.03	0.56	0.00
PJM	0.41	0.62	0.37	0.06	0.00	0.00	0.89	0.00	0.00	0.75	0.04
ECAR	0.83	0.84	0.73	0.83	0.09	0.00	0.99	0.00	0.00	0.11	0.01
MAIN	0.43	0.96	0.96	0.80	0.49	0.21	0.01	0.00	0.00	0.10	0.01
MAPP	0.57	0.46	0.42	0.58	0.80	0.10	0.15	0.00	0.47	0.32	0.47
ENT	0.89	0.62	0.52	0.77	0.35	0.83	0.22	0.00	0.00	0.07	0.00
SPP	0.91	0.84	0.63	0.52	0.34	0.73	0.25	0.00	0.00	0.00	0.00
ERCOT	0.67	0.34	0.39	0.09	0.10	0.98	0.31	0.00	0.80	0.63	0.00

Note: See list of acronyms in Appendix J for definitions of spot markets.

Table 2.5. Estimated Coefficients and Associated p-Values on Lagged Cooling Degree-Days (CDD) and Heating Degree-Days (HDD) and in the Two-Lag VAR Equations

	Estimated coefficients and p-value of Lagged HDD and CDD			
Market	HDD_{t-1}	p-value	CDD_{t-1}	p-value
MIDC	0.000	0.992	-0.002	0.332
PV	0.001	0.515	0.002	0.199
FC	0.001	0.188	0.002	0.219
NEPL	0.000	0.754	0.004	0.079
PJM	0.001	0.220	0.010	0.000
ECAR	0.002	0.079	0.012	0.000
MAIN	0.002	0.067	0.007	0.018
MAPP	0.003	0.002	0.009	0.000
ENT	0.001	0.192	0.009	0.001
SPP	0.001	0.109	0.010	0.000
ERCOT	0.000	0.702	0.002	0.211

Note: See list of acronyms in Appendix J for definitions of spot markets.

Table 2.6. Forecast Error Variance Decompositions from Two-Lag VAR

Step	MIDC	PV	FC	NEPL	PJM	ECAR	MAIN	MAPP	ENT	SPP	ERCOT
MIDC											
0	40.24	59.76	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	39.80	58.79	0.03	0.01	0.01	0.25	0.01	0.00	0.12	0.89	0.09
30	26.26	37.21	1.70	5.27	11.70	0.42	0.08	1.50	1.12	10.24	4.50
PV											
0	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	0.42	96.94	0.11	0.19	0.14	0.42	0.01	0.02	0.18	1.24	0.34
30	5.93	48.85	2.59	7.78	16.31	0.42	0.22	1.45	1.85	9.77	4.83
FC											
0	0.00	15.40	84.61	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	0.77	52.10	45.32	0.36	0.24	0.25	0.02	0.17	0.00	0.65	0.12
30	6.12	40.95	7.58	8.63	17.25	0.46	0.20	1.68	2.12	9.95	5.07
NEPL											
0	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	0.07	0.28	1.00	89.88	0.01	0.82	1.54	2.31	0.02	4.06	0.03
30	0.89	3.26	4.90	58.10	12.39	2.78	2.92	4.26	2.91	2.63	4.98
PJM											
0	0.00	0.00	0.00	3.81	95.61	0.21	0.00	0.00	0.29	0.00	0.08
1	0.06	0.14	0.26	5.81	73.78	3.83	2.97	3.97	1.37	7.57	0.23
30	0.59	2.78	1.33	6.33	36.65	3.09	7.24	8.02	1.49	29.54	2.95
ECAR											
0	0.00	0.00	0.00	0.23	0.00	35.94	0.00	0.00	50.54	0.00	13.28
1	0.02	0.10	0.11	0.12	1.96	22.10	2.41	4.73	38.93	21.48	8.03
30	0.54	2.32	0.21	0.35	2.90	9.71	2.95	4.98	17.03	53.44	5.58
MAIN											
0	0.00	0.00	0.00	0.07	0.00	10.91	28.19	0.00	48.19	0.00	12.66
1	0.03	0.01	0.01	0.07	0.27	9.39	23.71	2.73	44.07	9.33	10.39
30	0.32	1.38	0.12	0.49	0.99	6.20	16.51	3.79	27.73	34.86	7.61
MAPP											
0	0.00	0.00	0.00	0.00	0.00	0.68	11.45	25.96	5.59	54.84	1.47
1	0.01	0.02	0.00	0.13	0.09	0.58	8.05	27.13	4.31	58.76	0.93
30	0.70	2.66	0.33	0.50	0.84	0.35	7.54	19.06	2.22	64.81	1.00
ENT											
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	79.19	0.00	20.81
1	0.01	0.24	0.24	0.26	0.90	0.41	0.04	4.91	53.48	25.67	13.84
30	0.91	4.51	0.28	1.01	2.27	2.06	0.25	4.27	19.87	54.58	10.00
SPP											
0	0.00	0.00	0.00	0.02	0.00	2.65	0.00	0.00	6.85	88.68	1.80
1	0.00	0.02	0.05	0.19	0.37	1.74	0.47	2.98	5.45	87.50	1.23
30	0.51	2.40	0.12	0.79	1.04	0.99	1.34	3.81	3.93	82.63	2.45
ERCOT											
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00
1	0.02	0.29	0.04	0.19	1.18	0.13	0.06	1.92	0.68	8.73	86.78
30	1.65	8.40	0.45	2.09	3.02	3.17	0.23	3.22	3.51	29.52	44.73

Note: See list of acronyms in Appendix J for definitions of spot markets.

Table 3.1. Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and Associated Residual Tests of Non-Stationarity of Eight North American Natural Gas Spot Markets Using Logarithmic Transformed Data and Robust Estimator

	Dickey-Fuller			Augmented Dickey-Fuller			
Market	Test[1]	Q(15)[2]	Q(30)[3]	Test[4]	K[5]	Q(15)[6]	Q(30)[7]
AEC	--2.09	139.14(0.00)	160.47(0.00)	-2.19	2	15.46(0.21)	31.72(0.38)
MAL	-1.37	122.02(0.00)	192.72(0.00)	-2.26	10	7.07(0.95)	38.00(0.14)
OPA	--2.90	324.42(0.00)	370.05(0.00)	-2.59	5	20.49(0.15)	58.69(0.00)
WAH	-1.73	100.50(0.00)	162.49(0.00)	-1.80	2	39.04(0.00)	87.86(0.00)
HEN	-1.30	53.49(0.00)	80.55(0.00)	-1.69	2	16.79(0.33)	44.79(0.04)
ONG	-1.49	58.46(0.00)	106.22(0.00)	-1.85	2	33.38(0.00)	78.21(0.00)
CHI	-1.26	48.24(0.00)	80.90(0.00)	-1.87	2	26.68(0.03)	59.25(0.00)
ELL	-1.45	47.85(0.00)	63.51(0.00)	-2.71	1	31.35(0.01)	49.61(0.01)

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. This column gives DF test statistics for the null hypothesis that price data for each spot market is non-stationary in levels. The DF test 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 from each market (Greene, 2000). The DF test statistics are the t-statistics of the estimated coefficient on the lagged levels variable from the test regression. This t-statistic is not distributed as a standard t-distribution under the null hypothesis. However, the 5% and 10% critical values (-2.89, -2.58) are given in Fuller (1976). The null hypothesis is rejected when the observed t-statistics are less than this critical value.

2. 3. These columns indicate associated Q-statistics with 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom. This Q-statistics is the Lung-Box statistics on the estimated residuals from the test regression. The p-value associated with this Q-statistic is given in parenthesis. The Q statistic is distributed chi-squared with maximum 36 degrees of freedom under the null in this case. The null hypothesis of white noise residuals is rejected when the Q value is large or the p-value is small.

4. 5. ADF column refers to Augmented Dickey-Fuller test. In this test, the null hypothesis is same as DF test, but the regression form is modified from the DF test. K lags of the dependent variable are included in the ADF regression. ADF test statistics are the t-statistics of the estimated coefficient on the lagged level variable. The critical value of the t-statistic is same as in DF test. After the ADF regression is run using different K values ranging from 1 to 10, the lag number of K is determined by minimizing the Schwarz loss metric on values of K. The ADF test statistics are reported using the value at K where Schwarz loss metric is minimized.

6. 7. These columns indicate associated Q-statistics of 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom

Table 3.2. Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) of Non-Stationarity of the First Difference of Eight North American Natural Gas Spot Prices Using Non-Logarithmic Transformed Data and Robust Estimator

	Dickey-Fuller		Augmented Dickey-Fuller		
Market	Test[1]	Decision[2]	Test[3]	K[4]	Decision[5]
AEC	-6.1038	R	-5.7797	1	R
MAL	-3.1118	R	-2.5761	5	F
OPA	-14.9862	R	-6.5351	5	R
WAH	-10.6298	R	-10.3608	1	R
HEN	-11.1039	R	-3.3094	9	R
ONG	-9.1133	R	-4.1920	5	R
CHI	-6.4245	R	-2.2950	10	F
ELL	-7.0447	R	-6.1085	1	R

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. This column gives DF test statistics for the null hypothesis that the first difference of price data for each spot market is non-stationary. The DF test statistics are the t-statistics of the estimated coefficient on the lagged levels variable from the test regression. This t-statistic is not distributed as a standard t-distribution under the null hypothesis. However, the 5% and 10% critical values (-2.89, -2.58) are given in Fuller (1976). The null hypothesis is rejected when the observed t-statistics are less than this critical value.

2. 5. The decision column indicates whether the null hypothesis is rejected (R) or failed to reject (F) at 5% significance level.

3. 4. ADF column refers to Augmented Dickey-Fuller test. In this test, the null hypothesis is same as DF test, but the regression form is modified from the DF test. K lags of the dependent variable are included in the ADF regression. ADF test statistics are the t-statistics of the estimated coefficient on the lagged level variable. The critical value of the t-statistic is same as in DF test. After the ADF regression is run using different K values ranging from 1 to 10, the lag number of K is determined by minimizing the Schwarz loss metric on values of K. The ADF test statistics are reported using the value at K where Schwarz loss metric is minimized.

Table 3.3. Schwarz Loss, Akaike Loss, and Hannan and Quinn's Phi Measures on One to Fifteen Lags on Logarithmic Levels VAR on Daily Natural Gas Prices from Eight North American Spot Markets[1]

Number of lags	Schwarz	Akaike	HQ
1	-51.0268*	-51.5264	-51.2499
2	-51.0050	-51.8679	-51.3903
3	-50.9215	-52.1478	-51.4690*
4	-50.7247	-52.3144	-51.4345
5	-50.5574	-52.5104	-51.4294
6	-50.3498	-52.6662	-51.3840
7	-50.1472	-52.8269	-51.3437
8	-49.9588	-53.0019	-51.3175
9	-49.7294	-53.1358*	-51.2503
10	-49.4535	-52.2233	-51.1367
11	-49.2240	-52.3571	-51.0694
12	-48.9670	-52.4635	-50.9747
13	-48.7264	-52.5863	-50.8963
14	-48.4602	-52.6834	-50.7923
15	-48.1814	-52.7680	-50.6758

1. Schwarz loss, Akaike loss and Hannan and Quinn's phi metric are

$SL = \ln(\det(\sum)) + ((k)*8)*\ln(T)/T$,
$Akaike = \ln(\det(\sum)) + 2*((k)*8)/T$, and
$HQ = \ln(\det(\sum)) + ((k)*8)*(2.01)*\ln(\ln(T))/T$,

where $\sum$ is the residual covariance matrix estimated with k regressors in each equation, T is the total number of observations in each series, $\det(\sum)$ is the determinant of residual covariance matrix, and ln is natural logarithm. The asterisk "*" indicates the minimum values of each information criterion.

Table 3.4. Trace Tests on Number of Cointegrating Vectors in Eight North American Natural Gas Spot Markets[1]

	With constant			Without constant		
r	T*	C(1%)*	Decision	T	C(1%)	Decision
≤ 0	1379.32	177.42	R	1273.50	166.95	R
≤ 1	954.04	142.34	R	865.00	133.04	R
≤ 2	668.31	111.38	R	607.53	102.95	R
≤ 3	438.40	83.93	R	379.07	76.37	R
≤ 4	259.03	60.42	R	204.44	53.91	R
≤ 5	124.81	40.84	R	117.43	34.87	R
≤ 6	47.55	24.74	R	40.46	19.69	R
≤ 7	6.87	12.73	F	5.15	6.64	F
	With constant			Without constant		
r	T*	C(5%)*	Decision	T	C(5%)	Decision
≤ 0	1379.32	165.73	R	1273.50	155.75	R
≤ 1	954.04	132	R	865.00	123.04	R
≤ 2	668.31	101.84	R	607.53	93.92	R
≤ 3	438.40	75.74	R	379.07	68.68	R
≤ 4	259.03	53.42	R	204.44	47.21	R
≤ 5	124.81	34.8	R	117.43	29.38	R
≤ 6	47.55	19.99	R	40.46	15.34	R
≤ 7	6.87	9.13	F	5.15	3.841	F
	With constant			Without constant		
r	T*	C(10%)*	Decision	T	C(10%)	Decision
≤ 0	1379.32	159.74	R	1273.50	149.99	R
≤ 1	954.04	126.71	R	865.00	117.73	R
≤ 2	668.31	97.17	R	607.53	89.37	R
≤ 3	438.40	71.66	R	379.07	64.72	R
≤ 4	259.03	49.92	R	204.44	43.84	R
≤ 5	124.81	31.88	R	117.43	26.70	R
≤ 6	47.55	17.79	R	40.46	13.31	R
≤ 7	6.87	7.50	F	5.15	2.76	F

1. The trace test with and without constant indicates the number of cointegrating vectors (r). The critical values (c) at α = 1%,5%, and 10% are given in Hansen and Juselius (1995). The decision column indicates whether the null hypothesis is rejected (R) or failed to reject (F). The null hypothesis is the number of cointegrating vectors, given in the r column. As explained in Johansen and Juselius (1992), to find the number of cointegrating vectors, we start at left-top decision column in the column of "with constant", and go to right-top decision column in the column of "without constant," and move to next row sequentially until we find the F (fail to reject).

Table 3.5. Schwarz Loss and Hannan and Quinn's Phi Metrics on One to Ten Lags and One to Eight Ranks on Logarithmic VECM on Daily Natural Gas Prices from Eight North American Spot Markets[1]

		1-Rank	2-Rank	3-Rank	4-Rank	5-Rank	6-Rank	7-Rank	8-Rank
1-Lag	SL	-50.8174	-50.9283	-51.0279	-51.0968	-51.1087	-51.1240*	-51.1181	-51.1002
	HQ	-50.9025	-51.0535	-51.1881	-51.2870	-51.3240	-51.3593	-51.3684	-51.3605
2-Lags	SL	-50.9306	-50.9718	-51.0066	-51.0462	-51.0448	-51.0396	-51.0281	-51.0106
	HQ	-51.2161	-51.2973	51.36728	-51.4368	-51.4605	-51.4754	-51.4788	-51.4714
3-Lags	SL	-50.8556	-50.8783	-50.9001	-50.9254	-50.9176	-50.8992	-50.8780	-50.8602
	HQ	-51.3417	-51.4045	-51.4614	-51.5168	-51.5340	-51.5357*	-51.5295	-51.5217
4-Lags	SL	-50.5958	-50.6317	-50.6518	-50.6571	-50.6459	-50.6230	-50.5983	-50.5802
	HQ	-51.2828	-51.3588	-51.4140	-51.4494	-51.4633	-51.4604	-51.4508	-51.4427
5-Lags	SL	-50.3851	-50.4143	-50.4275	-50.4212	-50.4016	-50.3796	-50.3539	-50.3355
	HQ	-51.2732	-51.3426	-51.3909	-51.4147	-51.4202	-51.4183	-51.4076	-51.3992
6-Lags	SL	-50.1437	-50.1504	-50.1511	-50.1467	-50.1323	-50.1070	-50.0845	-50.0662
	HQ	-51.2332	-51.2801	-51.3159	-51.3416	-51.3524	-51.3472	-51.3396	-51.3314
7-Lags	SL	-49.8847	-49.8833	-49.8839	-49.8744	-49.8535	-49.8263	-49.8026	-49.7836
	HQ	-51.1759	-51.2146	-51.2503	-51.2710	-51.2752	-51.2681	-51.2595	-51.2505
8-Lags	SL	-49.6520	-49.6364	-49.6284	-49.6167	-49.5977	-49.5690	-49.5434	-49.5243
	HQ	-51.1449	-51.1696	-51.1968	-51.2152	-51.2214	-51.2128	-51.2022	-51.1935
9-Lags	SL	-49.3470	-49.3417	-49.3205	-49.3047	-49.2835	-49.2541	-49.2292	-49.2099
	HQ	-51.0420	-51.0770	-51.0910	-51.1054	-51.1094	-51.1001	-51.0903	-51.0810
10-Lags	SL	-49.0151	-49.0006	-48.9811	-48.9558	-48.9321	-48.9016	-48.8769	-48.8577
	HQ	-50.9125	-50.9382	-50.9540	-50.9589	-50.9604	-50.9500	-50.9404	-50.9312

1. The asterisk "*" indicates minimum values of Schwartz loss and Hannan and Quinn's Phi metrics.

Table 3.6. Tests of Exclusion of Each of Eight Natural Gas Spot Market in North America, HDD, and CDD from the Cointegration Space[1] and Tests on Weak Exogeneity on Eight Natural Gas Spot Market in North America[2]

Market	Tests of Exclusion		Tests on Weak Exogeneity	
	Chi-Squared Test	p-value	Chi-Squared Test	p-value
AEC	68.43	.00	67.47	.00
MAL	58.61	.00	26.24	.00
OPA	76.25	.00	35.68	.00
WAH	318.76	.00	79.86	.00
HEN	212.06	.00	65.25	.00
ONG	343.41	.00	100.02	.00
CHI	193.90	.00	101.39	.00
ELL	169.45	.00	131.47	.00
HDD	24.00	.00	-	-
CDD	44.00	.00	-	-

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. The null hypothesis of this test is that a market is not in the cointegration space. Under the null hypothesis, the test statistic is distributed Chi-squared with six degrees of freedom.

2. The null hypothesis of this test is that a market is weakly exogenous with respect to perturbations in the cointegrating vectors. Under the null hypothesis, the test statistic is distributed Chi-squared with six degrees of freedom.

Table 3.7. Forecast Error Variance Decompositions from the VECM for Case I (OPA ← MAL, CHI ←ONG)

Step	AEC	MAL	OPA	WAH	HEN	ONG	CHI	ELL
				AEC				
0	74.97	1.11	0.67	0.13	2.42	19.63	1.05	0.02
1	73.12	1.93	0.90	0.48	3.43	18.53	1.10	0.52
30	33.90	21.07	2.83	6.35	4.41	19.37	1.96	10.11
				MAL				
0	0.00	72.17	0.00	3.53	0.18	23.37	0.73	0.00
1	0.05	71.24	0.02	4.68	0.37	22.70	0.84	0.08
30	8.22	50.64	3.04	9.04	1.78	20.55	1.49	5.25
				OPA				
0	0.00	3.17	75.01	2.77	0.15	18.33	0.57	0.00
1	0.13	3.95	74.03	2.74	0.08	18.63	0.38	0.06
30	11.30	28.98	39.96	6.92	0.08	11.58	0.14	1.04
				WAH				
0	0.00	0.00	0.00	12.71	0.67	83.99	2.62	0.01
1	0.02	0.07	0.00	10.69	1.29	84.77	2.43	0.73
30	2.37	4.01	2.08	4.86	6.99	53.32	4.37	22.01
				HEN				
0	0.00	0.00	0.00	0.00	14.16	80.83	4.87	0.14
1	0.01	0.01	0.05	0.07	13.92	79.97	4.60	1.37
30	1.23	1.35	5.14	2.31	9.69	50.82	5.13	24.33
				ONG				
0	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00
1	0.00	0.07	0.00	0.33	0.53	98.39	0.14	0.54
30	1.97	3.48	2.52	3.43	7.07	55.48	4.09	21.96
				CHI				
0	0.00	0.00	0.00	0.00	0.00	79.98	20.02	0.00
1	0.00	0.08	0.01	0.01	0.27	81.49	17.32	0.83
30	1.72	3.26	3.02	2.89	6.79	52.77	6.67	22.89
				ELL				
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00
1	0.01	0.00	0.05	0.31	0.03	0.59	0.38	98.64
30	1.19	1.44	4.40	2.45	5.41	30.37	4.77	49.68

Note: See list of acronyms in Appendix J for definitions of spot markets.

Table 3.8. Forecast Error Variance Decompositions from the VECM for Case II (OPA ← MAL, CHI →ONG)

Step	AEC	MAL	OPA	WAH	HEN	ONG	CHI	ELL
				AEC				
0	74.97	1.11	0.67	0.13	2.42	1.14	19.54	0.02
1	73.12	1.93	0.90	0.48	3.43	0.98	18.65	0.52
30	33.90	21.07	2.83	6.35	4.41	0.54	20.89	10.11
				MAL				
0	0.00	72.17	0.00	3.54	0.19	1.96	22.14	0.00
1	0.05	71.24	0.02	4.68	0.37	1.73	21.82	0.08
30	8.22	50.64	3.04	9.04	1.78	0.91	21.14	5.25
				OPA				
0	0.00	3.17	75.01	2.77	0.15	1.54	17.36	0.00
1	0.13	3.95	74.03	2.74	0.08	1.99	17.02	0.06
30	11.30	28.98	39.96	6.92	0.09	1.57	10.14	1.04
				WAH				
0	0.00	0.00	0.00	12.71	0.67	7.04	79.57	0.01
1	0.02	0.07	0.00	10.69	1.29	7.43	79.77	0.73
30	2.37	4.01	2.08	4.86	6.99	2.37	55.32	22.01
				HEN				
0	0.00	0.00	0.00	0.00	14.16	4.20	81.50	0.14
1	0.01	0.01	0.05	0.07	13.92	4.34	80.23	1.37
30	1.23	1.35	5.14	2.31	9.69	1.52	54.43	24.33
				ONG				
0	0.00	0.00	0.00	0.00	0.00	20.02	79.98	0.00
1	0.00	0.07	0.00	0.33	0.53	17.87	80.66	0.54
30	1.97	3.48	2.52	3.43	7.07	3.60	55.97	21.96
				CHI				
0	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00
1	0.00	0.08	0.01	0.01	0.27	0.25	98.56	0.83
30	1.72	3.26	3.02	2.89	6.79	1.04	58.40	22.89
				ELL				
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00
1	0.01	0.00	0.05	0.31	0.03	0.05	0.93	98.64
30	1.19	1.44	4.40	2.45	5.41	0.38	35.05	49.68

Note: See list of acronyms in Appendix J for definitions of spot markets.

Table 3.9. Forecast Error Variance Decompositions from the VECM for Case III (OPA → MAL, CHI ←ONG)

Step	AEC	MAL	OPA	WAH	HEN	ONG	CHI	ELL
				AEC				
0	74.97	0.75	1.03	0.13	2.42	19.63	1.05	0.02
1	73.12	1.37	1.46	0.48	3.43	18.53	1.10	0.52
30	33.90	17.32	6.58	6.35	4.41	19.37	1.96	10.11
				MAL				
0	0.00	69.25	2.93	3.53	0.18	23.37	0.73	0.00
1	0.05	67.99	3.28	4.68	0.37	22.70	0.84	0.08
30	8.22	44.50	9.17	9.04	1.78	20.55	1.49	5.25
				OPA				
0	0.00	0.00	78.18	2.77	0.15	18.33	0.57	0.00
1	0.13	0.09	77.89	2.74	0.08	18.63	0.38	0.06
30	11.30	17.73	51.21	6.92	0.08	11.58	0.14	1.04
				WAH				
0	0.00	0.00	0.00	12.71	0.67	83.99	2.62	0.01
1	0.02	0.07	0.00	10.69	1.29	84.77	2.43	0.73
30	2.37	5.05	1.04	4.86	6.99	53.32	4.37	22.01
				HEN				
0	0.00	0.00	0.00	0.00	14.16	80.83	4.87	0.14
1	0.01	0.02	0.04	0.07	13.92	79.97	4.60	1.37
30	1.23	2.55	3.95	2.31	9.69	50.82	5.13	24.33
				ONG				
0	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00
1	0.00	0.07	0.00	0.33	0.53	98.39	0.14	0.54
30	1.97	4.60	1.40	3.43	7.07	55.48	4.09	21.96
				CHI				
0	0.00	0.00	0.00	0.00	0.00	79.98	20.02	0.00
1	0.00	0.08	0.00	0.01	0.27	81.49	17.32	0.83
30	1.72	4.47	1.80	2.89	6.79	52.77	6.67	22.89
				ELL				
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00
1	0.01	0.00	0.04	0.31	0.03	0.59	0.38	98.64
30	1.19	2.55	3.30	2.45	5.41	30.37	4.77	49.68

Note: See list of acronyms in Appendix J for definitions of spot markets.

Table 3.10. Forecast Error Variance Decompositions from the VECM for Case IV (OPA → MAL, CHI →ONG)

Step	AEC	MAL	OPA	WAH	HEN	ONG	CHI	ELL
				AEC				
0	74.97	0.75	1.03	0.13	2.42	1.14	19.54	0.02
1	73.12	1.37	1.46	0.48	3.43	0.98	18.65	0.52
30	33.90	17.32	6.58	6.35	4.41	0.54	20.89	10.11
				MAL				
0	0.00	69.25	2.93	3.54	0.19	1.96	22.14	0.00
1	0.05	67.99	3.28	4.68	0.37	1.73	21.82	0.08
30	8.22	44.50	9.17	9.04	1.78	0.91	21.14	5.25
				OPA				
0	0.00	0.00	78.18	2.77	0.15	1.54	17.36	0.00
1	0.13	0.09	77.89	2.74	0.08	1.99	17.02	0.06
30	11.30	17.73	51.21	6.92	0.09	1.57	10.14	1.04
				WAH				
0	0.00	0.00	0.00	12.71	0.67	7.04	79.57	0.01
1	0.02	0.07	0.00	10.69	1.29	7.43	79.77	0.73
30	2.37	5.05	1.04	4.86	6.99	2.37	55.32	22.01
				HEN				
0	0.00	0.00	0.00	0.00	14.16	4.20	81.50	0.14
1	0.01	0.02	0.04	0.07	13.92	4.34	80.23	1.37
30	1.23	2.55	3.95	2.31	9.69	1.52	54.43	24.33
				ONG				
0	0.00	0.00	0.00	0.00	0.00	20.02	79.98	0.00
1	0.00	0.07	0.00	0.33	0.53	17.87	80.66	0.54
30	1.97	4.60	1.40	3.43	7.07	3.60	55.97	21.96
				CHI				
0	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00
1	0.00	0.08	0.00	0.01	0.27	0.25	98.56	0.83
30	1.72	4.47	1.80	2.89	6.79	1.04	58.40	22.89
				ELL				
0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00
1	0.01	0.00	0.04	0.31	0.03	0.05	0.93	98.64
30	1.19	2.55	3.30	2.45	5.41	0.38	35.05	49.68

Note: See list of acronyms in Appendix J for definitions of spot markets.

Table 4.1. Estimated Coefficients and Associated p-values (in parentheses) for the Filtering Regressions

Market	Constant	HDD_{t-1}	CDD_{t-1}
AEC	2.0931	0.0479	0.0158
	(0.000)	(0.000)	(0.145)
MAL	1.8918	0.1273	0.0723
	(0.000)	(0.000)	(0.003)
OPA	1.7839	0.0660	0.0307
	(0.000)	(0.000)	(0.004)
WAH	2.2335	0.0575	0.0570
	(0.000)	(0.000)	(0.000)
HEN	2.3713	0.0562	0.0529
	(0.000)	(0.000)	(0.000)
ONG	2.2460	0.0563	0.0528
	(0.000)	(0.000)	(0.000)
CHI	2.3829	0.0608	0.0538
	(0.000)	(0.000)	(0.000)
ELL	2.3499	0.0870	0.0764
	(0.000)	(0.000)	(0.000)

Note: See list of acronyms in Appendix J for definitions of spot markets.

Table 4.2. Schwarz Loss Metrics on One to Five Lags and One and Two Cointegrating Rank on VECM for Daily Natural Gas Prices from Seven Pairs of North American Spot Markets Using Filtered Data[1]

Market Pairs		1-Lag	2-Lags	3-Lags	4-Lags	5-Lags
AEC-CHI	1 Rank	-6.071	-6.081	-6.122	-6.174	-6.218*
	2 Rank	-6.006	-6.076	-6.115	-6.167	-6.211
MAL-CHI	1 Rank	-2.420	-2.448	-2.430	-2.492	-2.495*
	2 Rank	-2.416	-2.443	-2.425	-2.486	-2.490
OPA-CHI	1 Rank	-5.627	-5.677	-5.700	-5.735*	-5.724
	2 Rank	-5.624	-5.672	-5.694	-5.729	-5.718
WAH-CHI	1 Rank	-6.880	-6.922	-7.028	-7.071*	-7.056
	2 Rank	-6.875	-6.915	-7.020	-7.063	-7.048
HEN-CHI	1 Rank	-7.004	-7.031	-7.158	-7.162*	-7.151
	2 Rank	-6.999	-7.023	-7.150	-7.154	-7.144
ONG-CHI	1 Rank	-6.611	-6.630	-6.791	-6.809*	-6.799
	2 Rank	-6.606	-6.623	-6.783	-6.801	-6.791
ELL-CHI	1 Rank	-3.815	-3.827	-3.857	-3.889*	-3.869
	2 Rank	-3.811	-3.822	-3.844	-3.882	-3.863

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. The asterisk "*" indicates minimum values of Schwartz loss metrics.
   Schwarz loss is
   $SL = \ln(\det(\sum)) + ((k)*8)*\ln(T)/T$,
   where $\sum$ is the residual covariance matrix estimated with k regressors in each equation, T is the total number of observations in each series, $\det(\sum)$ is the determinant of residual covariance matrix, and ln is natural logarithm.

Table 4.3. Bootstrap p-values for Testing VECM Versus Three-Regime TVECM and Numbers of Observations in Each Regime Using Filtered Data[1]

Market Pairs	Bootstrap P-values	No. of Obs in Regime 1	No. of Obs in Regime 2	No. of Obs in Regime 3
AEC-CHI	0.00	289	263	731
MAL-CHI	0.03	226	929	128
OPA-CHI	0.00	135	145	1,003
WAH-CHI	0.00	135	459	689
HEN-CHI	0.00	163	993	127
ONG-CHI	0.00	135	751	397
ELL-CHI	0.00	137	1,019	127

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. The bootstrap p-values indicate the percentage of bootstrapped LR statistics, which exceed the observed LR statistics (Hansen, 1999). Values smaller than the critical value (5% or 10%) imply that three-regime TVECM is significantly better than VECM (at 5% level or 10% level). The VECM and three-regime TVECM are estimated with one known cointegrating vector (-1,1) at four lags. Regime 1 indicates the regime below the lower threshold value. Regime 2 indicates the middle regime defined by the lower and upper threshold values. Regime 3 represents the regime above the upper threshold value.

Table 4.4. Schwarz Loss Metrics on VECM and Three-Regime TVECM at Four Lags Using Filtered Data[1]

Market Pairs	Models	
	VECM[2]	TVECM
AEC-CHI	-5.391	-3.991
MAL-CHI	-1.695	-0.114
OPA-CHI	-4.956	-3.509
WAH-CHI	-6.260	-4.816
HEN-CHI	-6.360	-4.897
ONG-CHI	-5.391	-3.991
ELL-CHI	-1.695	-0.114

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. Schwarz loss is

$$SL = \ln(\det(\Sigma)) + ((k)*8)*\ln(T)/T,$$

where Σ is the residual covariance matrix estimated with k regressors in each equation, T is the total number of observations in each series, $\det(\Sigma)$ is the determinant of residual covariance matrix, and ln is natural logarithm.

2. The VECM and three-regime TVECM are estimated with one known cointegrating vector (-1,1) at four lags.

Table 4.5. Estimated Threshold Values and Recovered Mean Values of Thresholds from Filtered Data and Numbers of Observation in Each Regime in Seven Market Pairs[1]

Market Pairs	$C^{(1)}$	$C^{(2)}$	$C^{(2)}$ - $C^{(1)}$	Average ($C^{(1)}$, $C^{(2)}$)	No. of Obs in Regime 1	No. of Obs in Regime 2	No. of Obs in Regime 3
	Estimated Values Using Filtered Data						
AEC-CHI	-0.1986	0.0167	0.2153	-0.0910	289	263	731
MAL-CHI	-0.8992	0.5923	1.4915	-0.1535	226	929	128
OPA-CHI	-0.7851	-0.2246	0.5605	-0.5049	135	145	1003
WAH-CHI	-0.0931	0.0076	0.1007	-0.0428	135	459	689
HEN-CHI	-0.0787	0.1125	0.1912	0.0169	163	993	127
ONG-CHI	-0.0980	0.0567	0.1547	-0.0207	135	751	397
ELL-CHI	-0.3901	0.3153	0.7054	-0.0374	137	1019	127
	Recovered Mean Values						
AEC-CHI	-0.8075	-0.5922	0.2153	n.a.	n.a.	n.a.	n.a.
MAL-CHI	-0.6290	0.8625	1.4915	n.a.	n.a.	n.a.	n.a.
OPA-CHI	-1.4458	-0.8853	0.5605	n.a.	n.a.	n.a.	n.a.
WAH-CHI	-0.2593	-0.1586	0.1007	n.a.	n.a.	n.a.	n.a.
HEN-CHI	-0.1408	0.0504	0.1912	n.a.	n.a.	n.a.	n.a.
ONG-CHI	-0.2847	-0.1300	0.1547	n.a.	n.a.	n.a.	n.a.
ELL-CHI	-0.0460	0.6594	0.7054	n.a.	n.a.	n.a.	n.a.

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. $C^{(1)}$ indicates estimated lower threshold value and $C^{(2)}$ indicates estimated upper threshold value. The last three columns in estimated values using filtered data represent the number of observations in each regime. The threshold values in recovered mean values represent the average values of each time-varying thresholds. Regime 1 indicates the regime below the lower threshold value. Regime 2 indicates the middle regime defined by the lower and upper threshold values. Regime 3 represents the regime above the upper threshold value. "n.a." indicates not applicable.

APPENDIX C

NON-STATIONARY TESTS OF ELECTRICITY PRICES

Table C1. Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and Associated Residual Tests of Non-Stationarity of 11 North American Electricity Spot Markets Using Non-Logarithmic Transformed Data and Robust Estimator

	Dickey-Fuller			Augmented Dickey-Fuller			
Market	Test[1]	Q(15)[2]	Q(30)[3]	Test[4]	K[5]	Q(15)[6]	Q(30)[7]
MIDC	-1.44	160.84(0.00)	257.46(0.00)	-1.55	6	16.91(0.32)	28.40(0.54)
PV	-2.07	294.63(0.00)	366.55(0.00)	-2.03	4	87.87(0.00)	142.35(0.00)
FC	-2.13	246.59(0.00)	302.37(0.00)	-1.52	7	30.25(0.01)	85.31(0.00)
NEPL	-2.31	69.45(0.00)	118.83(0.00)	-2.17	4	34.33(0.00)	67.82(0.00)
PJM	-3.69	194.34(0.00)	246.18(0.00)	-2.65	4	46.75(0.00)	126.39(0.00)
ECAR	-1.79	136.78(0.00)	321.81(0.00)	-2.20	2	47.19(0.00)	196.12(0.00)
MAIN	-1.75	142.42(0.00)	235.35(0.00)	-2.74	1	29.48(0.01)	106.15(0.00)
MAPP	-2.12	99.76(0.00)	102.52(0.00)	-3.02	2	11.40(0.72)	14.43(0.99)
ENT	-2.51	91.08(0.00)	174.49(0.00)	-2.92	2	16.70(0.34)	105.30(0.00)
SPP	-1.76	78.33(0.00)	129.62(0.00)	-1.86	4	15.60(0.41)	70.37(0.00)
ERCOT	-1.81	150.93(0.00)	177.75(0.00)	-1.53	6	30.82(0.01)	58.41(0.00)

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. This column gives DF test statistics for the null hypothesis that price data for each spot market is non-stationary in levels. The DF test 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 from each market (Greene, 2000). The DF test statistics are the t-statistics of the estimated coefficient on the lagged levels variable from the test regression. This t-statistic is not distributed as a standard t-distribution under the null hypothesis. However, the 5% and 10% critical values (-2.89, -2.58) are given in Fuller (1976). The null hypothesis is rejected when the observed t-statistics are less than this critical value.

2. 3. These columns indicate associated Q-statistics with 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom. This Q-statistics is the Lung-Box statistics on the estimated residuals from the test regression. The p-value associated with this Q-statistic is given in parenthesis. The Q statistic is distributed chi-squared with maximum 36 degrees of freedom under the null in this case. The null hypothesis of white noise residuals is rejected when the Q value is large or the p-value is small.

4. 5. ADF column refers to Augmented Dickey-Fuller test. In this test, the null hypothesis is same as DF test, but the regression form is modified from the DF test. K lags of the dependent variable are included in the ADF regression. ADF test statistics are the t-statistics of the estimated coefficient on the lagged level variable. The critical value of the t-statistic is same as in DF test. After the ADF regression is run using different K values ranging from 1 to 10, the lag number of K is determined by minimizing the Schwarz loss metric on values of K. The ADF test statistics are reported using the value at K where Schwarz loss metric is minimized.

6. 7. These columns indicate associated Q-statistics of 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom.

Table C2. Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and Associated Residual Tests of Non-Stationarity of 11 North American Electricity Spot Markets Using Logarithmic Transformed Data Without Using Robust Estimator

	Dickey-Fuller			Augmented Dickey-Fuller			
Market	Test[1]	Q(15)[2]	Q(30)[3]	ADF[4]	K[5]	Q(15)[6]	Q(30)[7]
MIDC	-3.74	228.14(0.00)	335.47(0.00)	-2.19	7	42.64(0.00)	105.17(0.00)
PV	-3.90	220.18(0.00)	388.26(0.00)	-2.44	10	25.29(0.05)	81.83(0.00)
FC	-3.94	176.84(0.00)	276.28(0.00)	-2.23	7	41.82(0.00)	92.33(0.00)
NEPL	-7.74	124.90(0.00)	176.47(0.00)	-4.00	7	18.79(0.22)	50.48(0.01)
PJM	-9.80	175.27(0.00)	218.98(0.00)	-7.78	3	44.20(0.00)	95.16(0.00)
ECAR	-9.77	176.12(0.00)	230.91(0.00)	-8.23	3	29.07(0.02)	94.49(0.00)
MAIN	-10.43	97.27(0.00)	177.33(0.00)	-9.55	2	25.26(0.05)	111.47(0.00)
MAPP	-8.68	68.21(0.00)	119.84(0.00)	-7.95	2	16.37(0.36)	60.68(0.00)
ENT	-8.23	139.69(0.00)	227.05(0.00)	-7.52	2	31.09(0.01)	119.15(0.00)
SPP	-8.49	105.15(0.00)	200.72(0.00)	-7.97	2	33.94(0.00)	125.81(0.00)
ERCOT	-5.41	110.75(0.00)	141.61(0.00)	-2.23	7	29.95(0.01)	55.03(0.00)

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. This column gives DF test statistics for the null hypothesis that price data for each spot market is non-stationary in levels. The DF test 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 from each market (Greene, 2000). The DF test statistics are the t-statistics of the estimated coefficient on the lagged levels variable from the test regression. This t-statistic is not distributed as a standard t-distribution under the null hypothesis. However, the 5% and 10% critical values (-2.89, -2.58) are given in Fuller (1976). The null hypothesis is rejected when the observed t-statistics are less than this critical value.

2. 3. These columns indicate associated Q-statistics with 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom. This Q-statistics is the Lung-Box statistics on the estimated residuals from the test regression. The p-value associated with this Q-statistic is given in parenthesis. The Q statistic is distributed chi-squared with maximum 36 degrees of freedom under the null in this case. The null hypothesis of white noise residuals is rejected when the Q value is large or the p-value is small.

4. 5. ADF column refers to Augmented Dickey-Fuller test. In this test, the null hypothesis is same as DF test, but the regression form is modified from the DF test. K lags of the dependent variable are included in the ADF regression. ADF test statistics are the t-statistics of the estimated coefficient on the lagged level variable. The critical value of the t-statistic is same as in DF test. After the ADF regression is run using different K values ranging from 1 to 10, the lag number of K is determined by minimizing the Schwarz loss metric on values of K. The ADF test statistics are reported using the value at K where Schwarz loss metric is minimized.

6. 7. These columns indicate associated Q-statistics of 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom.

Table C3. Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and Associated Residual Tests of Non-Stationarity of 11 North American Electricity Spot Markets Using Non-Logarithmic Transformed Data Without Using Robust Estimator

	Dickey-Fuller			Augmented Dickey-Fuller			
Market	Test[1]	Q(15)[2]	Q(30)[3]	ADF[4]	K[5]	Q(15)[6]	Q(30)[7]
MIDC	-15.35	160.84(0.00)	257.46(0.00)	-5.98	6	16.91(0.32)	28.41(0.55)
PV	-6.38	294.63(0.00)	366.55(0.00)	-3.41	7	45.62(0.00)	100.77(0.00)
FC	-6.47	246.59(0.00)	302.37(0.00)	-3.36	7	30.25(0.01)	85.31(0.00)
NEPL	-12.39	69.45(0.00)	118.83(0.00)	-8.41	4	34.33(0.00)	67.83(0.00)
PJM	-13.07	194.34(0.00)	246.18(0.00)	-10.44	4	46.75(0.00)	126.39(0.00)
ECAR	-16.84	136.78(0.00)	321.81(0.00)	-13.96	2	47.19(0.00)	196.12(0.00)
MAIN	-18.89	142.42(0.00)	235.35(0.00)	-12.74	5	29.48(0.01)	106.15(0.00)
MAPP	-18.84	99.76(0.00)	102.52(0.00)	-13.71	3	10.37(0.79)	13.44(0.99)
ENT	-18.17	91.08(0.00)	174.49(0.00)	-13.74	2	16.70(0.34)	105.31(0.00)
SPP	-18.63	78.33(0.00)	129.62(0.00)	-13.78	2	15.60(0.41)	70.37(0.00)
ERCOT	-8.75	150.93(0.00)	177.75(0.00)	-6.02	6	30.82(0.01)	58.42(0.00)

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. This column gives DF test statistics for the null hypothesis that price data for each spot market is non-stationary in levels. The DF test 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 from each market (Greene, 2000). The DF test statistics are the t-statistics of the estimated coefficient on the lagged levels variable from the test regression. This t-statistic is not distributed as a standard t-distribution under the null hypothesis. However, the 5% and 10% critical values (-2.89, -2.58) are given in Fuller (1976). The null hypothesis is rejected when the observed t-statistics are less than this critical value.

2. 3. These columns indicate associated Q-statistics with 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom. This Q-statistics is the Lung-Box statistics on the estimated residuals from the test regression. The p-value associated with this Q-statistic is given in parenthesis. The Q statistic is distributed chi-squared with maximum 36 degrees of freedom under the null in this case. The null hypothesis of white noise residuals is rejected when the Q value is large or the p-value is small.

4. 5. ADF column refers to Augmented Dickey-Fuller test. In this test, the null hypothesis is same as DF test, but the regression form is modified from the DF test. K lags of the dependent variable are included in the ADF regression. ADF test statistics are the t-statistics of the estimated coefficient on the lagged level variable. The critical value of the t-statistic is same as in DF test. After the ADF regression is run using different K values ranging from 1 to 10, the lag number of K is determined by minimizing the Schwarz loss metric on values of K. The ADF test statistics are reported using the value at K where Schwarz loss metric is minimized.

6. 7. These columns indicate associated Q-statistics of 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom.

APPENDIX D

DEFINITION OF EQUIVALENCE CLASS

Chickering (2003) provides a definition of equivalence class. When two directed acyclic graphs (DAGs), *G* and *G*'are equivalent, it is said that these two DAGs are in same equivalence class. To define equivalence classes of DAGs, equivalent DAGs must be defined. To define equivalent DAGs, the concept of distributionally equivalent and independence equivalent must be defined first. Two DAGs are *distributionally equivalent* if two corresponding Bayesian networks (a graphical model for probabilistic relationships among a set of variables; Heckerman, 1996) have the same probability distribution (Chickering, 2003, p. 510). Two DAGs are *independence equivalent* if the independence constraints in the two DAGs are identical (Chickering, 2003, p. 510). When two DAGs are both distributionally and independence equivalent, it is said that those two DAGs are equivalent (Chickering, 2003, p. 510). Consider the following DAGs examples suggested by Verma and Pearl (1991):

(D.D.1) (D.D.2)

$$
\begin{tikzcd}
 & A \arrow[dl] \arrow[dr] & \\
B \arrow[dr] & & C \arrow[dl] \\
 & D \arrow[d] & \\
 & E &
\end{tikzcd}
\qquad
\begin{tikzcd}
 & A \arrow[dr] & \\
B \arrow[ur] \arrow[dr] & & C \arrow[dl] \\
 & D \arrow[d] & \\
 & E. &
\end{tikzcd}
$$

The two DAGs, (D.D.1) and (D.D.2) are in an equivalence class (Verma and Pearl, 1991). Following the definition suggested by Chickering (2003), two DAGs have the same probability distribution:

for DAG (D.D.1), $Pr(A, B, C, D, E) = Pr(A)\ Pr(B|A)\ Pr(C|A)\ Pr(D|B,C)\ Pr(E|D)$,

for DAG (D.D.2), $Pr(A, B, C, D, E) = Pr(B)\ Pr(A|B)\ Pr(C|A)\ Pr(D|B,C)\ Pr(E|D)$,

where Pr denotes probability, $Pr(B|A) = Pr(B \cap A) / Pr(A)$, and $\cap$ indicates the set operator of intersection.

Here, for (D.D.1), because $Pr(A)\ Pr(B \cap A) / Pr(A) = Pr(B \cap A)$, $Pr(A, B, C, D, E) = Pr(B \cap A)\ Pr(C|A)\ Pr(D|B,C)\ Pr(E|D)$. For (D.D.2), $Pr(A, B, C, D, E)$ is equal to $Pr(A \cap B)\ Pr(A|B)\ Pr(C|A)\ Pr(D|B,C)\ Pr(E|D)$ because $Pr(B)\ Pr(A \cap B) / Pr(B) = Pr(A \cap B)$. As a result, both joint probability distributions are the same.

In addition, the two DAGs have the same independence constraints. For two DAGs to be equivalent, all independence constraints that hold in DAG (D.D.1) must hold in DAG (D.D.2), and vice versa. For example, the independence constraints such as $B \perp C \mid A$ (The symbol "$\perp$" indicates independence and "|" denotes "conditioning on" or "given". So, this formula indicates that B and C are conditional independent given A), $B \perp E \mid D$, and $C \perp E \mid D$ hold in two DAGs by the Markov condition assumption. Consequently, the DAGs (D.D.1) and (D.D.2) are in an equivalent class.

Chickering (2003) cites Theorem 1 of Verma and Pearl (1991) to characterize the equivalence class: Theorem 1 (Verma and Pearl, 1991): *Two DAGs are equivalent if and only if they have the same skeletons and the same v-structure.*

Here, the skeleton of any DAG is the undirected graph ignoring the directionality of every edge. For example, the v-structure in DAG *G* is an ordered triple of nodes (A, B, C) such that *G* contains the directed edges A → B and B ← C, and A and C are not adjacent in *G* (Chickering, 2003, p. 511). Consider the same examples used above. It is straightforward to show the two DAGs (D.D.1) and (D.D.2) have the same skeletons and the same v-structure (B → D ← C).

The v-structure, however, is not defined when a DAG has one edge as in the following two DAGs examples:

$$\begin{array}{ccc} & \text{(D.D.4)} & \\ & A & \\ \swarrow & & \\ B & & C \end{array} \qquad \begin{array}{ccc} & \text{(D.D.5)} & \\ & A & \\ \nearrow & & \\ B & & C. \end{array}$$

DAGs (D.D.4) and (D.D.5) are said to be in an equivalence class even though there is no v-structure in DAGs (Chickering, 2003). Accordingly, Theorem 1 of Verma and Pearl (1991) should be modified to include the above cases ((D.D.4) and (D.D.5)) as follows: Theorem: *Two DAGs are equivalent if and only if they have the same skeletons and the same v-structure or they have the same skeletons when the v-structure is not found in two DAGs.*

APPENDIX E

BAYESIAN SCORING CRITERION

TETRAD IV uses the Bayesian scoring criterion in GES Algorithm for continuous data. The Bayesian scoring criterion for DAG G measures the relative log posterior probability of the hypothesis G^h that the independence constraints in G are the same as the independence constraints in the true structure (Chickering, 2003; Heckerman, 1996).

The Bayesian Information Criterion approximation from Schwarz is expressed as follows (Chickering, 2003; Heckerman, 1996):

(E.1) $$S(G, \mathrm{D}) = \log p(D \mid \hat{\theta}, G^h) - \frac{d}{2} \log m,$$

where $\hat{\theta}$ denotes the maximum-likelihood estimate of the unknown parameters (θ : *uncertain variable* in Bayesian statistics and *random variable* in classical statistics), d denotes the number of free parameters (not equal to zero) of graph G, and m is the number of observations in data, D. For continuous variables, the Gaussian distribution is assumed for the posterior probability distribution (Chickering, 2003; Heckerman, 1996). The S function considers the trade off between fit (the first term of right hand side) and parsimony (the second term of right hand side).

APPENDIX F

NON-STATIONARY TESTS OF NATURAL GAS PRICES

Table F1. Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and Associated Residual Tests of Non-Stationarity of Eight North American Natural Gas Spot Markets Using Non-Logarithmic Transformed Data and Robust Estimator

	Dickey-Fuller			Augmented Dickey-Fuller			
Market	Test[1]	Q(15)[2]	Q(30)[3]	Test[4]	K[5]	Q(15)[6]	Q(30)[7]
AEC	-0.75	136.24(0.00)	186.65(0.00)	-0.66	2	53.94(0.00)	108.67(0.00)
MAL	-0.69	69.75(0.00)	80.61(0.00)	-0.59	6	13.40(0.57)	26.63(0.64)
OPA	-1.27	185.97(0.00)	267.59(0.00)	-0.90	6	35.35(0.00)	89.33(0.00)
WAH	-0.82	145.82(0.00)	242.42(0.00)	-0.69	2	103.60(0.00)	190.10(0.00)
HEN	-0.73	134.94(0.00)	244.63(0.00)	-0.96	10	24.57(0.06)	81.91(0.00)
ONG	-0.77	233.87(0.00)	383.34(0.00)	-0.62	6	63.12(0.00)	123.07(0.00)
CHI	-0.75	288.25(0.00)	356.56(0.00)	-0.53	7	107.46(0.00)	149.04(0.00)
ELL	-0.83	336.96(0.00)	362.48(0.00)	-0.62	2	37.01(0.00)	55.39(0.00)

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. This column gives DF test statistics for the null hypothesis that price data for each spot market is non-stationary in levels. The DF test 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 from each market (Greene, 2000). The DF test statistics are the t-statistics of the estimated coefficient on the lagged levels variable from the test regression. This t-statistic is not distributed as a standard t-distribution under the null hypothesis. However, the 5% and 10% critical values (-2.89, -2.58) are given in Fuller (1976). The null hypothesis is rejected when the observed t-statistics are less than this critical value.

2. 3. These columns indicate associated Q-statistics with 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom. This Q-statistics is the Lung-Box statistics on the estimated residuals from the test regression. The p-value associated with this Q-statistic is given in parenthesis. The Q statistic is distributed chi-squared with maximum 36 degrees of freedom under the null in this case. The null hypothesis of white noise residuals is rejected when the Q value is large or the p-value is small.

4. 5. ADF column refers to Augmented Dickey-Fuller test. In this test, the null hypothesis is same as DF test, but the regression form is modified from the DF test. K lags of the dependent variable are included in the ADF regression. ADF test statistics are the t-statistics of the estimated coefficient on the lagged level variable. The critical value of the t-statistic is same as in DF test. After the ADF regression is run using different K values ranging from 1 to 10, the lag number of K is determined by minimizing the Schwarz loss metric on values of K. The ADF test statistics are reported using the value at K where Schwarz loss metric is minimized.

6. 7. These columns indicate associated Q-statistics of 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom.

Table F2. Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and Associated Residual Tests of Non-Stationarity of Eight North American Natural Gas Spot Markets Using Logarithmic Transformed Data Without Using Robust Estimator

	Dickey-Fuller			Augmented Dickey-Fuller			
Market	Test[1]	Q(15)[2]	Q(30)[3]	Test[4]	K[5]	Q(15)[6]	Q(30)[7]
AEC	-3.10	139.14(0.00)	160.47(0.00)	-2.19	2	15.46(0.21)	31.72(0.38)
MAL	-2.86	122.02(0.00)	192.72(0.00)	-2.26	10	7.07(0.95)	38.00(0.14)
OPA	-4.14	324.42(0.00)	370.05(0.00)	-2.59	5	20.49(0.15)	58.69(0.00)
WAH	-2.19	100.50(0.00)	162.49(0.00)	-1.80	2	39.04(0.00)	87.86(0.00)
HEN	-2.00	53.49(0.00)	80.55(0.00)	-1.69	2	16.79(0.33)	44.79(0.04)
ONG	-2.18	58.46(0.00)	106.22(0.00)	-1.85	2	33.38(0.00)	78.21(0.00)
CHI	-2.21	48.24(0.00)	80.90(0.00)	-1.87	2	26.68(0.03)	59.25(0.00)
ELL	-3.11	47.85(0.00)	63.51(0.00)	-2.71	1	31.35(0.01)	49.61(0.01)

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. This column gives DF test statistics for the null hypothesis that price data for each spot market is non-stationary in levels. The DF test 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 from each market (Greene, 2000). The DF test statistics are the t-statistics of the estimated coefficient on the lagged levels variable from the test regression. This t-statistic is not distributed as a standard t-distribution under the null hypothesis. However, the 5% and 10% critical values (-2.89, -2.58) are given in Fuller (1976). The null hypothesis is rejected when the observed t-statistics are less than this critical value.

2. 3. These columns indicate associated Q-statistics with 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom. This Q-statistics is the Lung-Box statistics on the estimated residuals from the test regression. The p-value associated with this Q-statistic is given in parenthesis. The Q statistic is distributed chi-squared with maximum 36 degrees of freedom under the null in this case. The null hypothesis of white noise residuals is rejected when the Q value is large or the p-value is small.

4. 5. ADF column refers to Augmented Dickey-Fuller test. In this test, the null hypothesis is same as DF test, but the regression form is modified from the DF test. K lags of the dependent variable are included in the ADF regression. ADF test statistics are the t-statistics of the estimated coefficient on the lagged level variable. The critical value of the t-statistic is same as in DF test. After the ADF regression is run using different K values ranging from 1 to 10, the lag number of K is determined by minimizing the Schwarz loss metric on values of K. The ADF test statistics are reported using the value at K where Schwarz loss metric is minimized.

6. 7. These columns indicate associated Q-statistics of 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom.

Table F3. Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and Associated Residual Tests of Non-Stationarity of Eight North American Natural Gas Spot Markets Using Non-Logarithmic Transformed Data without Using Robust Estimator

	Dickey-Fuller			Augmented Dickey-Fuller			
Market	Test[1]	Q(15)[2]	Q(30)[3]	Test[4]	K[5]	Q(15)[6]	Q(30)[7]
AEC	-2.76	136.24(0.00)	186.65(0.00)	-1.96	2	53.94(0.00)	108.67(0.00)
MAL	-6.43	69.75(0.00)	80.61(0.00)	-3.93	6	13.40(0.57)	26.63(0.64)
OPA	-2.84	185.97(0.00)	267.59(0.00)	-1.92	6	35.35(0.00)	89.33(0.00)
WAH	-2.19	145.82(0.00)	242.42(0.00)	-1.77	2	103.60(0.00)	190.10(0.00)
HEN	-1.98	134.94(0.00)	244.63(0.00)	-2.26	10	24.57(0.06)	81.91(0.00)
ONG	-2.45	233.87(0.00)	383.34(0.00)	-1.72	6	63.12(0.00)	123.07(0.00)
CHI	-3.08	288.25(0.00)	356.56(0.00)	-1.71	7	107.46(0.00)	149.04(0.00)
ELL	-5.78	336.96(0.00)	362.48(0.00)	-2.74	2	37.01(0.00)	55.39(0.00)

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. This column gives DF test statistics for the null hypothesis that price data for each spot market is non-stationary in levels. The DF test 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 from each market (Greene, 2000). The DF test statistics are the t-statistics of the estimated coefficient on the lagged levels variable from the test regression. This t-statistic is not distributed as a standard t-distribution under the null hypothesis. However, the 5% and 10% critical values (-2.89, -2.58) are given in Fuller (1976). The null hypothesis is rejected when the observed t-statistics are less than this critical value.

2. 3. These columns indicate associated Q-statistics with 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom. This Q-statistics is the Lung-Box statistics on the estimated residuals from the test regression. The p-value associated with this Q-statistic is given in parenthesis. The Q statistic is distributed chi-squared with maximum 36 degrees of freedom under the null in this case. The null hypothesis of white noise residuals is rejected when the Q value is large or the p-value is small.

4. 5. ADF column refers to Augmented Dickey-Fuller test. In this test, the null hypothesis is same as DF test, but the regression form is modified from the DF test. K lags of the dependent variable are included in the ADF regression. ADF test statistics are the t-statistics of the estimated coefficient on the lagged level variable. The critical value of the t-statistic is same as in DF test. After the ADF regression is run using different K values ranging from 1 to 10, the lag number of K is determined by minimizing the Schwarz loss metric on values of K. The ADF test statistics are reported using the value at K where Schwarz loss metric is minimized.

6. 7. These columns indicate associated Q-statistics of 15 degrees of freedom and the associated Q-statistics of 30 degrees of freedom.

APPENDIX G

ESTIMATION RESULTS OF VECM

Table G1. Estimated Elements of β Matrix[1]

$$\beta = \begin{array}{r} \text{AEC} \\ \text{MAL} \\ \text{OPA} \\ \text{WAH} \\ \text{HEN} \\ \text{ONG} \\ \text{CHI} \\ \text{ELL} \\ \text{HDD} \\ \text{CDD} \\ \text{CONT} \end{array} \begin{pmatrix} 0.917 & 2.029 & -0.536 & -0.584 & -6.638 & -0.949 \\ 0.130 & -2.091 & -0.120 & -0.126 & 1.045 & 5.786 \\ 0.004 & -2.179 & -1.139 & 0.318 & 2.190 & -3.162 \\ -42.292 & 9.546 & 26.715 & -3.343 & -1.237 & -3.109 \\ -4.235 & -41.837 & -14.348 & -10.611 & -3.042 & -1.238 \\ 48.212 & 11.437 & 12.635 & -10.814 & 5.635 & -2.567 \\ -5.124 & 24.213 & -27.726 & 17.902 & 2.866 & 4.306 \\ 2.481 & -1.408 & 4.100 & 7.746 & -0.096 & -0.718 \\ -0.003 & 0.027 & -0.039 & -0.034 & -0.022 & -0.001 \\ 0.053 & 0.015 & -0.118 & 0.004 & -0.048 & -0.004 \\ 0.167 & 0.486 & 2.565 & -2.045 & -1.100 & 0.689 \end{pmatrix}$$

Note: See list of acronyms in Appendix J for definitions of spot markets.
1. The values in parenthesis indicate t-values. CONT is the constant.

Table G2. Estimated Elements of α Matrix[1]

$$\alpha = \begin{pmatrix} -0.004 & -0.010 & 0.006 & 0.008 & 0.010 & 0.005 \\ (-1.972) & (-4.697) & (2.714) & (4.176) & (4.871) & (2.656) \\ -0.004 & -0.002 & 0.003 & 0.004 & -0.007 & -0.009 \\ (-1.956) & (-1.024) & (1.120) & (1.795) & (-2.909) & (-4.069) \\ 0.006 & 0.004 & 0.007 & 0.003 & -0.012 & 0.013 \\ (2.047) & (1.566) & (2.419) & (1.065) & (-4.472) & (4.611) \\ 0.005 & -0.007 & 0.000 & 0.007 & -0.005 & 0.002 \\ (3.829) & (-5.052) & (-0.185) & (5.412) & (-3.505) & (1.833) \\ 0.000 & -0.001 & 0.005 & 0.007 & -0.003 & 0.002 \\ (0.299) & (-0.636) & (4.639) & (6.130) & (-2.617) & (1.981) \\ -0.006 & -0.007 & 0.002 & 0.008 & -0.005 & 0.003 \\ (-4.344) & (-5.702) & (1.656) & (5.946) & (-3.769) & (2.095) \\ 0.003 & -0.008 & 0.008 & 0.004 & -0.004 & 0.002 \\ (1.998) & (-6.522) & (6.170) & (3.263) & (-3.346) & (1.857) \\ -0.009 & 0.007 & -0.007 & -0.017 & 0.001 & 0.003 \\ (-4.957) & (4.000) & (-4.065) & (-9.286) & (0.447) & (1.883) \end{pmatrix}$$

Note: See list of acronyms in Appendix J for definitions of spot markets.
1. The values in parenthesis indicate t-values. CONT is the constant.

Table G3. Estimated Elements of Π Matrix[1]

AEC	MAL	OPA	WAH	HEN	ONG	CHI	ELL	HDD	CDD	CONT
-0.102	0.059	0.022	0.168	0.211	-0.283	-0.160	0.087	-0.001	-0.001	-0.016
(-7.045)	(4.672)	(2.346)	(1.619)	(2.260)	(-2.641)	(-1.893)	(4.631)	(-7.639)	(-5.202)	(-2.166)
0.041	-0.058	0.018	0.26	0.069	-0.269	-0.091	0.042	0.000	0.000	-0.003
(2.483)	(-4.012)	(1.751)	(2.211)	(0.653)	(-2.227)	(-0.951)	(1.978)	(-0.973)	(-0.606)	(-0.344)
0.079	0.052	-0.084	-0.054	-0.313	0.275	-0.038	0.051	0.000	0.000	0.037
(4.001)	(2.975)	(-6.598)	(-0.379)	(-2.452)	(1.874)	(-0.325)	(1.964)	(-0.007)	(0.334)	(3.709)
0.015	0.022	-0.001	-0.303	0.192	0.054	-0.054	0.073	0.000	0.000	-0.011
(1.649)	(2.778)	(-0.111)	(-4.586)	(3.248)	(0.788)	(-1.012)	(6.143)	(-3.988)	(2.403)	(-2.312)
0.010	0.010	-0.016	0.096	-0.119	-0.024	-0.041	0.079	0.000	0.000	0.004
(1.182)	(1.404)	(-3.046)	(1.600)	(-2.200)	(-0.387)	(-0.837)	(7.244)	(-5.632)	(-2.859)	(0.938)
0.004	0.024	-0.003	0.194	0.229	-0.441	-0.073	0.063	0.000	0.000	-0.007
(0.438)	(2.978)	(-0.538)	(2.968)	(3.907)	(-6.548)	(-1.372)	(5.295)	(-5.251)	(-2.224)	(-1.633)
0.005	0.025	-0.006	0.007	0.190	0.052	-0.359	0.081	-0.001	-0.001	0.014
(0.539)	(3.203)	(-1.085)	(0.108)	(3.256)	(0.775)	(-6.792)	(6.890)	(-7.437)	(-3.966)	(3.161)
0.012	0.007	-0.022	0.296	0.012	-0.264	0.141	-0.195	0.001	0.000	0.019
(0.903)	(0.643)	(-2.631)	(3.204)	(0.149)	(-2.783)	(1.878)	(-11.67)	(9.366)	(1.503)	(2.942)

Note: See list of acronyms in Appendix J for definitions of spot markets.
1. The values in parenthesis are t-values. CONT is the constant.

APPENDIX H

LAG SEARCH, p-VALUES, AND ESTIMATION OF THRESHOLD VALUES

Table H1. Schwarz Loss Metrics on One to Five Lags and One to Two Rank on VECM on Daily Natural Gas Prices from Seven Pairs of North American Spot Markets Using Filtered and Logarithmic Transformed Data[1]

Market Pairs		1-Lag	2-Lags	3-Lags	4-Lags	5-Lags
AEC-CHI	1 Rank	-11.346	-11.421*	-11.413	-11.394	-11.409
	2 Rank	-11.339	-11.414	-11.406	-11.386	-11.401
MAL-CHI	1 Rank	-11.026	-11.044*	-11.032	-11.020	-11.004
	2 Rank	-11.019	-11.037	-11.023	-11.012	-10.996
OPA-CHI	1 Rank	-10.580	-10.684	-10.701	-10.701	-10.721*
	2 Rank	-10.574	-10.677	-10.693	-10.692	-10.713
WAH-CHI	1 Rank	-13.540	-13.573	-13.573	-13.576*	-13.557
	2 Rank	-13.533	-13.565	-13.565	-13.567	-13.549
HEN-CHI	1 Rank	-13.832	-13.864*	-13.847	-13.840	-13.827
	2 Rank	-13.825	-13.856	-13.839	-13.831	-13.819
ONG-CHI	1 Rank	-13.538	-13.551*	-13.550	-13.537	-13.518
	2 Rank	-13.531	-13.544	-13.541	-13.528	-13.510
ELL-CHI	1 Rank	-11.241	-11.255*	-11.240	-11.221	-11.209
	2 Rank	-11.234	-11.247	-11.232	-11.213	-11.201

Note: See list of acronyms in Appendix J for definitions of spot markets.
1. The asterisk “*” indicates minimum values of Schwartz loss metrics.

Table H2. Schwarz Loss Metrics on One to Five Lags and One to Two Rank on VECM on Daily Natural Gas Prices from Seven Pairs of North American Spot Markets Using Unfiltered and Logarithmic Transformed Data[1]

Market Pairs		1-Lag	2-Lags	3-Lags	4-Lags	5-Lags
AEC-CHI	1 Rank	-11.5980	-11.6589*	-11.6399	-11.6191	-11.6257
	2 Rank	-11.5902	-11.6509	-11.6318	-11.6111	-11.6176
MAL-CHI	1 Rank	-11.2872	-11.2897*	-11.2694	-11.2558	-11.2413
	2 Rank	-11.2794	-11.2811	-11.2608	-11.2473	-11.2331
OPA-CHI	1 Rank	-10.8379	-10.9322	-10.9463	-10.9446	-10.9709*
	2 Rank	-10.8301	-10.9237	-10.9378	-10.9361	-10.9627
WAH-CHI	1 Rank	-13.7808	-13.7929*	-13.7815	-13.7892	-13.7743
	2 Rank	-13.7730	-13.7842	-13.7728	-13.7806	-13.7660
HEN-CHI	1 Rank	-14.0820	-14.0880*	-14.0693	-14.0600	-14.0453
	2 Rank	-14.0740	-14.0792	-14.0605	-14.0514	-14.0368
ONG-CHI	1 Rank	-13.7892*	-13.7833	-13.7734	-13.7592	-13.7412
	2 Rank	-13.7813	-13.7747	-13.7648	-13.7506	-13.7329
ELL-CHI	1 Rank	-11.6067*	-11.6054	-11.5830	-11.5606	-11.5463
	2 Rank	-11.5984	-11.5968	-11.5744	-11.5522	-11.5378

Note: See list of acronyms in Appendix J for definitions of spot markets.
1. The asterisk "*" indicates minimum values of Schwartz loss metrics.

Table H3. Bootstrap p-values For Testing VECM Versus Three-Regime TVECM Using Filtered and Logarithmic Transformed Data and Unfiltered and Logarithmic Transformed Data[1]

Market Pairs	Bootstrap p-value	
	Filtered and Logarithmic Transformed data	Unfiltered and Logarithmic Transformed data
AEC-CHI	0.00	0.00
MAL-CHI	0.00	0.08
OPA-CHI	0.00	0.00
WAH-CHI	0.00	0.00
HEN-CHI	0.00	0.00
ONG-CHI	0.00	0.00
ELL-CHI	0.00	0.00

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. The bootstrap p-values indicate the percentage of bootstrapped LR statistics, which exceed the observed LR statistics (Hansen, 1999). Values smaller than the critical value (5% or 10%) imply that three-regime TVECM is significantly better than VECM (at 5% level or 10% level). The VECM and three-regime TVECM are estimated with one known cointegrating vector (-1,1) at four lags.

Table H4. Schwarz Loss Metrics on VECM and Three-regime TVECM with One to Five Lags Using Filtered and Non-Logarithmic Transformed Data[1]

Market Pairs	1-Lag		2-Lags		3-Lags		4-Lags		5-Lags	
	I[2]	III	I	III	I	III	I	III	I	III
AEC-CHI	-5.754	-5.198	-5.611	-4.735	-5.494	-4.398	-5.391	-3.991	-5.193	-3.546
MAL-CHI	-2.100	-1.427	-1.967	-0.984	-1.795	-0.479	-1.695	-0.114	-1.453	0.360
OPA-CHI	-5.312	-4.757	-5.208	-4.322	-5.077	-3.950	-4.956	-3.509	-4.700	-3.030
WAH-CHI	-6.544	-5.878	-6.426	-5.450	-6.359	-5.158	-6.260	-4.816	-6.005	-4.366
HEN-CHI	-6.679	-6.026	-6.549	-5.586	-6.505	-5.335	-6.360	-4.897	-6.106	-4.444
ONG-CHI	-6.265	-5.610	-6.125	-5.167	-6.103	-4.958	-5.983	-4.577	-5.733	-4.051
ELL-CHI	-3.490	-3.153	-3.351	-2.674	-3.213	-2.319	-3.104	-2.063	-2.838	-1.645

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. Schwarz loss is

$$SL = \ln(\det(\Sigma)) + ((k)*8)*\ln(T)/T,$$

where Σ is the residual covariance matrix estimated with k regressors in each equation, T is the total number of observations in each series, $\det(\Sigma)$ is the determinant of residual covariance matrix, and ln is natural logarithm.

2. I indicates the linear VECM and III represents the three-regime TVECM.

Table H5. Schwarz Loss Metrics on VECM and Three-regime TVECM with One to Five Lags Using Filtered and Logarithmic Transformed Data[1]

Market Pairs	1-Lag		2-Lags		3-Lags		4-Lags		5-Lags	
	I[2]	III	I	III	I	III	I	III	I	III
AEC-CHI	-11.031	-10.494	-10.952	-10.094	-10.790	-9.592	-10.615	-9.094	-10.386	-8.624
MAL-CHI	-10.707	-10.053	-10.569	-9.553	-10.400	-9.047	-10.234	-8.535	-9.972	-8.022
OPA-CHI	-10.268	-9.663	-10.217	-9.240	-10.078	-8.761	-9.923	-8.330	-9.699	-7.818
WAH-CHI	-13.225	-12.572	-13.102	-12.111	-12.945	-11.671	-12.794	-11.193	-12.531	-10.680
HEN-CHI	-13.520	-12.870	-13.397	-12.405	-13.225	-11.890	-13.062	-11.420	-12.805	-10.914
ONG-CHI	-13.225	-12.605	-13.082	-12.094	-12.924	-11.597	-12.757	-11.106	-12.494	-10.597
ELL-CHI	-10.929	-10.279	-10.787	-9.803	-10.617	-9.292	-10.442	-8.787	-10.185	-8.287

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. Schwarz loss is

$$SL = \ln(\det(\sum)) + ((k)*8)*\ln(T)/T,$$

where $\sum$ is the residual covariance matrix estimated with k regressors in each equation, T is the total number of observations in each series, $\det(\sum)$ is the determinant of residual covariance matrix, and ln is natural logarithm.

2. I indicates the linear VECM and III represents the three-regime TVECM.

Table H6. Schwarz Loss Metrics on VECM and Three-regime TVECM with One to Five Lags Using Unfiltered and Logarithmic Transformed Data[1]

Market Pairs	1-Lag		2-Lags		3-Lags		4-Lags		5-Lags	
	I[2]	III	I	III	I	III	I	III	I	III
AEC-CHI	-11.285	-10.779	-11.191	-10.368	-11.016	-9.853	-10.840	-9.349	-10.602	-8.868
MAL-CHI	-10.968	-10.289	-10.814	-9.790	-10.638	-9.278	-10.470	-8.776	-10.210	-8.273
OPA-CHI	-10.526	-9.920	-10.465	-9.477	-10.324	-8.990	-10.167	-8.530	-9.948	-8.049
WAH-CHI	-13.467	-12.804	-13.323	-12.345	-13.155	-11.902	-13.008	-11.430	-12.749	-10.930
HEN-CHI	-13.771	-13.103	-13.621	-12.627	-13.447	-12.167	-13.282	-11.663	-13.023	-11.175
ONG-CHI	-13.476	-12.824	-13.314	-12.322	-13.148	-11.834	-12.978	-11.339	-12.716	-10.814
ELL-CHI	-11.295	-10.664	-11.138	-10.212	-10.960	-9.699	-10.783	-9.203	-10.524	-8.711

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. Schwarz loss is

$$SL = \ln(\det(\Sigma)) + ((k)*8)*\ln(T)/T,$$

where Σ is the residual covariance matrix estimated with k regressors in each equation, T is the total number of observations in each series, $\det(\Sigma)$ is the determinant of residual covariance matrix, and ln is natural logarithm.

2. I indicates the linear VECM and III represents the three-regime TVECM.

Table H7. Estimated Threshold Values and Numbers of Observations in Each Regime in Seven Market Pairs Using Unfiltered and Logarithmic Transformed Data [1]

Market Pairs	$C^{(1)}$	$C^{(2)}$	$C^{(2)}$ - $C^{(1)}$	Average ($C^{(1)}$, $C^{(2)}$)	No. of Obs in Regime 1	No. of Obs in Regime 2	No. of Obs in Regime 3
AEC-CHI	0.6278	0.9051	0.2774	0.7664	151	989	146
MAL-CHI	0.8428	0.9425	0.0997	0.8927	155	477	654
OPA-CHI	0.6140	0.7455	0.1315	0.6798	146	144	996
WAH-CHI	0.9180	0.9692	0.0512	0.9436	157	854	275
HEN-CHI	0.9685	0.9833	0.0148	0.9759	266	365	655
ONG-CHI	0.9355	0.9437	0.0083	0.9396	418	180	688
ELL-CHI	1.0123	1.1923	0.1800	1.1023	172	942	172

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. $C^{(1)}$ indicates estimated lower threshold value and $C^{(2)}$ indicates estimated upper threshold value. The last three columns represent the number of observations in each regime. The logarithmic values of thresholds are converted using exponent. Regime 1 indicates the regime below the lower threshold value. Regime 2 indicates the middle regime defined by the lower and upper threshold values. Regime 3 represents the regime above the upper threshold value.

Table H8. Estimated Threshold Values and Numbers of Observations in Each Regime in Seven Market Pairs Using Filtered and Logarithmic Transformed Data [1]

Market Pairs	$C^{(1)}$	$C^{(2)}$	$C^{(2)}$ - $C^{(1)}$	Average ($C^{(1)}$, $C^{(2)}$)	No. of Obs in Regime 1	No. of Obs in Regime 2	No. of Obs in Regime 3
AEC-CHI	0.8274	1.0978	0.2704	0.9626	159	790	336
MAL-CHI	0.8498	1.1159	0.2661	0.9829	152	900	233
OPA-CHI	0.8479	1.1117	0.2638	0.9798	167	697	421
WAH-CHI	0.9705	1.0233	0.0527	0.9969	145	915	225
HEN-CHI	1.0078	1.0160	0.0082	1.0119	846	157	282
ONG-CHI	1.0005	1.0070	0.0065	1.0038	584	149	552
ELL-CHI	0.9047	0.9706	0.0660	0.9376	152	345	788

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. $C^{(1)}$ indicates estimated lower threshold value and $C^{(2)}$ indicates estimated upper threshold value. The last three columns represent the number of observations in each regime. The logarithmic values of thresholds are converted using exponent. Regime 1 indicates the regime below the lower threshold value. Regime 2 indicates the middle regime defined by the lower and upper threshold values. Regime 3 represents the regime above the upper threshold value.

APPENDIX I

ESTIMATION RESULTS OF TVECM

Table I1. Estimated Coefficients of Three-Regime TVECM for AEC-CHI[1]

	Regime 1		Regime 2		Regime 3	
	Coefficients	t-ratio	Coefficients	t-ratio	Coefficients	t-ratio
$Cont_{CHI}$	0.1045	4.0038	-0.0246	-1.3443	0.0444	1.9304
α_{CHI}	0.3234	6.7941	0.1568	2.2022	0.3924	1.7636
$\Delta P_{t-1,CHI}$	0.0608	1.1922	-0.3449	-3.9016	-0.7109	-7.5387
$\Delta P_{t-2,CHI}$	-0.3946	-6.1656	0.5097	5.1123	0.5402	4.8667
$\Delta P_{t-3,CHI}$	0.2550	4.3147	-0.2984	-4.7290	-0.2504	-2.1907
$\Delta P_{t-4,CHI}$	-0.1441	-1.6659	0.1806	2.1917	0.0205	0.1755
$\Delta P_{t-1,AEC}$	0.3933	7.5635	-0.2650	-3.3001	0.2316	2.2398
$\Delta P_{t-2,AEC}$	-0.4425	-5.3442	0.0659	0.7202	0.1743	1.5209
$\Delta P_{t-3,AEC}$	-0.2141	-4.2312	-0.0845	-1.0917	-0.1967	-1.8013
$\Delta P_{t-4,AEC}$	0.0259	0.3036	-0.1060	-1.2156	0.4801	4.0447
$Cont_{AEC}$	0.0288	1.0435	0.0309	1.4174	-0.0027	-0.1765
α_{AEC}	0.3531	1.3230	0.0687	1.7305	0.0056	0.0944
$\Delta P_{t-1,AEC}$	-1.0647	-9.4138	0.0201	0.4729	-0.0513	-0.6961
$\Delta P_{t-2,AEC}$	1.0476	7.8708	-0.4270	-8.0113	0.1000	1.2034
$\Delta P_{t-3,AEC}$	-0.3958	-2.8848	0.2189	4.4402	-0.0897	-1.7053
$\Delta P_{t-4,AEC}$	0.1703	1.2156	-0.3545	-4.9168	0.0130	0.1892
$\Delta P_{t-1,CHI}$	0.1701	1.3707	0.0484	1.1178	-0.1496	-2.2362
$\Delta P_{t-2,CHI}$	0.2172	1.5796	-0.2292	-3.3217	0.0015	0.0197
$\Delta P_{t-3,CHI}$	-0.2463	-1.8802	0.0069	0.1635	0.0363	0.5628
$\Delta P_{t-4,CHI}$	0.6240	4.3789	-0.2779	-3.9086	-0.0078	-0.1073

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. CONT represents the constant. Regime 1 indicates the regime below the lower threshold value. Regime 2 indicates the middle regime defined by the lower and upper threshold values. Regime 3 represents the regime above the upper threshold value.

Table I2. Estimated Coefficients of Three-Regime TVECM for MAL-CHI[1]

	Regime 1		Regime 2		Regime 3	
	Coefficients	t-ratio	Coefficients	t-ratio	Coefficients	t-ratio
$Cont_{CHI}$	-0.1315	-1.7463	-0.0635	-2.4237	-0.0015	-0.0361
α_{CHI}	-0.1164	-2.0034	0.0243	5.1702	-0.0940	-0.8777
$\Delta P_{t-1,CHI}$	-0.1633	-2.0362	-0.0327	-0.6399	-0.0758	-0.2626
$\Delta P_{t-2,CHI}$	0.1016	2.0862	0.1092	16.8000	-0.0404	-0.2489
$\Delta P_{t-3,CHI}$	-0.3212	-2.4880	-0.1578	-4.1746	-0.1157	-0.3817
$\Delta P_{t-4,CHI}$	0.0794	1.2890	-0.0458	-4.9247	-0.1645	-1.0545
$\Delta P_{t-1,MAL}$	-0.1838	-1.4943	0.3982	9.0090	-0.1788	-0.7905
$\Delta P_{t-2,MAL}$	0.0164	0.2898	0.0031	0.3780	-0.1507	-1.0968
$\Delta P_{t-3,MAL}$	-0.2202	-2.2401	-0.0972	-3.0857	-0.0012	-0.0054
$\Delta P_{t-4,MAL}$	-0.0153	-0.3000	-0.1048	-11.3913	-0.1631	-1.4472
$Cont_{MAL}$	-0.0077	-0.8953	-0.3545	-0.9726	0.5785	4.5587
α_{MAL}	-0.0421	-1.9050	-0.3206	-1.1409	-0.1989	-8.8400
$\Delta P_{t-1,MAL}$	0.0089	0.1493	0.1777	0.4575	-1.5196	-6.1472
$\Delta P_{t-2,MAL}$	-0.0122	-0.3642	-0.0222	-0.0942	0.0134	0.4295
$\Delta P_{t-3,MAL}$	-0.0500	-0.7987	-0.6378	-1.0208	0.2932	1.6031
$\Delta P_{t-4,MAL}$	-0.0911	-2.8292	0.2134	0.7159	0.3221	7.1419
$\Delta P_{t-1,CHI}$	-0.0199	-0.4261	-0.5245	-0.8811	0.4607	2.1528
$\Delta P_{t-2,CHI}$	-0.0722	-2.5423	0.1673	0.6106	-0.1271	-3.2177
$\Delta P_{t-3,CHI}$	-0.3190	-6.9197	-0.0871	-0.1831	0.5240	3.4338
$\Delta P_{t-4,CHI}$	0.0725	3.1116	-0.0154	-0.0624	-0.0490	-1.0938

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. CONT represents the constant. Regime 1 indicates the regime below the lower threshold value. Regime 2 indicates the middle regime defined by the lower and upper threshold values. Regime 3 represents the regime above the upper threshold value.

Table I3. Estimated Coefficients of Three-Regime TVECM for OPA-CHI[1]

	Regime 1		Regime 2		Regime 3	
	Coefficients	t-ratio	Coefficients	t-ratio	Coefficients	t-ratio
$Cont_{CHI}$	0.5266	6.4534	0.0224	1.6000	-0.0301	-0.4181
α_{CHI}	0.4099	6.7864	-0.0516	-1.1862	-0.0180	-0.1286
$\Delta P_{t-1,CHI}$	-0.1094	-2.0037	-0.1779	-2.1748	0.2814	3.5219
$\Delta P_{t-2,CHI}$	-0.1555	-2.0116	0.0876	1.1984	-0.2999	-3.4196
$\Delta P_{t-3,CHI}$	0.2179	3.2866	-0.1727	-2.0246	-0.2618	-4.3779
$\Delta P_{t-4,CHI}$	-0.1335	-1.8263	-0.0452	-0.5855	0.0332	0.4134
$\Delta P_{t-1,OPA}$	0.3516	5.9796	0.0893	1.0159	-0.3874	-6.3612
$\Delta P_{t-2,OPA}$	0.1553	2.2249	-0.0851	-1.0442	-0.0530	-0.7020
$\Delta P_{t-3,OPA}$	-0.2048	-3.3740	-0.0546	-0.6312	-0.4494	-7.8842
$\Delta P_{t-4,OPA}$	0.1085	1.5049	0.0838	1.0744	0.1941	2.5573
$Cont_{OPA}$	-0.0338	-0.4289	0.0654	0.8767	0.0210	1.6535
α_{OPA}	-0.0467	-0.3048	0.0226	0.4102	-0.0726	-1.8241
$\Delta P_{t-1,OPA}$	-0.0052	-0.0595	-0.1286	-2.5772	0.0943	1.2607
$\Delta P_{t-2,OPA}$	0.0009	0.0094	-0.0808	-1.1445	-0.1535	-2.3013
$\Delta P_{t-3,OPA}$	-0.2887	-4.4076	0.1758	2.9010	0.0173	0.2221
$\Delta P_{t-4,OPA}$	0.0569	0.6473	-0.4619	-6.9250	-0.2478	-3.5149
$\Delta P_{t-1,CHI}$	-0.4764	-7.1532	0.1327	2.4711	0.0677	0.8431
$\Delta P_{t-2,CHI}$	0.0942	1.1404	-0.1880	-2.9467	-0.1430	-1.9195
$\Delta P_{t-3,CHI}$	-0.4636	-7.4295	-0.1123	-2.0234	0.0936	1.1848
$\Delta P_{t-4,CHI}$	0.0801	0.9639	-0.0746	-1.1337	-0.0650	-0.9116

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. CONT represents the constant. Regime 1 indicates the regime below the lower threshold value. Regime 2 indicates the middle regime defined by the lower and upper threshold values. Regime 3 represents the regime above the upper threshold value.

Table I4. Estimated Coefficients of Three-Regime TVECM for WAH-CHI[1]

	Regime 1		Regime 2		Regime 3	
	Coefficients	t-ratio	Coefficients	t-ratio	Coefficients	t-ratio
$Cont_{CHI}$	0.1043	3.8918	0.0074	0.4512	0.0016	0.1053
α_{CHI}	0.3935	5.6295	0.0111	0.0614	0.3365	0.9670
$\Delta P_{t-1,CHI}$	0.0072	0.0910	-0.5609	-3.5034	0.6397	3.2017
$\Delta P_{t-2,CHI}$	-0.2438	-1.8126	0.5904	3.6831	-0.6186	-3.0353
$\Delta P_{t-3,CHI}$	0.3716	4.2860	-0.1354	-1.3210	-0.0453	-0.2320
$\Delta P_{t-4,CHI}$	-0.6779	-5.0779	-0.0640	-0.5498	-0.2006	-1.0015
$\Delta P_{t-1,WAH}$	-0.1567	-1.6724	0.1058	1.0475	0.4821	2.7176
$\Delta P_{t-2,WAH}$	0.5733	4.1394	-0.2801	-2.4810	-0.5562	-3.1212
$\Delta P_{t-3,WAH}$	-0.9208	-12.0052	0.1643	1.5559	0.3017	1.8880
$\Delta P_{t-4,WAH}$	1.3016	10.4968	-0.1645	-1.3964	-0.3592	-2.2255
$Cont_{WAH}$	0.0003	0.0156	0.0460	2.1801	0.0236	1.8154
α_{WAH}	0.4601	1.0447	0.0133	0.2405	-0.3387	-2.3718
$\Delta P_{t-1,WAH}$	0.4264	1.6860	0.1363	2.1808	-0.3422	-2.7051
$\Delta P_{t-2,WAH}$	-0.3663	-1.4198	-0.4452	-4.1881	0.3756	2.9668
$\Delta P_{t-3,WAH}$	-0.1362	-0.5510	0.1061	1.5489	-0.1587	-1.9593
$\Delta P_{t-4,WAH}$	-0.0735	-0.2899	-0.3904	-3.7005	-0.0899	-0.9772
$\Delta P_{t-1,CHI}$	0.4418	1.9671	-0.1810	-2.4459	0.0531	0.6654
$\Delta P_{t-2,CHI}$	-0.4704	-2.0851	0.1309	1.1965	-0.1906	-2.1368
$\Delta P_{t-3,CHI}$	0.2717	1.3437	-0.4842	-7.9901	0.2243	2.6894
$\Delta P_{t-4,CHI}$	-0.2952	-1.4449	0.4821	4.9244	-0.2297	-2.4672

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. CONT represents the constant. Regime 1 indicates the regime below the lower threshold value. Regime 2 indicates the middle regime defined by the lower and upper threshold values. Regime 3 represents the regime above the upper threshold value.

Table I5. Estimated Coefficients of Three-Regime TVECM for HEN-CHI[1]

	Regime 1		Regime 2		Regime 3	
	Coefficients	t-ratio	Coefficients	t-ratio	Coefficients	t-ratio
$Cont_{CHI}$	0.0823	3.4435	-0.0073	-0.1221	-0.0012	-0.1905
α_{CHI}	0.7570	9.6803	0.4838	1.5754	0.1484	1.1320
$\Delta P_{t-1,CHI}$	-0.0293	-0.3649	-0.0919	-0.2750	-0.1713	-2.0564
$\Delta P_{t-2,CHI}$	-0.0122	-0.0912	0.2512	0.7285	0.1991	1.9910
$\Delta P_{t-3,CHI}$	0.6703	6.7164	0.0656	0.2042	-0.3819	-5.1678
$\Delta P_{t-4,CHI}$	-0.7078	-4.6444	-0.0723	-0.2152	0.1760	1.9405
$\Delta P_{t-1,HEN}$	0.4247	4.0104	0.1966	1.3484	-0.4504	-3.1191
$\Delta P_{t-2,HEN}$	0.0380	0.2545	-0.3142	-1.7761	0.3870	2.4713
$\Delta P_{t-3,HEN}$	0.0897	0.8726	0.3332	2.3220	-0.4689	-7.0300
$\Delta P_{t-4,HEN}$	0.1443	1.0745	-0.4888	-2.6696	0.5135	5.9988
$Cont_{HEN}$	-0.0031	-0.3605	0.0050	0.2825	-0.0124	-0.2805
α_{HEN}	0.2797	1.5767	0.1486	2.5709	0.3843	1.6937
$\Delta P_{t-1,HEN}$	-0.1986	-1.7622	0.0587	0.9899	0.2104	0.8522
$\Delta P_{t-2,HEN}$	0.2364	1.7459	-0.1907	-1.9302	-0.1282	-0.5031
$\Delta P_{t-3,HEN}$	-0.3023	-3.0230	0.2737	3.7137	0.1530	0.6445
$\Delta P_{t-4,HEN}$	0.0679	0.5534	-0.4037	-3.5853	-0.2009	-0.8091
$\Delta P_{t-1,CHI}$	-0.5085	-2.6024	-0.0010	-0.0128	0.1107	1.0279
$\Delta P_{t-2,CHI}$	0.4021	1.8976	0.0701	0.6355	-0.1953	-1.4943
$\Delta P_{t-3,CHI}$	-0.7014	-7.7674	0.0048	0.0632	0.3329	3.1406
$\Delta P_{t-4,CHI}$	0.7474	6.4542	-0.0380	-0.3831	-0.5020	-3.7103

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. CONT represents the constant. Regime 1 indicates the regime below the lower threshold value. Regime 2 indicates the middle regime defined by the lower and upper threshold values. Regime 3 represents the regime above the upper threshold value.

Table I6. Estimated Coefficients of Three-Regime TVECM for ONG-CHI[1]

	Regime 1		Regime 2		Regime 3	
	Coefficients	t-ratio	Coefficients	t-ratio	Coefficients	t-ratio
$Cont_{CHI}$	0.1072	4.0000	-0.0439	-1.1285	-0.0055	-0.6707
α_{CHI}	0.3054	4.8399	0.5819	1.6970	0.0821	0.4121
$\Delta P_{t-1,CHI}$	-0.0483	-0.7241	-0.4696	-2.0742	0.1481	0.7630
$\Delta P_{t-2,CHI}$	-0.2622	-2.6948	0.6695	2.8870	-0.2422	-1.2074
$\Delta P_{t-3,CHI}$	-0.0349	-0.5073	-0.0803	-0.3115	0.3883	2.2748
$\Delta P_{t-4,CHI}$	-0.2325	-2.4019	-0.0124	-0.0458	-0.6527	-3.5667
$\Delta P_{t-1,ONG}$	0.0317	0.3875	0.3275	2.8478	-0.0282	-0.1555
$\Delta P_{t-2,ONG}$	0.3682	3.3656	-0.5493	-4.4478	-0.1257	-0.6623
$\Delta P_{t-3,ONG}$	-0.4330	-6.0559	0.3587	2.8446	-0.0486	-0.3030
$\Delta P_{t-4,ONG}$	0.3146	3.3186	-0.3779	-2.6575	0.0583	0.3506
$Cont_{ONG}$	-0.0065	-0.6436	0.0404	1.8618	-0.0411	-1.3006
α_{ONG}	0.2043	0.8312	-0.0938	-1.8356	0.4724	1.6999
$\Delta P_{t-1,ONG}$	-0.1846	-0.7708	0.0739	1.3660	-0.0577	-0.3144
$\Delta P_{t-2,ONG}$	0.1227	0.4958	-0.4426	-5.6168	0.2347	1.2484
$\Delta P_{t-3,ONG}$	0.1826	0.8670	-0.1394	-2.4982	0.0665	0.3182
$\Delta P_{t-4,ONG}$	-0.4310	-1.9096	-0.1407	-1.7924	-0.1535	-0.6990
$\Delta P_{t-1,CHI}$	-0.1976	-0.8829	-0.2403	-3.6244	0.2120	2.2747
$\Delta P_{t-2,CHI}$	0.0653	0.2788	0.1659	1.8703	-0.4017	-4.0130
$\Delta P_{t-3,CHI}$	-0.1151	-0.5816	-0.3194	-5.5164	0.5800	5.6751
$\Delta P_{t-4,CHI}$	0.1217	0.5931	0.0225	0.2926	-0.6059	-5.2550

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. CONT represents the constant. Regime 1 indicates the regime below the lower threshold value. Regime 2 indicates the middle regime defined by the lower and upper threshold values. Regime 3 represents the regime above the upper threshold value.

Table I7. Estimated Coefficients of Three-Regime TVECM for ELL-CHI[1]

	Regime 1		Regime 2		Regime 3	
	Coefficients	t-ratio	Coefficients	t-ratio	Coefficients	t-ratio
$Cont_{CHI}$	0.3579	6.3011	0.0943	3.2075	-0.0014	-0.1120
α_{CHI}	0.6900	6.0954	-0.0287	-1.0996	-0.2189	-2.9422
$\Delta P_{t-1,CHI}$	-0.1307	-1.9192	0.1158	1.7545	0.1795	2.0775
$\Delta P_{t-2,CHI}$	0.2399	2.6076	0.0221	0.8805	-0.0901	-1.3039
$\Delta P_{t-3,CHI}$	-0.3199	-4.8840	-0.2819	-4.7699	-0.0850	-0.9269
$\Delta P_{t-4,CHI}$	-0.0007	-0.0104	0.0360	1.4754	-0.0340	-0.4620
$\Delta P_{t-1,ELL}$	-0.3384	-5.0282	0.6386	10.2504	-0.1849	-2.2467
$\Delta P_{t-2,ELL}$	0.2956	3.9049	0.0920	3.8819	-0.0560	-0.8023
$\Delta P_{t-3,ELL}$	-0.2899	-3.9767	-0.4140	-8.2635	-0.0048	-0.0700
$\Delta P_{t-4,ELL}$	0.0968	1.2670	0.0484	2.6304	-0.0573	-1.0956
$Cont_{ELL}$	0.0030	0.3750	-0.2747	-3.0970	0.2600	5.6645
α_{ELL}	0.0135	0.2830	-0.6973	-3.9462	-0.4301	-10.5417
$\Delta P_{t-1,ELL}$	0.0873	1.5758	-0.6181	-5.8092	0.9397	9.1233
$\Delta P_{t-2,ELL}$	-0.1059	-2.3959	-0.6605	-4.5964	-0.2513	-6.4107
$\Delta P_{t-3,ELL}$	-0.1160	-1.9761	-0.6006	-5.8767	0.0961	1.0412
$\Delta P_{t-4,ELL}$	-0.0606	-1.2866	0.1497	1.4217	0.0233	0.6115
$\Delta P_{t-1,CHI}$	-0.0891	-1.6907	-1.2142	-11.5528	-0.0483	-0.4964
$\Delta P_{t-2,CHI}$	-0.0150	-0.3356	-0.0388	-0.3283	0.0821	2.2189
$\Delta P_{t-3,CHI}$	-0.0609	-1.3841	0.8008	7.0307	-0.1079	-1.3780
$\Delta P_{t-4,CHI}$	-0.0310	-0.9254	0.8639	7.2414	0.0139	0.4860

Note: See list of acronyms in Appendix J for definitions of spot markets.

1. CONT represents the constant. Regime 1 indicates the regime below the lower threshold value. Regime 2 indicates the middle regime defined by the lower and upper threshold values. Regime 3 represents the regime above the upper threshold value.

APPENDIX J

LIST OF ACRONYMS

J1. List of Acronyms of Electricity Spot Markets

MIDC: Mid-Columbia

PV: Palo Verde

FC: Four Corners

PJM: Pennsylvania-New Jersey-Maryland

NEPL: Northeast Power Pool

MAPP: Mid-Continent Area Power Pool

MAIN: Mid-America Interconnected Network

ECAR: East Central Area Reliability Coordination Agreement

SPP: Southwest Power Pool

ENT: Entergy

ERCOT: Electric Reliability Council of Texas

J2. List of Acronyms of Natural Gas Spot Markets

WAH: Waha Hub, Texas

HEN: Henry Hub, Louisiana

ONG: ONG Hub, Oklahoma

OPA: Opal Hub, Wyoming

CHI: Chicago Hub, Illinois

ELL: Ellisburg-Leidy Hub, Pennsylvania

MAL: Malin Hub, Oregon

AEC: AECO Hub, Alberta, Canada

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