THE PAST, PRESENT, AND FUTURE OF THE U.S. ELECTRIC POWER SECTOR: EXAMINING REGULATORY CHANGES USING MULTIVARIATE TIME SERIES APPROACHES

A Dissertation

by

KYLE EDWIN BINDER

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Chair of Committee,	James W. Mjelde
Committee Members,	David A. Bessler
	Richard T. Woodward
	James M. Griffin
Head of Department,	C. Parr Rosson III

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ABSTRACT

The U.S. energy sector has undergone continuous change in the regulatory, technological, and market environments. These developments show no signs of slowing. Accordingly, it is imperative that energy market regulators and participants develop a strong comprehension of market dynamics and the potential implications of their actions. This dissertation contributes to a better understanding of the past, present, and future of U.S. energy market dynamics and interactions with policy. Advancements in multivariate time series analysis are employed in three related studies of the electric power sector. Overall, results suggest that regulatory changes have had and will continue to have important implications for the electric power sector. The sector, however, has exhibited adaptability to past regulatory changes and is projected to remain resilient in the future.

Tests for constancy of the long run parameters in a vector error correction model are applied to determine whether relationships among coal inventories in the electric power sector, input prices, output prices, and opportunity costs have remained constant over the past 38 years. Two periods of instability are found, the first following railroad deregulation in the U.S. and the second corresponding to a number of major regulatory changes in the electric power and natural gas sectors.

Relationships among Renewable Energy Credit prices, electricity prices, and natural gas prices are estimated using a vector error correction model. Results suggest that Renewable Energy Credit prices do not completely behave as previously theorized in the literature. Potential reasons for the divergence between theory and empirical evidence are the relative immaturity of current markets and continuous institutional intervention.

Potential impacts of future CO_2 emissions reductions under the Clean Power Plan on economic and energy sector activity are estimated. Conditional forecasts based on an outlined path for CO_2 emissions are developed from a factor-augmented vector autoregressive model for a large dataset. Unconditional and conditional forecasts are compared for U.S. industrial production, real personal income, and estimated factors. Results suggest that economic growth will be slower under the Clean Power Plan than it would otherwise; however, CO_2 emissions reductions and economic growth can be achieved simultaneously.

DEDICATION

To Mom, Dad, Jaime, Jenna, and Chloe.

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CHAPTER I

INTRODUCTION

The U.S. energy sector is a popular subject of debate in the national media, the U.S. political arena, and the academic literature (Burtraw et al. 2014; Bushnell et al. 2015; McConnell 2015; U.S. Environmental Protection Agency (EPA) 2015b). This sector is continuously evolving in response to technology improvements, changing market conditions, and adjustments in the regulatory environment. Major changes in the energy sector over the last three decades include (but are not limited to) market restructuring in both the natural gas and electricity sectors (U.S. Federal Energy Regulatory Commission (FERC) 2015a, 2015b), the beginning and end of a national emissions permit trading program (Evans and Woodward 2013), the introduction of state level Renewable Portfolio Standards (Database of State Incentives for Renewable Energy 2015), and a substantial increase in domestic crude oil and natural gas production resulting in considerable price decreases in these markets (U.S. Energy Information Administration (EIA) 2015a). Energy sector developments show no signs of slowing in the near future.

Given the importance of the U.S. energy sector to the domestic and global economies, it is crucial for policy makers and energy market participants to have a strong awareness of the potential implications of their actions. The overall objective of this dissertation is to contribute to a better understanding of the past, present, and future of U.S. energy market dynamics and interactions with policy by: (1) characterizing market relationships and investigating the consequences of past regulatory changes and shifts in market conditions; (2) examining current program functionality; and (3) projecting the impacts of future policy implementation. To achieve this broad objective, three related empirical investigations of issues in the electric power sector are conducted (Chapters II-IV), drawing on insights from advancements in multivariate time series analysis.

Energy Market Relationships: Past Changes in Regulation and Market Conditions

Economic relationships governing inventory behavior in the electric power sector are characterized in Chapter II. Specific objectives are to determine how coal inventories at electric power plants are related to movements in various economic factors and to examine whether these relationships have remained constant over time in the face of aforementioned changes. Monthly data spanning 38 years and encompassing numerous changes in the electricity and natural gas industries are used to estimate a vector error correction model. This model allows for cointegration among coal inventories, input and output prices, and opportunity costs. Tests for stability of the long run relationships among the variables are conducted following Hansen and Johansen (1999); the tests help to understand how inventory behavior of firms in the electric power sector changes when confronted with regulatory changes or shifts in market conditions. Two sustained periods of instability are found: the first following deregulation of the U.S. railroad industry and the second following the Clean Air Act Amendments of 1990 and coinciding with restructuring of both the natural gas and electricity industries. Results suggest policy changes that alter the regulatory environment can result in considerable fluctuations in how firms' inventory decisions interact with input and output markets and opportunity costs; however, the system is highly resilient as the long run relationships remain constant over approximately 68% of the 38 year sample period.

Current Program Functionality

Renewable Portfolio Standards, programs that require electricity suppliers to provide a minimum percentage of total sales from renewable energy, currently exist in the majority of U.S. states (Database of State Incentives for Renewable Energy 2015). Empirical analyses of tradable rights programs are necessary to determine if such programs are a move towards efficiency. There is a lack of empirical analyses of RPS programs in the literature (Felder 2011; Fischer 2010). This gap is addressed in Chapter III, with the objective of improving our understanding of the functionality of currently existing RPS programs. This goal is accomplished by determining whether the dynamic relationships among Renewable Energy Credit (REC) prices in Massachusetts and Connecticut, natural gas prices, and electricity prices are consistent with economic theory. As in the study characterizing inventory behavior, a vector error correction model is employed. Results indicate REC prices in the two states do not respond to shocks in electricity prices or natural gas prices as theorized in the literature. Additionally, only weak evidence is found regarding whether REC prices are integrated across states. Possible reasons for the divergence between theorized relationships and empirical evidence are the relative immaturity of the REC markets and continuous institutional intervention. It appears that although Renewable Portfolio Standards have been promoted and implemented as market-based incentives for encouraging renewable generation, regulators have not succeeded in creating an efficient, fundamental-driven market under current RPS programs in these two states.

Projecting Impacts of Future Policy Implementation

In Chapter IV, potential future impacts of a recently introduced national policy to reduce CO_2 emissions from the electric power sector (the Clean Power Plan) are estimated using advancements in time series techniques for handling large datasets. Factors extracted from a large number of monthly macroeconomic, financial, and energy related time series represent the underlying sources of variation in larger U.S. economic and energy sector activity. These factors are included in a factor-augmented vector autoregressive model alongside three variables of interest: electric power sector CO_2 emissions, U.S. industrial production, and U.S. real personal income. Unconditional and conditional forecasts are compared for industrial production, real personal income, and the estimated factors. The conditional forecasts are based on a constrained path of CO_2 emissions reductions. Results suggest that growth in economic activity will be slower under the Clean Power Plan than it would be otherwise, but that economic growth and CO_2 emissions reductions can be achieved simultaneously.

CHAPTER II

TESTING STABILITY IN THE ELECTRIC POWER SECTOR: CHARACTERIZING FUEL PRICE AND INVENTORY RELATIONSHIPS

Energy markets in the U.S. have experienced several substantial changes in the last quarter century, including restructuring of both the natural gas and electricity industries. Additionally, the U.S. has seen a steady increase in natural gas supplies in recent years because of shale gas exploitation, leading to a decrease in prices. Real monthly natural gas prices paid by electric power generators (October 2014 dollars) have dropped from a peak of $14.38/million BTU (mmBTU) in October 2005 to $3.06/mmBTU by September 2015 (U.S. Energy Information Administration (EIA) 2015a). In this changing environment, inventory management remains an essential function, having consequences for a company's profitability (Chen, Xue, and Yang 2013).

Inventory decisions in the electric power sector are made in the presence of varying input prices and stochastic seasonal demands by using both spot market purchases and long-term contracts. As noted, the energy sector has a history of regulatory changes and continues to be the subject of proposed regulation. It is important, therefore, to understand how firms behave when faced with a changing regulatory environment or with major shifts in market conditions. Jha (2015) motivates this importance; he finds that U.S. electric power plants which face deregulated electricity markets save approximately 3% per month in coal procurement and storage costs compared to regulated plants. The objectives of this chapter are to determine how coal stocks at electric power plants are related to movements in various economic factors and whether these relationships have remained constant over a period spanning several major events in the electricity industry, including market deregulation.

To achieve these objectives, multivariate time-series techniques are employed, using five different U.S. aggregate monthly data series. Previous literature and economic theory suggest that input inventory decisions are affected by input and output price expectations and opportunity costs (Jha 2015; Takriti, Supatgiat, and Wu 2001; Twisdale and Chu 1979). Applying this intuition to the electric power industry suggests that coal inventories are expected to be related to fuel input prices, electricity (output) prices, and the opportunity cost of holding inventories. Accordingly, two input costs to electric power plants are considered: coal and natural gas. Coal and natural gas are the focus as they are the two largest fuel sources in the U.S. electric power sector. In June 2014, coal accounted for about 40% of total electricity generation; natural gas was the second largest source at 26% (U.S. EIA 2015a). The third series is a measure of coal inventories at electric power plants. Data for natural gas inventories are not included. Both the inherent dangers of natural gas storage and the ease in transportation cause natural gas to usually be stored within the gas sector and not the electric power sector. Electricity prices and Aaa corporate bond rates are included, representing output prices and opportunity costs. Data are for the period July 1976 to October 2014. Dynamic long run relationships between coal inventories and input and output prices in the electricity sector are presented. To the author’s knowledge, such coal relationships have not been examined in the literature.

Literature Review

There is a relatively vast literature employing time-series methods to address issues in energy-related markets, as well as a large volume of literature on inventory control. A non-exhaustive list of inventory behavior literature dates back to Arrow, Harris, and Marschak (1951), and includes works such as Holt, Modigliani, and Simon (1955), Feldstein et al. (1976), and Blinder (1986). Generally, inventory studies focus on the determination of optimal stocking levels of goods. The present study takes a different approach by studying the dynamic long run relationships between input inventory levels and input and output prices in the electricity sector.

While inventory literature contains many studies of optimal finished goods levels, little attention has been given to the optimal stocking of inputs (raw or intermediate goods). Ramey (1989) develops an optimization method for inventories at different stages of production. She shows that input inventories are much more volatile than output inventories. The theory introduced was a major departure from past inventory literature, as she treated inventories as a factor of production, rather than a stage between production and sale of goods. Humpreys, Maccini, and Schuh (2001) note that Ramey's approach to modeling input inventories implies that optimal stocking rates stem from factor demand theory. They argue that Ramey's approach does not properly capture the flow of inputs in the production process, i.e. the benefits and costs from holding inventories of raw and intermediate goods. Humphreys, Maccini, and Schuh (2001) provide a model for inventory management which includes ordering, usage, and stocking of inputs in the durable and nondurable goods industries. Their model shows that input inventories respond positively to sales and negatively to raw material price shocks. Considine (1997) uses a model which simultaneously determines input and output inventories to investigate the determinants of each in the petroleum refining industry. He finds that the elasticity of crude oil stocks with respect to a basket of energy and material prices is small and negative in both the short and long run.

There are a small number of studies addressing fuel inventory and purchase decisions in the electric power industry. Jha (2015) estimates a dynamic, plant-level model for optimal coal purchases at coal-fired electric power plants. He finds that firms which face wholesale market electricity prices save roughly 3% per month in coal purchase and storage costs compared to a firm under output price regulation. Twisdale and Chu (1979) develop a multiperiod, dynamic programming framework in which they study optimal coal inventory management. They find that coal purchases tend to follow a seasonal, sawtooth pattern from month to month. Sensitivity analyses show that potential replacement costs (the cost to replace power when the plant is short on coal) and/or revenue losses greatly affect the optimal strategy. Takriti, Supatgiat, and Wu (2001) study the problem of a natural gas power plant's fuel purchase decision under uncertainty of natural gas prices, electricity prices, and natural gas demand. They propose a mixed integer programming approach to inform the decision maker when to buy or sell natural gas, and when to burn natural gas to produce electricity under stochastic scenarios. They find that their stochastic model outperforms a deterministic alternative by a factor of three to four percent.

Applications of multivariate time-series techniques to the energy sector are prevalent in the literature. Most of these studies pertain to energy price relationships, but a few studies address the relationships between management decisions and economic variables. One such study is Considine and Heo (2000), who investigate relationships in petroleum prices, inventories, production, and net imports. They find that under periods of high prices, oil refiners reduce crude oil stocks but increase finished product inventories. Pindyck (2001) develops an explanation for how prices, production, and inventory levels of commodities are related to each other. He shows that price volatility is important in driving the dynamics of storage markets. In a related paper, Pindyck (2004) argues that higher volatility in petroleum markets increases the demand for inventories, as inventories are meant to be a smoothing mechanism. He specifies a model for petroleum product prices, inventories, and volatility, and finds that while price volatility does influence inventory levels, it is to a lesser extent than expected.

Applications of time series techniques to input and output price data from the energy sector provide a starting point for the current study. Borenstein and Shepard (2002) use time series methods to explore the dynamics between crude oil prices and wholesale gasoline prices using a model in which holding inventories is costly. They discover that wholesale gasoline (output) price has a lagged response to shocks in crude oil price (input cost). Panagiotidis and Rutledge (2007) test the hypothesis of decoupling of natural gas and oil prices in the UK. They find a cointegrating relationship between natural gas and oil prices, providing evidence against the hypothesis of decoupling of the markets. Mohammadi (2009) and Mjelde and Bessler

(2009) both use vector error correction models to examine long run relationships between electricity prices and major fuel markets. Mohammadi (2009) finds a relationship between coal prices and electricity prices in the long run. Mjelde and Bessler (2009), using four major fuel source prices and two different electricity markets within the United States, conclude that the largest responses in electricity prices generally come from shocks in the coal market. They conclude that price discovery is found in the fuel source markets.

Data

Data used in the empirical analysis includes national level monthly observations of seven different series for the period July 1976 to October 2014, giving a total of 459 observations. Five endogenous series are: cost of coal and natural gas receipts at electric generating plants[1] (representing input prices); electricity prices (output prices); coal inventories (input stocks); and Moody's Aaa Corporate Bond ratings (opportunity costs). The four energy series are from the EIA's Monthly Energy Review (U.S. EIA 2015a). Coal inventory is constructed by dividing the amount of coal on hand at electric power plants in a given month by the previous month's consumption of coal, thereby approximating the number of months of coal on hand at electric power plants.[2] The Moody's data are from the U.S. Federal Reserve (2015). Additionally, cooling degree

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[1] These series are from Table 9.9 "Cost of Fossil-Fuel Receipts at Electric Generating Plants" of the Monthly Energy Review (U.S. EIA 2015a) and are referred to as coal and natural gas costs throughout this chapter.

[2] As a robustness check, the empirical analysis was carried out for an alternative measure of coal inventory: current end-of-month coal on hand divided by the following month's consumption in the previous year, i.e. $inventory_t = \frac{coal\ on\ hand_t}{coal\ consumption_{t-11}}$. The test for parameter stability is robust to this alternative measure (Appendix A).

days and heating degree days are treated as exogenous series. Cooling and heating degree days are national level, population weighted monthly observations from the U.S. National Oceanic and Atmospheric Administration (2015). All five endogenous series are converted to October 2014 dollars using the Producer Price Index (U.S. Bureau of Labor Statistics 2015).

The electricity price series is constructed from two different series. Pre-2001 electricity prices are average U.S. retail electricity prices, whereas after December 2000 wholesale prices are used. January 2001 is the first month in which sufficient data are available on deregulated wholesale electricity prices to generate a U.S. national price. Wholesale prices are the preferred measure because of their relevance as the price that power plants receive for their product. Retail prices are included as they are tied to the price received by plants; however, they are less volatile than wholesale prices. The monthly average retail price comes from U.S. EIA (2015a). The wholesale price was constructed as a weighted average using EIA price and volume data (U.S. EIA 2015b) from four major U.S. hubs (PJM West, Mid-Columbia, Palo Verde, and New England – Massachusetts). Because of the nature of the electricity price series, a 0-1 dummy variable (equal to one pre-2001 and zero after) to account for the difference in the series is included in the model following suggestions by Juselius (2006) and Estima (2006) to handle a known break.

All endogenous series are in natural logarithm form for the analysis. The endogenous series are abbreviated as follows: real coal costs to electric power plants (Coal), real natural gas costs to electric power plants (NG), coal inventories at electric power plants (Coal Inv), Aaa corporate bond rates (Bonds), and real electricity prices (Elec). Graphs of the five endogenous (before taking natural logarithms) and two exogenous series are presented in figure 2.1.

Methodology

Previous studies have shown that economic variables in the electricity sector tend to be integrated in the long run, confirming economic theory (Mjelde and Bessler 2009; Samuelson 1971). An appropriate dynamic modeling technique to capture both short and long run relationships is the vector error correction model (VECM). The VECM framework affords the opportunity to model long run relationships by allowing for the existence of cointegration among a set of non-stationary variables (Juselius 2006). Cointegration is present when there exists a linear combination of two or more non-stationary variables which is itself stationary (the series are thought to move together in the long run).

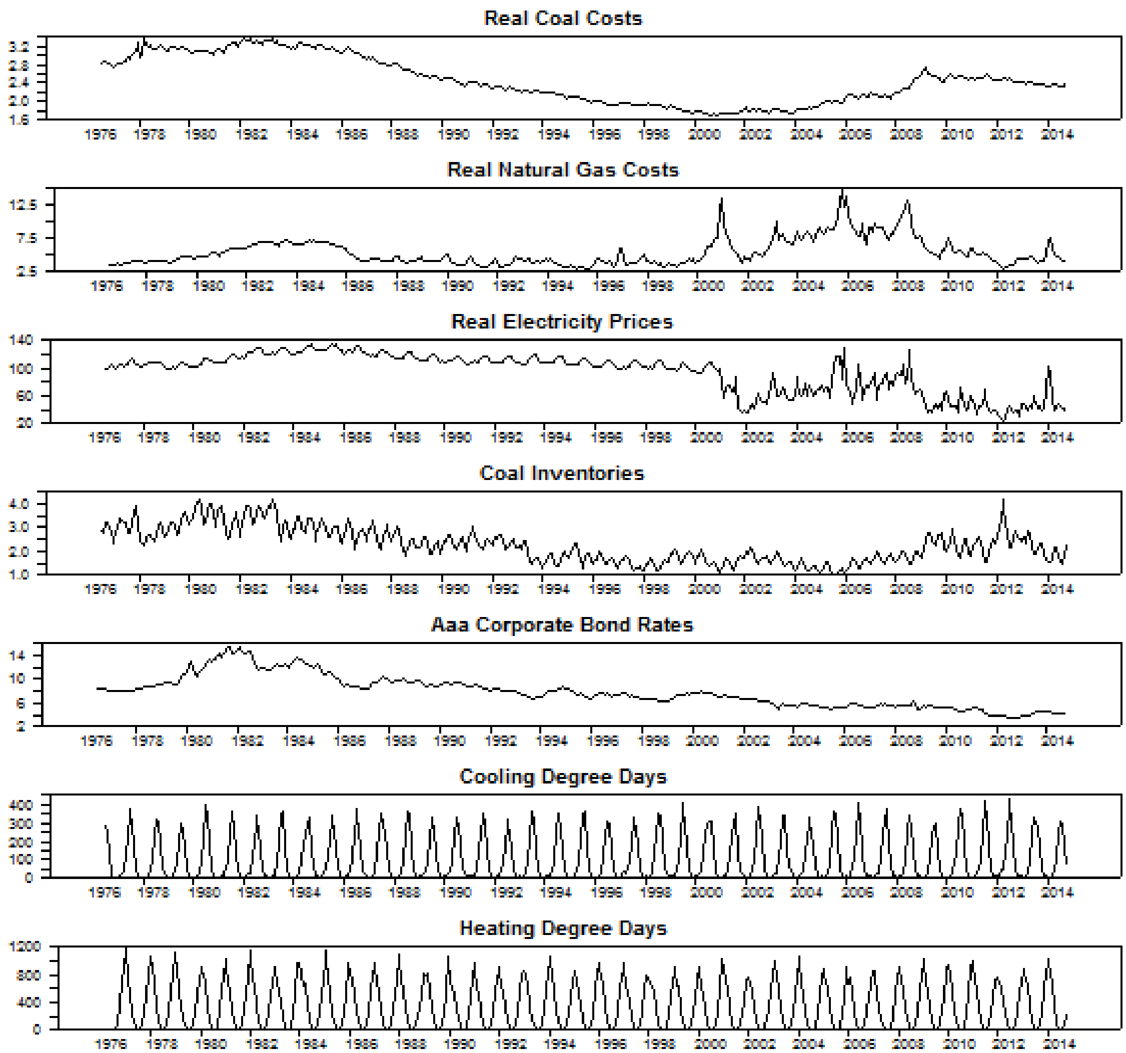

Figure 2.1. Data series (monthly) included in the analysis (July 1976-October 2014). Units: Coal and natural gas costs ($/mmBtu), electricity prices ($/MWh), coal inventories (number of coal months on hand)

It is important, therefore, to first test whether each of the five endogenous series is stationary. Three separate tests for stationarity are reported in table 2.1. Under the first test, Augmented Dickey-Fuller (Fuller 1996), the null hypothesis of a unit root (nonstationarity) cannot be rejected for the natural logarithm of each of the five series. Taking the first difference of the natural logs leads to a rejection of the null hypothesis for each of the five series, implying that the series are non-stationary in natural logarithm of levels, but the first difference natural log transformation leads to stationarity. The second test (Z-A) examines the null hypothesis of a unit root while allowing for an unknown breakpoint in both the intercept and linear trend of the series (Zivot and Andrews 1992). The null hypothesis is again rejected for the natural log of all series, but cannot be rejected for the first difference natural logs of all series except coal costs. The third test, KPSS (Kwiatkowski et al. 1992), results in a rejection of the null hypothesis of stationarity for all series in natural logs. The null of stationarity is not able to be rejected for the first difference natural logs of all five series. Taking the results of the three tests together, it appears that the natural log of all series are integrated of order one, or $I(1)$, providing statistical credence of the potential for cointegration and the use of the VECM framework.

Table 2.1. Various Tests for Unit Root

	ADF (H_0: Unit Root)		Z-A (H_0: Unit Root)		KPSS (H_0: Stationarity)	
	Statistic	Decision[a]	Statistic	Decision[b]	Statistic	Decision[c]
			log(Series)			
Coal	-1.38	F	-3.79	F	4.48	R
NG	-1.84	F	-3.51	F	1.14	R
Coal Inv	-1.30	F	-3.79	F	4.24	R
Bonds	-0.22	F	-4.80	F	6.54	R
Elec	-0.40	F	-3.31	F	5.36	R
			diff(log(Series)			
Coal	-3.74	R	-4.85	F	0.39	F
NG	-5.03	R	-6.00	R	0.05	F
Coal Inv	-5.49	R	-6.56	R	0.05	F
Bonds	-5.72	R	-6.68	R	0.16	F
Elec	-5.35	R	-6.38	R	0.06	F

[a]Based on the 5% critical value of -2.87
[b]Based on the 5% critical value of -5.08
[c]Based on the 5% critical value of 0.46

Vector Error Correction Model

Given the results of the tests for stationarity along with the findings of previous studies which show the existence of long run relationships among the endogenous series, it is appropriate to use the VECM representation:

(2.1) $\Delta Y_t = \gamma + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \Pi Y_{t-1} + \lambda X_t + \varepsilon_t$

where:

ΔY_t is a (5×1) vector of first differences of the endogenous series;

γ is a (5×1) vector of constants;

ΔY_{t-i} represents lagged values of order i;

Γ_i is the corresponding (5×5) coefficient matrix;

k is the optimal number of lags in a levels vector autoregressive representation;

X_t is a (3×1) vector of exogenous series (cooling and heating degree days, and a 0-1 qualitative variable to capture retail-wholesale electricity price differences);

λ is a (5×3) coefficient matrix;

ε_t is a (5×1) vector of innovations; and

ΠY_{t-1} is known as the "error correction" term, where Π is (5×5) vector of coefficients and Y_{t-1} is (5×1).

Writing Π as:

(2.2) $\quad \Pi = \alpha\beta'$

where α and β are both $(5 \times r)$ matrices gives an interpretation of the long run relationships among the five series and where r is the rank of Π. Because Y_{t-1} is non-stationary and ΔY_t is stationary, $\alpha\beta'$ contains stationary linear combination(s) of the five variables, provided cointegration is present. The r columns of β are known as the cointegrating vectors (Tsay 2014). Statistical tests are performed on Π, α, and β to determine r and to further characterize the long run structure between the five series.

Test of Parameter Stability

To address the issue of stability of the long run relationships, a test for constancy of β is conducted following Hansen and Johansen (1999). The test is performed by recursively estimating the VECM for subsamples of the data spanning from t_0 to $t = t_b, t_{b+1}, t_{b+2}, \dots. T$ where T is the full sample, t_0 is the time of the first observation, and t_b is the starting point of the recursion chosen to allow a minimal base sample as a function of the number of parameters in the model $(t_0 < t_b < T)$. To test the constancy of β, estimates $\hat{\beta}^{(t)}$ are compared to $\hat{\beta}^{(T)}$, where $\hat{\beta}^{(t)}$ is the estimate of β for the subsample including data up until time t. Define:

(2.3) $$c = \begin{bmatrix} \hat{\beta}^{(T)} \\ 0 \end{bmatrix}, \; c_{\perp} = \begin{bmatrix} \hat{\beta}_{\perp}^{(T)} & 0 \\ 0 & 1 \end{bmatrix}, \; \bar{c} = c(c'c)^{-1}$$

where $c_{\perp}$ is the orthogonal complement of c such that $c'_{\perp}c = 0$ (likewise for $\hat{\beta}_{\perp}^{(T)}$). $\hat{\beta}^{(T)}$ is normalized on $\bar{c}$ such that $\hat{\beta}_{c}^{(T)} = \hat{\beta}^{(t)}(\bar{c}'\hat{\beta}^{(t)})^{-1}$. Additionally, define $\hat{\alpha}_{c}^{(t)} = \hat{\alpha}^{(t)}\hat{\beta}^{(t)\prime}\bar{c}$ such that $\hat{\alpha}_{c}^{(t)}\hat{\beta}_{c}^{(t)\prime} = \hat{\alpha}^{(t)}\hat{\beta}^{(t)\prime}$. Then the test statistic at each point in the sample t is:

(2.4) $$Q_{T}^{(t)} = \left(\frac{t}{T}\right)^{2} trace\left\{(V^{(T)})^{-1}S^{(t)\prime}(M^{(T)})^{-1}S^{(t)}\right\}$$

where:

(2.5) $$V^{(T)} = \hat{\Lambda}^{(T)}\left(I_{r} - \hat{\Lambda}^{(T)}\right)^{-1};$$

(2.6) $$M^{(T)} = \left(\frac{1}{T}\right) c'_{\perp}S_{11}c_{\perp} \text{ ; and}$$

(2.7) $$S^{(t)} = c'_{\perp}(S_{01}^{(t)} - \hat{\alpha}_{c}^{(t)}\hat{\beta}_{c}^{(T)\prime}S_{11}^{(t)})'(\hat{\Omega}^{(T)})^{-1}\hat{\alpha}_{c}^{(t)}.$$

$S_{ij}^{(t)}$ is the product moment matrix of residuals from the VECM using the sample up until time t, $\hat{\Lambda}^{(T)}$ is the diagonal matrix of the r largest eigenvalues corresponding to the r estimated cointegrating vectors from the full sample, and $\hat{\Omega}^{(T)}$ is the covariance matrix of innovations based on the full sample (Hansen and Johansen 1999).

By examining the sequence of test statistics $Q_{T}^{(t)}$, a test of whether $\hat{\beta}^{(t)} = \hat{\beta}^{(T)}$for each $t = t_{b}, t_{b+1}, t_{b+2}, \dots . T$ is performed (null hypothesis at each t). For a thorough explanation of the test and the asymptotic distribution of the test statistic $Q_T^{(t)}$, see Hansen and Johansen (1999), Juselius (2006), and the CATS 2.0 Manual (Estima, 2006).

Innovation Accounting Procedures

Impulse response functions (IRFs) and forecast error variance decompositions (FEVDs) help to characterize the dynamic relationships among coal inventories, coal and natural gas costs, electricity prices, and Aaa corporate bond rates. IRFs show the effect of a one-time shock in one variable on the future values of the remaining variables, and FEVDs are calculated as the percentage of variance in forecast error in one variable that can be explained by unexpected shocks to the other variables.

Innovation accounting procedures (IRFs and FEVDs) are conducted based on the levels vector autoregressive (VAR) form of the VECM in equation (2.1):

(2.8) $\quad Y_t = \gamma + (1 + \Pi + \Gamma_1)Y_{t-1} - \sum_{i=1}^{k-2}(\Gamma_i - \Gamma_{i+1})Y_{t-i+1} - \Gamma_{k-1}Y_{t-k} + \lambda X_t + \varepsilon_t.$

An issue that arises when conducting innovation accounting procedures is that the contemporaneous covariance matrix of ε_t in Equation (2.8), Σ_ε, is usually not a diagonal matrix in empirical applications (the components of the error term are contemporaneously correlated). If this is the case, then any particular series cannot necessarily be shocked without affecting another series; innovation accounting procedures are nonsensical if contemporaneous correlation exists (Tsay 2014). To overcome this limitation, the innovations ε_t must be orthogonalized. Consider a Bernanke (1986) ordering, where the correlated innovations ε_t are written as a function of the underlying (structural) sources of variation (σ_t) which are assumed to be orthogonal:

(2.9) $\varepsilon_t = A^{-1}\sigma_t$.

To conduct the innovation accounting procedures, the VAR representation (equation 2.8) is pre-multiplied by the matrix A.

A form for the matrix A is obtained through causal flow methods (Pearl 2000; Spirtes, Glymour, and Scheines. 2000). Directed Acyclic Graphs (DAGs) provide a visual summary of contemporaneous causal flows among innovations from the estimated vector error correction model. The GES algorithm (Chickering 2003) in TETRAD V (2015) is employed to generate DAGs using the covariance matrix of error terms. In DAGs, an arrow from A to B implies that A causes B. An undirected line from A to B with no arrow (or a line with an arrow on each end) signifies flows between the two, but the algorithm cannot determine whether A causes B or B causes A. If there is no information flow between A and B, the algorithm will not generate a line of any type connecting the two. The GES algorithm starts from a DAG representation where all variables are independent of each other (no lines), and searches over more complicated representations for improvements in the Bayesian Information Criterion. The algorithm picks the DAG representation such that no added line or change of direction improves the criterion.

Results

Model Diagnostics for the Full Model

The first step in the modeling procedure is to estimate the VECM representation in equation (2.1). First, in accordance with Hansen and Johansen (1999), the constant term γ is restricted such that no deterministic trend is allowed in the model (the constant is constrained to the cointegrating space). Next, under the restricted constant model, simultaneous determination of optimal lag length (k) and cointegrating rank (r) using information criteria is performed following Wang and Bessler (2005). Results of this process are reported in table 2.2. The Hannan and Quinn loss metric reaches a minimum value at two lags and three cointegrating vectors.

Table 2.2. Results of Simultaneous Determination of r and k Following Wang and Bessler (2005), Using the Hannan and Quinn M Loss Metric

	r (cointegrating rank)				
k (lags)	1	2	3	4	5
1	-31.12	-31.17	-31.19	-31.17	-31.15
2	-31.23	-31.25	**-31.26**	-31.24	-31.21
3	-31.20	-31.19	-31.19	-31.16	-31.13
4	-31.08	-31.08	-31.06	-31.03	-30.99
5	-30.98	-30.97	-30.95	-30.92	-30.88
6	-30.85	-30.83	-30.81	-30.77	-30.74
7	-30.63	-30.60	-30.57	-30.54	-30.51
8	-30.44	-30.40	-30.37	-30.34	-30.30
9	-30.34	-30.31	-30.28	-30.24	-30.22
10	-30.13	-30.11	-30.08	-30.04	-30.01

There are a suite of tests available to further examine the cointegrating space. Results of these tests are reported in table 2.3. The null hypothesis of the variable stationarity test is that one or more of the cointegrating vectors does not represent a linear combination of non-stationary series, but rather arises because one of the series is stationary given the optimal lag length and cointegrating rank of the VECM. This hypothesis is rejected at the 5% level for all series. The second test is for variable exclusion, which tests the null hypothesis that a particular series is not a part of the cointegrating space. The null hypothesis is rejected at the 5% level for all five endogenous series. Lastly, the test for weak exogeneity examines whether a variable responds to disruptions to the long run relationships characterizing the data. The null hypothesis of weak exogeneity is rejected at the 5% level for all five endogenous series. These three tests suggest that cointegration exists, all endogenous series are included in the cointegrating space, and all series respond to shocks in the system.

Table 2.3. Test for Variable Exclusion, Stationarity, and Weak Exogeneity for the Full Sample Period. P-values in Parentheses

Test	Coal	NG	Coal Inv	Bonds	Elec
Stationarity	34.17	11.00	34.79	34.15	35.21
	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)
Exclusion	19.71	22.11	31.22	16.42	36.94
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Weak Exogeneity	25.41	12.04	30.00	9.24	35.83
	(0.00)	(0.01)	(0.00)	(0.03)	(0.00)

Testing Constancy of β

As Hansen and Johansen (1999) note, the test of parameter constancy outlined above does not require any additional restrictions for identification of β. The sequence of test statistics $Q_T^{(t)}$ for each $t = t_b, t_{b+1}, t_{b+2}, \ldots . T$, therefore, is calculated recursively for the VECM with two lags and three cointegrating vectors. The minimum t_b allowable given the number of parameters in the model is April 1980, thus, the base sample for the recursive estimation is September 1977 to April 1980. Each successive estimation in the recursive process can be done in one of two ways, either by re-estimating all parameters in the model in each step (referred to as the X-Form) or by re-estimating α and β while holding the short-run parameters fixed (R1-Form). The series of test statistics $Q_T^{(t)}$ are reported for both forms in figure 2.2. By construction, the sequence converges to zero at the end of the sample.

Estimates of $\hat{\beta}^{(t)}$ are not constant over the entire sample for both the X- and R1-Forms, suggesting the long run relationships among coal inventories, coal and natural gas costs, electricity prices, and Aaa bond rates contain some degree of instability. The X-Form displays a period of instability from mid-1994 to mid-2001 as $Q_T^{(t)}$ exceeds the critical value during this period, leading to a rejection of the null hypothesis of parameter constancy. The R1-Form contains the same period of instability, but also shows some instability near the beginning of the sample (mid-1981 to mid-1986).

A timeline of major developments related to the U.S. electricity generating process during the sample period is presented in table 2.4. The first major event in the sample was the Staggers Rail Act of 1980, which lifted constraints on the railroad industry and allowed railroad operators more flexibility in pricing and delivery (U.S. Federal Railroad Administration 2011). This flexibility had implications for coal inventory decisions in the electricity industry, as the majority of coal is transported by rail. The initial period of instability in the R1-Form begins roughly 10 months after the Staggers Rail Act was signed into law. Wilson (1994) estimates the effects of the Staggers Act on rail rates for a number of commodities. He finds that the law initially increased rail rates for coal, but by 1988 the effect of regulation had reversed. In addition, Dennis (2000) shows that coal-related rate reductions were an important factor in explaining the large overall rate reduction seen by the railroad industry in the 16 years following the Staggers Act. It is possible that the instability shown in the R1-Form, which holds the short-run VECM parameters fixed, is reflective of the effects of policy changes in the railroad industry.

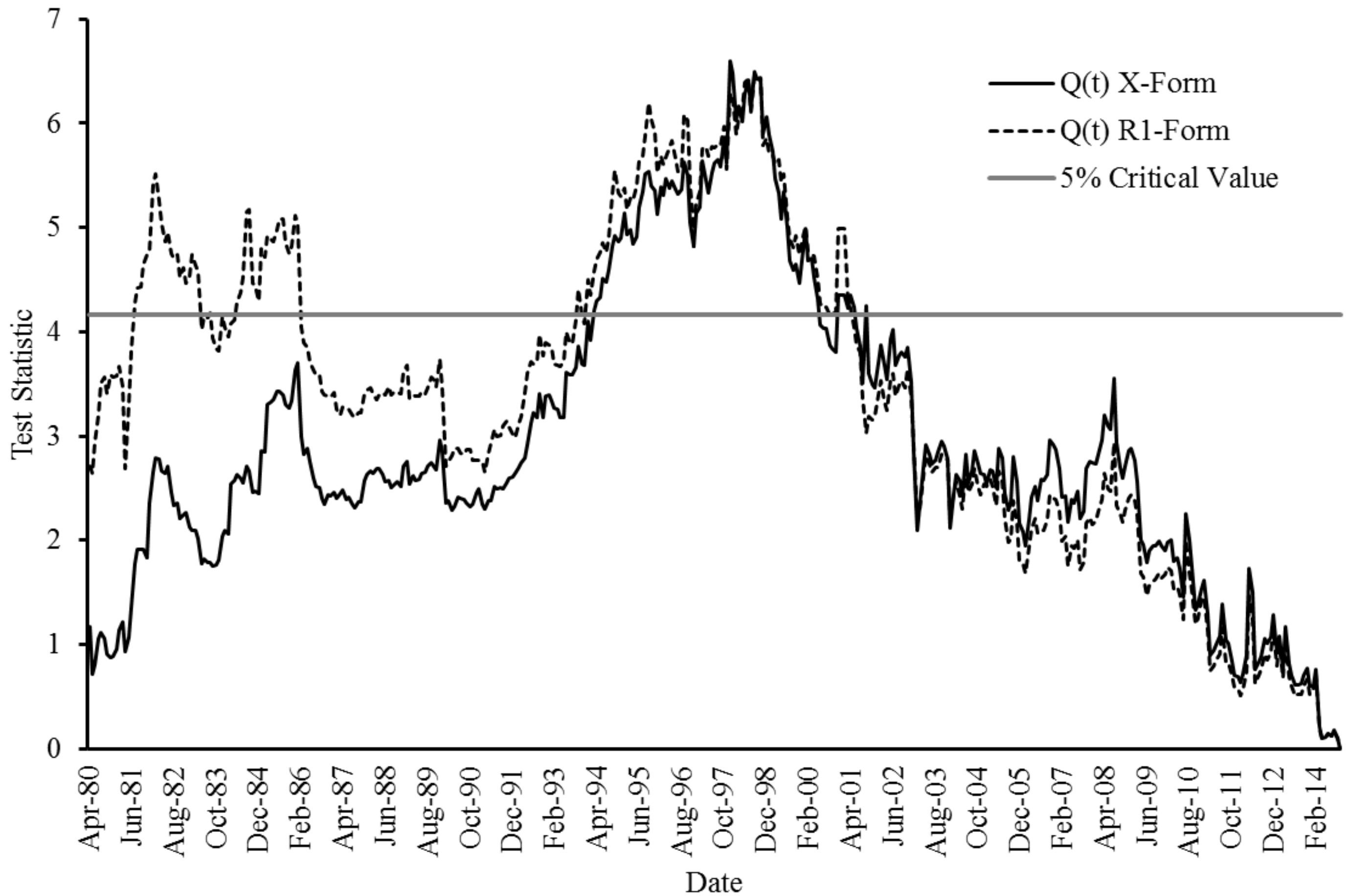

Figure 2.2. Results of test for constancy of $\boldsymbol{\beta}$ following Hansen and Johansen (1999) for VECM with $k = 2$ and $r = 3$. The null hypothesis at each t is that $\widehat{\boldsymbol{\beta}}^{(t)} = \widehat{\boldsymbol{\beta}}^{(T)}$. The 5% critical value for the test is 4.17.

Table 2.4. Timeline of Major Events Pertaining to the Electric Power and Natural Gas Sectors

Date	Event	Description
10/14/80	Staggers Rail Act	Deregulation of U.S. railroad services
11/15/90	Clean Air Act Amendments	Promotes use of low-sulfur coal and natural gas. Establishes SO_2 permit trading program.
4/8/92	FERC Order 636	Unbundling of sales from transportation services in natural gas industry
10/24/92	Energy Policy Act	Goals for increasing clean energy use and improving energy efficiency
1/1/94	NAFTA	Trilateral trade agreement between U.S., Mexico, and Canada
4/24/96	FERC Order 888	Promotes competition in U.S. electricity sector
12/11/97	Kyoto Protocol	International agreement to reduce greenhouse gas emissions
12/20/99	FERC Order 2000	Advances formation of RTOs
8/8/05	Energy Policy Act	Authorizes subsidies for clean energy sources, promotes clean coal initiatives
Aug-Sep. ‘05	Hurricanes Katrina and Rita	Major disruptions in U.S. Gulf state natural gas and petroleum infrastructure
’07-‘08	Onset of U.S. shale gas boom	Natural gas supply increase and subsequent decrease in price
7/6/11	Cross-State Air Pollution Rule	State level caps on SO_2 emissions; national cap from ’90 Clean Air Act Amendments no longer binding[1]

[1]See Evans and Woodward (2013) for a detailed discussion regarding the 1990 Clean Air Act Amendments.

The second period (mid-1994 to mid-2001) of parameter instability (present in both the X- and R1-Forms) corresponds to the implementation of several regulatory measures directly related to the electric power industry. In November of 1990, a new set of amendments to the U.S. Clean Air Act were signed into law. The new amendments encouraged reduction of sulfur dioxide emissions (among other toxics) by establishing emissions trading programs and by promoting the use of low sulfur coal and natural gas (U.S. Environmental Protection Agency 2015a). One and a half years later, in April 1992, the U.S. Federal Energy Regulatory Commission (FERC) issued Order No. 636, which unbundled sales and transportation services in the natural gas industry, creating a new level of competition in the marketplace (U.S. FERC 2015a). The second period of parameter instability begins about two years after Order No. 636, in 1994. In April 1996, FERC passed Order No. 888, which intended to promote competition in wholesale electricity markets (U.S. FERC 2015b). FERC passed Order No. 2000 in December 1999, encouraging participation in wholesale electricity markets by advancing the creation of Regional Transmission Organizations (U.S. FERC 2015c). The second period of instability ends approximately a year and a half afterward, in mid-2001. Given the results of the test displayed in figure 2.2, it is possible that this era of regulatory action in the U.S. electricity sector caused disruptions in the long run relationships characterizing inventory behavior, input and output prices, and opportunity costs in the electricity industry.

Constancy is present in the estimates of $\hat{\beta}^{(t)}$ after mid-2001. There is a spike in $Q_T^{(t)}$ around mid-2008, which approximately corresponds to the onset of the U.S. shale gas boom. The test statistics, however, do not reach the rejection region. This result suggests that the U.S. shale gas boom did not coincide with the same level of instability in the long run relationship as that of the regulatory environment of the 1990s.

Testing Constancy of β in Subsets of the Variables

To further investigate the possible sources of the parameter instability uncovered in the previous sub-section, VECMs are estimated for the 26 potential subsets of the five endogenous variables (exogenous variables are included in each model). Each VECM is specified following the simultaneous determination procedure described above. The same test for constancy of β following Hansen and Johansen (1999) is carried out for each of the 26 models. For brevity, only a few results are discussed in the text. Graphs of the test statistics for all 26 models are in Appendix A.

In all possible four-variable model combinations which contain both coal inventory and coal costs, a similar pattern of rejection of constancy is present in the beginning of the sample. As in the full model, the R1-Form of the test statistic rejects constancy during the period mid-1981to mid-1986. Conversely, the four-variable model omitting coal costs (containing coal inventory, natural gas costs, electricity price, and bonds) does not exhibit rejection in this initial period. A similar result is found in the four-variable model in which coal inventory is omitted. These findings suggest that the initial period of parameter instability in the full model may be attributed to occurrences in the coal inventory series, the coal cost series, or the relationship(s) between them. This evidence aligns with the proposition that the Staggers Rail Act of 1980 may be influencing the initial period of instability in the long run relationships; the coal market was likely affected more by this act than the natural gas or wholesale electricity markets.

A second pattern emerges from examining the 26 models. In all models which contain both natural gas cost and electricity price, the second period of parameter instability appears (mid-1994 to mid-2001). In the 18 models which omit one or both of the natural gas and electricity price series, this period of rejection does not occur except in three cases (in these three cases, the period of rejection is shorter and the test statistic is only slightly above the critical value). Of the three cases where a period of rejection occurs, electricity price appears in two and natural gas cost is included in the third. This result is consistent with the idea that deregulation of both the natural gas and electricity markets might have contributed to the second period of instability in the long run relationships. Duangnate (2015), who investigates the stability of long run relationships among eight North American daily natural gas spot markets, finds three periods of instability, one from approximately 1996 to 2000. These findings are compatible with that of the current study; the natural gas market may be a source of instability in the long run relationships across the coal inventory, coal and natural gas costs, electricity price, and bond market relationships.

A third period of rejection (2007-2009) is present in some of the models, roughly coinciding with the onset of the U.S. shale gas boom. This period of instability appears in models which include natural gas and electricity price. Because the shale gas boom affected natural gas prices, which in turn may have affected electricity prices, this finding is not surprising. This period of rejection is generally not present in models which include both the coal inventory and bonds series, suggesting that inventory may have been acting as a smoothing mechanism. This inference is consistent with the economic theory of inventory management.

Innovation Accounting in Three Subperiods

Given the results of the tests for parameter constancy in the full model, it is instructive to break the data into three subperiods. Tests for variable exclusion, stationarity, and weak exogeneity are carried out for each subperiod. Impulse response functions (IRFs) and forecast error variance decompositions (FEVDs) are computed separately for each subperiod and compared to examine how the relationships between coal inventory and input, output, and opportunity costs have changed over time.

The three subperiods for which the analysis is implemented, based on the test results displayed in figure 2.2, are: July 1976 to September 1993, October 1993 to December 2001, and January 2002 to October 2014. As outlined above, the middle period (October 1993 to December 2001) is wholly characterized by long run parameter instability, possibly brought on by the introduction and continued alterations of new policies in the energy industry. For each of these three subperiods, a VECM is specified and fit to the data. Results of tests for variable exclusion, stationarity, and weak exogeneity for each of the three subperiods are in table 2.5. All three hypotheses are rejected for the coal inventory series in the first two subperiods. In the third subperiod, the hypotheses of exclusion and weak exogeneity of coal inventory are unable to be rejected, suggesting that coal inventories are not part of the cointegrating space and do not respond to shocks in the system during this subperiod (January 2002 – October

2014). This finding provides further evidence that inventory behavior was likely affected by the changing policy landscape of the 1990s, but was fairly stable over more recent market developments (Hurricanes Katrina and Rita in 2005 and the onset of the U.S. shale gas boom in the mid-to-late 2000s).

DAGs for each of the three subperiods are presented in figures 2.3-2.5. The first subperiod exhibits contemporaneous causal flows from coal, natural gas, and electricity prices to coal inventories, and from Aaa corporate bond rates to electricity prices. In the second subperiod, the flows from coal costs and electricity prices to coal inventories are not present. The DAG for the third subperiod differs from the first two. Contemporaneous flows exist from bond rates to coal inventories (this is not the case in either of the first two subperiods). Additionally, there are flows from coal inventories and coal costs to natural gas costs, and from natural gas costs to electricity prices.

IRFs, which show the effect of a one-time shock in one variable on the future values of the remaining variables, are displayed for each of the three subperiods in figures 2.6-2.8.[3] The responses of coal inventory to the four economic factors are generally unchanged across the three subperiods. Coal inventories respond negatively to shocks in natural gas costs in all three subperiods and negatively to electricity price shocks in the first and third subperiods. During the second subperiod, however, the response of coal inventories to shocks in electricity price is minimal. Recall that the second subperiod contains numerous regulatory shifts in the electricity industry. It is

[3] The IRFs are standardized by dividing through by the standard error of innovations for each series.

possible that power plants were less willing to adjust their inventory schedules according to electricity price fluctuations during this period of regulatory change.

Coal inventories respond positively to shocks in coal costs in all three subperiods; the largest response is in the first subperiod. The first subperiod contains the Staggers Rail Act of 1980; it is likely that power plants adjusted inventories after seeing the effects of the Act on coal rates. Another interesting takeaway from the IRF analysis is that coal inventories respond positively to shocks in Aaa corporate bond rates in all three subperiods.

The IRFs concerning relationships among the non-inventory variables are generally consistent across subperiods; several results are noted here. The first is that coal and natural gas costs both respond negatively to shocks in electricity price during the second subperiod, which might be the result of adjustment to electricity market restructuring during the period. Electricity prices show a relatively strong positive response to natural gas cost shocks in the third subperiod, which contains the U.S. shale gas boom (a large increase in domestic natural gas supply).

Forecast error variance decompositions show the percentage of variance in forecast error for a given variable that can be explained by shocks to the other variables at various time horizons (tables 2.6-2.8). In the first subperiod, 82% of forecast error variance in coal inventories at a one-month horizon is explained by own shocks. This number falls to 59% at a twelve-month horizon, with natural gas shocks contributing to 19% of the variance, and the other three economic series contributing between 6% and 9%. FEVDs of coal inventories in the second subperiod differ from the first. Own shocks to coal inventories explain 92% of variance at a one-month horizon, but this number falls quickly, reaching 37% at the twelve-month horizon. Natural gas shocks explain 60% of variance in coal inventories at the twelve month horizon, providing evidence that regulatory changes in the natural gas sector affected coal inventory behavior during this period. Coal inventories are largely exogenous in the third subperiod, with over 90% of variance explained by own shocks at all forecast horizons. These findings show that inventory behavior was affected by regulatory changes in the 1990s to a larger extent than natural shocks to energy markets in the 2000s.

FEVDs for the electricity price series vary across the three subperiods. The percentage error explained by natural gas costs increases from 3% at a twelve-month horizon in the first subperiod, to 28% in the second subperiod, to 70% in the third subperiod. This evidence points towards an increasing level of interaction between the two markets as the U.S. shifted from a heavily regulated electricity industry to a more competitive landscape.

Table 2.5. Test for Variable Exclusion, Stationarity, and Weak Exogeneity for the Three Subperiods. P-values in Parentheses

Test	Coal	NG	Coal Inv	Elec	Bonds
			July 1976-September 1993		
Stationarity	26.29	25.40	23.34	25.34	18.43
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Exclusion	6.27	11.24	6.15	0.27	9.66
	(0.01)	(0.00)	(0.01)	(0.60)	(0.00)
Weak Exogeneity	5.09	9.94	10.06	1.25	3.11
	(0.02)	(0.00)	(0.00)	(0.27)	(0.08)
			October 1993-December 2001		
Stationarity	12.33	14.04	15.66	11.86	15.08
	(0.03)	(0.02)	(0.01)	(0.04)	(0.01)
Exclusion	7.89	16.86	9.88	15.06	4.23
	(0.05)	(0.00)	(0.02)	(0.00)	(0.238)
Weak Exogeneity	32.97	10.88	15.88	18.86	8.87
	(0.00)	(0.01)	(0.00)	(0.00)	(0.03)
			January 2002-October 2014		
Stationarity	25.99	10.19	21.11	8.24	22.37
	(0.00)	(0.07)	(0.00)	(0.144)	(0.00)
Exclusion	2.48	33.91	2.43	32.65	6.55
	(0.29)	(0.00)	(0.30)	(0.00)	(0.04)
Weak Exogeneity	13.87	4.60	0.02	14.86	7.66
	(0.00)	(0.10)	(0.99)	(0.001)	(0.02)

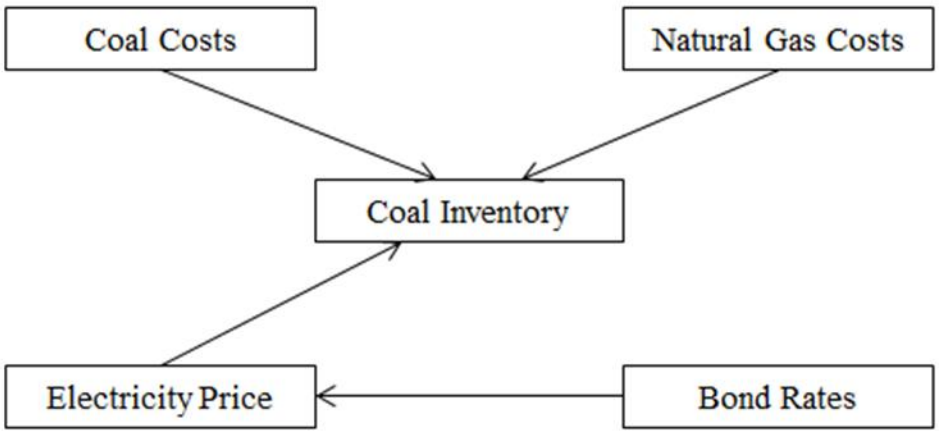

Figure 2.3 Directed Acyclic Graph for the subperiod July 1976 – September 1993

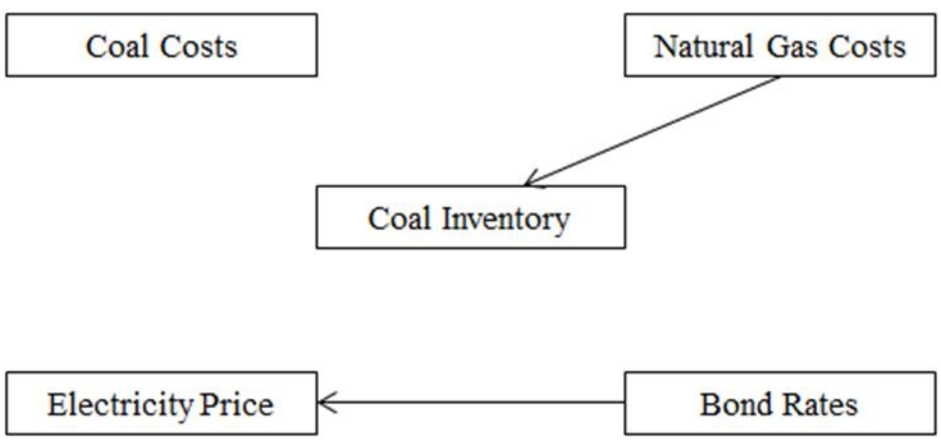

Figure 2.4 Directed Acyclic Graph for the subperiod October 1993 – December 2001

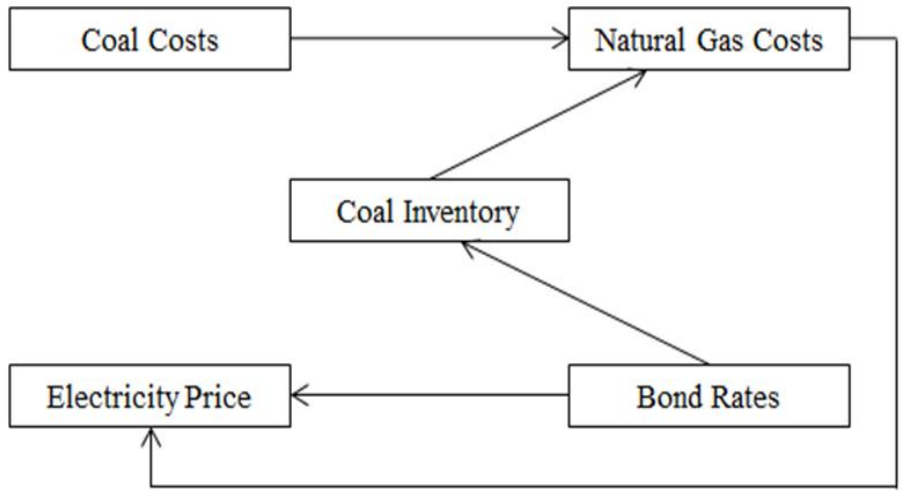

Figure 2.5 Directed Acyclic Graph for the subperiod January 2002 – October 2014

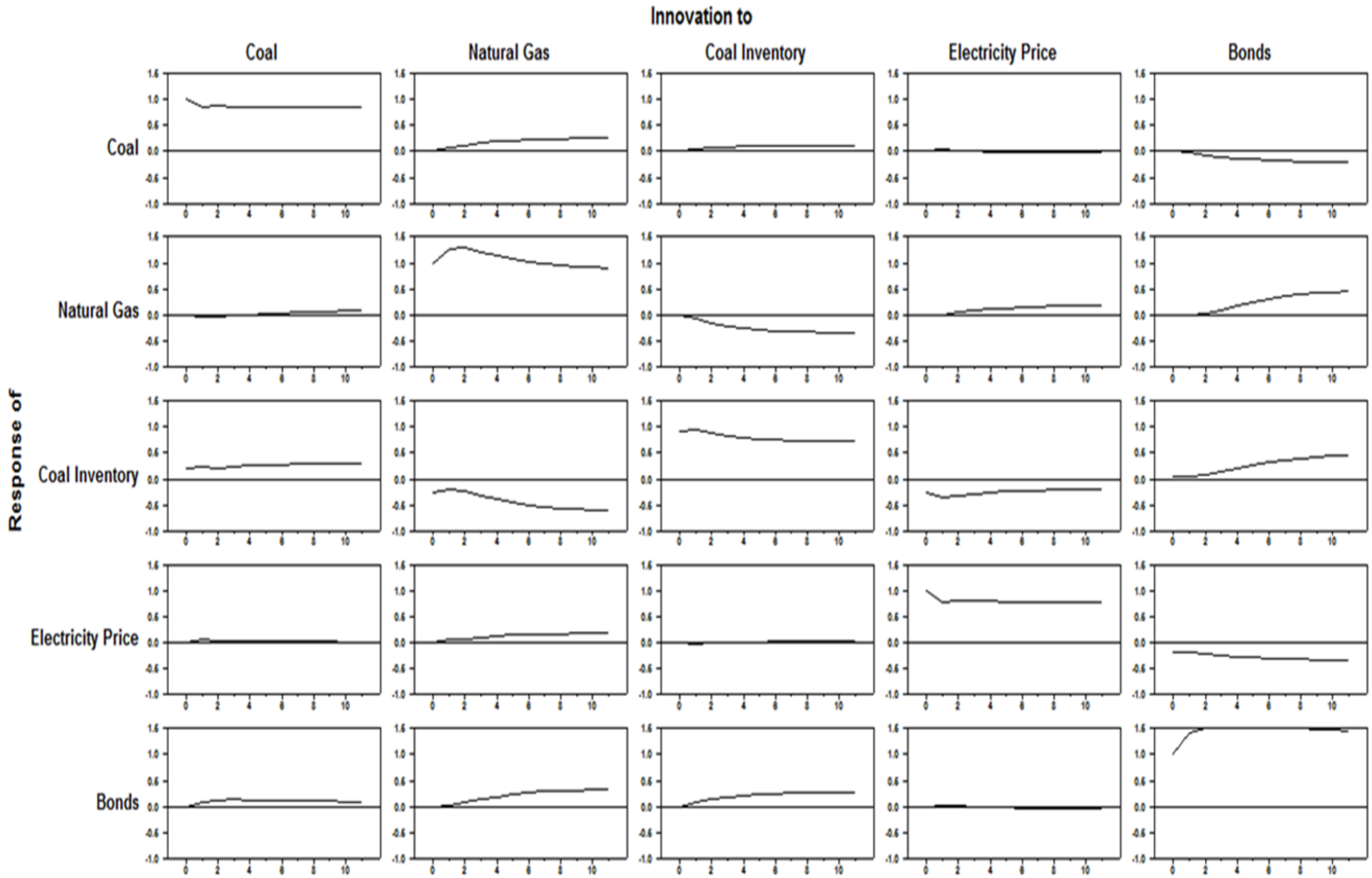

Figure 2.6 Impulse Response Functions for the subperiod July 1976 – September 1993

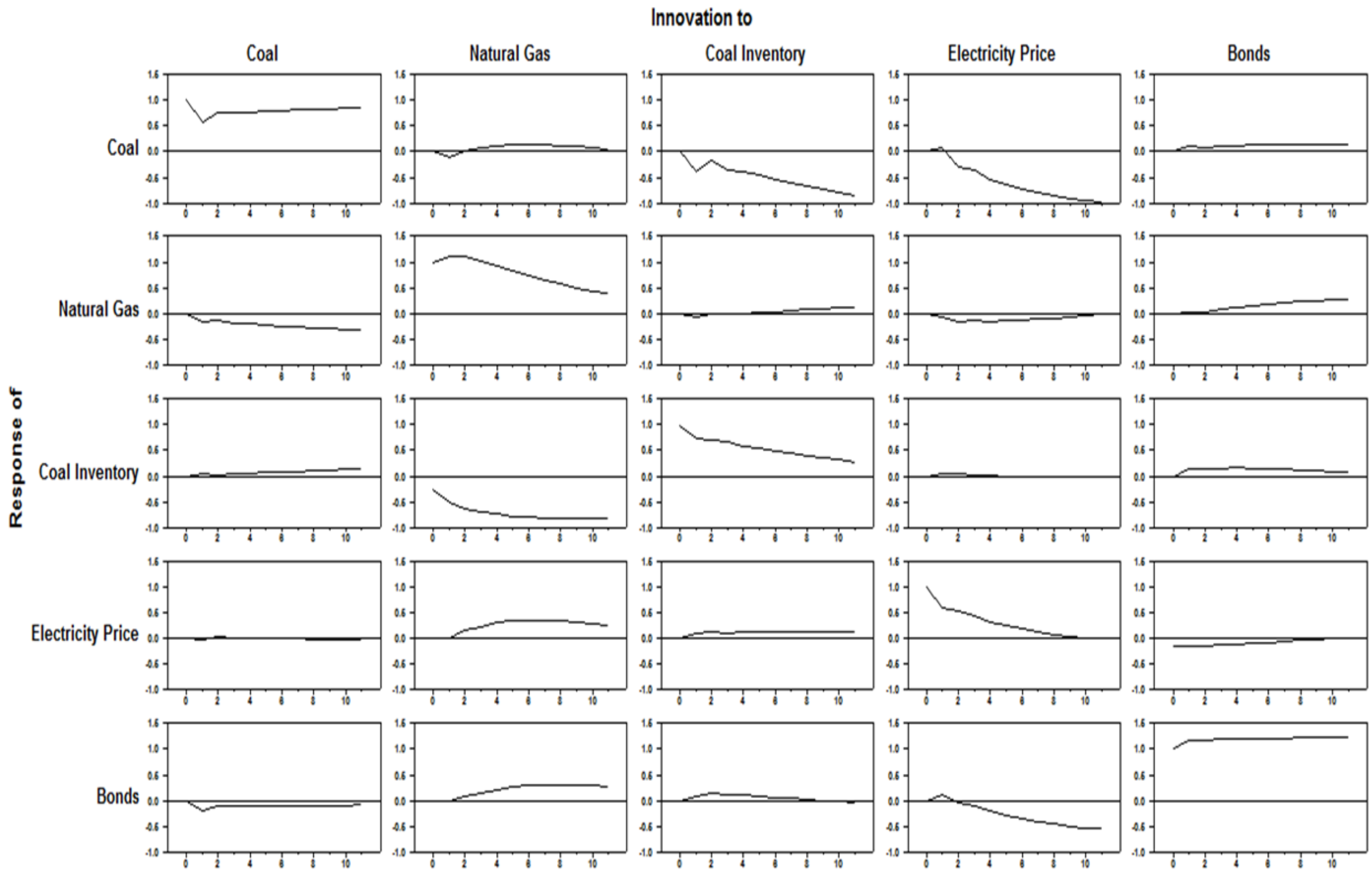

Figure 2.7 Impulse Response Functions for the subperiod October 1993 – December 2001

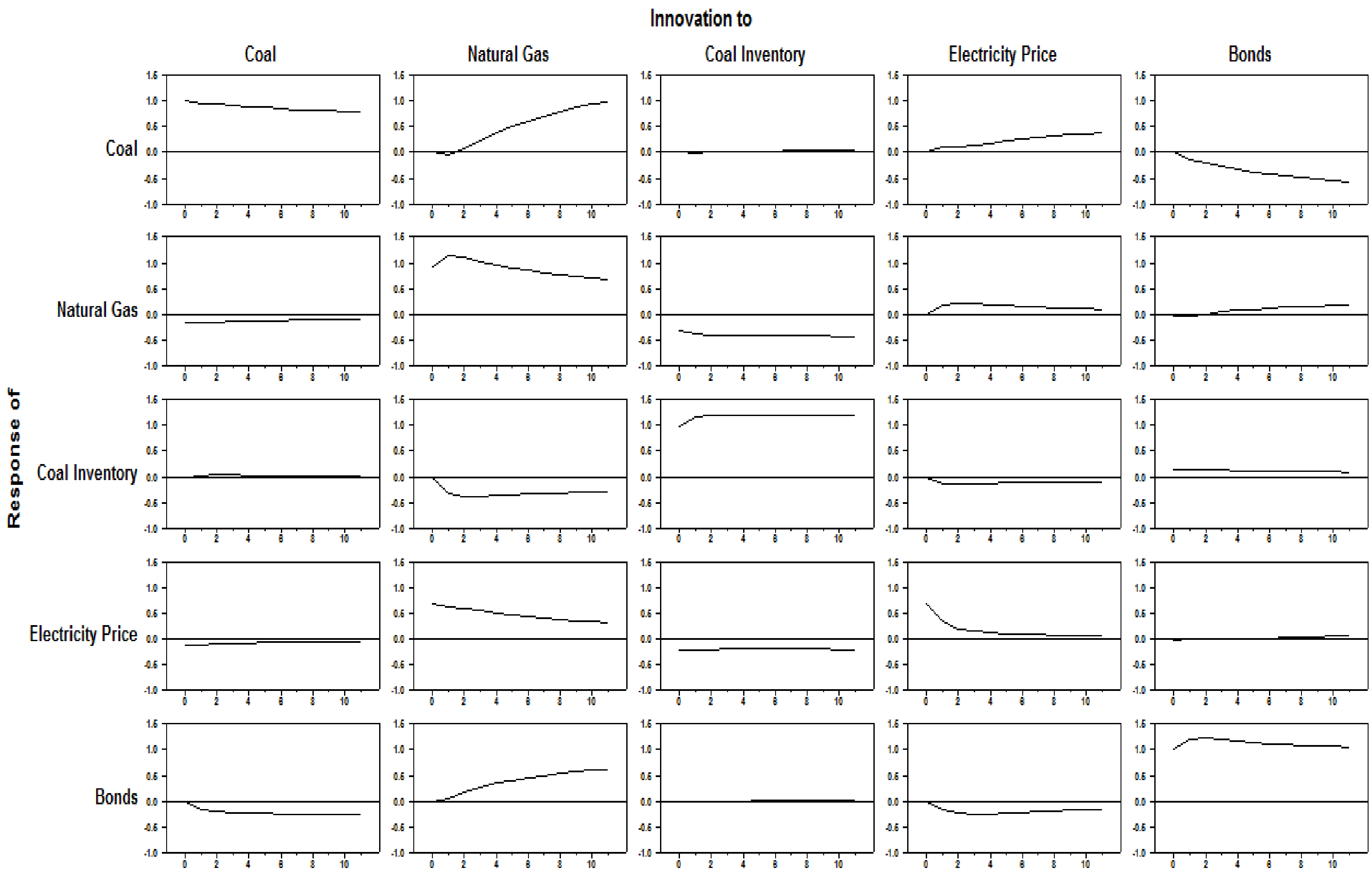

Figure 2.8 Impulse Response Functions for the subperiod January 2002 – October 2014

Table 2.6. Forecast Error Variance Decompositions for the Subperiod July 1976 – September 1993

		Contribution of				
Series	Months Ahead	Coal	Natural Gas	Coal Inv	Elec	Bonds
Coal	1	100.00	0.00	0.00	0.00	0.00
	4	97.69	1.35	0.43	0.06	0.48
	8	93.70	3.50	0.88	0.05	1.88
	12	91.01	4.86	1.14	0.06	2.93
Natural Gas	1	0.00	100.00	0.00	0.00	0.00
	4	0.02	98.45	1.19	0.15	0.15
	8	0.07	92.73	3.51	0.80	2.90
	12	0.19	86.48	5.16	1.40	6.78
Coal Inv	1	3.84	7.28	82.46	6.18	0.24
	4	4.68	6.83	78.50	9.28	0.72
	8	5.90	14.18	67.71	7.40	4.80
	12	6.56	19.45	59.15	5.94	8.90
Electricity	1	0.00	0.00	0.00	96.24	3.76
	4	0.29	0.68	0.03	93.50	5.50
	8	0.20	1.84	0.04	89.58	8.34
	12	0.15	2.63	0.06	86.81	10.35
Bonds	1	0.00	0.00	0.00	0.00	100.00
	4	0.51	0.30	0.81	0.02	98.36
	8	0.52	1.45	1.63	0.03	96.37
	12	0.49	2.42	2.12	0.05	94.92

Table 2.7. Forecast Error Variance Decompositions for the Subperiod October 1993 – December 2001

		Contribution of				
Series	Months Ahead	Coal	Natural Gas	Coal Inv	Elec	Bonds
Coal	1	100.00	0.00	0.00	0.00	0.00
	4	80.32	0.66	10.60	7.46	0.96
	8	57.77	1.10	15.52	24.49	1.12
	12	44.83	0.73	20.99	32.39	1.05
Natural Gas	1	0.00	100.00	0.00	0.00	0.00
	4	1.50	97.22	0.07	0.98	0.24
	8	3.71	92.87	0.13	1.48	1.82
	12	6.90	86.52	0.62	1.32	4.64
Coal Inv	1	0.00	7.62	92.38	0.00	0.00
	4	0.19	33.15	64.81	0.09	1.77
	8	0.38	50.25	47.21	0.05	2.12
	12	0.88	60.14	37.09	0.03	1.86
Electricity	1	0.00	0.00	0.00	97.84	2.16
	4	0.15	3.75	1.64	90.09	4.37
	8	0.12	19.37	3.60	72.41	4.50
	12	0.20	27.94	5.05	62.85	3.97
Bonds	1	0.00	0.00	0.00	0.00	100.00
	4	1.12	0.57	0.79	0.55	96.67
	8	0.85	2.86	0.57	3.78	91.96
	12	0.69	3.64	0.36	7.66	87.65

Table 2.8. Forecast Error Variance Decompositions for the Subperiod January 2002 – October 2014

		Contribution of				
Series	Months Ahead	Coal	Natural Gas	Coal Inv	Elec	Bonds
Coal	1	100.00	0.00	0.00	0.00	0.00
	4	93.73	1.83	0.01	0.95	3.50
	8	73.29	15.14	0.03	2.94	8.60
	12	55.89	27.94	0.05	4.60	11.53
Natural Gas	1	2.74	88.25	8.83	0.00	0.19
	4	1.76	85.40	10.19	2.55	0.10
	8	1.57	82.14	12.98	2.71	0.60
	12	1.46	79.13	15.49	2.49	1.43
Coal Inv	1	0.00	0.00	97.90	0.00	2.10
	4	0.06	7.04	90.42	1.10	1.39
	8	0.05	7.24	90.61	0.99	1.10
	12	0.04	6.66	91.48	0.88	0.94
Electricity	1	1.44	46.55	4.66	47.26	0.10
	4	1.88	64.06	7.25	26.76	0.05
	8	1.84	68.90	9.37	19.81	0.08
	12	1.78	69.36	11.58	16.96	0.32
Bonds	1	0.00	0.00	0.00	0.00	100.00
	4	1.99	2.09	0.01	2.52	93.39
	8	2.86	7.20	0.01	2.87	87.07
	12	3.37	12.14	0.02	2.53	81.94

Alternative Specifications of the Full Model

An alternative to using the simultaneous determination procedure of Wang and Bessler (2005) is a two-step process in which optimal lag order (k) is selected in the first step, and then cointegrating rank (r) is determined in the second step. Information criteria are used to select k in a levels VAR, then a trace test following Johansen (1992) is performed to select r. Results of the first step are reported in table 2.9. There is a disagreement between the two criteria, as the Schwarz loss metric is minimized at $k = 1$ lag and the Hannan and Quinn loss metric is minimized at $k = 3$ lags. Because of this discrepancy, the trace test is carried out for both scenarios, and the sequence of test statistics $Q_T^{(t)}$ is calculated recursively for each. The trace test finds three cointegrating vectors ($r = 3$) for the one lag case, and one cointegrating vector in the three lag case (table 2.10).

Parameter constancy tests (the sequence $Q_T^{(t)}$) for the $k = 1$ and $r = 3$ are displayed in figure 2.9 (Case 2), and for $k = 3$ and $r = 1$ in figure 2.10 (Case 3). Only the R1-Form is reported in Case 2; by definition, a choice of $k = 1$ leads to the absence of short-run parameters in the estimated VECM. The test statistic follows a similar pattern in both Case 2 and 3, as well as in the original scenario where $k = 2$ and $r = 3$ (Case 1). The pattern of rejection, however, differs between the three cases. Case 2, which has one less lag but the same number of cointegrating vectors as Case 1, rejects continuously over the sample period 1981 to roughly mid-2001. Case 2 more readily rejects the null hypothesis of parameter constancy than does Case 1. On the other hand,

Table 2.9. Optimal Lag Length Determination

k	Schwarz Information Criterion	Hannan-Quinn Information Criterion
1	**-29.94**	-30.29
2	-29.90	-30.44
3	-29.76	**-30.50**
4	-29.43	-30.35
5	-29.11	-30.23
6	-28.91	-30.22
7	-28.48	-29.99
8	-28.06	-29.77
9	-27.78	-29.68
10	-27.37	-29.45
11	-27.03	-29.31
12	-26.63	-29.10
13	-26.47	-29.14
14	-26.12	-28.98

Table 2.10. Results of Trace Test for Lag Order $k = 1$ and $k = 3$

r	Trace	Critical Value (5%)	P-Value
		$k = 1$	
0	339.331	111.420	0.000
1	129.640	82.351	0.000
2	67.979	57.190	0.005
3	24.381	35.854	0.442
4	10.370	18.084	0.410
		$k = 3$	
0	142.257	111.420	0.000
1	82.661	82.351	0.047
2	44.174	57.190	0.377
3	13.589	35.854	0.963
4	1.360	18.084	1.000

The null hypothesis for each $i = 0,1, \ldots ,4$ is that $r \leq i$. The first rejection occurs at $r = 3$, therefore three cointegrating vectors are selected.

the sequence $Q_T^{(t)}$ never reaches the rejection region in Case 3, which has one more lag and one less cointegrating vector than Case 1.

These results suggest the possibility that fitting the model with a higher degree of short-run dependence leads to a lower probability of rejection of constancy in the long run parameters. It might also be the case that fitting a model with a lower number of cointegrating vectors leads to a similar result. Simulation studies to examine these possibilities are left as a suggestion for further research.

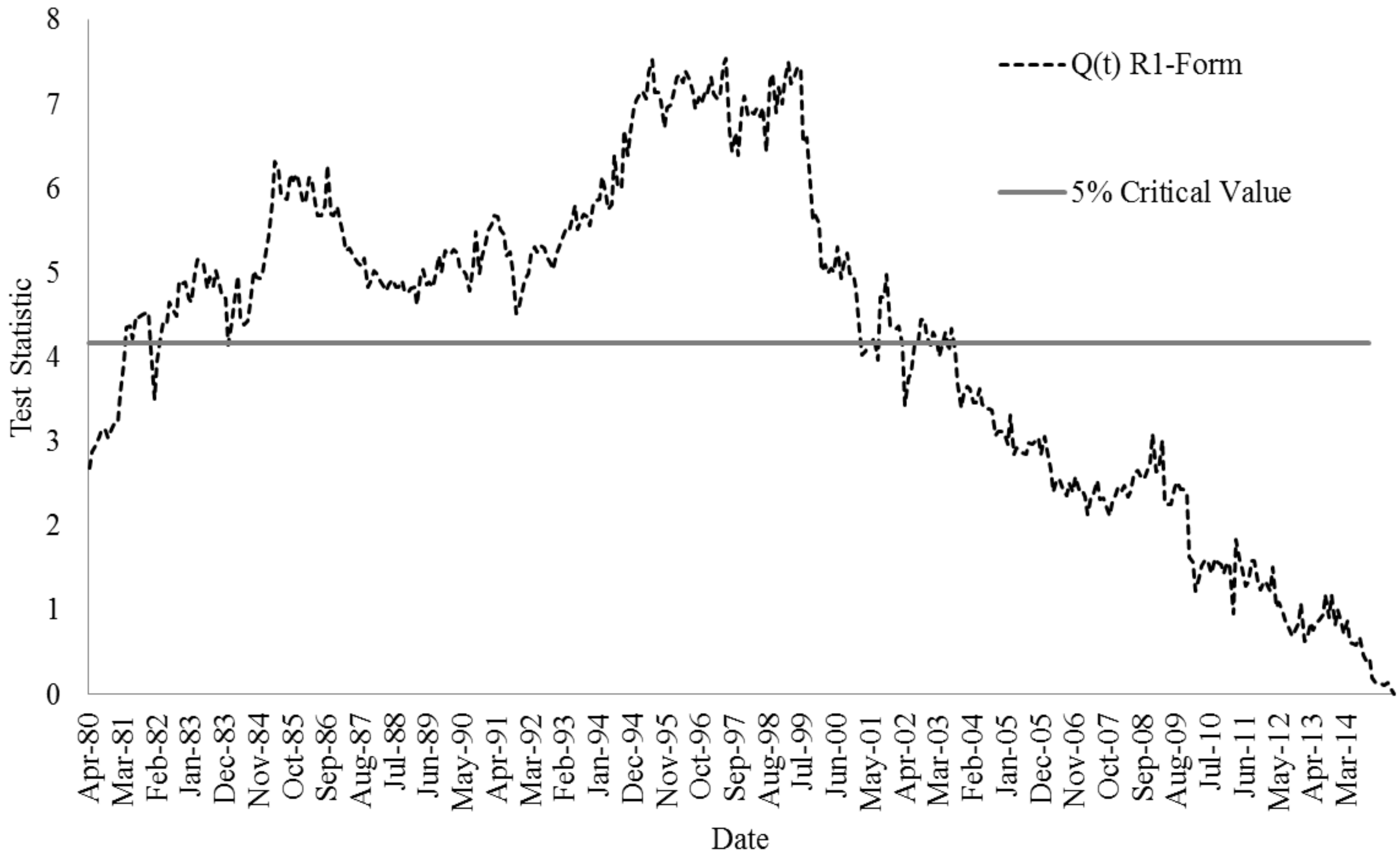

Figure 2.9. Results of test for constancy of $\boldsymbol{\beta}$ following Hansen and Johansen (1999) for VECM with $\boldsymbol{k = 1}$ and $\boldsymbol{r = 3}$. The null hypothesis at each $\boldsymbol{t}$ is that $\widehat{\boldsymbol{\beta}}^{(t)} = \widehat{\boldsymbol{\beta}}^{(T)}$. The 5% critical value for the test is 4.17.

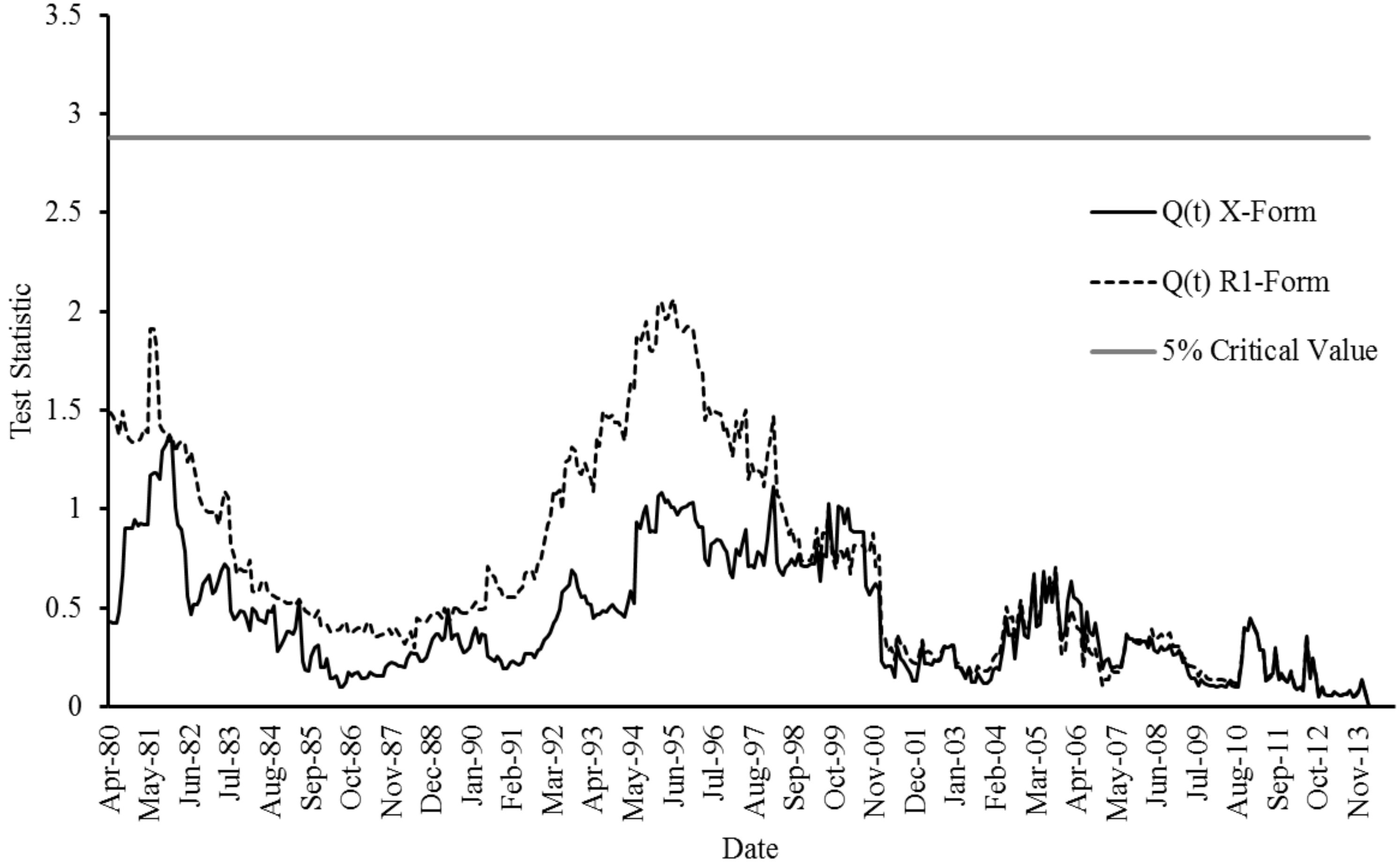

Figure 2.10. Results of test for constancy of $\boldsymbol{\beta}$ following Hansen and Johansen (1999) for VECM with $k = 3$ and $r = 1$. The null hypothesis at each t is that $\widehat{\boldsymbol{\beta}}^{(t)} = \widehat{\boldsymbol{\beta}}^{(T)}$. The 5% critical value for the test is 2.88.

Conclusions

This study characterizes the long run relationships concerning coal inventory behavior in the U.S. electric power sector. In line with previous studies, cointegrating relationships are found among the five endogenous series in the study: coal inventory, coal and natural gas costs to electric power plants (input prices), electricity prices (output prices), and Aaa corporate bond rates (opportunity costs). All series are found to be contained in the long run relationships and react to shocks in the system to bring it back to equilibrium. A test for parameter constancy in a VECM containing the five series reveals two periods of instability in the long run relationships, from mid-1981 to mid-1986, and from mid-1994 to mid-2001.

The Staggers Rail Act of 1980 had large impacts on the coal industry, resulting in changes in railroad practices and rail rates. The initial period of instability shows that the long run relationships among coal inventory, prices, and opportunity costs were likely affected by the passage of the Act. Following the initial period of parameter instability, the long run relationships remain constant for approximately eight years. During this span, The Clean Air Act Amendments of 1990 were signed into action, FERC issued an order to unbundle sales from transportation in the natural gas industry, the Energy Policy Act of 1992 was introduced, and NAFTA was established in January of 1994. Following the Clean Air Act Amendments, an upward trend in the test statistic $Q_T^{(t)}$ begins, and reaches the rejection region in mid-1994, where it remains for a period of seven years. During this period of instability, FERC issued several orders pertaining to deregulation of the electric power sector and promotion of wholesale power competition. Additionally, the Kyoto Protocol was signed in late 1997. It is plausible that the long run relationships entered an unstable period following the new regulations of the early 1990s and stayed there because of continued regulatory and policy fluctuations throughout the decade.

Following the second period of instability, the test is unable to reject the hypothesis of parameter constancy for the remainder of the sample, which includes two major shocks to energy markets (Hurricanes Katrina and Rita in 2005 and the onset of the U.S. shale gas boom in the mid-to-late 2000s). These shifts in market conditions did not result in the same level of instability which was observed during the changing regulatory environment of the 1990s. This idea is supported by the finding that natural gas shocks contribute up to 60% of the forecast error variance in coal inventories during the subperiod October 1993-December 2001, but less than 7% during the subperiod January 2002-October 2014. This is not to say that decision makers in the electric power sector did not react to price changes caused by these events, but rather that the long run relationship between inventory decisions, prices, and opportunity costs did not change as a result.

To explore the potential sources of instability, all 26 subsets of the five endogenous variables are examined for parameter constancy. This investigation reveals evidence supporting the hypothesis that the initial period of instability is related to structural changes in the coal industry caused by the Staggers Rail Act. Additionally, natural gas costs and electricity prices are found to be a major contributor to the second period of instability. Deregulation of natural gas and electricity markets is a likely source of this instability.

Following the investigation of parameter instability, the sample period is split into three subperiods (July 1976-September 1993, October 1993-December 2001, and January 2002-October 2014). Innovation accounting procedures are carried out for each subperiod. IRFs and FEVDs show that the contribution of unexpected shocks to input and output prices and opportunity costs to the behavior of the coal inventory series showed some fluctuation across the three subperiods. In particular, inventory behavior shows larger responses to coal costs following the Staggers Rail Act of 1980, and to natural gas costs during the period of regulatory instability in the 1990s than in the other two subperiods.

This study shows that major policy changes in the 1990s appear to have disrupted long run relationships characterizing management behavior in the electricity industry. Further, these policy changes are shown to be larger sources of instability than natural shifts in market conditions (natural gas supply shock). Policy makers should be aware that altering the regulatory environment can cause considerable fluctuations in how firms' inventory decisions interact with input and output markets and opportunity costs in the long run. Finally, the system shows a high level of resiliency. Despite all of the events over the last 40 years, the system long run relationships remain constant approximately 68% of the time. External and internal events will continue to influence the coal inventory system, but there is no reason to think the system will not continue to be highly resilient.

CHAPTER III

PRICE INTERACTION IN STATE LEVEL RENEWABLE ENERGY CREDIT TRADING PROGRAMS

Over the course of the last fifteen years, the majority of U.S. states have adopted policies for encouraging the use of renewable energy sources. As of June 2015, 29 states and the District of Columbia had some form of a Renewable Portfolio Standard (RPS); eight more states had declared goals to achieve standards in the near future (Database of State Incentives for Renewables & Efficiency 2015). RPS programs generally require retail electricity suppliers to provide a minimum percentage of total generation from renewable sources; suppliers comply with the requirement by redeeming an appropriate amount of Renewable Energy Credits (RECs). A utility whose electricity portfolio is entirely made up of fossil fuel sources, for example, will need to purchase an adequate number of RECs to achieve the minimum requirement set forth by the RPS. A REC is a certificate equivalent to a unit of electricity generated from an approved renewable source. RECs are produced contemporaneously with the unit of qualified electricity, but they are bought and sold separately from the electricity. This creates a distinct market in which RECs may be traded before compliance submission.

In the last decade, there has been a marked expansion in the use of tradable rights programs to address environmental goals, both in the U.S. and internationally (Goulder 2013). In August 2015, the U.S. Environmental Protection Agency (EPA) released a final rule to reduce carbon dioxide emissions from the electric power sector (U.S. EPA

2015b). The rule has been under heavy scrutiny from politicians, media members, and researchers alike; it has recently been described as "… more or less a forced Renewable Portfolio Standard…" (McConnell 2015). It is important, therefore, to understand the functionality of currently existing programs as U.S. states move towards an energy future that is more reliant on renewables. This chapter helps accomplish this goal by evaluating the dynamic relationships among REC prices in Massachusetts and Connecticut, electricity prices, and natural gas prices. Previous studies have pointed out the need for additional empirical analysis of RPS programs (Felder 2011; Fischer 2010). This chapter contributes to the RPS literature by exploiting a modeling framework (multivariate time series analysis) to examine market relationships which have been introduced in the literature with little empirical examination.

By using a multivariate time-series approach, data-driven results are obtained to describe the REC market relationships mentioned above. First, the dynamic causal relationships between REC and electricity prices are examined in this study. As Felder (2011) argues, theory suggests that the price of a REC is determined by the difference between the cost of generation for the renewable resource and the revenue obtained from producing electricity. An increase (decrease) in electricity prices, therefore, is expected to correspond to a decrease (increase) in REC prices.

Second, the empirical analysis examines the relationship among REC prices across states. Many states allow RECs from qualified out-of-state renewable sources to be used for in-state compliance. Both the Massachusetts and Connecticut RPS rules, for example, consider any source from within the ISO-New England (ISO-NE) regional transmission organization (RTO) as a qualified source. As noted by Schmalensee (2011), however, REC markets are generally fragmented and differences in prices from state to state may be large.

Literature Review

The literature on the general structure, cost-effectiveness, and economic implications of state level RPS programs is expanding. Berry (2002), writing in the early years of RPS implementation, hypothesizes that the price of RECs should be tied to the excess cost of electricity generation from renewable sources over that of traditional sources. REC prices should represent the "cost premium" of renewable power.

Several studies evaluate the potential effects of RPS on various elements of the electric power sector. Palmer and Burtraw (2005), for instance, employ the Haiku electricity market simulation model to evaluate the cost-effectiveness of numerous hypothetical national RPS scenarios. They find that as the percentage requirement of the RPS increases, electricity and REC prices increase, and coal and natural gas generation decline. Nogee, Deyette, and Clemmer (2007), in reviewing studies of RPS programs, conclude that a national RPS system would reduce fossil-fuel prices (especially natural gas) and also reduce electricity prices. Assuming that REC prices represent the above-market cost of renewable energy, Wiser et al. (2007) estimate that RPS mandates caused retail electricity rates to increase between zero and one percent for the seven states considered. Chen et al. (2009) review 31 studies which were generally conducted during the proposed or adoption phase of RPS. They find that the majority of studies predict electricity rate increases of less than one percent, though they stress that there is large uncertainty in the estimates. Based generally on simulation models, projected electricity rates range from a decrease of 5.2% to an 8.8% increase.

Taking a somewhat different stance from other studies, Felder (2011) suggests that a more holistic approach is needed to evaluate the existence of a “price-suppression effect.” This effect characterizes the displacement of higher marginal cost resources with low marginal cost renewable sources, resulting in a decrease of the wholesale price of electricity. Fischer (2010) attempts to account for the variability in studies regarding the cost impacts of RPS programs (whether RPS program increase or decrease electricity prices). She finds that the elasticity of supply from renewable sources relative to conventional sources and the stringency of the RPS help explain some of the variation in estimated cost impacts. Fischer (2010) remarks that better empirical evidence is necessary to properly evaluate the impacts of RPS programs. Assessing the efficiency of RPS programs, Schmalensee (2011) observes high levels of price dispersion between state REC prices. He concludes that this variation is a result of fragmented markets with high transaction costs.

The empirical literature on RPS programs, while growing, has resulted in inconclusive and contrasting findings regarding the relationship between REC prices and electricity prices (Chen et al. 2009). Other studies (Berry 2002; Felder 2011; Schmalensee 2011) develop hypotheses about this relationship, as well as the interaction of REC prices across states, without any econometric or statistical techniques to test the hypotheses empirically. This lack of empirical examination of RPS programs is noted in the literature (Chen et al. 2009; Felder 2011; Fischer 2010).

REC Market Fundamentals

To provide an understanding of the fundamentals of the REC market, consider the simple case in which a state has an RPS requirement that five percent of its electricity must come from renewable sources. For each megawatt hour (MWh) that a renewable source generates and sells, one REC is created. For every 20 MWh of total electricity sold onto the grid, one REC must be retired. Hence, a renewable source that generates 20 MWh will have 19 surplus RECs that can be sold. These RECs may be bought by electricity suppliers whose generation portfolio is composed of less than five percent renewables.

In RPS programs, there are a number of important institutional details that influence REC markets. Connecticut and Massachusetts are discussed here as they are the states included in the empirical analysis. Institutional details summarized here are from the Database of State Incentives for Renewables & Efficiency Sources (2015). Sources eligible for REC generation are typically divided into two classes (or tiers) based on the fuel or the age of the source. In both states, electricity suppliers must meet two different requirements; percentage requirements from Class I sources and from Class II sources. Class I RECs can be used for compliance with the Class II requirement, but the reverse is not true. Eligible generation sources in the Massachusetts RPS include geothermal, solar thermal, solar PV, wind, biomass, hydroelectric, and waste-to-energy. The Massachusetts Class I REC distinction requires that the source of generation be installed after December 31, 1997. Connecticut accepts similar sources of electricity generation, but the Connecticut Class I distinction requires that the source be specifically from solar, wind, fuel cells, geothermal, ocean thermal, tidal, small hydroelectric facilities, and a few other advanced technologies (but not waste-to-energy or older hydroelectric plants).

The Massachusetts RPS also contains provisions for a solar “carve-out” in which a certain percentage of Class I requirements must be met specifically from solar sources, creating the MA Solar REC (SREC) trading instrument. Connecticut does not contain such a provision. There are a number of institutional complications in SREC programs which may drive prices[4] (Coulon, Khazaei, and Powell 2015; Felder and Loxley 2012; Massachusetts Department of Energy Resources 2015; SRECTrade 2015). Additionally, the overall costs of generation from solar photovoltaic generation have decreased in recent years (U.S. Energy Information Administration (EIA) 2013). These regulatory idiosyncrasies in the MA SREC market may have a large influence on market performance, making it unwarranted to include SREC prices in the econometric analysis.[5]

An important feature of both the Connecticut and Massachusetts RPS programs is that both Class I requirements can be met with RECs that were generated by sources within the ISO-NE RTO (eligible sources do not necessarily have to be in-state). A wind turbine in Connecticut, for example, produces RECs that are eligible to be used for the MA Class I requirement. Both states have legislation in place to prevent double-

[4] For instance, the MA SREC market contains a price support in which the state ensures that end-of-period unsold SRECs will be purchased in a clearinghouse auction at a fixed price (Massachusetts Department of Energy Resources 2015).

[5] As a check, the specified model was extended to include the MA SREC price series. Results of statistical tests for variable exclusion and weak exogeneity provide confirmatory evidence that the MA SREC series is determined outside of the estimated system.

counting of RECs (the same REC being used for compliance in two states). The Massachusetts solar carve-out, however, only accepts eligible in-state sources.

Massachusetts and Connecticut RECs can be banked for up to two years; giving a useful life of three years to each REC. The year in which the REC is generated is called its “vintage,” for instance a REC generated in 2011 would be a Vintage 2011 REC and could be used for compliance in 2011, 2012, or 2013. In this study, the price of a current-year vintage of each REC instrument is used as the price observation for a given time period. As a penalty for non-compliance, states generally charge an Alternative Compliance Payment (ACP) to suppliers who fall short of their requirement. The level of the ACP in Massachusetts is adjusted annually based on the Consumer Price Index. The 2014 ACP rate for the Massachusetts Class I standard was $66.16/MWh, for Class II was $27.16/MWh, and for SREC was $523.00/MWh. Connecticut has a fixed Class I ACP at $55/MWh. The ACP essentially creates a price cap for RECs, as any electricity provider that is short of the requirement would typically pay the ACP if faced with a REC price that exceeds the ACP.

Economic theory helps provide insights into REC price formation. REC prices are determined by supply and demand conditions in the REC market. The key to understanding REC prices lies in the dependence of the supply and demand of RECs on the market for wholesale electricity (and in turn, on the markets for renewable and conventional generation). Basic economics of the REC market are depicted in figure 3.1. The total marginal revenue received by a renewable electricity producer (the vertical axis) is equal to the sum of the REC price and the electricity price ($P_R + P_E$).

The demand for RECs is largely a function of the RPS requirement, which is determined by the state legislatures (Felder and Loxley 2012; Lamontagne 2013). For a given RPS requirement, the annual aggregate demand curve for RECs is a step function in which the REC price (P_R) is equal to the ACP for quantities less than the RPS requirement and falls to zero above the requirement. The simplified demand curve in figure 3.1 excludes the possibility that firms may demand RECs in excess of their percentage requirement to hedge future risks or to give the appearance of being "green" or environmentally friendly.

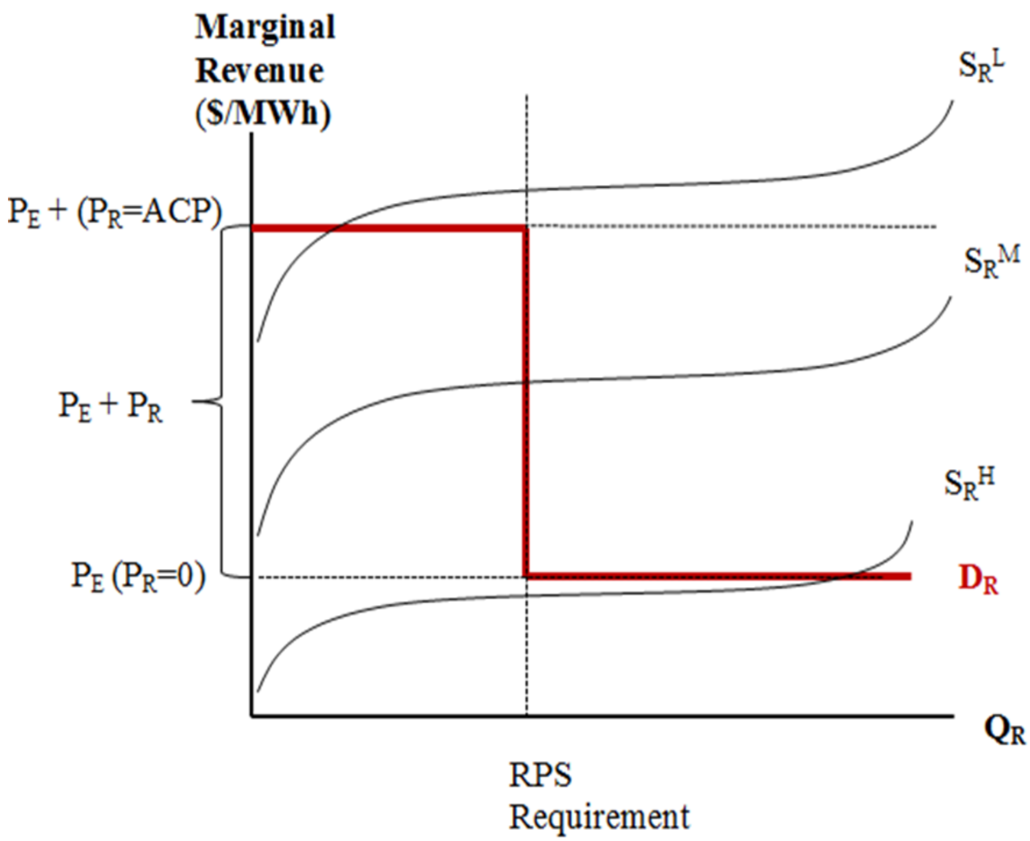

Figure 3.1. REC market supply and demand fundamentals

The quantity of RECs supplied is directly proportional to the amount of qualified renewable energy generation. For illustrative purposes, the shape of the three supply curves in figure 3.1 follow those outlined in New England States Committee on Electricity (2012) for wind. In the case of a low, medium, or high level of renewable energy generation, the supply of RECs follows supply curve S_R^L, S_R^M, or S_R^H. In the case of relatively low levels of qualified renewable generation (S_R^L), the REC price will fall at or near the ACP. For high levels of renewable generation (S_R^H), the renewable producer will receive only the price of electricity and the REC price will be at or near zero. For a medium level of renewable generation (S_R^M) which intersects the vertical (inelastic) portion of the demand curve, the REC price will be susceptible to changes in electricity price.

Assuming that renewable generation is more costly than conventional (nuclear, natural gas, or coal) generation, Berry (2002) states that REC price should represent the cost premium of renewable sources over their conventional counterparts. Thus, a decrease in the price of conventional generation should lead to an increase in the price of RECs. Felder (2011) claims that REC prices should be determined by the difference between the cost of renewable generation and the revenue obtained by generating the electricity. In Felder's (2011) framework, a decrease in the price of electricity moves the demand curve for RECs downward, leading to an increase in the difference between the supply curve and P_E, thus increasing the price of RECs. This framework does not directly contradict Berry (2002), as the fall in electricity prices may have been caused by a decrease in the cost of conventional generation. Changes in electricity prices can certainly be precipitated by other market forces (e.g. demand shifts or renewable supply shifts), nonetheless, electricity prices and costs of conventional generation are potentially important sources of REC price formation.

An increase in the supply of RECs corresponds to an increase in the supply of renewable generation. In figure 3.1, this increase in supply of RECs would decrease the REC price, ceteris paribus. This outward shift in the supply curve for electricity, however, should also lead to a decrease in the price of wholesale electricity, which Felder (2011) calls the price-suppression effect. This price-suppression effect would lead to an increase in the price of RECs (Felder 2011). The effect of a renewable electricity supply shock on REC prices, therefore, depends on the magnitude of the price suppression effect.

It is important to point out, however, that when the supply curve intersects demand in either horizontal range (S_R^H or S_R^L), shifts in supply or demand will have no effect on the REC price, they will remain fixed at the ACP or zero. Only if the supply curve intersects demand in the middle range (S_R^M), does theory predict that changes in the supply or demand curve lead to changes in the REC price.

Data

The empirical analysis uses four endogenous price variables. All endogenous series are in natural logarithms in the empirical analysis. Graphs of the natural logarithms of the four endogenous price series are presented in figure 3.2. Weekly REC prices, based on trade data or derived from indicative quotes when trades are unavailable, are obtained from Skystream Markets (2014). Two Class I REC price series are included in the

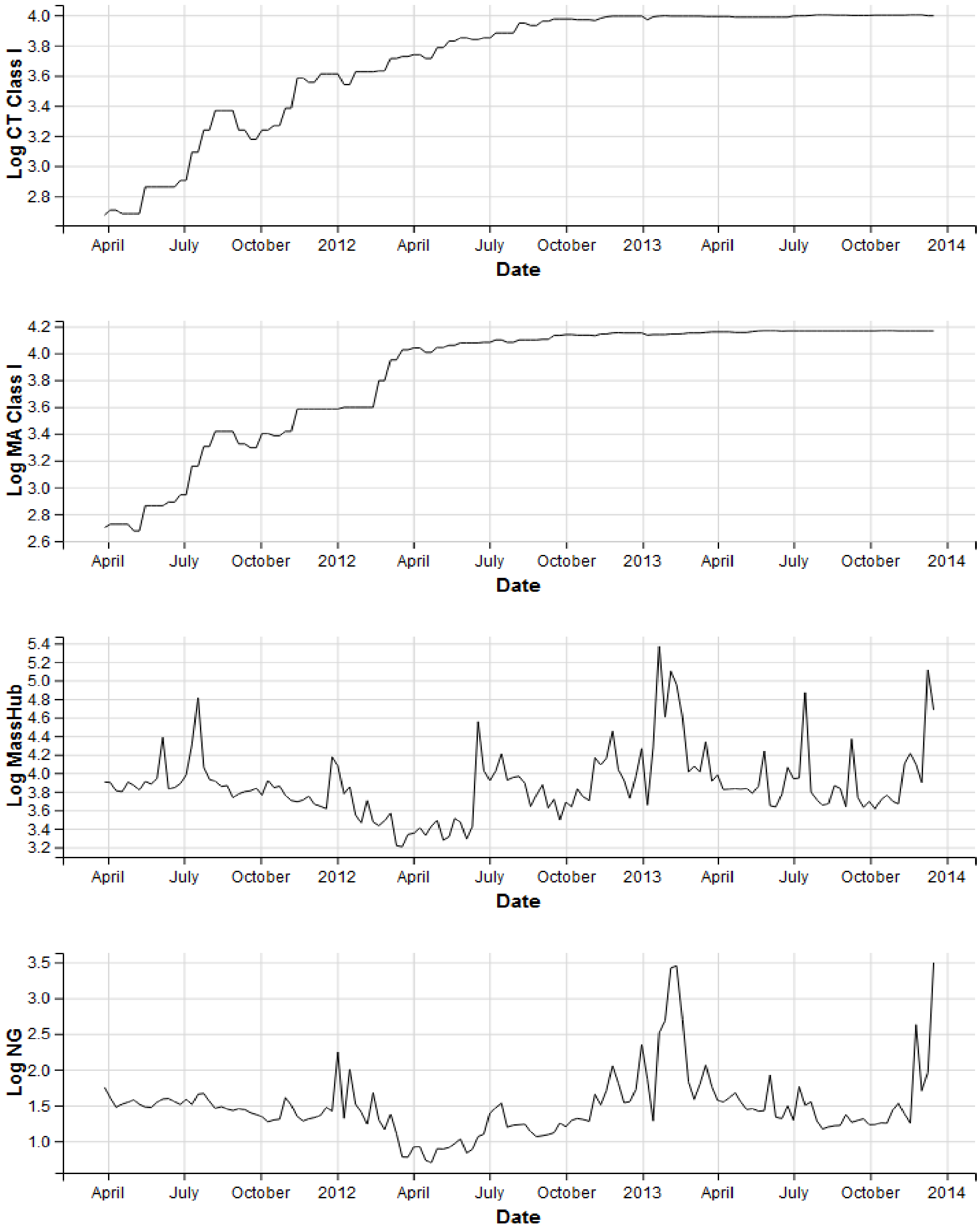

Figure 3.2. Endogenous price series used in estimating the vector error correction model

analysis (Connecticut and Massachusetts, denoted as CT Class I and MA Class I) for the period March 2011 to December 2013. These price data are the midpoint between bid and offer prices for current-year vintages reported by Skystream Markets.

Unfortunately, data for volume of trades is unavailable. The previous week's price is used to fill in any missing observations in the weekly REC price data. The U.S. EIA (2015b) publishes wholesale electricity price data for the ISO-NE RTO. The third endogenous price series is a weighted average of daily on-peak wholesale electricity prices based on volume traded to provide a weekly electricity price for the region (denoted as MassHub). Natural gas spot prices (denoted as NG) from the Algonquin Hub in Massachusetts (Bloomberg 2015) are included as the final endogenous variable to capture the costs of conventional electricity generation. Data on cooling and heating degree days for the New England region (U.S. National Oceanic and Atmospheric Administration 2015), which roughly aligns geographically with the ISO-NE RTO, are exogenous variables in the model.

As seen in figure 3.2, the CT and MA Class I REC prices are essentially unchanging in the final third of the sample. Both price series are at or near the ACP level defined by the respective state RPS (the market price is determined in the initial horizontal portion of the demand curve in figure 3.1). In this case, the market is short and REC price is not expected to react. The sample is reduced for this reason; it is constrained to a period where the market is in the vertical portion of the demand curve. Weekly observations for the period March 28, 2011 to December 17, 2012 are used to carry out the empirical analysis (a total of 91 observations).

Methodology

The vector error correction model (VECM) provides a flexible framework to characterize the REC market relationships. Let n be the number of endogenous variables and m be the number of exogenous variables in the model. The VECM (Juselius 2006) takes the form:

(3.1) $\Delta Y_t = \gamma + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \Pi Y_{t-1} + \lambda X_t + \varepsilon_t$

where:

Y_t is a $(n \times 1)$ vector of the endogenous variables at time t;

ΔY_t is a $(n \times 1)$ vector of first differences of the endogenous series;

γ is a $(n \times 1)$ vector of constants;

ΔY_{t-i} represents lagged values of order i;

Γ_i is the corresponding $(n \times n)$ coefficient matrix;

k is the optimal number of lags in a levels vector autoregressive representation;

X_t is a $(m \times 1)$ vector of exogenous series (cooling and heating degree days);

ε_t is a $(n \times 1)$ vector of innovations; and

ΠY_{t-1} is the "error correction" term, where Π is $(n \times n)$.

The VECM allows long run, equilibrium relationships among the variables to be characterized by examining the existence of cointegration. Cointegration is present when there exists at least one linear combination of non-stationary variables which is itself stationary (Tsay 2014). A key assumption for the estimation of a VECM is that the endogenous variables (Y_t) are non-stationary, but that they are stationary in first differences (ΔY_t). Three tests for stationarity are considered, two common pre-model estimation tests and one post-model estimation test. Results of Augmented Dickey-Fuller (Fuller 1996) and KPSS (Kwiatkowski et al. 1992) tests for stationarity of the four endogenous series are reported in table 3.1 (pre-model estimation tests). Under the Augmented Dickey-Fuller test, all series are non-stationary in natural log levels, but stationary in first differences, except for the CT Class I REC price. Further investigation using the KPSS test (Kwiatkowski et al. 1992) reveals that all four series are non-stationary in natural log levels, and stationary in first differences. As noted, a third test for stationarity is performed after model estimation.

Table 3.1. Results of Tests for Presence of Unit Root

	ADF (H_0: Unit Root)		KPSS (H_0: Stationarity)	
Series	Test Statistic	Decision[a]	Test Statistic	Decision
log(Series)				
CT Class I	-1.89	F	2.19	R
MA Class I	-1.89	F	2.20	R
MassHub	-2.64	R	0.35	R
NG	-2.35	F	0.59	R
diff(log(Series))				
CT Class I	-2.51	F	0.25	F
MA Class I	-4.53	R	0.30	F
MassHub	-4.02	R	0.05	F
NG	-3.57	R	0.14	F

[a]Based on the 10% critical value of -2.58.
[b]Based on the 10% critical value of 0.35.

Post-Estimation Hypothesis Tests

Decomposing Π as:

(3.2) $\Pi = \alpha\beta'$

where α and β are $(n \times r)$ matrices, and r is the rank of Π, provides an interpretation of the long run relationships among the endogenous series. Because Y_{t-1} is non-stationary and ΔY_t is stationary, $\alpha\beta'$ contains stationary linear combination(s) of the n endogenous variables, provided cointegration is present. The r columns of β are known as the cointegrating vectors (Tsay 2014). Statistical tests are performed on Π, α, and β to determine r and to further characterize the long run structure between the endogenous series (Juselius 2006; Mjelde and Bessler 2009).

The first test for examining the cointegrating space is a test for variable stationarity. The null hypothesis is that at least one of the cointegrating vectors exists because a particular variable is itself stationary given the number of lags and cointegrating vectors found in the system. In other words, the cointegrating vector does not represent a stationary linear combination of non-stationary variables, but rather a transformation of an otherwise stationary variable. Results of this test complement the Augmented Dickey-Fuller and KPSS tests for stationarity presented in table 3.1.

Variable exclusion tests the null hypothesis that a particular series is not in the cointegrating space:

(3.3) $\quad H_0\colon E'\beta = 0$

where E is a matrix containing zero restrictions for excluding a particular series from the cointegrating space. Failure to reject the null hypothesis for a given series implies that the corresponding series is excluded from the long run relationships characterizing the system (β contains the parameters characterizing these long run relationships).

A third statistical test is for weak exogeneity; the null hypothesis is that a particular series does not adjust to disruptions in the long run relationships. As β contains the parameters characterizing the long run relationships, α comprises the parameters which describe how the series adjust to disruptions, bringing the long run relationships back to equilibrium. The null hypothesis of the test for weak exogeneity is:

(3.4) $H_0\colon W'\alpha = 0$

where W, like E, contains zero restrictions for excluding the corresponding α parameters for a particular series. Failure to reject the null hypothesis for a given series implies that the corresponding series does not respond to deviations from the long run equilibrium relationship.

Innovation Accounting

In addition to statistical tests concerning the cointegrating space, innovation accounting procedures (impulse response functions and forecast error variance decompositions) are helpful in characterizing dynamic relationships among economic variables. Impulse response functions (IRFs) show the effect of a one-time shock in one variable on the future values of the remaining variables. Forecast error variance decompositions (FEVDs) measure the percentage of forecast error for a given series that is explained by shocks to each of the series. To conduct innovation accounting procedures, the VECM in equation (3.1) is rewritten in a levels vector autoregressive (VAR) model:

(3.5) $Y_t = \gamma + (1 + \Pi + \Gamma_1)Y_{t-1} - \sum_{i=1}^{k-2}(\Gamma_i - \Gamma_{i+1})Y_{t-i+1} - \Gamma_{k-1}Y_{t-k} + \lambda X_t + \varepsilon_t.$

An issue that arises when conducting innovation accounting procedures is that the contemporaneous covariance matrix of the error term ε_t in equation (3.5), Σ_ε, is usually not a diagonal matrix in empirical applications (the components of the error term are contemporaneously correlated). If this is the case, then any particular series cannot necessarily be shocked without affecting another series; innovation accounting procedures are nonsensical if contemporaneous correlation exists (Tsay 2014). To overcome this limitation, the innovations ε_t must be orthogonalized. Consider a Bernanke (1986) ordering, where the correlated innovations ε_t are written as a function of the underlying orthogonal sources of variation, σ_t:

(3.6) $\varepsilon_t = A^{-1}\sigma_t$.

To conduct the innovation accounting procedures, the VAR representation, equation (3.5), is pre-multiplied by the matrix A.

The matrix A is obtained through causal flow methods (Pearl 2000; Spirtes, Glymour, and Scheines 2000). Directed Acyclic Graphs (DAGs) provide a visual summary of contemporaneous causal flows among innovations from the estimated VECM. The GES algorithm (Chickering 2003) in TETRAD V (2015) is employed to generate a DAG using the covariance matrix of error terms from the estimated VECM. In DAGs, an arrow from node A to node B implies that A causes B. An undirected line from A to B with no arrow (or a line with an arrow on each end) signifies flows between the two series, but the algorithm cannot determine whether A causes B or B causes A. If there is no information flow between A and B, the algorithm will not generate a line connecting the two series. The GES algorithm starts with a DAG representation where all variables are independent of each other (no lines), and searches over more complicated representations for improvements in the Bayesian Information Criterion.

The algorithm picks the DAG representation such that no added line or change of direction improves the criterion.

To summarize, results from the empirical analysis help characterize the dynamic relationships among REC and electricity prices. First, the existence of cointegration implies that REC and electricity prices move together in the long run. Statistical tests for variable exclusion further investigate whether a particular price series is included in the estimated long run relationships. Tests for weak exogeneity will show whether a given series responds to disruptions in the long run relationships. Further, DAGs show how the endogenous price series are related in contemporaneous time. Impulse response functions show the direction of effects of an increase in a particular series on all the other endogenous series over time. Finally, forecast error variance decompositions show the percentage of forecast error of each series that can be explained by shocks in the other series.

Similarly, these procedures shed light on the relationship between MA and CT REC prices. Perhaps most importantly, the existence of cointegration, along with tests for variable exclusion and weak exogeneity, provides statistical evidence regarding the existence of a long run equilibrium relationship among REC prices. DAGs and innovation accounting procedures further characterize the dynamic relationships across state REC prices.

Results and Discussion

A two-step procedure is followed to test for cointegration. First, the optimal lag length (k) in a VAR(k) representation is determined (table 3.2). The lag length (k) is chosen to be two under the Akaike Information Criterion in the rest of the chapter; the choice of $k = 1$ lag would lead to the absence of short run parameters and the inability to conduct innovation accounting procedures. Next, the cointegrating rank (r) is determined following the trace test of Johansen (1991). One cointegrating vector ($r = 1$) is chosen (table 3.3). The remaining discussion of the empirical results is based on a VECM specification in equation (3.1) with $k = 2$ lags and $r = 1$ cointegrating vector.

Table 3.2. Optimal Lag Length Determination

Lag Order (k)	Schwarz Information Criterion	Akaike Information Criterion	Hannan-Quinn Information Criterion
0	-12.77	-13.86	-13.13
1	**-17.80**	-19.33	**-18.62**
2	-16.60	**-19.58**	-17.90
3	-15.67	-19.11	-17.44
4	-14.34	-18.23	-16.58
5	-13.12	-18.46	-15.84
6	-11.77	-17.65	-14.98
7	-10.70	-17.15	-14.42
8	-9.54	-17.58	-13.76
9	-8.36	-17.03	-13.10
10	-7.34	-16.67	-12.62

Table 3.3. Results of Trace Test for Lag Order $k = 2$

r	Trace	Critical Value (5%)	P-Value
0	78.91	73.02	0.02
1	41.57	49.96	0.23
2	13.57	30.78	0.87
3	4.35	15.25	0.84

The null hypothesis for each $i = 0,1, \ldots ,4$ is that $r \leq i$. The first failure to reject occurs at $r \leq 1$, therefore one cointegrating vector is selected.

Post-Estimation Tests

Statistical tests for variable exclusion, weak exogeneity, and stationarity are shown in table 3.4. The hypothesis of variable stationarity is rejected at the 5% level for all four series. The cointegrating relationship does not arise because of individual stationarity of any of the endogenous price series. The null hypothesis of variable exclusion cannot be rejected at the 5% level for both MA and CT Class I REC price series. This implies that the estimated long run relationship might be the result of integration between natural gas and electricity prices only. Additionally, the hypothesis of weak exogeneity cannot be rejected at the 5% level for each of the MA and CT Class I REC price series, providing evidence that MA and CT Class I REC prices do not respond to disruptions in the cointegrating relationship. Results of the variable exclusion and weak exogeneity tests suggest that the two REC markets are not integrated with regional electricity and natural gas markets.

Table 3.4. Test for Variable Exclusion, Stationarity, and Weak Exogeneity. P-values in Parentheses

Test	CT Class I	MA Class I	MassHub	NG
Exclusion	0.62	1.42	15.82	15.42
	(0.43)	(0.23)	(0.00)	(0.00)
Weak Exogeneity	0.24	0.00	9.29	6.04
	(0.63)	(0.99)	(0.00)	(0.01)
Stationarity	17.62	18.68	22.10	23.74
	(0.00)	(0.00)	(0.00)	(0.00)

Contemporaneous Causality

The DAG generated from the correlation structure of innovations in the VECM is presented in figure 3.3. Causal flows are found between MassHub electricity prices and natural gas prices, and between MA and CT Class I REC prices, but the algorithm is unable to determine the direction of flows in either case. Regarding the relationship between natural gas and electricity prices, it is important to note that natural gas is the most common fuel source used for on-peak power generation.[6] Periods of high electricity demand result in demand spikes in the natural gas market. Likewise, periods of high natural gas prices increase generation costs for on-peak power generation, which is expected to affect wholesale electricity prices.[7]

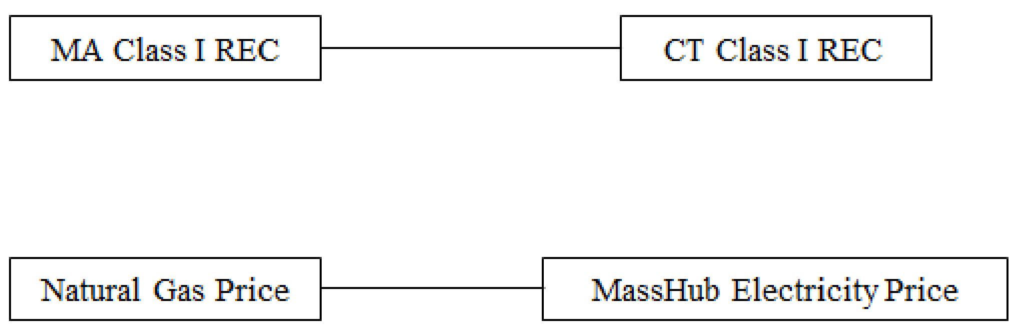

Figure 3.3. Directed Acyclic Graph (DAG) for contemporaneous causal flows among innovations

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[6] Natural gas is a large portion of the overall electricity generation portfolio in both Massachusetts (58% in 2014) and Connecticut (44%) (U.S. EIA 2015c).
[7] Mjelde and Bessler (2009) find contemporaneous causal flows from on-peak electricity prices to natural gas prices using weekly data for the period June 2001 – April 2008 and the GES algorithm.

As noted above, the MA and CT Class I requirements both allow RECs from out-of-state (but within the ISO-NE RTO). The MA renewable generation market is much larger than the CT market, but the renewable proportion of total electric generation capacity is similar in both states.[8] Accordingly, there is no a priori reasoning to eliminate a possible direction of contemporaneous flows between either natural gas and electricity prices or the two state REC prices. All four possible combinations of contemporaneous causal flows are considered (innovation accounting procedures are carried out for four different versions of the matrix A in equation 3.6).

Innovation Accounting Procedures

IRFs and FEVDs computed from each of the four possible combinations of directed flows in the DAG are presented in figures 3.4-3.7 and tables 3.5-3.8.[9,10] The IRFs show strong links between natural gas and electricity prices in all DAG specifications (consistent with previous literature).[11] Natural gas prices respond positively to shocks in electricity prices, and vice versa. IRFs across each DAG specification are consistent in suggesting that CT Class I REC and the MA Class I REC prices do not respond to shocks in either electricity or natural gas prices. Similarly, neither electricity nor natural gas prices respond to shocks in REC prices. FEVDs show that natural gas and electricity prices each explain less than one percent of forecast error variance in REC prices at all

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[8] The U.S. EIA (2012) reports that Massachusetts had 0.566 GW of renewable capacity in 2010 (4.1% of total electric capacity), about twice as much renewable generating capacity as Connecticut (0.281 GW; 3.3% of total).

[9] Figure 3.8 and table 3.9 show the IRF and FEVD for the assumption of no contemporaneous causal flows between the MA Class I and CT Class I REC price series.

[10] As in Chapter II, all IRFs are standardized by dividing through by the standard error of innovations of each series.

[11] See for example Mjelde and Bessler (2009).

horizons. In addition to the results of the variable exclusion and weak exogeneity tests above, these findings provide further evidence of little interaction between REC markets and the ISO-NE electricity and Algonquin Hub natural gas markets.

The IRFs and FEVDs suggest a relationship between MA and CT Class I REC prices, however, the characterization of this relationship is sensitive to the direction of contemporaneous causal flows in the DAG. Assuming contemporaneous causal flows from MA to CT Class I REC prices, the MA Class I series explains around 67% of forecast error variance in CT Class I REC prices at all horizons (tables 3.5 and 3.6). CT Class I REC prices respond positively to shocks in MA Class I REC prices and the MA Class I REC series is almost entirely exogenous (figures 3.4 and 3.5). When the direction of contemporaneous causal flows is reversed, so are these results. Sixty-seven percent of forecast error variance in MA Class I REC prices is explained by CT Class I REC prices, MA Class I REC prices respond positively to shocks in CT Class I REC prices, and the CT Class I REC series is exogenous (figures 3.6 and 3.7; tables 3.7 and 3.8). The asymmetric relationships between these REC prices is surprising since, as noted above, Connecticut allows RECs from qualified generation in Massachusetts and vice versa. An explanation for this finding is the nature of the ACP structure mentioned previously (MA 2014 Class I ACP was $66.16/MWh and CT Class I ACP was $55/MWh). A Massachusetts REC buyer will look to purchase in the Connecticut REC market if faced with a MA REC price higher than the CT ACP, thus increasing the demand for CT RECs. Conversely, a CT REC seller will look to sell RECs in the MA REC market if the current MA price is above the CT ACP. The CT seller is willing to.

Table 3.5. Forecast Error Variance Decompositions (Contemporaneous Causal Flows from MA Class I to CT Class I and MassHub to NG)

		Contribution of			
Series	Weeks Ahead	CT Class I	MA Class I	MassHub	NG
CT Class I	1	32.92	67.08	0.00	0.00
	4	32.49	66.85	0.21	0.46
	8	32.30	66.91	0.25	0.54
	12	32.23	66.94	0.25	0.58
MA Class I	1	0.00	100.00	0.00	0.00
	4	0.01	99.87	0.07	0.04
	8	0.01	99.93	0.04	0.02
	12	0.01	99.95	0.03	0.01
MassHub	1	0.00	0.00	100.00	0.00
	4	0.06	0.18	87.30	12.46
	8	0.10	0.12	80.96	18.83
	12	0.11	0.10	77.89	21.91
NG	1	0.00	0.00	25.40	74.60
	4	0.23	1.74	55.99	42.05
	8	0.27	1.48	61.62	36.64
	12	0.28	1.39	64.08	34.25

Table 3.6. Forecast Error Variance Decompositions (Contemporaneous Causal Flows from MA Class I to CT Class I and NG to MassHub)

		Contribution of			
Series	Weeks Ahead	CT Class I	MA Class I	MassHub	NG
CT Class I	1	32.92	67.08	0.00	0.00
	4	32.49	66.85	0.53	0.14
	8	32.30	66.91	0.63	0.15
	12	32.23	66.94	0.66	0.17
MA Class I	1	0.00	100.00	0.00	0.00
	4	0.01	99.87	0.11	0.01
	8	0.01	99.93	0.06	0.00
	12	0.01	99.95	0.04	0.00
MassHub	1	0.00	0.00	74.60	25.40
	4	0.06	0.18	52.89	46.87
	8	0.10	0.12	41.05	58.73
	12	0.11	0.10	35.38	64.42
NG	1	0.00	0.00	0.00	100.00
	4	0.23	1.74	20.25	77.78
	8	0.27	1.48	19.95	78.31
	12	0.28	1.39	20.05	78.28

Table 3.7. Forecast Error Variance Decompositions (Contemporaneous Causal Flows from CT Class I to MA Class I and NG to MassHub)

		Contribution of			
Series	Weeks Ahead	CT Class I	MA Class I	MassHub	NG
CT Class I	1	100.00	0.00	0.00	0.00
	4	99.33	0.00	0.53	0.14
	8	99.21	0.00	0.63	0.15
	12	99.17	0.00	0.67	0.17
MA Class I	1	67.08	32.92	0.00	0.00
	4	66.20	33.68	0.11	0.01
	8	66.20	33.74	0.06	0.00
	12	66.20	33.76	0.04	0.00
MassHub	1	0.00	0.00	74.60	25.40
	4	0.78	0.06	52.89	46.87
	8	0.16	0.06	41.05	58.73
	12	0.15	0.06	35.38	64.42
NG	1	0.00	0.00	0.00	100.00
	4	0.75	1.22	20.25	77.78
	8	0.55	1.19	19.95	78.31
	12	0.48	1.19	20.05	78.28

Table 3.8. Forecast Error Variance Decompositions (Contemporaneous Causal Flows from CT Class I to MA Class I and MassHub to NG)

		Contribution of			
Series	Weeks Ahead	CT Class I	MA Class I	MassHub	NG
CT Class I	1	100.00	0.00	0.00	0.00
	4	99.33	0.00	0.21	0.46
	8	99.21	0.00	0.25	0.54
	12	99.17	0.00	0.25	0.58
MA Class I	1	67.08	32.92	0.00	0.00
	4	66.20	33.68	0.07	0.04
	8	66.20	33.74	0.04	0.02
	12	66.20	33.76	0.03	0.01
MassHub	1	0.00	0.00	100.00	0.00
	4	0.18	0.06	87.30	12.46
	8	0.16	0.06	80.96	19.81
	12	0.15	0.06	77.89	21.91
NG	1	0.00	0.00	25.40	74.60
	4	0.75	1.22	56.00	42.05
	8	0.56	1.19	61.62	36.64
	12	0.48	1.19	64.08	34.25

Table 3.9. Forecast Error Variance Decompositions (Contemporaneous Causal Flows from MassHub to NG and no flows between MA Class I and CT Class I)

		Contribution of			
Series	Weeks Ahead	CT Class I	MA Class I	MassHub	NG
CT Class I	1	100.00	0.00	0.00	0.00
	4	99.31	0.00	0.24	0.45
	8	99.18	0.01	0.31	0.51
	12	99.14	0.01	0.33	0.53
MA Class I	1	0.00	100.00	0.00	0.00
	4	0.03	99.86	0.07	0.04
	8	0.03	99.91	0.04	0.02
	12	0.03	99.93	0.03	0.02
MassHub	1	0.00	0.00	100.00	0.00
	4	0.19	0.17	87.21	12.45
	8	0.29	0.17	80.78	18.77
	12	0.34	0.17	77.68	21.83
NG	1	0.00	0.00	25.40	74.60
	4	0.68	3.62	54.65	41.05
	8	0.79	3.53	60.01	35.67
	12	0.84	3.54	62.32	33.30

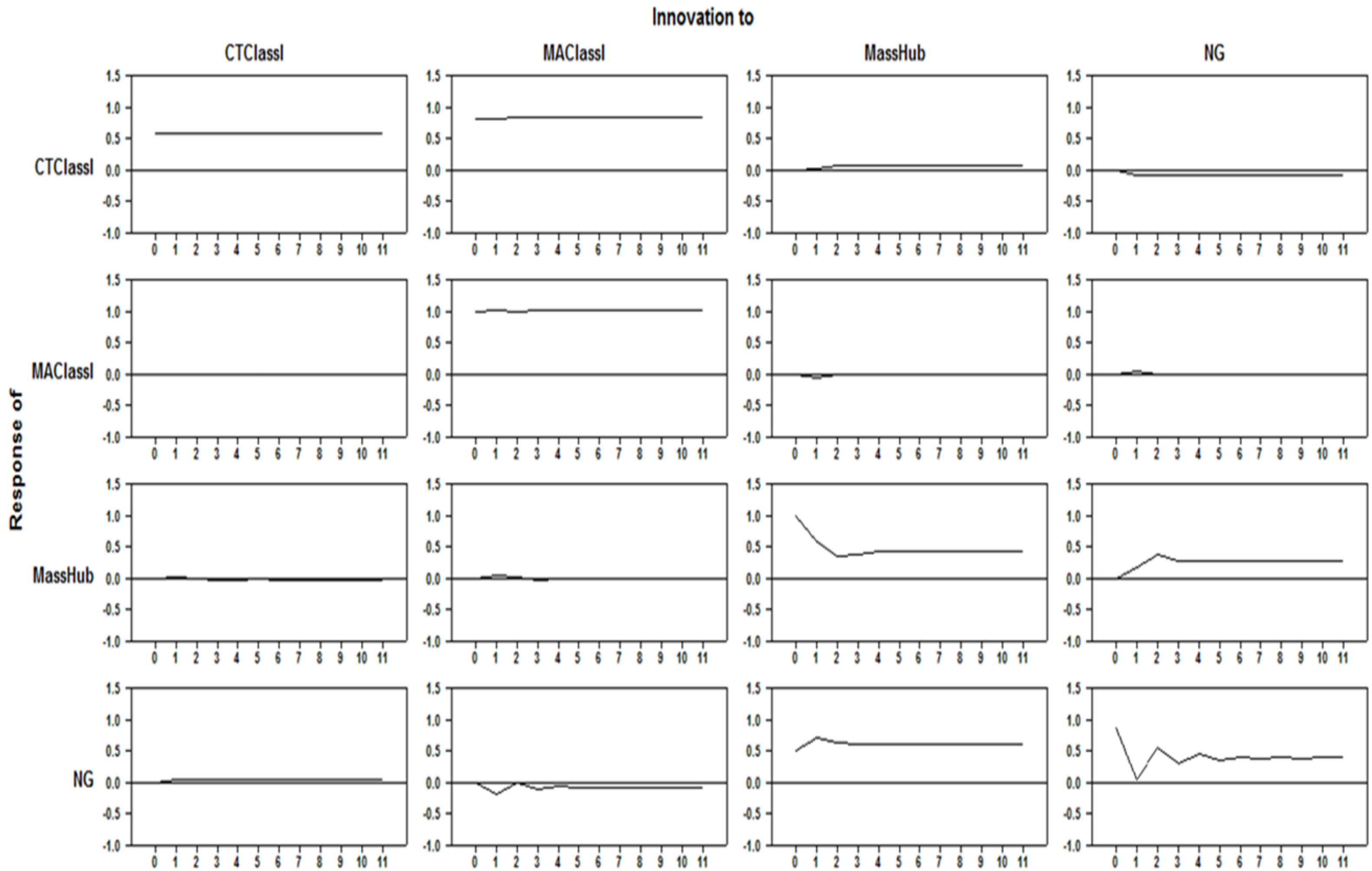

Figure 3.4 Impulse Response Functions (causal flows from MA Class I to CT Class I and MassHub to NG)

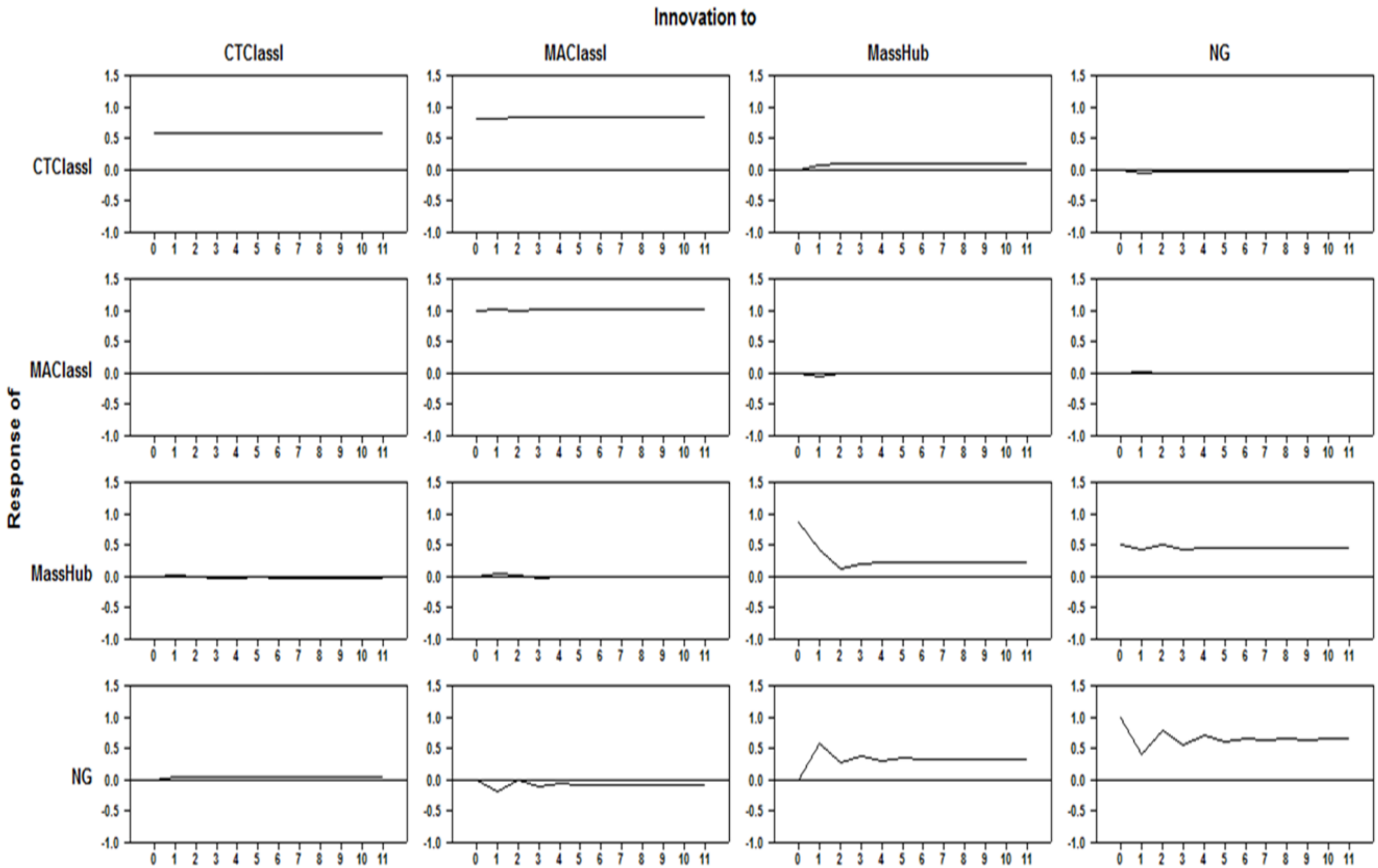

Figure 3.5 Impulse Response Functions (causal flows from MA Class I to CT Class I and NG to MassHub)

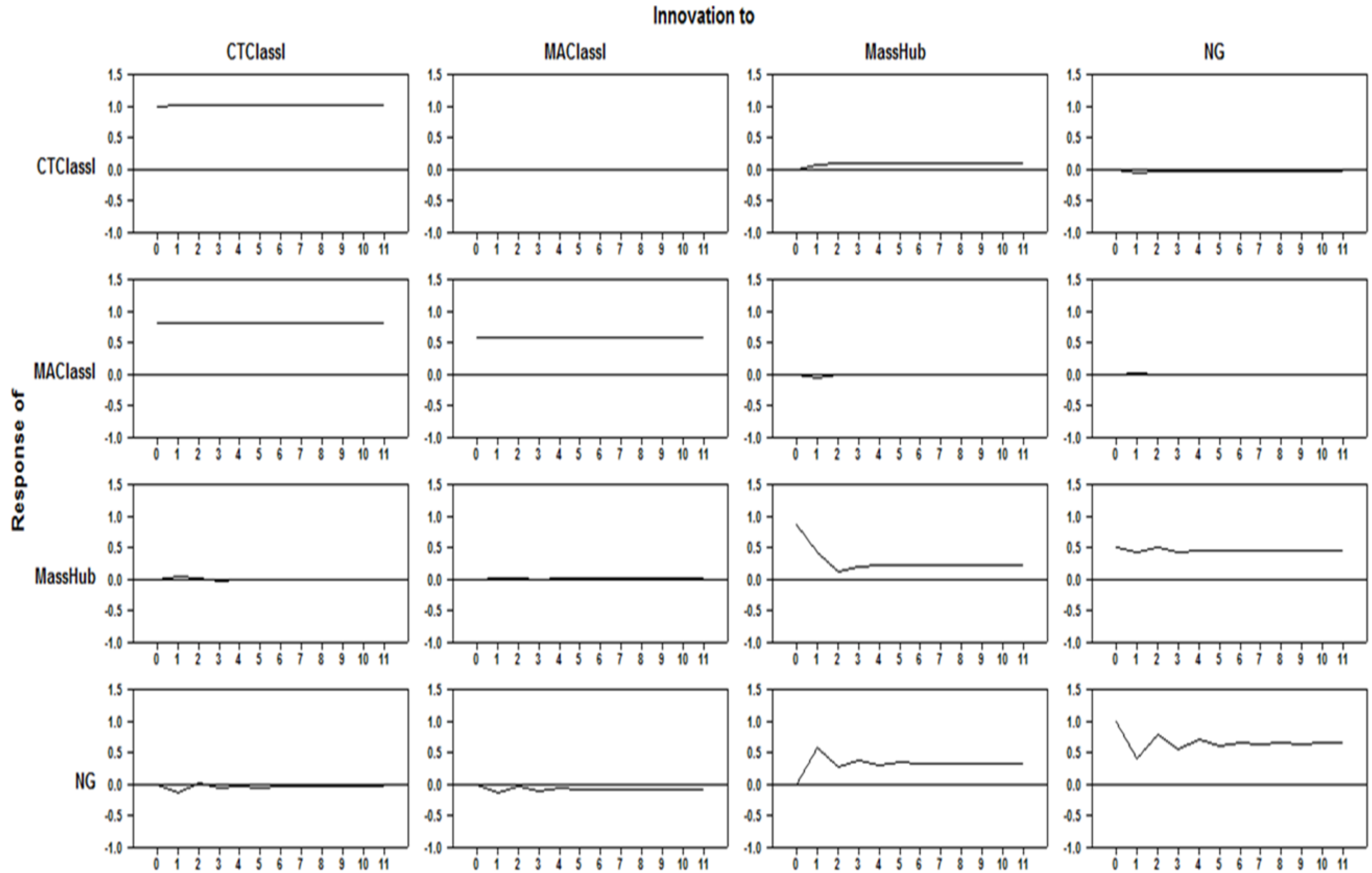

Figure 3.6 Impulse Response Functions (causal flows from CT Class I to MA Class I and NG to MassHub)

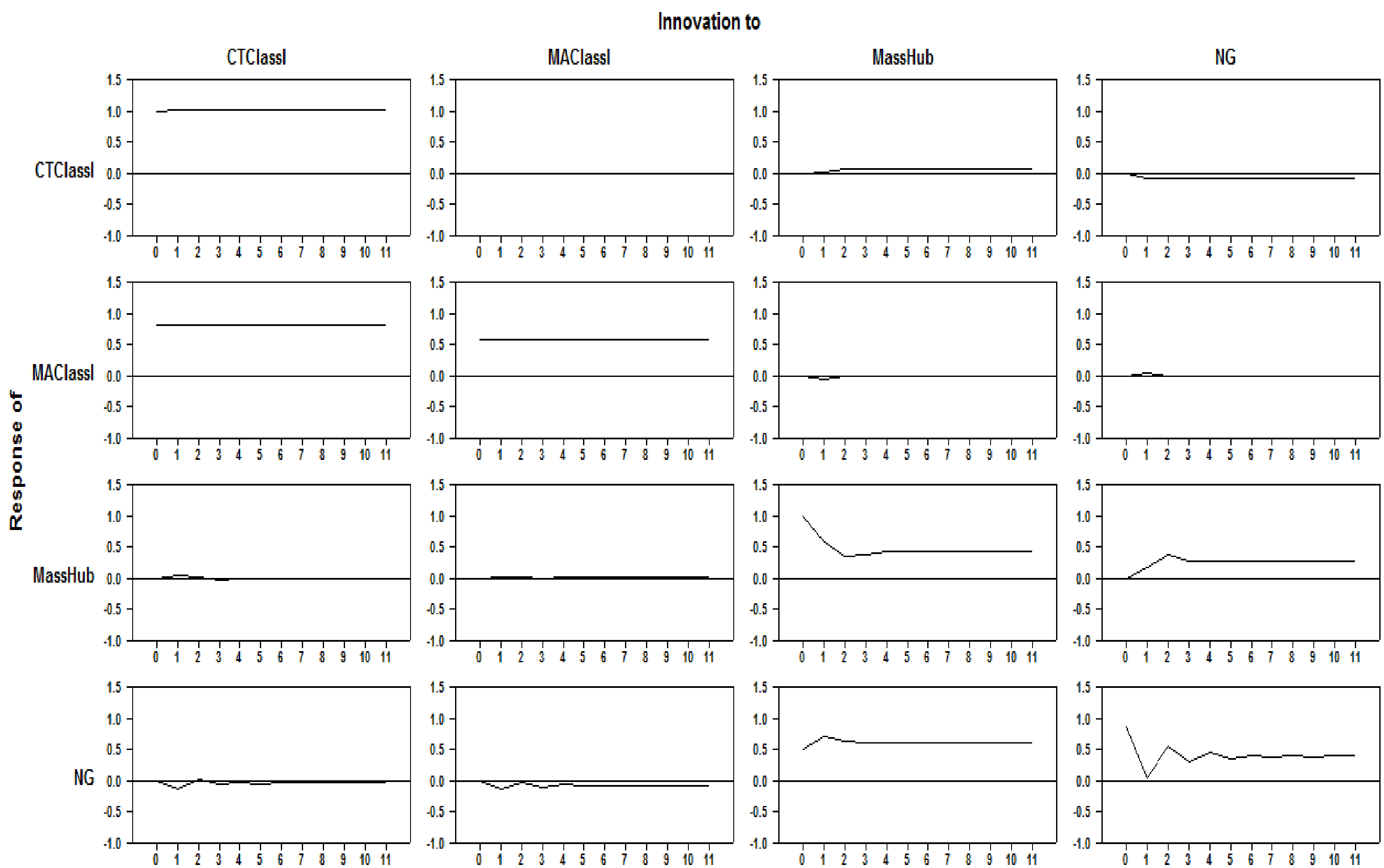

Figure 3.7 Impulse Response Functions (causal flows from CT Class I to MA Class I and MassHub to NG)

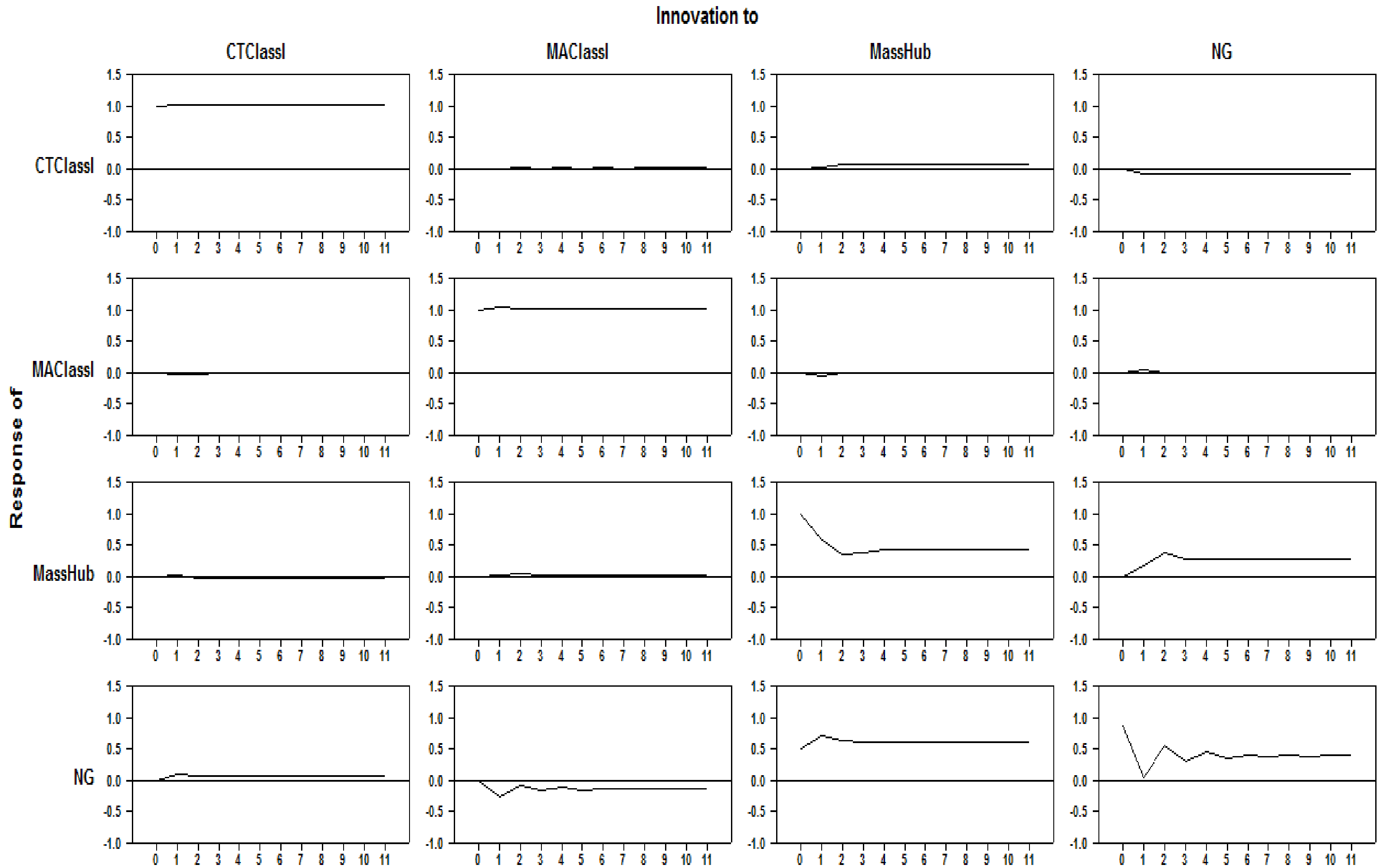

Figure 3.8 Impulse Response Functions (causal flows from MassHub to NG and no flows between MA Class I and CT Class I)

settle at a price lower than the MA market price, putting downward pressure on the MA price. The direction of contemporaneous causality is important in characterizing which state's market plays a bigger role in price formation

Investigating the Potential of a Structural Break

Close inspection of the data reveals a jump in the level of the MA Class I REC price series in early 2012. The price increased by $8.00, or 22%, from January 23, 2012 to February 20, 2012 and by another $8.00 on March 5, 2012 (a 17% increase from February 20). The magnitude of this jump warrants inspection of the possibility of a structural break in the relationships between MA and CT REC, natural gas, and electricity prices.

Two tests for structural breaks are carried out; the first introduced by Bai and Perron (2003) and the second following Hansen and Johansen (1999). The test of Bai and Perron (2003) treats both the number and date of breaks as unknown. This is done by partitioning the dataset multiple times, estimating the coefficients of the model for each partition, and finding where the sum of squared residuals is minimized. F-statistics are computed for two types of hypotheses, the first testing the null of no structural breaks against the alternative of m breaks and the second being a sequential test of m versus $m + 1$ breaks. The Bai and Perron (2003) test is conducted for the four equations of a VAR model of MA and CT Class I REC prices, electricity prices, and natural gas prices. Each equation is tested under a VAR model in natural logarithms and under a VAR model in first difference natural logarithms. Results (Appendix B) show no potential breaks in any of the four equations for either VAR model, suggesting that there are no breaks in the short or long run relationships among the series.

Hansen and Johansen (1999) present a test for parameter constancy which is based on the recursive estimation of a VECM model. In this study, the VECM specified above (two lags, one cointegrating vector) is re-estimated in a recursive fashion, adding one observation at a time. Estimates of the long run (β) parameters at each step in the recursion are compared to the full sample estimates to look for deviations. See Chapter II for a detailed explanation of the test. Results of the Hansen and Johansen (1999) test (Appendix B) exhibit stability of the β parameters over the entire sample.

Taken together, the tests of Bai and Perron (2003) and Hansen and Johansen (1999) reject the possibility of a structural break in the model parameters. While there is a jump in the levels of the MA Class I price series in early 2012, the relationship governing the joint behavior of the four variables appears not to change. Accordingly, inferences based on the full sample estimates of model parameters about how REC prices are related to electricity and natural gas prices, and to each other across states, are discussed further below.

Divergence between Theory and the Data

As discussed above, theory suggests that an increase in electricity prices or in natural gas prices should result in a decrease in REC prices (Felder 2011; Berry 2002). The results above point to a lack of integration between REC prices and electricity and natural gas markets. Specifically, REC prices do not respond to shocks in either electricity prices or natural gas prices. Further, MA and CT Class I REC prices are not found to be a part of the cointegrating space, evidence that the REC markets across states are less integrated than expected. Possible reasons why the Connecticut and Massachusetts REC markets have not behaved according to fundamentals are presented below.

First, it is worthwhile to note that the Connecticut and Massachusetts REC markets are relatively immature (the first compliance year in Massachusetts was 2003, and in Connecticut was 2006). Any market will have an initial period of learning and adaptation for market participants. As explained below, these REC markets in particular are characterized by additional complications which may extend the learning curve and present a high level of uncertainty for all parties. Schmalensee (2011 p. 61) summarizes this argument, explaining that REC markets are fragmented and thin, do not work well, and "are sometimes markedly out of line with their fundamental determinants." A lack of information may cause market participants to heavily weight the most recent trading price as the signal, rather than taking into account market conditions. Additionally, Schmalensee (2011) notes that transaction costs appear to be large in REC markets. High transaction costs may conflate the inability of market participants to properly take into account all available information. The gradual climb in REC prices observed in figure 3.2 may be the result of high uncertainty in the marketplace.

Perhaps most importantly, institutional intervention in RPS programs may be contributing in driving REC markets away from fundamentals. Felder and Loxley (2012) discuss this issue in SREC markets, but some of their analysis can be generalized to REC markets. They explain that volatile SREC prices solicit complaints from both solar providers and ratepayers alike. Pressure from market participants may provoke policy makers to alter RPS legislation. There is evidence of this occurring in both the Massachusetts and Connecticut REC markets. For example, in July 2008, five years after the Massachusetts program was introduced, the state legislature introduced a bill that required electricity suppliers to enter at least two long-term contracts for RECs during a three year period (Database of State Incentives for Renewables & Efficiency 2015). The provisions of this legislation were amended in June 2010, August 2012, and March 2013. Connecticut legislators passed a similar bill in 2011. Other changes to the Connecticut RPS mandate include altering the qualifications for Class I and Class II sources, and planned decreases in REC price for less-desirable renewables (Database of State Incentives for Renewables & Efficiency 2015). Thin and fragmented markets make it difficult for policy makers to understand market developments. This may have caused policy makers to modify RPS legislation, resulting in additional uncertainty for market participants.

An additional potential contributing factor is the near-verticality of the demand curve for RECs. As with any good for which demand is highly inelastic, the market price of RECs is especially sensitive to supply shifts. Felder and Loxley (2012) discuss this issue in SREC markets specifically. They note that a change in supply, however small in magnitude, can cause a large swing in price. This might encourage large renewable producers to withhold RECs from the market to increase price. Importantly, supply shifts like these are not driven by electricity or conventional generation price expectations and will not be captured by the model implemented here.

Conclusions

The relationships between REC prices, wholesale electricity prices, and costs of conventional generation have been contemplated in the literature without much statistical investigation. The empirical analysis shows that neither Massachusetts nor Connecticut Class I REC prices respond to shocks in MassHub electricity prices. This result is inconsistent with the theory outlined by Felder (2011), who hypothesized that REC prices should represent the difference between the cost of renewable electricity generation and the revenue obtained for producing it. An increase in electricity prices should result in a decrease in REC prices in this framework. Similarly, the empirical analysis presented here does not find a relationship between Algonquin Hub natural gas prices and REC prices in either state. Berry (2002) hypothesized that REC prices should represent the cost premium of renewable generation over conventional sources, i.e. REC prices should respond negatively to positive natural gas price shocks.

Mixed evidence is found regarding the question of whether REC prices are integrated across states. The trace test of Johansen (1991) resulted in one cointegrating vector characterizing the long run relationship between the four endogenous price series. However, statistical tests show both the MA and CT Class I REC prices are excluded from the cointegrating space and do not respond to disruptions in the long run relationship. An asymmetric relationship between MA and CT Class I REC prices is found as well. The question of whether Massachusetts REC prices drive Connecticut REC prices, or vice versa, is sensitive to the specification of causal flows in the DAG.

Several explanations for the disparity between theory and the empirical evidence are discussed. The relative immaturity of the REC markets may be contributing to the divergence between REC price fundamentals and actual market outcomes. In addition, institutional interventions are continuously altering the market landscape, potentially affecting the expectations of market participants, increasing uncertainty, and disrupting market fundamentals. Transaction costs may be large in these markets; potentially hindering integration between REC markets in Massachusetts and Connecticut. Lastly, the inelasticity of the market demand curve for RECs can encourage large renewable producers to withhold production of RECs and alter price discovery.

Renewable Portfolio Standards have been promoted and implemented as market-based incentives for encouraging renewable generation. As this study has shown, markets for RECs in Massachusetts and Connecticut do not behave according to hypothesized fundamentals. Regardless of the reason for this divergence, regulators have not succeeded in creating an efficient, fundamental-driven market under current RPS programs in the two states.

Overall, the main contribution of this study is that it provides data-driven results testing the hypothesized negative relationships between REC and electricity prices, and REC and natural gas prices, in addition to examining the link between REC prices across states. Empirical investigation into these issues has been lacking in the literature. The results of this analysis do not align with theory previously introduced in the literature; several reasons are presented as to why this is the case.

One limitation of this study is the relatively short time frame for which data is available. Additionally, only two states are included; there are RPS programs in many other states. Taking the results from this study and previous studies indicates that REC markets may still be in their infancy. It appears transaction costs are large in the market. The sensitivity of the estimated relationship between REC prices in Massachusetts and Connecticut, along with the finding that the two prices are not part of the estimated cointegrating relationship, suggests that these REC markets have not matured to the point of being efficient. A limited number of transactions may be restricting market integration. Future empirical investigation into RPS programs and REC pricing mechanisms is required as programs mature and data becomes available.

CHAPTER IV

PROJECTING IMPACTS OF CARBON DIOXIDE EMISSIONS REDUCTIONS IN THE ELECTRIC POWER SECTOR: EVIDENCE FROM A DATA-RICH APPROACH

In August 2015, the United States Environmental Protection Agency (EPA) released a heavily anticipated final rule for reducing the amount of carbon dioxide (CO_2) emissions from fossil-fuel run electricity generating plants (U.S. EPA 2015b). This rule provides guidelines for achieving a reduction in nationwide CO_2 emission levels in the electric utility sector of approximately 32% from 2005 levels by 2030. The World Resources Institute (2014) posits that emissions reductions and economic growth can be achieved simultaneously. On the other hand, the Institute for 21st Century Energy estimates that U.S. GDP will average $51 billion less per year in the EPA regulation case than in the base case (U.S. Chamber of Commerce 2014). This chapter contributes to the literature by addressing how the EPA rule (Clean Power Plan or CPP) may impact the U.S. economy, using a dynamic, data-rich model, the factor-augmented vector autoregression (FAVAR). The empirical analysis serves as a data-driven complement to structural analyses of policy changes in the energy and electricity sectors (Burtraw et al. 2014; Bushnell et al. 2014; Electric Reliability Council of Texas 2015; Harrison et al. 2014; Hopkins 2015; U.S. Chamber of Commerce 2014; U.S. EPA 2015c).

The FAVAR approach allows for the use of a large number of time-series variables, overcoming the need to select a particular subset of variables to represent larger economic activity as required by most time series approaches, commonly referred to as the "curse of dimensionality" (Aastveit 2014; Bernanke, Boivin, and Eliasz 2005). Bernanke, Boivin, and Eliasz (2005), for example, use 120 macroeconomic time series in their application of the FAVAR model in studying the effects of monetary policy. Zagaglia (2010) uses 239 different series in his study of oil price dynamics in the context of the macroeconomy. The basic concept of the FAVAR approach is that a small number of underlying latent factors can be extracted from a high-dimensional dataset; these factors can then be used in a conventional multivariate time series framework (vector autoregression) alongside particular variables of interest to examine dynamic relationships or to develop forecasts.

The objective of this chapter is to estimate the potential implications of the 2015 EPA Clean Power Plan for the U.S. economy. Factors are estimated from a large number of monthly macroeconomic, financial, and energy related time series representing the underlying sources of variation in U.S. economic and energy sector activity. These factors are included in a FAVAR model with nationwide CO_2 emissions from the electric power sector, U.S. industrial production, and U.S. real personal income as the variables of interest. Expected paths, both conditional and unconditional, are presented for U.S. industrial production, real personal income, and CO_2 emissions, as well as for the factors. Conditional forecasts based on the CO_2 emissions reductions path outlined by the CPP are generated from the FAVAR model. Inferences suggest that CO_2 emissions reductions and economic growth can be achieved simultaneously, but that the regulation will slow growth and increase variability in economic activity.

Literature Review

The vector autoregressive (VAR) framework was introduced and explored in the context of econometric analysis by works such as Sargent (1979) and Sims (1980). The advancement of the VAR framework provided a new degree of flexibility to empirical analysis in economics; the methodology has been a staple ever since. As Bernanke, Boivin, and Eliasz (2005, p. 398) point out, VAR analysis is an "…antidote to incredible identifying restrictions…" that plague economic models, meaning that causal inference can be conducted without having to make too many assumptions about the underlying model structure. Sims, Goldfeld, and Sachs (1982) explore the suitability of VAR models for policy analysis. They argue that careful applications of VAR models can be useful in making projections on the likely impacts caused by different policy scenarios. Sims, Goldfeld, and Sachs (1982) account for policy endogeneity in their model, something that had been previously ignored. Sims (1986) extends this idea, giving examples of how a VAR model can be identified in the context of an endogenous policy instrument(s). He argues that VAR models should not be considered inferior to rational expectations models, as they can provide useful information for policy analysis without relying on assumptions for market structure, behavior, functional form, etc. Cooley and Leroy (1985) motivate the importance of developing a strong economic justification for the underlying structure of VAR models. They contend that identifying a VAR model without economic justification leads to unsupportable interpretations of the results.

An extension of the VAR framework, the FAVAR, has its foundation in the work of Stock and Watson (2002a, 2002b) and Bernanke, Boivin, and Eliasz (2005). Stock and Watson (2002a) establish a method for forecasting in which a large number of time series predictors are summarized into a much smaller number of latent factors, which they call indexes. The authors use principal components analysis (PCA) to estimate the indexes. Stock and Watson (2002b) use a similar method to construct an array of models from 215 predictor series, referring to the extracted factors as diffusion indexes. Models making use of the diffusion indexes perform better than alternatives such as univariate autoregressive models and VAR models in forecasting exercises for most of the eight variables considered. Bernanke, Boivin, and Eliasz (2005) formally introduce the FAVAR structure in the context of the U.S. monetary policy transmission mechanism (the dynamic causal effects of shocks to the federal funds rate on various measures of economic activity). They estimate a VAR model using the federal funds rate alongside latent factors extracted from a large panel of macroeconomic variables (hence the factor-augmented nomenclature). The authors conclude that the FAVAR approach makes use of important information that would otherwise be ignored in a smaller-dimension VAR framework.

The FAVAR model has been applied to a variety of research questions since its introduction. In the monetary policy arena, Mumtaz, Zabczyk, and Ellis (2011) study the effects of UK monetary policy and aggregate demand shocks on various measures of the UK macroeconomy, including inflation, real activity, and asset prices. By allowing the FAVAR parameters to vary over time, they find that inflation has a much larger response to aggregate demand shocks at the beginning of their sample. Moench (2008) uses a FAVAR approach to forecast the U.S. Treasury bond yield curve by building up a term structure model from the dynamics of the short term interest rate. He finds that the ability of the FAVAR model to predict the yield curve outperforms a variety of models, including AR, VAR, and several factor-based models previously introduced in the literature. Barnett, Mumtaz, and Theodoridis (2014) compare the forecasting performance of a variety of models for UK GDP, inflation, and interest rates. They find that a FAVAR model with time-varying parameters performs best for all three variables at longer (four-quarter ahead) forecast horizons. Vargas-Silva (2008) investigates the effects of a monetary policy shock on U.S. housing starts. He uses the same 120 series as in Bernanke, Boivin, and Eliasz (2005) to find that housing starts respond negatively to monetary policy shocks. Gupta and Kabundi (2010) show U.S. house price inflation responds negatively to positive monetary policy shocks by using a FAVAR model based on 126 quarterly macroeconomic variables. Apergis, Christou, and Payne (2014) study the dynamics of precious metal markets in the context of a FAVAR model. They find that factors related to macroeconomic variables provide information that helps explain gold and silver price movements, whereas a stock market factor does not contribute to the same extent.

Ielpo (2015) introduces a method for improving the power of swap yields in forecasting policy rates of both the Federal Reserve and European Central Bank. He shows that his method, which corrects for the cyclical premium of yields, outperforms a FAVAR approach using the simple yields themselves in empirical examples. Favero, Niu, and Sala (2012) forecast the U.S. yield curve using both no-arbitrage restrictions and large information via factor-based methods. The authors find that large information sets help at longer time horizons for longer maturities, but that no model strictly dominates the others in their empirical setting. Koop (2013) compares the forecasting performance of a FAVAR approach with that of several Bayesian shrinkage methods for forecasting U.S. GDP, CPI, and the federal funds rate using a large information set. He shows that Bayesian methods using the Minnesota prior tend to outperform the FAVAR approach in medium and large VARs.

In an energy-related application of the FAVAR approach, Zagaglia (2010) makes use of a large dimension (239 variables) dataset containing energy, macroeconomic, and financial information to forecast crude oil spot and futures prices. He finds that the FAVAR model improves the forecasting ability of time-series models for oil prices over two alternative VAR-type models: one including only oil returns and the second including only the factors as right-hand side variables. Building off of this study, Ipatova (2014) applies both FAVAR and Factor-Augmented Vector Error Correction Model techniques to forecast crude oil futures at different maturities. Comparing these models to a variety of univariate approaches, her findings are similar to Zagaglia (2010) that factor-augmented models have superior performance to alternative time series models in forecasting oil futures. Binder et al. (2016) compare various methods for factor extraction in terms of forecasting performance for oil price returns. The authors construct separate FAVAR models for each factor extraction method. The methods perform similarly in terms of probabilistic forecasting, but the traditional PCA method is shown to outperform the method introduced by Lam and Yao (2012) in deterministic forecasts at short horizons (the reverse is true at longer horizons). Additional results in

Binder et al. (2016) suggest that the choice of the number of factors in a FAVAR is an equally important matter in developing a FAVAR model for forecasting. Hong (2012) shows that crude oil price shocks are not exogenous in contemporaneous time when modeled alongside factors extracted from a large panel of macroeconomic time series. He also shows that a FAVAR model outperforms AR models in forecasting oil price returns. Duangnate (2015) investigates the implications of the number of factors included in a FAVAR model on probabilistic forecasting performance. Interested in forecasting U.S. natural gas withdrawals, she finds that including estimated factors improves forecasting performance, but using too many factors in a FAVAR model may have detrimental effects (parsimony is important). Chevallier (2011) uses factors extracted from macroeconomic, financial, and commodities indicators to study the reaction of European carbon prices to international shocks represented by the factors in a FAVAR model.

Conditional Forecasting

In unconditional forecasting, future values of endogenous variables are predicted solely using data up until the present. Conditional forecasting differs in that the future path of at least one variable is assumed to be known (Bloor and Matheson 2011). Forecasts of the variables in the system are made given the assumed path of at least one variable (often referred to as a scenario). Conditional forecasts are commonly developed from estimated VAR models; early applications used VAR models to make projections of macroeconomic variables, such as GDP or inflation, conditional on a future path of monetary policy (Doan, Litterman, and Sims 1984; Dokko et al. 2011; Jarocinski and

Smets 2008; Luciani 2015; Meyer and Zaman 2013; Sims, Goldfeld, and Sachs 1982). Giannone et al. (2014) develop forecasts of Euro area short-term inflation conditional on different future paths of oil prices and price index determinants, showing that their model is useful for scenario analysis. Clark and McCracken (2014) present tests of predictive ability (bias, efficiency, and equal accuracy) for conditional forecasts from a variety of estimated models. Other recent examples of conditional forecasting include Banbura, Giannone, and Lenza (2015), Stock and Watson (2012), Bloor and Matheson (2011), and Lenza, Pill, and Reichlin (2010). These studies generate conditional forecasts from several different models to explore monetary policy effects and macroeconomic dynamics during the global financial crisis of 2007-2009.

Banbura, Giannone, and Lenza (2015) note that there is a lack of investigation into conditional forecasting from VAR models for large datasets. The authors generate forecasts, both unconditional and conditional on realized paths of several key variables, for a large set of Euro area macroeconomic and financial indicators. They employ two models, one using Bayesian shrinkage methods and the other a dynamic factor model, to forecast their 26 variable system. Additionally, the authors develop a Kalman filter based procedure to estimate conditional forecasts for linear systems that can be written in a state-space form. They find that both Bayesian methods and dynamic factor models produce accurate unconditional forecasts and reliable scenarios, and that the forecasts from each model are very similar.

Brief Introduction to the Clean Power Plan

The Clean Power Plan final rule, officially "Carbon Pollution Emission Guidelines for Existing Stationary Sources: Electric Utility Generating Units," was released in 2015 by the U.S. Environmental Protection Agency (U.S. EPA 2015b). This rule was released approximately one year after a proposed version, allowing the EPA to address comments and concerns from states, government agencies, utilities, private corporations, and the public. Despite the EPA's review of comments, many entities are still strongly opposed to the plan and continue to battle its implementation (Hogan 2015; Potts and Zoppo 2015). [12,13]

The goal of the CPP is to achieve a 32% reduction in nationwide CO_2 emissions from electric utility generating units by establishing emissions performance rates for existing fossil-fuel fired power plants. In addition, the EPA outlines unique rate- and mass-based goals for each state, based on each state's current electricity generating mix. The EPA has given flexibility to states in the choice of a strategy or combination of strategies (emissions taxes, trading programs, incentives for renewables, etc.) to achieve these standards. Each state is required to submit an implementation plan outlining their choice and how it will meet the standards. The CPP not only allows, but encourages states to work together to achieve CO_2 reductions (U.S. EPA 2015b). See Burtraw et al. (2014), Burtraw, Bushnell, and Munnings (2015), Bushnell et al. (2015), Hogan (2015),

[12] See Potts and Zoppo (2015) for a discussion of the legal issues surrounding the Clean Power Plan and its likelihood of being upheld in the U.S. Supreme Court.

[13] No claims about the legal issues surrounding the Clean Power Plan are made in this study; the sole purpose of the study is to evaluate the potential implications of the rule in its current iteration.

Michel and Nielsen (2015), and Paul, Palmer, and Woerman (2013) for detailed discussions regarding how states can plan for emissions reductions.

In establishing the CO_2 emissions performance goals for existing electric power plants, the EPA established three 'building blocks' to achieving emissions reductions "…that are available to all affected electricity generating units" (U.S. EPA 2015b, p. 64667). The blocks are: (1) improving heat efficiency at existing coal-fired plants; (2) substituting generation from existing natural gas combined cycle units for generation from higher-emitting sources; and (3) substituting generation from zero-emitting sources for generation from fossil-fuel units. The EPA recognizes that CO_2 emissions reductions may be achieved through other measures, including demand-side energy efficiency improvements, and therefore does not require states to use the three building blocks exclusively, or even at all, in their implementation plans.

Under the guidelines set forth by the CPP, the EPA projects annual national CO_2 emissions to be 22-23% below 2005 levels in 2020, 28-29% below in 2025, and 32% below in 2030 (U.S. EPA 2015b). These projections are used to develop scenarios under which conditional forecasts are generated in this study.

Hopkins (2015) compares the findings of six studies that estimate the projected impacts of the CPP. He notes that the studies generally agree on several key points. One common theme among the studies is that energy efficiency improvements are the most cost-effective way to reduce CO_2 emissions and electricity consumption is projected to decline as a result under the CPP. Additionally, the studies project that overall cost increases, including costs to electricity consumers, will be manageable.

Hopkins (2015) also notes that the studies show decreases in electricity generation from coal and that increased generation from renewables and nuclear will help states meet CPP goals. These increases in renewables and nuclear under the CPP, however, are not different than what would happen in base case scenarios. As noted above, this chapter serves as a complement to existing structural analyses of impacts to the electricity and energy sectors by projecting the impacts of the CPP on larger economic activity in a data-rich setting.

Methodology

FAVAR Approach

The FAVAR model uses information from a large number of time series by extracting underlying, latent factors which drive variation in the data. These factors are then included in a traditional VAR along with observed variable(s) of interest for which forecasting or specific dynamic relationships are desired. Let X_t be a large, n-dimensional panel of time series variables, where each element $X_{1t}, \dots, X_{nt}$ contains observations of an individual time series over the period $t = 1, \dots, T$. Let F_t be a $k \times 1$ vector of latent factors which describe the information contained in X_t. Additionally, let Y_t be a $m \times 1$ vector of variables of interest. The relationship between the latent factors and observed time series is:

(4.1) $X_t = \Lambda^f F_t + \Lambda^y Y_t + \varepsilon_t$

for $t = 1, \dots, T$. Λ^f is an $n \times k$ matrix of factor loadings, Λ^y is $n \times m$ matrix of coefficients relating Y_t and X_t, and ε_t is an $n \times 1$ vector of mean zero idiosyncratic components, or error terms, with diagonal covariance matrix. No assumptions regarding the magnitude of n and T are needed at this time, however, as Stock and Watson (2002a) show, the restriction that $n \gg m + k$ is needed for consistent estimation of the factors. The number of information time series must be much greater than the number of latent factors plus observed variables of interest.

From equation (4.1), both F_t and Y_t contain information that drives X_t. The information provided in the observed time series Y_t and X_t can be utilized to estimate F_t in the context of equation (4.1). The dynamic relationships between the factors (F_t) and series of interest (Y_t) are:

$$(4.2) \qquad \begin{bmatrix} Y_t \\ F_t \end{bmatrix} = \sum_{i=1}^{p} \phi_i \begin{bmatrix} Y_{t-i} \\ F_{t-i} \end{bmatrix} + \nu_t$$

where $\phi_i, i = 1, \ldots, p$ are $(k + m) \times (k + m)$ matrices of coefficients relating past values of Y_t and F_t to values at time t, and ν_t is a vector of mean zero innovations with covariance matrix Ω.

Bernanke, Boivin, and Eliasz (2005) present two options for estimating a FAVAR, the first of which is a two-step method that initially extracts factors from X_t following the PCA procedure used by Stock and Watson (2002a, 2002b). PCA of the informational time series X_t, t=1,…,T is based on the k largest eigenvalues of its sample contemporaneous covariance matrix $\hat{\Gamma}_X(0) = \frac{1}{T}\sum_{t=1}^{T}(X_t - \bar{X})(X_t - \bar{X})'$ (Stock and Watson 2002a). The i^{th} column of the loading matrix Λ^f in equation (4.1) is proportional to the eigenvector corresponding to the i^{th} largest eigenvalue of $\hat{\Gamma}_X(0)$. From equation (4.1), the estimated factors $\hat{F}_t$ are obtained using least-squares. In the second step, the factors are placed into a VAR model as endogenous series, joining the observable time series of interest. They also propose a one-step procedure which estimates the factors and the FAVAR system simultaneously using a Gibbs sampling procedure. They find any benefits from using the fully parametric one-step procedure are small. For this reason, as well as the relative computational ease of the alternative, the two-step procedure is used in this chapter.

As noted above, equation (4.1) allows both F_t and Y_t to contain information that drives X_t. Thus, the multivariate time series X_t must be adjusted for the linear effect of Y_t in some manner. The following procedure following Binder et al. (2016) is used here. Let $\tilde{X}_t = X_t - \hat{\Lambda}^y Y_t$, and $\hat{\Lambda}^y = \left(\hat{\lambda}_1^y, \dots, \hat{\lambda}_N^y\right)$ where $\hat{\lambda}_i^y = (\frac{1}{T}\sum_{t=1}^{T} Y_t Y_t')^{-1}(\frac{1}{T}\sum_{t=1}^{T} X_{i,t} Y_t')$. After this adjustment, the two-step procedure following Bernanke, Boivin, and Eliasz (2005) is conducted. Specifically, in the first step, PCA is carried out on the matrix $\tilde{X}_t$ to obtain estimates of the factors, $\hat{F}_t$(equation 4.1). In the second step, a FAVAR specification including $\hat{F}_t$ and Y_t is estimated following equation (4.2), using least-squares techniques.

Conditional Forecasting

This chapter builds on the work of Banbura, Giannone, and Lenza (2015) by developing conditional forecasts from a VAR model for a high-dimensional dataset. The authors use both Bayesian methods and a dynamic factor model to employ the large dataset. A slightly different approach, however, is taken here by applying a FAVAR model to make use of the information contained in the large dataset. The future path of U.S. CO_2 emissions from the electric power sector is assumed known, based on the EPA's outlined path under the CPP.[14] Following the previous section, factors are extracted in the first step, and then the FAVAR parameters of equation (4.2) are estimated using OLS.[15] To compute conditional forecasts, first re-write equation (4.2) in terms of its moving-average (MA) representation:

(4.3) $$\begin{bmatrix} Y_t \\ F_t \end{bmatrix} = \Psi(L)\nu_t$$

where $\Psi(L)$ are the MA coefficients of the model. When fixing a future value of an endogenous variable the associated forecast error is, by definition, constrained (the difference between the constrained value and the unconditional forecast is set) (Robertson and Tallman 1999). The l-step ahead forecast error of $\begin{bmatrix} Y_{h+l} \\ F_{h+l} \end{bmatrix}$ with forecast origin $t = h$ is:

(4.4) $$\sum_{j=0}^{l-1} \Psi_j \nu_{h+l-j} \ .$$

In effect, by constructing a conditional forecast, linear constraints are placed on the innovations $\nu_{h+1}, \ldots, \nu_{h+l-1}$.

As explained in Chapters II and III, the innovations ν_t are, in general, non-orthogonal ($E[\nu_t \nu_t'] = \Sigma_\nu$ is not a diagonal matrix). It is often beneficial to consider the 'orthogonalized' innovations, as the co-movement of the endogenous variables over time

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[14] CO_2 emissions are treated as the policy variable for which future values are constrained in this forecasting exercise. The implication is that CO_2 emissions shocks are assumed to generate the same response of economic activity whether emissions levels are set by policy or not. Sims, Goldfeld and Sachs (1982) and Sims (1986) argue that this implication is solely a cautionary reality, not a rejection, of using forecasting models in policy analysis. Bessler and Kling (1989, p. 504) expound upon this point by noting that "one should be careful in his/her use of an econometric model where extreme values of the policy variables are considered."

[15] Clark and McCracken (2014), using Monte Carlo experiments, find little difference between the conditional forecasting performance of VARs estimated via Bayesian methods and those estimated via OLS.

needs to be taken into account. In computing the conditional forecasts, orthogonal innovations following a Bernanke (1986) ordering are used. Correlated innovations ν_t are written as a function of the underlying orthogonal sources of variation, η_t:

(4.5) $\nu_t = A^{-1}\eta_t$.

As in Chapters II and III, a form for the matrix A is obtained through causal flow methods (Pearl 2000; Spirtes, Glymour, and Scheines 2000), specifically the GES algorithm (Chickering 2003) in TETRAD V (2015).

Using orthogonalized innovations, the forecast error in equation (4.4) is re-written as:

(4.6) $\sum_{j=0}^{l-1} \Psi_j A^{-1}\eta_{h+l-j}$.

The linear constraints on the innovations are:

(4.7) $RH = r$

where H is a vector of the orthogonalized innovations $\eta_{h+1}, \dots, \eta_{h+l-1}$ (forecast period errors), r is a vector of differences between the known path of the constrained variable and its unconstrained forecast values, and R is a matrix relating elements of H to r. To generate conditional forecasts, the vector H which minimizes $H'H$ subject to the constraint in equation (4.7) is found. The solution to this minimization problem is:

(4.8) $\widehat{H} = R'(RR')^{-1}r$

(Doan, Litterman, and Sims 1984; Van der Knoop 1987). The solution can be thought of as the set of innovations to the FAVAR that best meet the conditioned path for the constrained variable(s) according to the least-squares criterion (Clark and McCracken 2014). Conditional forecasts of the unconstrained endogenous variables are constructed by modifying unconditional forecasts with the elements of $\widehat{H}$ (Robertson and Tallman 1999). Waggoner and Zha (1999) developed a Gibbs sampling technique for efficiently computing the mean and variance of the conditional distribution of innovations (extended by Jarocinski 2010). Clark and McCracken (2014) find that conditional forecasts are not affected when using the algorithm of Wagooner and Zha (1999) instead of Doan, Litterman, and Sims (1984).

Data

The model is estimated using monthly data for the period July 1976 to December 2014, giving 462 observations. As previously noted, three observed series of interest are included in Y_t: U.S. carbon dioxide emissions from the electric power sector (U.S. Energy Information Administration (EIA) 2015a), U.S. industrial production index (Federal Reserve Bank of St. Louis Economic Research 2015), and U.S. real personal income (Federal Reserve Bank of St. Louis Economic Research 2015). Based on monthly data availability, industrial production and real personal income are chosen to represent producer and consumer welfare. The informational time series, matrix X_t, contains monthly observations of 166 variables including macroeconomic and financial indicators, stock indices and share prices, and energy prices and quantities (Appendix C). Macroeconomic data comprises employment indicators, consumer and producer price indices, consumption measures, housing indicators, and production and manufacturing indices. Financial data includes government and corporate bond rates, stock market indices, and share prices of major energy firms. Energy data includes generation totals from various fuel sources, fuel prices, electricity prices, natural gas and crude oil drilling and shipment activity, electricity sales to different sectors, gas and petroleum product stocks, and energy production and consumption measures from various sources and sectors.

All data series are in natural logarithms for the analysis, except those that are in terms of percentages. The PCA procedure requires stationarity of each of the individual components of X_t for estimation of the factors (Stock and Watson 2002b; Moench 2008; Aastveit 2014; Tsay 2014). Each of the variables is transformed to a stationary process before any of the modeling procedure is undertaken (Appendix C). Additionally, all data series are standardized to have mean zero and unit variance as an initial pre-adjustment following Moench (2008).

Results

Model Specification

Bai and Ng (2002) develop a formal selection procedure for determining the number of factors (k) in the factor model of equation (4.1) based on information criteria. As noted by Duangnate (2015), the estimated number of factors can vary heavily across information criteria in empirical applications. The number of factors in this chapter ranges from 1-20 across the seven information criteria proposed by Bai and Ng (2002) (table 4.1). Moench (2008) and Zagaglia (2010) discuss the importance of considering parsimony when determining the number of factors to include in a FAVAR model. Additionally, Duangnate (2015) finds forecasting performance may decline when the number of factors included in a FAVAR model increases. For these reasons, four factors are included in the FAVAR model. The optimal lag order (p) considered in the FAVAR model (equation 4.2) is 12, based on the minimum value of the AIC loss metric (table 4.2). Twelve lags are chosen to help capture the seasonal behavior that is characteristic of the electricity sector. The remaining results are based on an estimated FAVAR specification with $k = 4$ factors and $p = 12$ lags.

Table 4.1. Bai and Ng (2002) Information Criteria for Selecting Number of Factors[1]

Criterion	Number of Factors
IC_1	20
IC_2	14
IC_3	20
AIC_1	20
BIC_1	20
AIC_3	20
BIC_3	1

[1]Maximum number of factors allowed in the computation of the information criteria is 20.

Table 4.2. Optimal Lag Order Selection for the FAVAR

Lags	SIC	AIC	HQ
0	9.28	9.28	9.28
1	1.53	1.09	1.28
2	1.37	0.49	0.84
3	1.18	-0.14	0.39
4	**0.93**	-0.82	-0.12
5	1.24	-0.96	-0.08
6	1.37	-1.27	**-0.23**
7	1.81	-1.27	-0.06
8	2.28	-1.23	0.14
9	2.71	-1.24	0.32
10	3.03	-1.37	0.37
11	3.19	-1.64	0.26
12	3.37	**-1.89**	0.18
13	3.83	-1.88	0.37
14	4.32	-1.83	0.59
15	4.81	-1.78	0.82

Properties of the Factors

It is important to develop an interpretation for the estimated factors to provide economic intuition to the FAVAR model and the ensuing forecasts. To provide a sense of the information contained in the factors, each estimated factor is regressed on each individual component of the large informational time series X_t. The ten largest R^2 values for each factor are reported in tables 4.3-4.6. All 167 R^2 values for each factor are charted in figures 4.1-4.4, with the individual components of X_t grouped into 10 categories. Factor 1 appears to be heavily related to macroeconomic indicators, particularly consumer price indices, personal consumption, and labor force measures (table 4.3 and figure 4.1). Additionally, Factor 1 is correlated with electricity generation from (and consumption of) coal and petroleum in the electric power sector, end-use electricity sales, and stocks of crude oil and other petroleum products (figure 4.1). Factor 2 is related to crude oil prices, both imported and domestic, as well as producer price and manufacturing indices (table 4.4 and figure 4.2). Factor 3 is also correlated with various oil price measures, but additionally relates to capacity utilization in the oil and gas extraction and manufacturing industries (table 4.5 and figure 4.3). Finally, Factor 4 is related to natural gas storage activity, total and primary energy consumption in the commercial and residential sectors, and petroleum product stocks (table 4.6 and figure 4.4).

The proportion of total variance in X_t explained by each of the first four factors is also displayed in tables 4.3-4.6. The proportion of variance explained by $F_i, i = 1, \ldots, 4$ is given by $\lambda_i / \sum_{i=1}^{n} \lambda_i$ where λ_i is the i^{th} largest eigenvalue of $\hat{\Gamma}_X(0)$ (the

Table 4.3. Variance Explained by Factor 1 and Ten Highest R^2 Values from Regressing Factor 1 on Individual Components of X_t[1]

18.0% of total variance[2]	
Series Description	R^2
Consumer Price Index for All Urban Consumers: Services	0.932
Consumer Price Index for All Urban Consumers: All items less medical care	0.931
Consumer Price Index for All Urban Consumers: All Items	0.929
Consumer Price Index for All Urban Consumers: Commodities	0.927
Consumer Price Index for All Urban Consumers: All items less shelter	0.926
Consumer Price Index for All Urban Consumers: Transportation	0.908
Personal Consumption Expenditures: Services	0.902
All Employees: Education & Health Services	0.883
Consumer Price Index: All Items Less Food & Energy	0.883
Civilian Labor Force	0.873

[1] R^2 values are from the regressions $\hat{F}_{1t} = X_{it} + \epsilon_t$ for $i = 1, \dots, 167$
[2] Percentage of variance in X_t explained by Factor 1.

Table 4.4. Variance Explained by Factor 2 and Ten Highest R^2 Values from Regressing Factor 2 on Individual Components of X_t[1]

6.7% of total variance[2] Series Description	R^2
Refiner Acquisition Cost of Crude Oil, Composite	0.385
Refiner Acquisition Cost of Crude Oil, Imported	0.379
Producer Price Index: Supplies & Components	0.376
Landed Cost of Crude Oil Imports	0.371
Refiner Acquisition Cost of Crude Oil, Domestic	0.369
Crude Oil Domestic First Purchase Price	0.369
Free on Board Cost of Crude Oil Imports	0.363
Producer Price Index by Commodity for Finished Consumer Goods	0.307
Producer Price Index by Commodity for Finished Goods	0.282
ISM Manufacturing: PMI Composite Index©	0.203

[1] R^2 values are from the regressions $\hat{F}_{1t} = X_{it} + \epsilon_t$ for $i = 1, \ldots, 167$
[2] Percentage of variance in X_t explained by Factor 2.

Table 4.5. Variance Explained by Factor 3 and Ten Highest R^2 Values from Regressing Factor 3 on Individual Components of X_t[1]

5.3% of total variance[2]

Series Description	R^2
Crude Oil Domestic First Purchase Price	0.322
Refiner Acquisition Cost of Crude Oil, Composite	0.320
Refiner Acquisition Cost of Crude Oil, Imported	0.312
Landed Cost of Crude Oil Imports	0.311
Refiner Acquisition Cost of Crude Oil, Domestic	0.310
Free on Board Cost of Crude Oil Imports	0.302
Capacity Utilization: Oil and gas extraction	0.278
Capacity Utilization: Manufacturing (NAICS)	0.263
Capacity Utilization: Manufacturing (SIC)	0.251
Capacity Utilization: Total Industry	0.242

[1] R^2 values are from the regressions $\hat{F}_{1t} = X_{it} + \epsilon_t$ for $i = 1, \dots, 167$
[2] Percentage of variance in X_t explained by Factor 3.

Table 4.6. Variance Explained by Factor 4 and Ten Highest R^2 Values from Regressing Factor 4 on Individual Components of X_t[1]

5.1% of total variance[2]

Series Description	R^2
Natural Gas Storage Activity, Injections	0.528
Natural Gas Storage Activity, Withdrawals	0.459
Liquefied Petroleum Gases Stocks	0.384
Total Energy Consumed by the Residential Sector	0.373
Electricity Retail Sales to the Industrial Sector	0.250
Total Energy Consumed by the Commercial Sector	0.231
Distillate Fuel Oil Stocks	0.218
Hydroelectric Power Consumption	0.213
Electricity Net Generation From Conventional Hydroelectric Power	0.212
Natural Gas in Underground Storage, Total	0.200

[1] R^2 values are from the regressions $\hat{F}_{1t} = X_{it} + \epsilon_t$ for $i = 1, \ldots, 167$

[2] Percentage of variance in X_t explained by Factor 4.

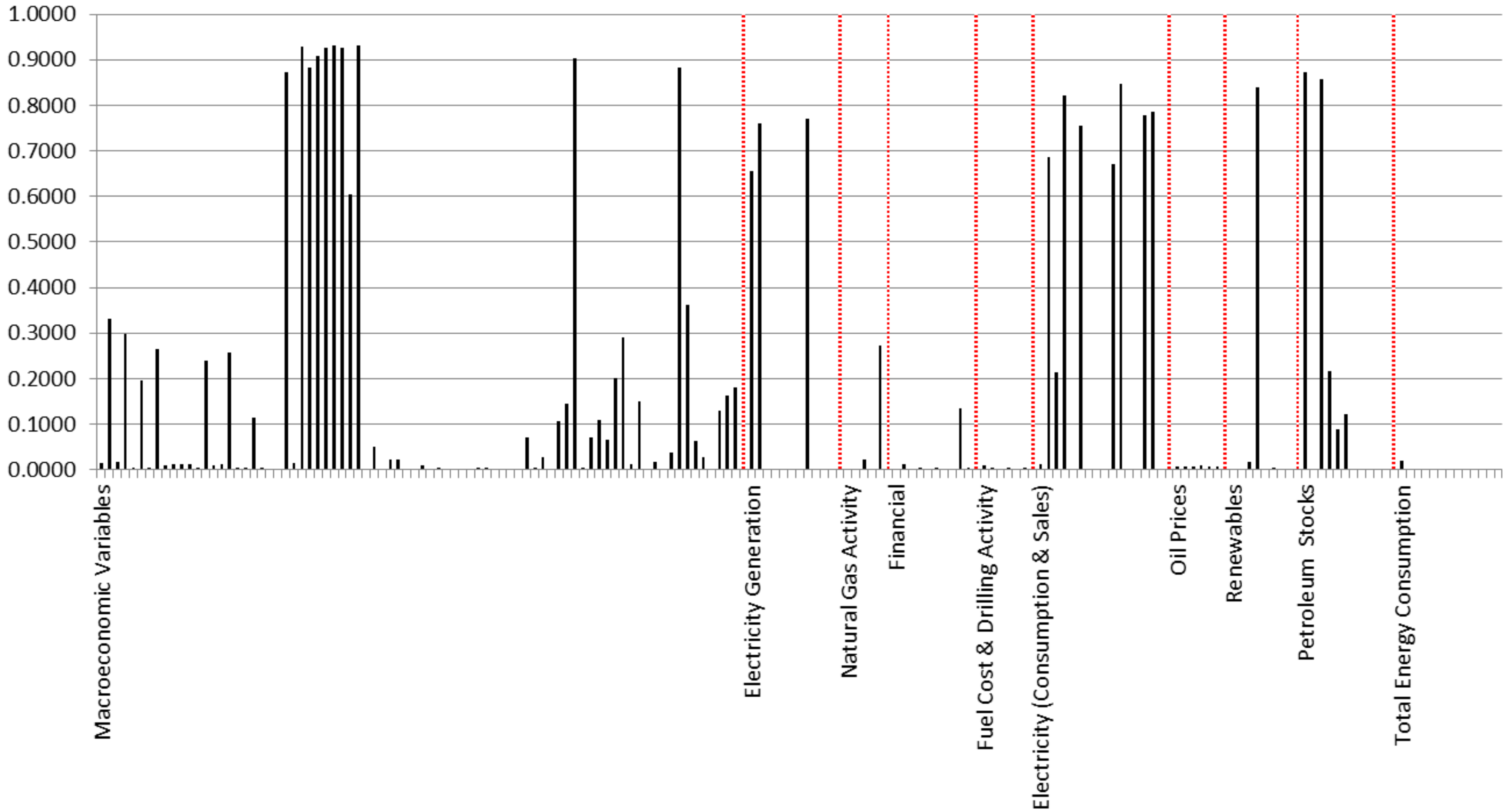

Figure 4.1. Chart of R^2 values from regressing Factor 1 on individual components of X_t

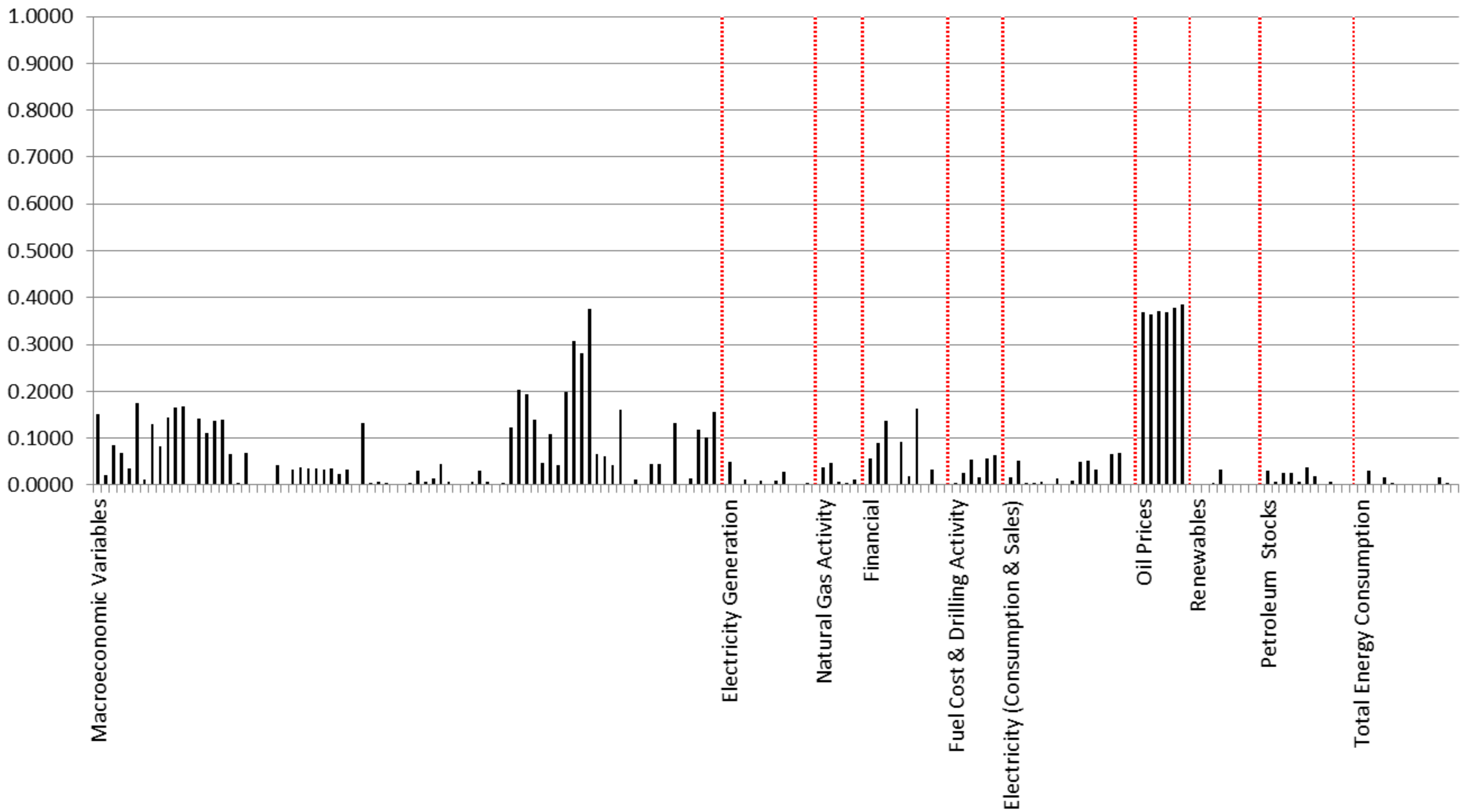

Figure 4.2. Chart of R^2 values from regressing Factor 2 on individual components of X_t

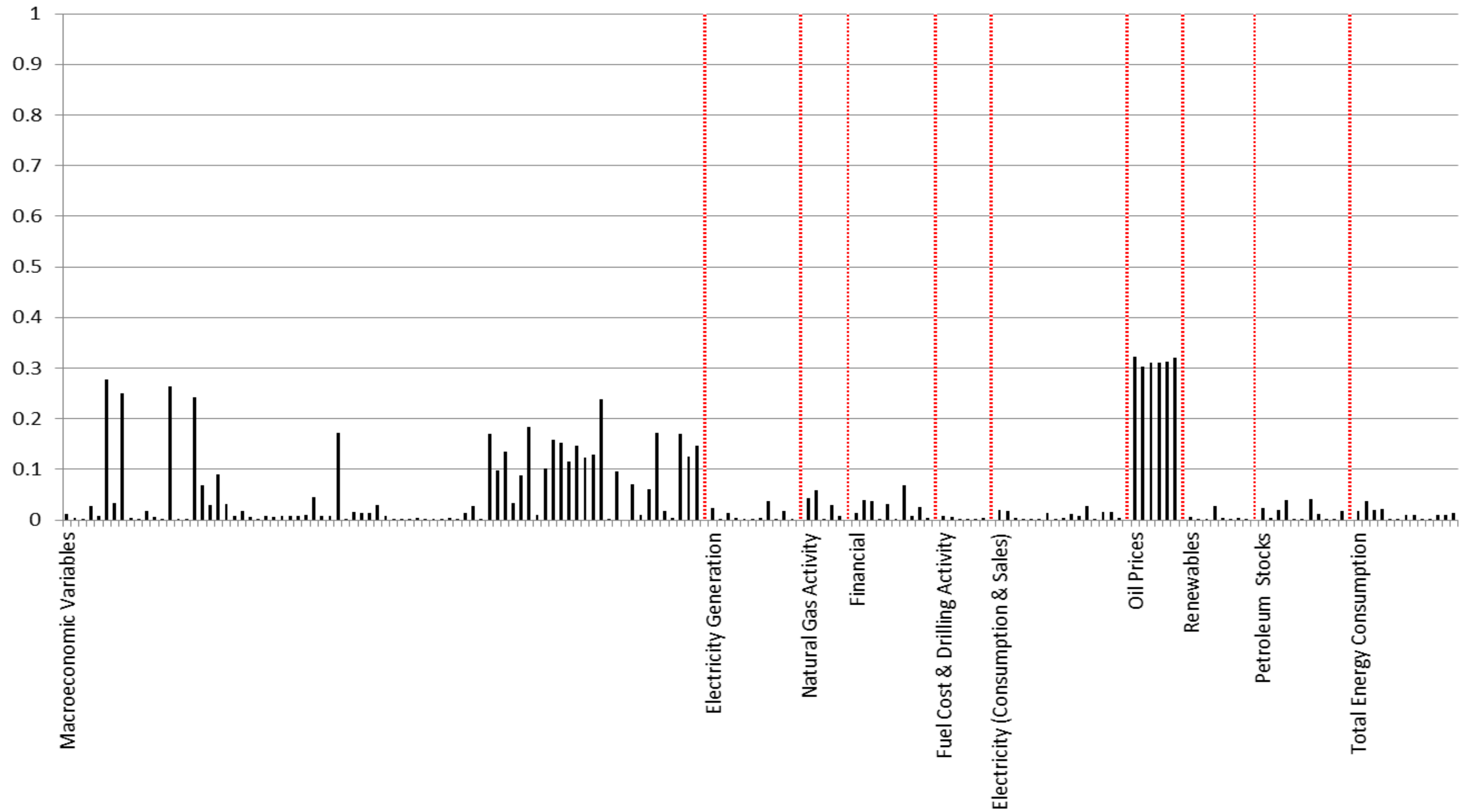

Figure 4.3. Chart of R^2 values from regressing Factor 3 on individual components of X_t

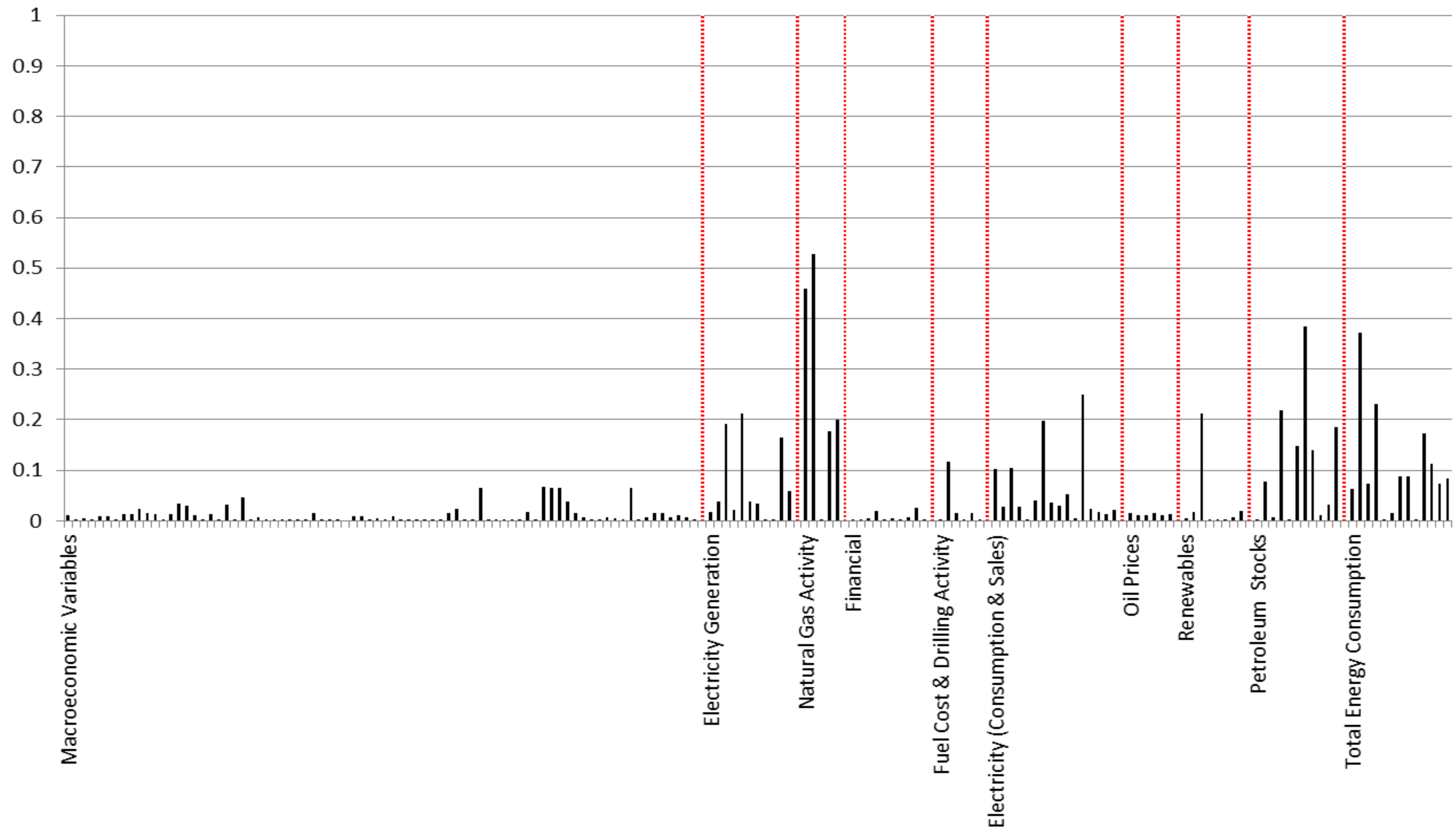

Figure 4.4. Chart of R^2 values from regressing Factor 4 on individual components of X_t

contemporaneous covariance matrix of X_t) (Tsay 2014). Factor 1 accounts for the largest portion of variance in X_t (18%), while the first four factors together explain 35% of the total variance in X_t.

Contemporaneous Causality

The Directed Acyclic Graph (DAG) generated by the GES algorithm is presented in figure 4.5. The DAG is used to provide the causal ordering for innovations in the FAVAR (matrix A in equations 4.5 and 4.6). Contemporaneous causal flows are present from industrial production innovations to real personal income and to Factor 1. Additional flows exist from Factors 1 and 2 to real personal income. There are also contemporaneous information flows from Factors 1 and 3 to Factor 2 and from Factor 2 and CO2 to Factor 4.[16]

Forecasting Results

Unconditional and conditional forecasts are constructed for the seven variables in the FAVAR (CO_2 emissions, industrial production, real personal income, and Factors 1-4). Out-of-sample forecasts from January 2015 to December 2030 are graphed in figures 4.6-4.12. The constraints placed on the forecast period are that monthly CO_2 emissions levels in the electric power sector must be 22% below corresponding monthly 2005 levels in the year 2020, 28% below 2005 levels in 2025, and 32% below 2005 levels in

[16] As noted by Demiralp and Hoover (2003), graphical methods for detecting contemporaneous causality in VARs generally perform well in identifying the skeleton of a causal structure, but do not always identify the direction of causal arrows correctly. Prior beliefs or additional statistical information may be used to supplement graphical algorithms. For this reason, in addition to the causal structure outlined in Figure 4.5, forecasts are generated from a model where the direction of flow from CO_2 to Factor 4 is reversed (i.e. Factor 4 to CO_2). Forecasting results are robust to this specification (industrial production has 3.97% annual growth in the conditional case and 3.92% annual growth in the unconditional case; real personal income 3.27% and 3.43%).

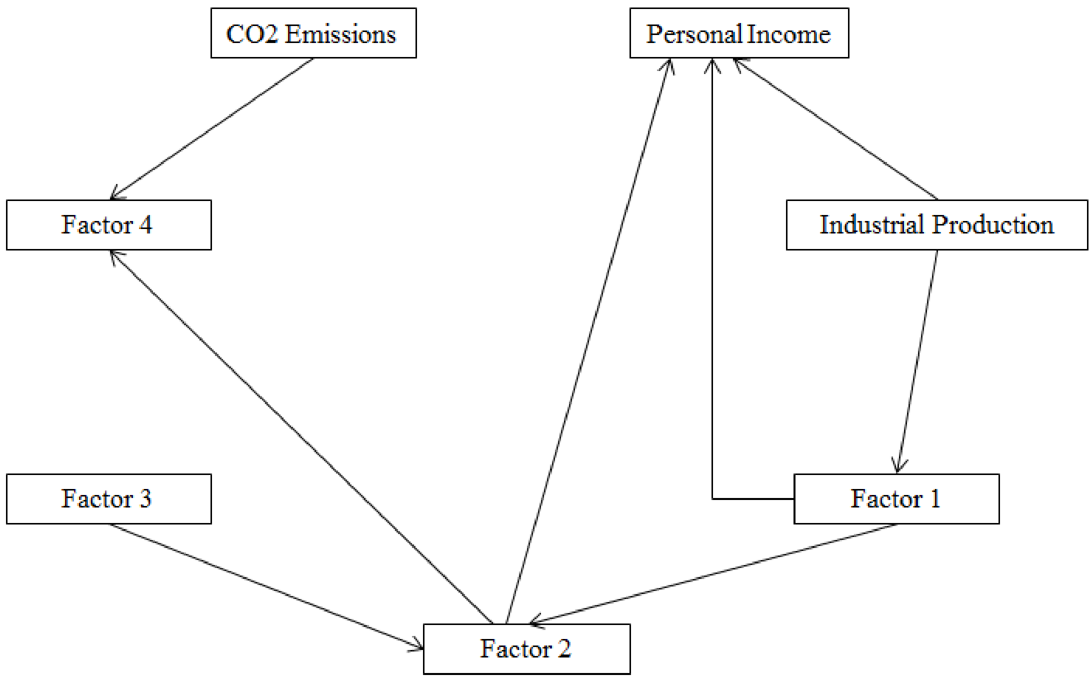

Figure 4.5. Directed Acyclic Graph for contemporaneous causal flows among contemporaneous innovations from the FAVAR

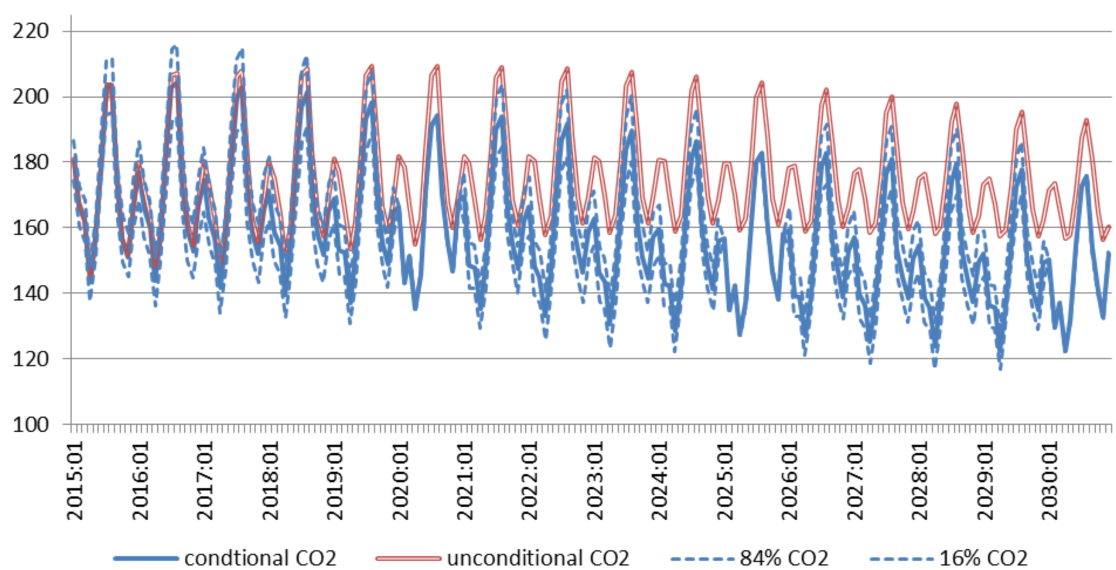

Figure 4.6. Forecasts of CO_2 emissions levels from the electric power sector

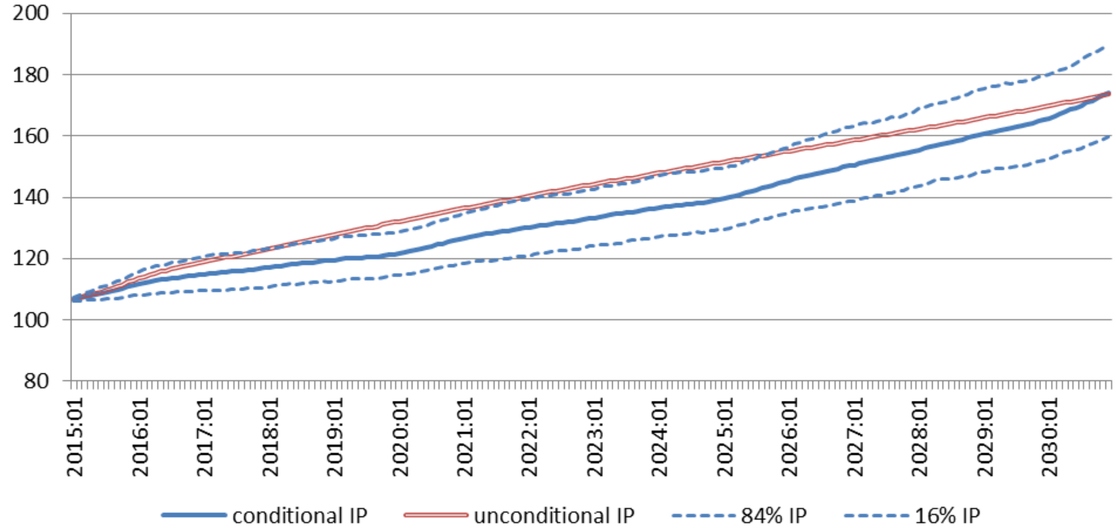

Figure 4.7. Forecasts of U.S. industrial production index

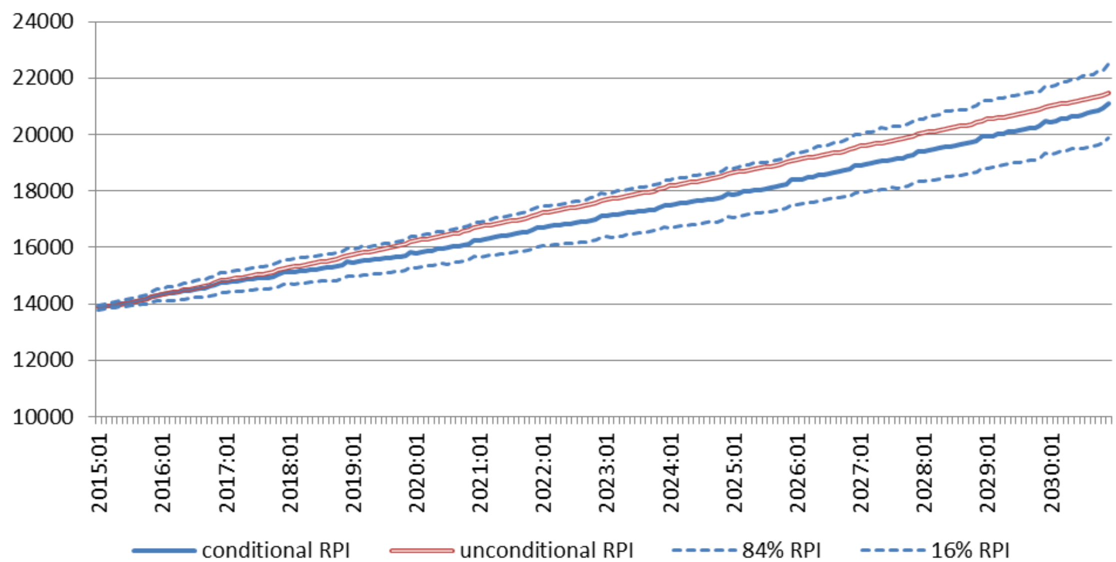

Figure 4.8. Forecasts of U.S. real personal income

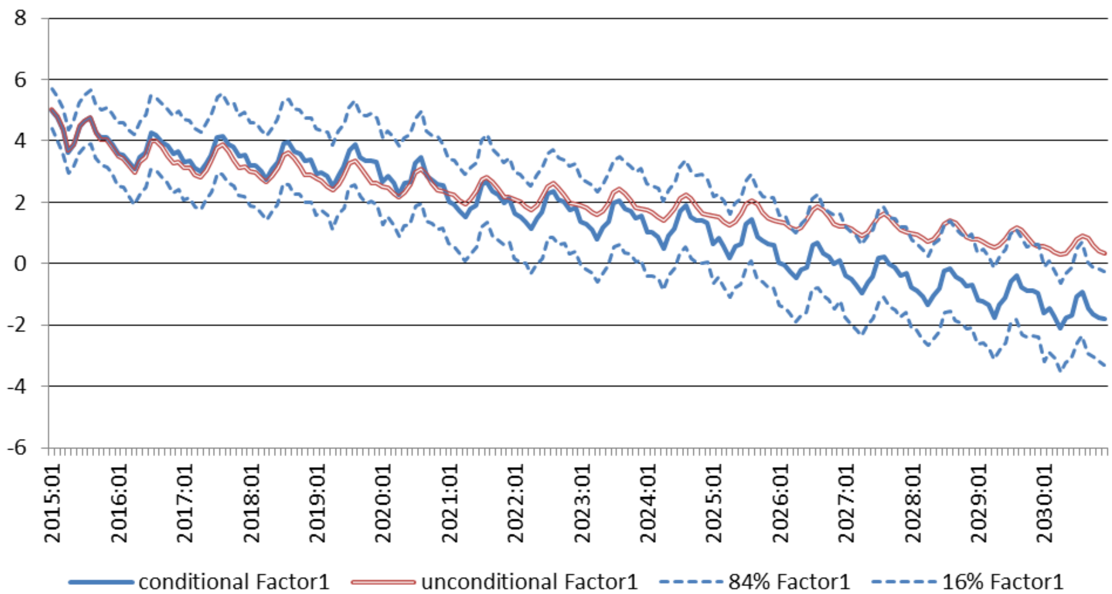

Figure 4.9. Forecasts of Factor 1

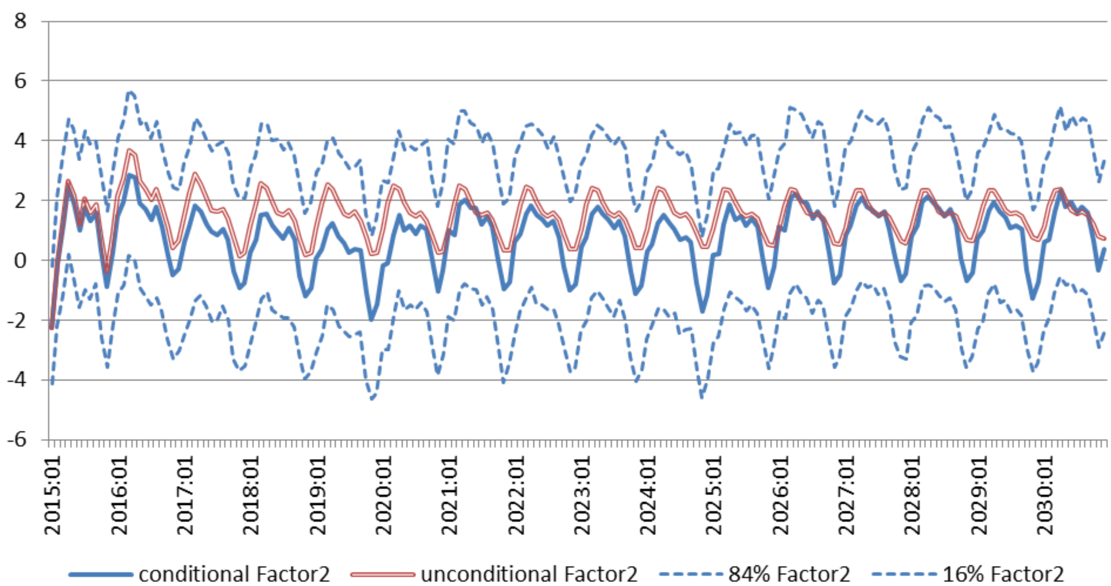

Figure 4.10. Forecasts of Factor 2

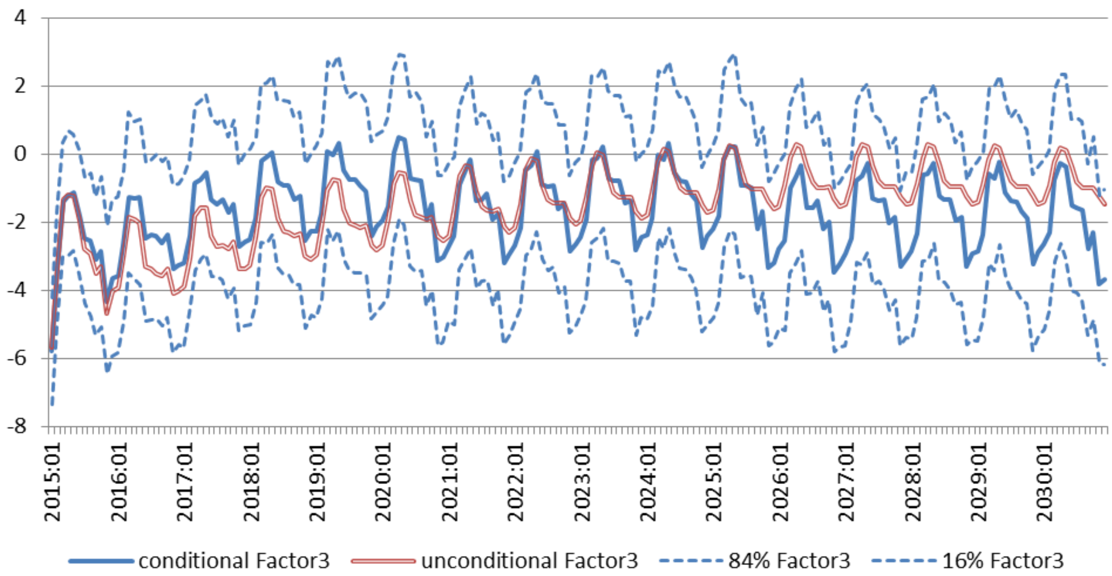

Figure 4.11. Forecasts of Factor 3

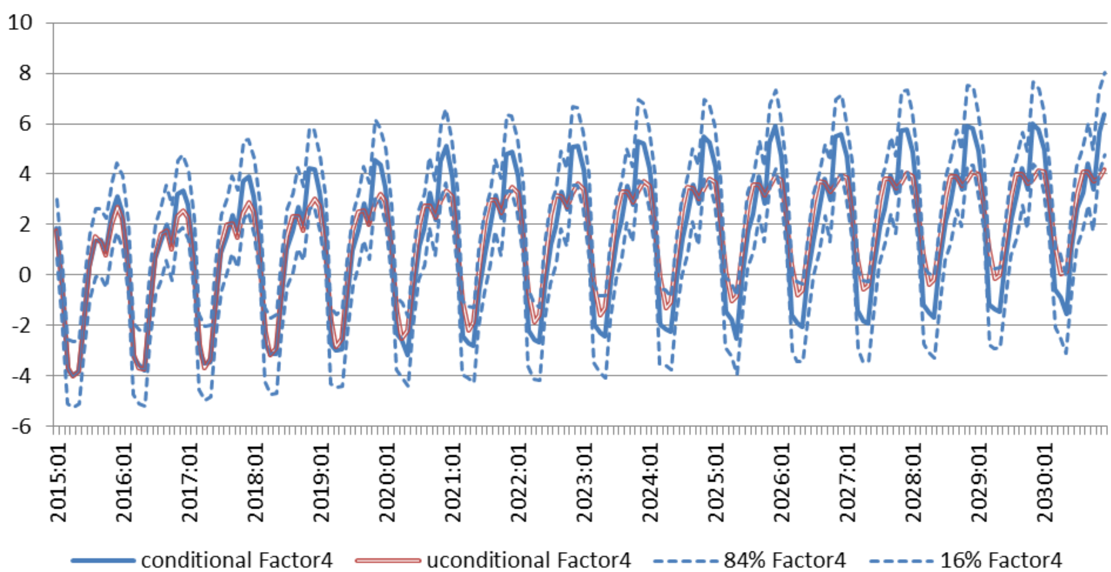

Figure 4.12. Forecasts of Factor 4

2030, for a total of 36 linear constraints in equation 4.7. The set of forecast period innovations that best meet this path for CO_2 emission reductions are computed and used to construct the conditional forecasts. Confidence intervals for the conditional forecasts are constructed by simulating 1,000 draws from the distribution of forecasts under the constrained path of CO_2 emissions. The 16th and 84th percentiles of the distribution are displayed in figures 4.6-4.12 (approximately one standard deviation from the mean, assuming normally distributed innovations) (Estima 2013). Checks for sensitivity are conducted by varying the constraints in numerous ways, including gradually increasing the CO_2 emissions reductions in each year of the forecast period, only keeping the constraint in the last year (2030), and both shortening and lengthening the forecast period by five years. Inferences based on comparing conditional and unconditional forecasts are approximately the same across the sensitivity checks.

The forecasts for CO_2 emissions provide a visualization of the constraint (figure 4.6). The mean of the conditional forecast for CO_2 emissions is the same as the 16th and 84th percentiles of the distribution in 2020, 2025, 2030; this is a direct implication of imposing the constraints as described. Also of note is that the solution to the minimization problem (equation 4.8) corresponds to a steady decrease in CO_2 emissions, rather than large drops in the years in which the constraint is imposed. Lastly, both the conditional and unconditional forecasts for CO_2 emissions are characterized by seasonal patterns that are present in the electric power industry.

Industrial production is projected to be lower in the CPP CO_2 emissions reduction scenario than in the unconditional case over most of the forecast period (figure

4.7). The maximum difference between the two forecasts occurs in late 2024 when the mean conditional industrial production forecast is 8% lower than the unconditional forecast. Unconditional and conditional forecasts for industrial production converge by the end of the forecast period. The average annual growth rate over the entire forecast period, therefore, is equal in the conditional and unconditional cases (3.9%). The average annual growth rate for 2015 to 2025, however, is 4.4% in the unconditional case and 3.3% in the conditional case. Additionally, the upper confidence band for the conditional forecast is near or below the unconditional forecast from 2017 to 2025. After 2025, the unconditional forecast falls within the confidence bands for the conditional forecast. Variance of the industrial production forecast is three percent lower in the conditional case than the unconditional.

The forecasted path of real personal income is projected to be lower in the conditional case than in the unconditional over the entire forecast period. The mean conditional forecast for real personal income reaches a maximum difference of 4.1% lower than the unconditional forecast in late 2025 and is 1.7% lower at the end of the forecast period. On average, real personal income is projected to grow 3.3% per year in the CPP scenario and 3.5% per year in the unconditional case. However, the upper confidence band of the conditional forecast for real personal income is slightly above the unconditional forecast for the entire forecast period. The variance of the conditional forecast of real personal income is 17% lower than the unconditional forecast.

The conditional forecast of Factor 1 tracks the unconditional forecast closely over the first half of the forecast period, but falls below the unconditional forecast around late 2021 and remains below for the rest of the forecast period. The gap between the two forecasts increases over this time frame; in fact, the upper confidence band for the conditional forecast is below the unconditional forecast by the end of the forecast period. The variance of the conditional forecast of Factor 1 is 200% higher than that of the unconditional forecast. The forecast results imply that the CO_2 emissions scenario will have a negative impact (in comparison with the unconditional case) on Factor 1, and that additional volatility may be present. Recall, Factor 1 is highly correlated with various consumer price indices, consumption, labor force measures, electric generation from fossil fuels, and end-use electricity sales. These economic indicators and energy measures may be negatively impacted by the CPP in the second half of the forecast period.

Factor 2 is forecasted to be slightly lower under the conditional case than the unconditional case for the majority of the forecast period, with a 75% increase in variance in the conditional case. Conditional forecasts of Factor 3 are projected slightly above unconditional forecasts in the beginning third of the forecast period, and slightly below the unconditional forecasts in the final third of the forecast period. The variance of the two forecasts for Factor 3 are approximately equal (0.2% difference). As Factors 2 and 3 are both most related to crude oil price measures, the impact of the CPP on oil price measures is ambiguous. The forecasts for Factor 3 imply that capacity utilization in the manufacturing and oil and gas extraction industries could initially be positively impacted by the CPP scenario, with this effect reversing in the latter third of the forecast period. The conditional forecast of Factor 4 tracks the unconditional forecast closely, however with increased volatility in the conditional case (63% increase in variance). This result suggests that the CPP could result in more volatile natural gas storage activity and total energy consumption.

Conclusions

Conditional forecasts are developed using information from a dynamic, data-rich environment. Previous applications have focused on Bayesian methods or dynamic factor models to conduct conditional forecasting or scenario analysis using large datasets. In this chapter, a FAVAR model is used to employ a large multivariate time series dataset, with the purpose of examining the potential impacts of the U.S. EPA's goal to reduce CO_2 emissions from the electric power sector. The conditional forecasting exercise uses the projected reductions in CO_2 emissions outlined by the EPA's Clean Power Plan to fix a path for one of the endogenous variables in the FAVAR model (electric power sector CO_2 emissions). Differences between conditional and unconditional forecasts are examined as potential impacts of U.S. policy to reduce CO_2 emissions.

The issue of whether climate policy will positively or negatively impact economic growth is an important consideration as the U.S. moves forward with implementation of the CPP. Results of this study suggest that both U.S. real personal income and industrial production will initially see lower growth under the CPP CO_2 emissions reduction scenario than in the unconditional case. Growth in real personal income will continue to be lower in the conditional case than the unconditional case over the entire forecast period. Interestingly, the conditional forecast of industrial production converges to the unconditional forecast at the end of the forecast period. A possible explanation of this feature is that the economy will show resiliency in adjusting to the CO_2 emissions constraint. This is only speculation, however, and further research into the convergence of these forecasts is required to determine its source.

Forecasts of the first factor show that coal and petroleum use in the electric power sector may be negatively impacted by the CPP. This result is consistent with other studies and the idea that reduction in coal-fired generation is an easy and cost-effective way to achieve emissions reductions (Hogan 2015; U.S. Chamber of Commerce 2014). Additionally, end-use electricity sales may be lower under the CPP scenario than in the unconditional case (consistent with Hopkins 2015). Price levels, personal consumption, and labor force measures may be negatively impacted as well. Increased volatility under the CPP is also possible for the variables associated with Factor 1. Factor 2 and 3 forecasts suggest the projected impact of the CPP on various crude oil price levels is ambiguous. The Factor 4 forecasts suggest the potential for increased volatility in natural gas storage activity and overall energy consumption.

Generally, the forecasting exercise shows little difference between unconditional and conditional forecasts of the variables in the early part of the forecast period, suggesting that impacts of the CPP are small while the constraints are less stringent. Results also suggest substantial increases in the variance of forecasts for Factors 1 and 4 under the CPP scenario. Both economic and energy sector activity are projected to be more volatile under the CPP. Additionally, confidence intervals for the conditional forecasts show a high level of uncertainty as the intervals overlap with the unconditional forecast for many of the variables.

Overall, the results of this study suggest that economic activity may grow more slowly under CPP implementation than it would otherwise; however, economic growth and CO_2 reductions can be achieved simultaneously. The results serve as a data-driven complement to structural analyses of policy change in the energy sector. Future research into climate policy can be improved by continued investigation into methods that employ information from large datasets.

CHAPTER V

CONCLUSIONS

The U.S. energy sector is continuously evolving amidst regulatory changes, technological innovations, and shifts in market conditions. Given this constantly changing environment, it is imperative to improve our understanding of the dynamics in which the U.S. energy sector operates. The overall objective of this dissertation is to contribute to a better understanding of the past, present, and future of U.S. energy market dynamics and interactions with policy by: (1) characterizing market relationships and investigating the consequences of past regulatory changes and shifts in market conditions; (2) examining current program functionality; and (3) projecting the impacts of future policy implementation.

To achieve this overall objective, gaps present in energy-related economics literature are addressed by examining three related issues associated with the electric power sector. Advancements in multivariate time series analysis are employed. First, inventory management of inputs in the energy sector has received little attention in the literature. Addressing this deficiency, long-term past inventory management behavior is characterized in Chapter II by examining coal inventories at U.S. electric power plants. Specific objectives are to investigate how coal inventories are related to movements in economic factors and to determine whether these relationships have remained constant over time. Next, market-based tradable right programs have received considerable attention; however, there is a lack of empirical examination of the performance of such programs, especially Renewable Portfolio Standards (Felder 2011; Fischer 2010). This gap in the literature is addressed in Chapter III by exploring the pricing dynamics of Renewable Energy Credits (RECs) with the goal of improving our understanding of the functionality of currently existing RPS programs. Finally, there has been speculation about the potential economic impacts of reducing U.S. CO_2 emissions through the Clean Power Plan. A data-rich time series approach, which is lacking in the energy policy literature, is used to estimate the potential impacts of emissions reductions on economic and energy sector activity in Chapter IV.

Overall, results suggest that changes in the regulatory environment have had and will continue to have important implications for the electric power sector. The sector, however, has exhibited adaptability to past regulatory changes and is projected to remain resilient in the future.

Energy Market Relationships: Past Changes in Regulation and Market Conditions

While studies concerning inventory management are relatively abundant, most previous studies pertain to optimal stocking of finished goods (Arrow et al. 1951; Blinder 1986; Feldstein et al. 1976; Holt, Modigliani, and Simon 1955), and not input inventory management. Further, very few studies investigate inventory behavior in the energy sector, especially the electric power sector. This gap in the literature is addressed by examining the response of coal (input) inventories at U.S. electric power plants to movements in economic factors. Past regulatory changes have had implications for the profitability of firms in the electric power sector, as shown by Jha (2015), who finds that U.S. electric power plants that face deregulated electricity markets save approximately 3% per month in coal procurement and storage costs compared to regulated plants. A test for stability of the long run parameters in a vector error correction model following Hansen and Johansen (1999) is employed in Chapter II to determine whether long run, dynamic relationships governing coal inventory behavior have remained constant over time. There is a lack of empirical applications of tests for structural breaks in the long run relationships estimated in vector error correction models. This dissertation provides an economically intuitive setting for an application of the Hansen and Johansen (1999) test and gives a detailed interpretation of the results.

Results suggest two sustained periods of instability in the long run relationships, the first from mid-1981 to mid-1986, and the second from mid-1994 to mid-2001. The first period of instability follows the implementation of the Staggers Rail Act of 1980. This Act, which altered railroad industry practices and rates, is one likely cause of this initial period of instability in the long run relationships among the variables. The second period of instability is preceded by and contains several major regulatory changes in the natural gas and electric power sectors, including the Clean Air Act Amendments of 1990, the Energy Policy Act of 1992, the introduction of NAFTA, the unbundling of natural gas sales and transportation, and deregulation of the electric power sector. Following the second period of instability, the long run relationships remain constant for the rest of the sample. This latter period of stability in the sample includes two major shocks to energy markets (Hurricanes Katrina and Rita in 2005 and the onset of the U.S. shale boom in the mid-to-late 2000s). Taken together, these results suggest that the fluctuating regulatory environment of the 1990s was a larger source of instability in the inventory behavior of electric generating firms than the shifts in market conditions of the mid-to-late 2000s. Policy makers should be aware that altering the regulatory environment can cause considerable fluctuations in how firms' inventory decisions interact with input and output markets and opportunity costs in the long run.

Current Program Functionality

The academic literature is also lacking empirical studies of the performance of Renewable Portfolio Standards (RPS) (Fischer 2011; Felder 2010). RPS programs have been implemented by the majority of U.S. states as market-based, tradable rights mechanisms to encourage increased electric generation from renewable sources. To the author's knowledge, there have been no empirical investigations into the pricing dynamics of Renewable Energy Credits (RECs). A multivariate time series approach is taken in this dissertation, using data from Massachusetts and Connecticut to examine if REC pricing relationships behave as theorized in the literature.

Relationships among Renewable Energy Credit prices in Massachusetts and Connecticut, electricity prices, and natural gas prices are estimated using a vector error correction model. Results indicate that REC prices do not behave as previously theorized in the literature. Several reasons for the disparity between theory and the empirical evidence are presented, including the relative immaturity of the markets and continuous regulatory intervention in the marketplace. Although RPS programs have been promoted as market-based incentives for renewable generation, the analysis suggests that policy-makers have not succeeded in creating a fundamental-driven market for RECs in Massachusetts or Connecticut.

Projecting Impacts of Future Policy Implementation

There has been speculation about the potential impacts of the recently introduced Clean Power Plan (CPP) (Hopkins 2015; U.S. Chamber of Commerce 2014; World Resources Institute 2014). This dissertation complements the growing literature in this area by offering a data-rich approach to estimate the impacts of the CPP on economic activity. To accomplish this, a factor-augmented vector autoregressive (FAVAR) approach which has been utilized in the monetary policy and macroeconomic literature (Bernanke, Boivin, and Eliasz 2005; Ielpo 2015; Moench 2008), but less so in energy-related applications (Chevallier 2011; Zagaglia 2010), is employed. The FAVAR approach makes use of the information in a large dataset to project the impacts of CO_2 emissions reductions outlined by the CPP. Another gap in the literature is noted by Banbura, Giannone, and Lenza (2015), who point out that there is a lack of investigation into developing conditional forecasts from vector autoregressive models for large datasets. This dissertation contributes to this gap in the literature by constructing conditional forecasts from a FAVAR model.

The effect of reducing CO_2 emissions in the electric power sector is quantified by developing conditional forecasts from a FAVAR model for a large macroeconomic and energy-related dataset. Results suggest that growth in real personal income will be slower under the CPP than it would be otherwise. Additionally, growth in U.S. industrial production will be lower under the CPP over the majority of the forecast period, but the constrained forecast for industrial production converges to the forecast not constrained by CO_2 emissions at the end of the period (suggesting a level of economic resiliency to CO_2 emissions reductions). Forecasts of the factors show that factors related to coal and petroleum consumption, electricity sales, overall price levels, and personal consumption will be negatively impacted and see increased volatility under the CPP. Additionally, increased volatility in factors related to natural gas storage activity and overall energy consumption is forecasted under the CPP. Overall inference is that economic activity may grow more slowly under CPP implementation than it would otherwise; however, economic growth and CO_2 emissions reductions can be achieved simultaneously.

Limitations and Suggestions for Future Research

It is important to acknowledge the limitations of the analysis conducted in this dissertation, and by doing so areas for continued research become apparent. As noted previously, the test for parameter constancy (Hansen and Johansen 1999) conducted in Chapter II has not been used extensively in empirical applications. The test does not result in a specific breakpoint in the parameters, such as that of Bai and Perron (2003). The interpretation of the test results is not concrete and requires further investigation to develop meaningful inference. Additionally, the power of the test appears to be affected by the specification of number of lags and cointegrating vectors in the vector error correction model. Studies concerning further exploration of these issues are a suggestion for future research.

Data quality and availability is a limitation of the research in Chapter III. REC pricing data is relatively sparse and not readily available. Only two states are considered (Massachusetts and Connecticut), while there are RPS programs in 29 states. The sample size considered in the empirical analysis is only a short snapshot of the history of RPS programs in these states. Future empirical research into the performance of RPS programs is required as data becomes available. Application of methods to handle sparse data and immature markets may be an inviting avenue of future research into RPS programs. Additionally, there may be some degree of influence of the market for CO_2 permits traded under the Regional Greenhouse Gas Initiative (RGGI). Future research into the links between RPS programs and the RGGI in northeastern states will be beneficial.

The research conducted in Chapter IV is a high-level, purely data-driven analysis of the impacts of the Clean Power Plan. The analysis is meant to serve as a complement to more structural, bottom-up models of energy sector policy and economic activity, rather than a complete, definitive impact analysis of the CPP. Additionally, monthly data for U.S. GDP is not available for the entire sample period considered. As such, industrial production and real personal income were chosen to represent larger economic activity and serve as proxies for producer and consumer welfare. Future research is required to determine why forecasts for industrial production (unconditional and conditional) converge at the end of the forecast period.

Selection of the number of factors to include in a FAVAR model has been shown to have important implications for forecasting performance (Duangnate 2015; Binder et al. 2016). A balance between the information criteria approach of Bai and Ng (2002) and the desire for parsimony in VAR models is a common discussion in the FAVAR literature (Moench 2008; Zagaglia 2010). Research into the effect of the number of factors on conditional forecasting performance and scenario analysis is left for future exploration.

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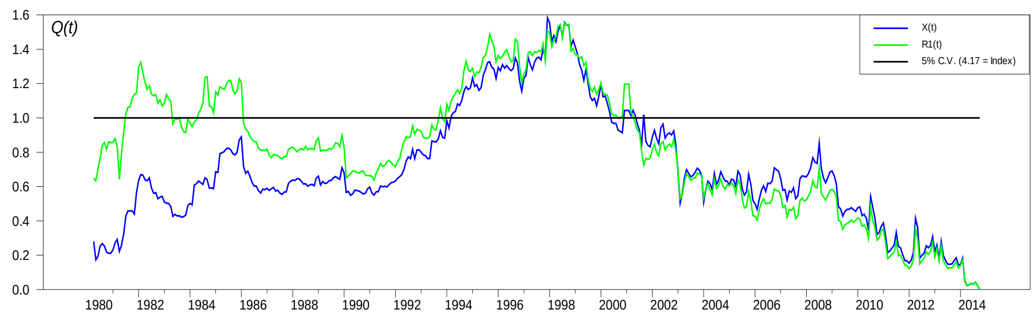
APPENDIX A

Graphs of the sequence of test statistics $Q_T^{(t)}$ for all 26 two, three, four, and five variable subsets of the five endogenous series (Chapter II).

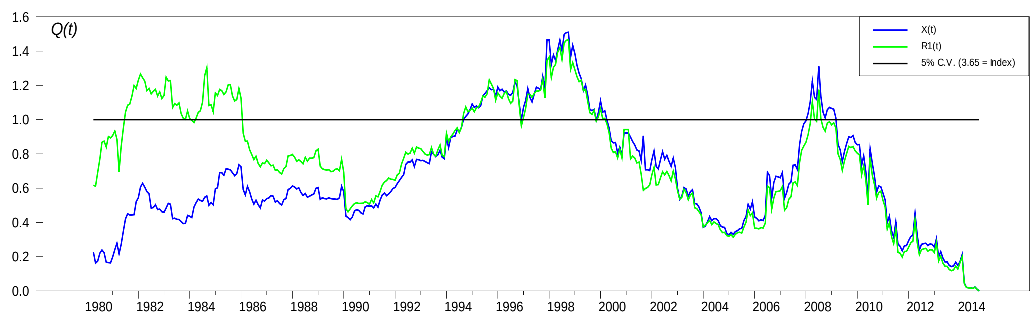
1. (Full model) Coal Inv, Coal, NG, Elec, Bonds

Test of Beta Constancy



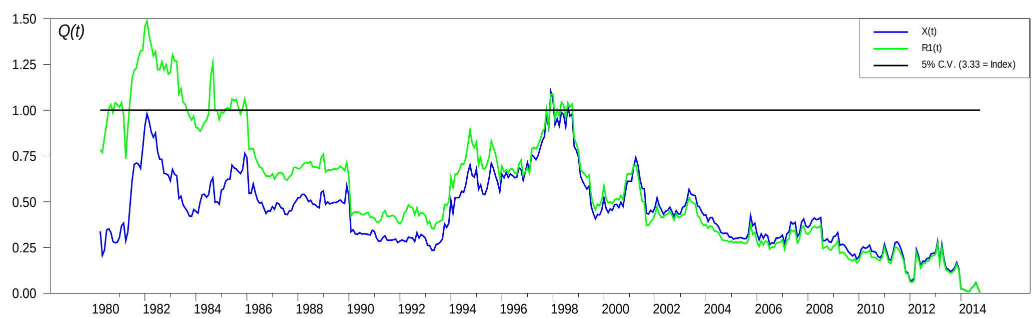
2. Coal Inv, Coal, NG, Elec

Test of Beta Constancy

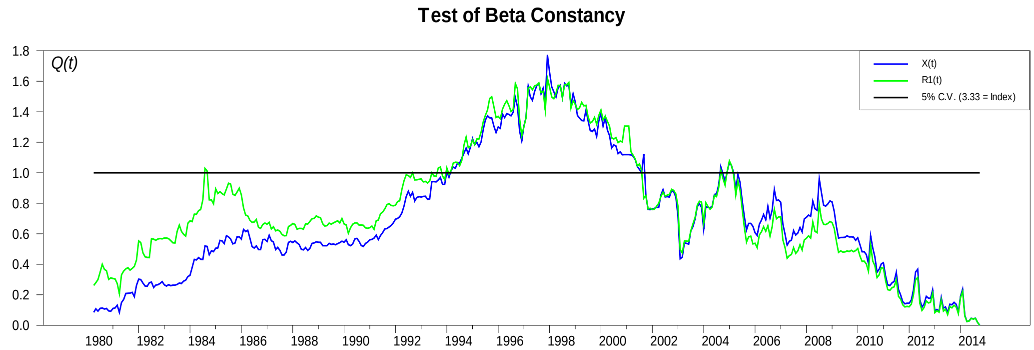


3. Coal Inv, Coal, NG, Bonds

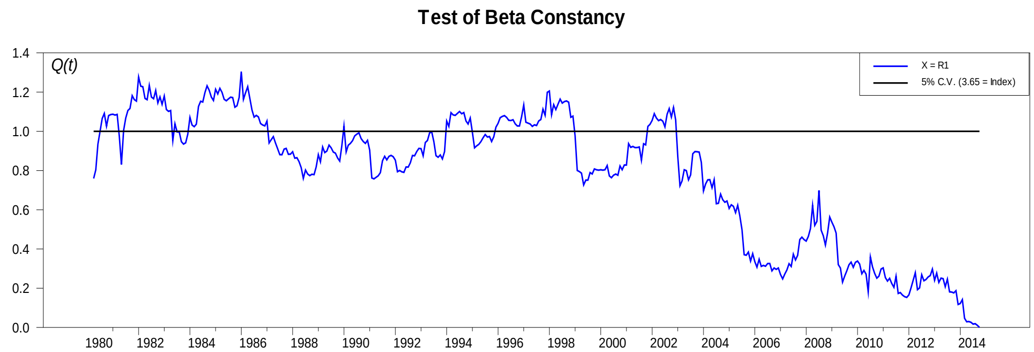
Test of Beta Constancy



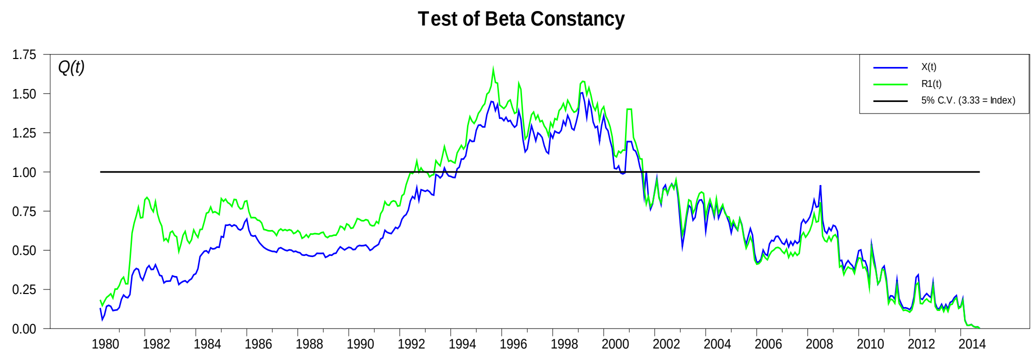
4. Coal Inv, NG, Elec, Bonds



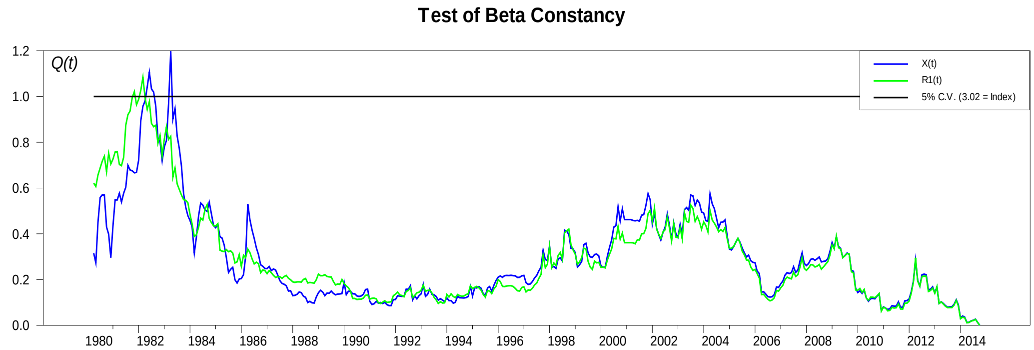
5. Coal Inv, Coal, Elec, Bonds



6. Coal, NG, Elec, Bonds

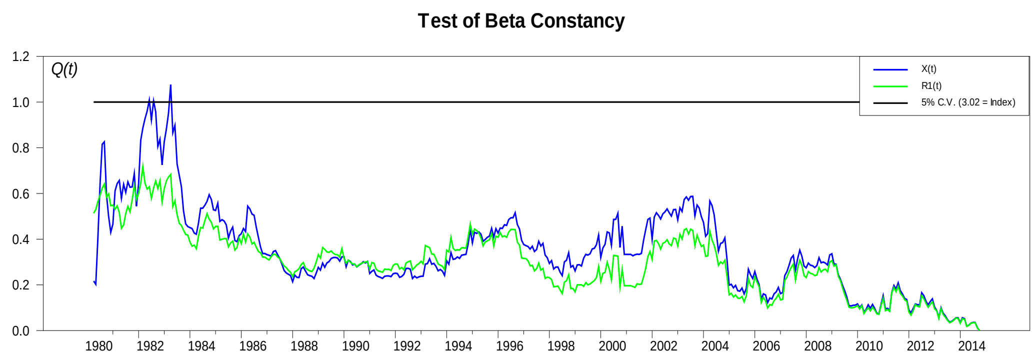


7. Coal Inv, Coal, NG

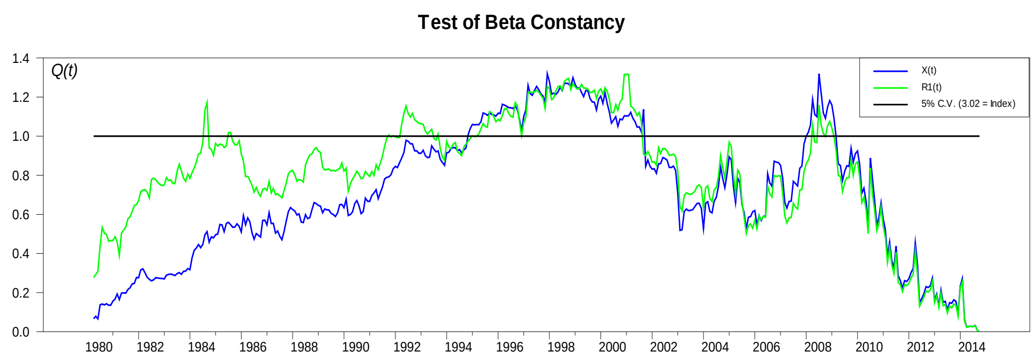


8. Coal Inv, Coal, Elec
Π is full rank

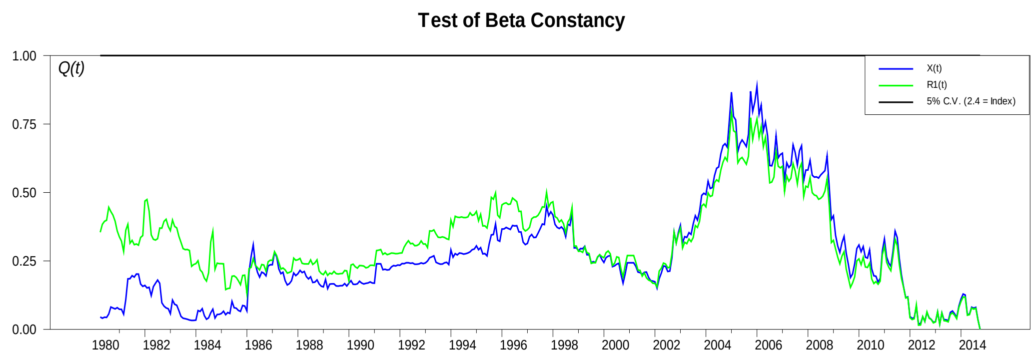
9. Coal Inv, Coal, Bonds



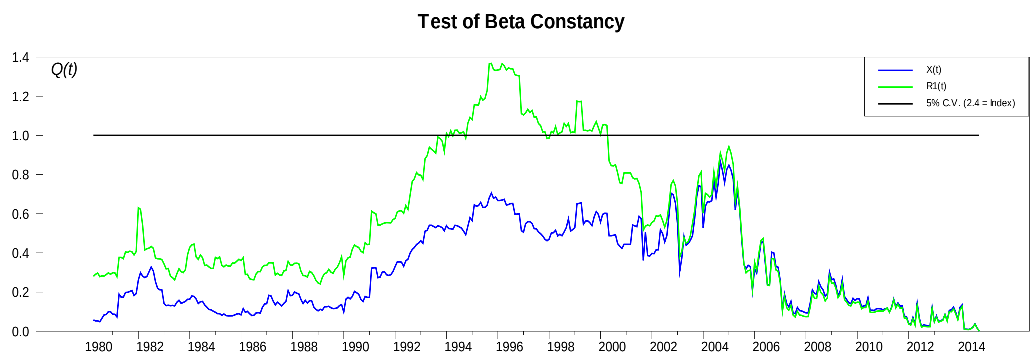
10. Coal Inv, NG, Elec



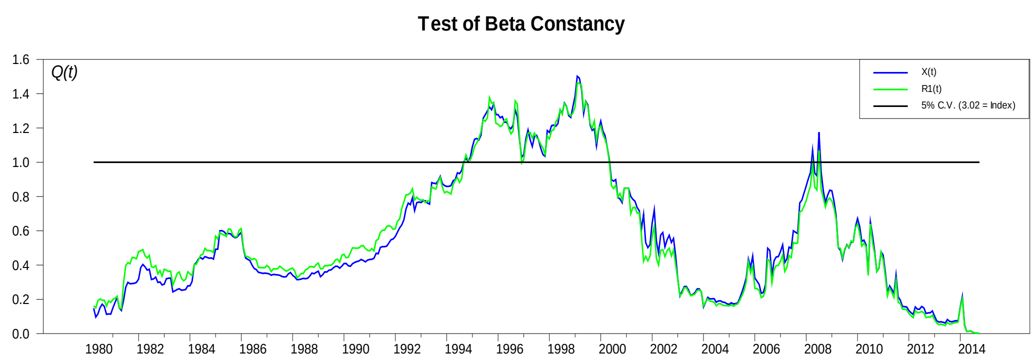
11. Coal Inv, NG, Bonds



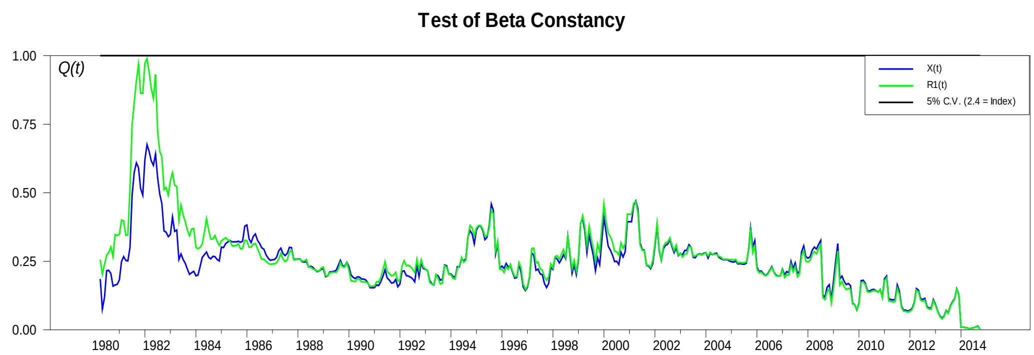
12. Coal Inv, Elec, Bonds



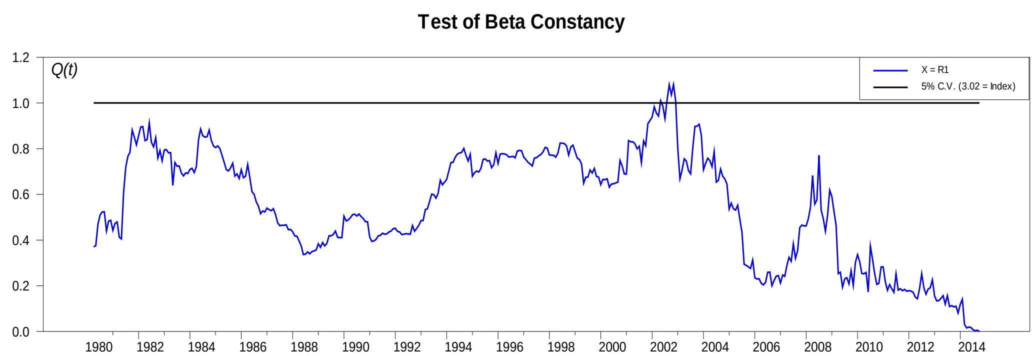
13. Coal, NG, Elec



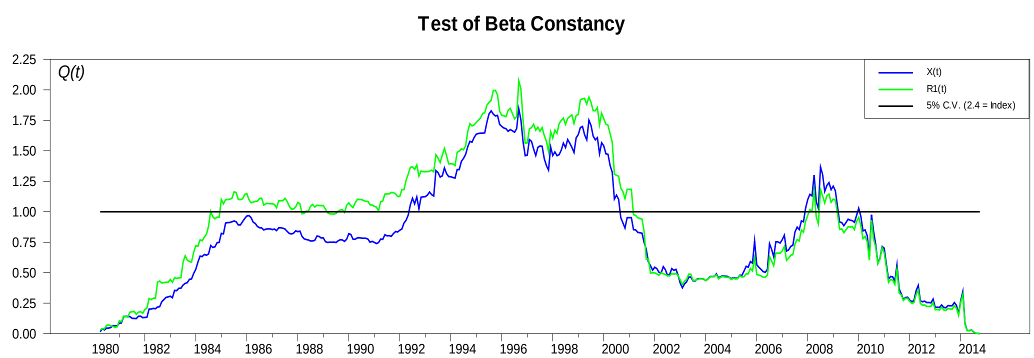
14. Coal, NG, Bonds



15. Coal, Elec, Bonds

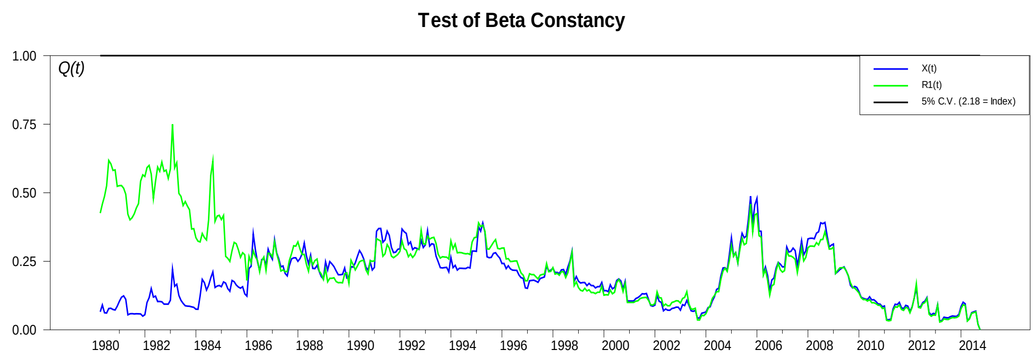


16. NG, Elec, Bonds

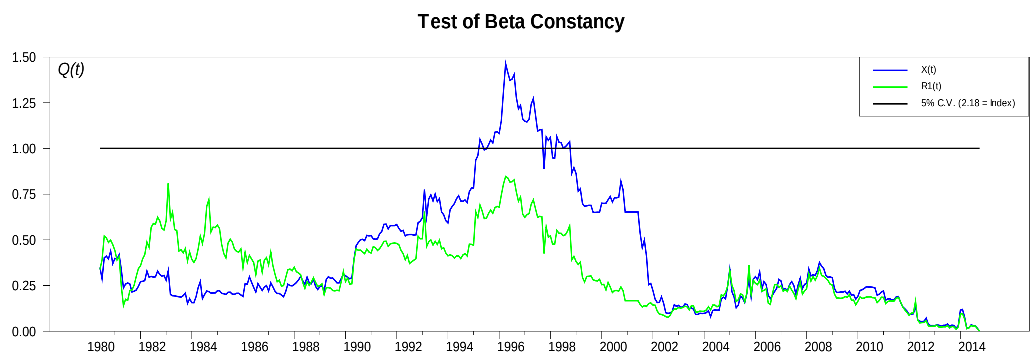


17. Coal Inv, Coal
Recursive estimation unable to converge.

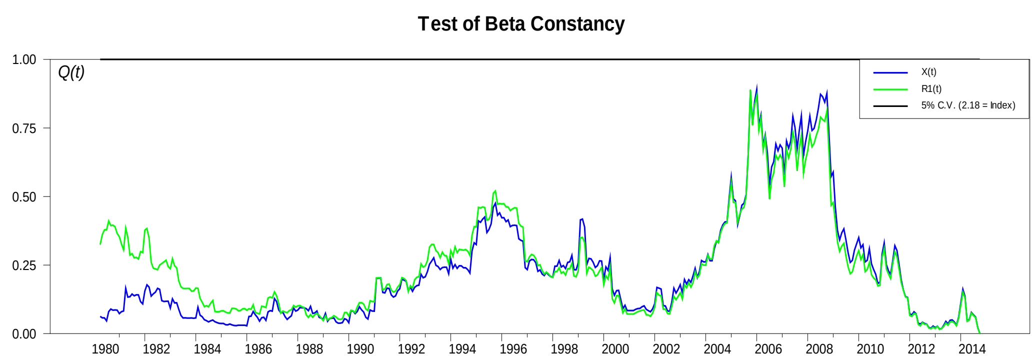
18. Coal Inv, NG



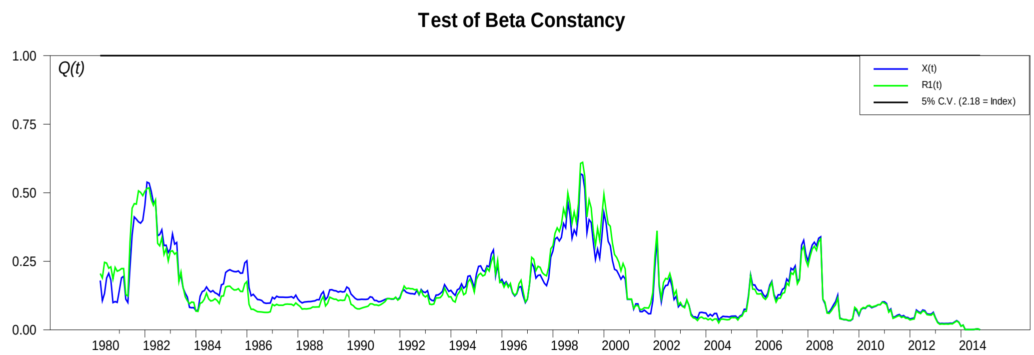
19. Coal Inv, Elec



20. Coal Inv, Bonds

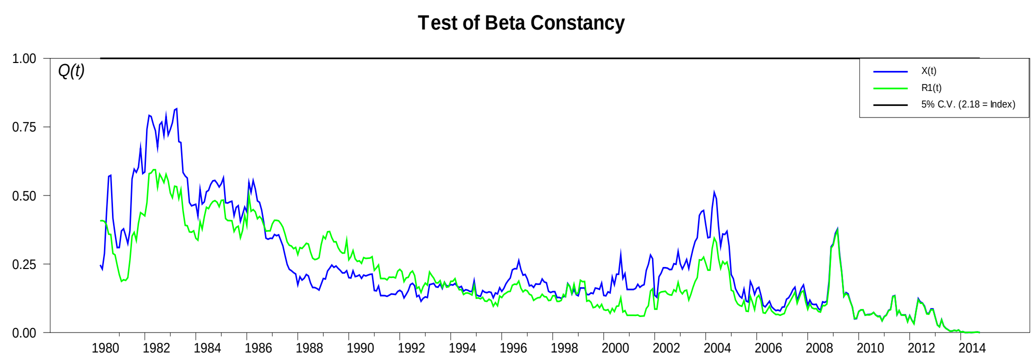


21. Coal, NG

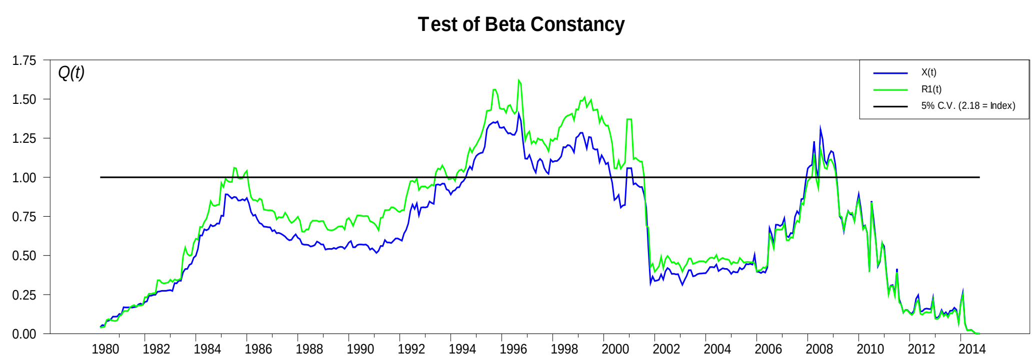


22. Coal, Elec
Π is full rank

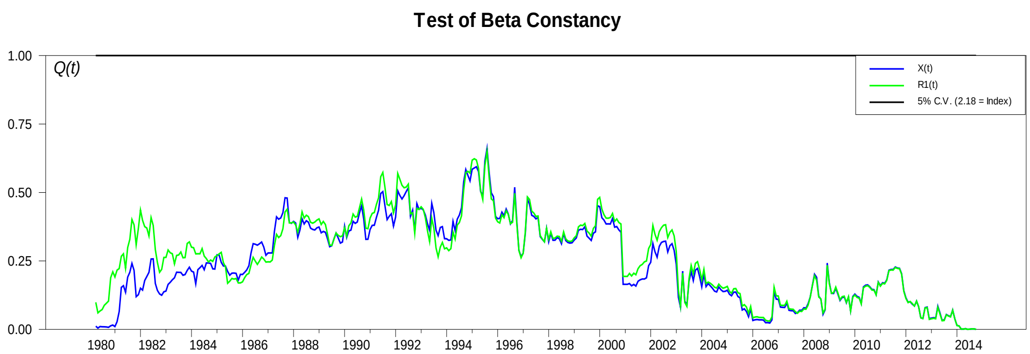
23. Coal, Bonds



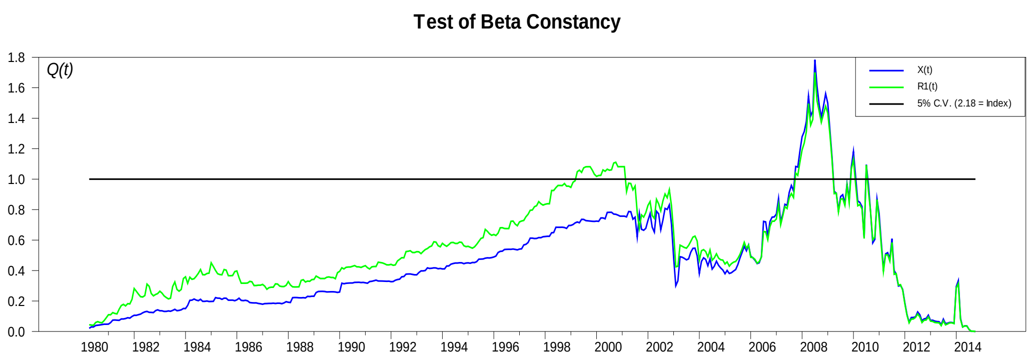
24. NG, Elec



25. NG, Bonds



26. Elec, Bonds



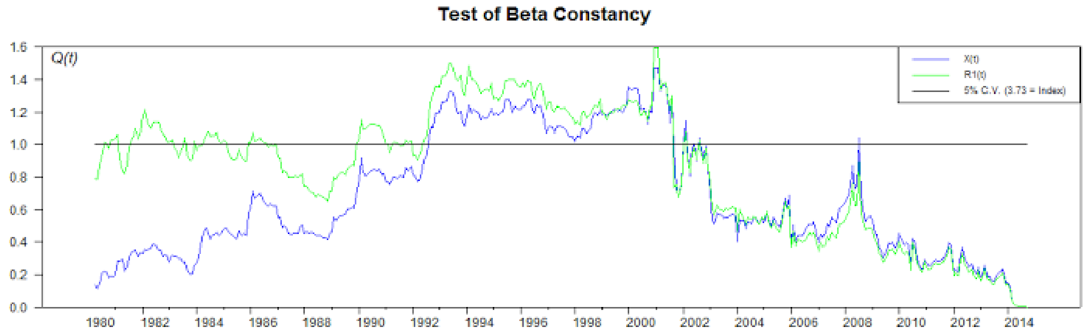


Figure A.2. Hansen and Johansen (1999) test for parameter stability when current end-of-month coal on hand is divided by the following month's consumption in the previous year, $inventory_t = \frac{coal\ on\ hand_t}{coal\ consumption_{t-11}}$.

APPENDIX B

Results of Bai and Perron (2003) and Hansen and Johansen (1999) tests for structural break (Chapter III).

Table B.1. Bai and Perron (2003) Test for Structural Breaks in a VAR(2) Model

Hypothesis	CT Class I	MA Class I	MassHub	NG	10% critical value
Series in First Difference Natural Logarithms					
1 vs. 0	3.54	2.30	0.66	1.51	15.53
2 vs. 0	4.59	2.47	1.60	1.92	14.65
3 vs. 0	3.05	2.02	1.29	1.86	13.63
2|1	4.19	2.26	2.43	2.12	17.54
3|2	0.56	1.06	0.78	1.47	18.55
Min BIC (# of breaks)	0	0	0	0	
Series in Natural Logarithms					
Hypothesis	CT Class I	MA Class I	MassHub	NG	10% critical value
1 vs. 0	2.68	3.63	4.48	3.53	15.53
2 vs. 0	2.69	4.19	3.56	5.32	14.65
3 vs. 0	1.88	2.50	2.47	4.45	13.63
2|1	2.27	3.55	2.04	5.21	17.54
3|2	0.59	0.17	0.65	1.67	18.55
Min BIC (# of breaks)	0	0	0	2	

Note: Minimum span allowed between breaks set to 15 observations.

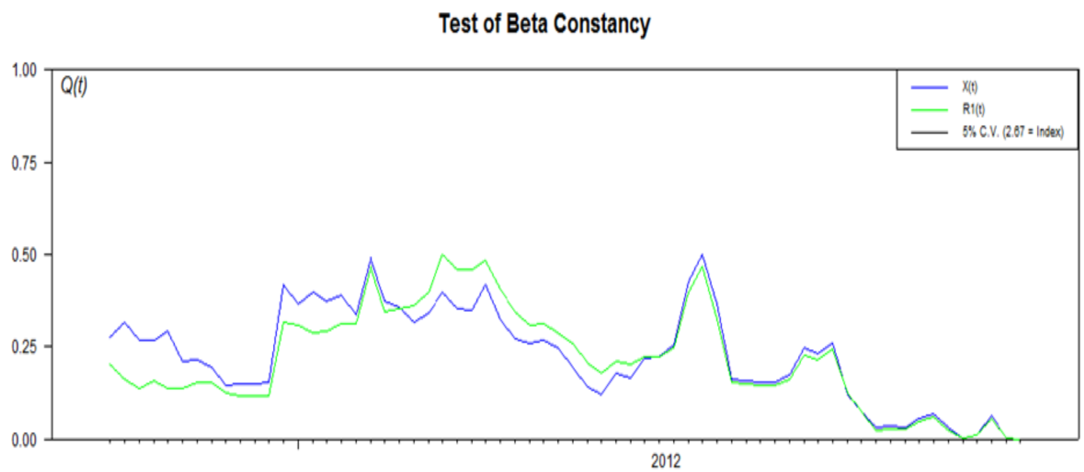


Figure B.1. Hansen and Johansen (1999) test for parameter constancy in a VECM(2) model with one cointegrating vector

APPENDIX C

List of all data series used in the Chapter IV analysis.

Series Description	Units	Source	Code[a]
Total Energy Electric Power Sector CO2 Emissions	Million Metric Tons of CO2	EIA	2
Industrial Production Index	Index 2007=100	FRED	2
Real Personal Income	Billions of Chained 2009 Dollars	FRED	2
Moody's Corporate Bond AAA	Percent	FRED	3
Moody's Seasoned Aaa Corporate Bond Minus Federal Funds Rate	Percent	FRED	0
Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing	Hours	FRED	2
Moody's Corporate Bond BAA	Percent	FRED	3
Moody's Seasoned Baa Corporate Bond Minus Federal Funds Rate	Percent	FRED	0
Commercial and Industrial Loans, All Commercial Banks	Billions of Dollars	FRED	2
Capacity Utilization: Oil and gas extraction	Percent of Capacity	FRED	3
Capacity Utilization: Durable manufacturing	Percent of Capacity	FRED	0
Capacity Utilization: Nondurable manufacturing	Percent of Capacity	FRED	3
Average Weekly Hours of Production and Nonsupervisory Employees: Goods-Producing	Hours	FRED	2
Average Weekly Hours of Production and Nonsupervisory Employees: Mining and Logging	Hours	FRED	2
Average Weekly Hours of Production and Nonsupervisory Employees: Construction	Hours	FRED	2
Civilian Labor Force	Thousands of Persons	FRED	0
Consumer Loans at All Commercial Banks	Billions of Dollars	FRED	2
Consumer Price Index for All Urban Consumers: All Items	Index 82-84=100	FRED	1
Consumer Price Index for All Urban	Index 82-84=100	FRED	1

Consumers: All Items Less Food & Energy			
Consumer Price Index for All Urban Consumers: Transportation	Index 82-84=100	FRED	1
Capacity Utilization: Manufacturing (SIC)	Percent of Capacity	FRED	0
Consumer Price Index for All Urban Consumers: All items less shelter	Index 82-84=100	FRED	1
Consumer Price Index for All Urban Consumers: All items less medical care	Index 82-84=100	FRED	1
Consumer Price Index for All Urban Consumers: Commodities	Index 82-84=100	FRED	1
Consumer Price Index for All Urban Consumers: Durables	Index 82-84=100	FRED	0
Consumer Price Index for All Urban Consumers: Services	Index 1982-84=100	FRED	1
Real personal consumption expenditures: Goods: Durable goods	Percent Change from Preceding Period	FRED	0
All Employees: Durable goods	Thousands of Persons	FRED	2
Real personal consumption expenditures	Percent Change from Preceding Period	FRED	0
Real personal consumption expenditures: Services (chain-type quantity index)	Index 2009=100	FRED	2
Real personal consumption expenditures: Services	Percent Change from Preceding Period	FRED	0
Effective Federal Funds Rate	Percent	FRED	3
1-Year Treasury Constant Maturity Rate	Percent	FRED	3
10-Year Treasury Constant Maturity Rate	Percent	FRED	3
5-Year Treasury Constant Maturity Rate	Percent	FRED	3
Weekly Overtime Hours: Manufacturing for the United States	Hours	FRED	2
Housing Starts: Total: New Privately Owned Housing Units Started	Thousands of Units	FRED	2
Industrial Production: Business Equipment	Index 2007=100	FRED	2

Industrial Production: Consumer Goods	Index 2007=100	FRED	2
Industrial Production: Durable Consumer Goods	Index 2007=100	FRED	2
Industrial Production: Durable Manufacturing (NAICS)	Index 2007=100	FRED	2
Industrial Production: Durable Materials	Index 2007=100	FRED	2
Industrial Production: Final Products (Market Group)	Index 2007=100	FRED	2
Industrial Production: Manufacturing (SIC)	Index 2007=100	FRED	2
Industrial Production: Materials	Index 2007=100	FRED	2
Industrial Production: Mining	Index 2007=100	FRED	2
Industrial Production: Nondurable Consumer Goods	Index 2007=100	FRED	2
Industrial Production: Nondurable Manufacturing (NAICS)	Index 2007=100	FRED	2
Industrial Production: Nondurable Materials	Index 2007=100	FRED	2
Industrial Production: Electric and Gas Utilities	Index 2007=100	FRED	2
Labor Force Participation Rate - Black or African American	Percent	FRED	3
All Employees: Manufacturing	Thousands of Persons	FRED	2
Capacity Utilization: Manufacturing (NAICS)	Percent of Capacity	FRED	0
ISM Manufacturing: PMI Composite Index©	Index	FRED	0
ISM Manufacturing: Inventories Index	Index	FRED	0
ISM Manufacturing: New Orders Index	Index	FRED	0
All Employees: Nondurable goods	Thousands of Persons	FRED	2
All Employees: Total nonfarm	Thousands of Persons	FRED	2
Personal Consumption Expenditures: Services	Billions of Dollars	FRED	1
Producer Price Index by Commodity for Crude Materials for Further Processing	Index 1982=100	FRED	2

Producer Price Index by Commodity for Finished Consumer Goods	Index 1982=100	FRED	2
Producer Price Index by Commodity for Finished Goods	Index 1982=100	FRED	2
Producer Price Index by Commodity Intermediate Materials: Supplies & Components	Index 1982=100	FRED	2
All Employees: Service-Providing Industries	Thousands of Persons	FRED	2
3-Month Treasury Bill: Secondary Market Rate	Percent	FRED	3
6-Month Treasury Bill: Secondary Market Rate	Percent	FRED	3
Capacity Utilization: Total Industry	Percent of Capacity	FRED	0
Number of Civilians Unemployed for 15 to 26 Weeks	Thousands of Persons	FRED	2
Number of Civilians Unemployed for 27 Weeks and Over	Thousands of Persons	FRED	2
Number of Civilians Unemployed for 5 to 14 Weeks	Thousands of Persons	FRED	0
Number of Civilians Unemployed - Less Than 5 Weeks	Thousands of Persons	FRED	2
Average (Mean) Duration of Unemployment	Weeks	FRED	2
Civilian Unemployment Rate	Percent	FRED	0
Production of Total Industry in United States	Index 2010=100	FRED	2
All Employees: Construction	Thousands of Persons	FRED	2
All Employees: Education & Health Services	Thousands of Persons	FRED	1
All Employees: Financial Activities	Thousands of Persons	FRED	2
All Employees: Goods-Producing Industries	Thousands of Persons	FRED	2
All Employees: Government	Thousands of Persons	FRED	2
All Employees: Mining and logging	Thousands of Persons	FRED	2
All Employees: Total Private Industries	Thousands of Persons	FRED	2
All Employees: Trade, Transportation & Utilities	Thousands of Persons	FRED	2

All Employees: Wholesale Trade	Thousands of Persons	FRED	2
Electricity Net Generation From Coal, Electric Power Sector	Million kWh	EIA	1
Electricity Net Generation From Petroleum, Electric Power Sector	Million kWh	EIA	0
Electricity Net Generation From Natural Gas, Electric Power Sector	Million kWh	EIA	2
Electricity Net Generation From Nuclear Electric Power, Electric Power Sector	Million kWh	EIA	2
Electricity Net Generation From Conventional Hydroelectric Power, Electric Power Sector	Million kWh	EIA	0
Electricity Net Generation From Wood, Electric Power Sector	Million kWh	EIA	2
Electricity Net Generation From Waste, Electric Power Sector	Million kWh	EIA	2
Electricity Net Generation From Geothermal, Electric Power Sector	Million kWh	EIA	1
Electricity Net Generation Total, Electric Power Sector	Million kWh	EIA	2
Coal Stocks, Electric Power Sector	Thousand Short Tons	EIA	2
Total Petroleum Stocks, Electric Power Sector	Thousand Barrels	EIA	2
Natural Gas Storage Activity, Withdrawals	billion cubic feet	EIA	2
Natural Gas Storage Activity, Injections	Billion Cubic Feet	EIA	2
Natural Gas in Underground Storage, End of Period, Base Gas	Billion Cubic Feet	EIA	2
Natural Gas in Underground Storage, End of Period, Working Gas	Billion Cubic Feet	EIA	2
Natural Gas in Underground Storage, End of Period, Total	Billion Cubic Feet	EIA	1
Exxon Mobil Share Price	US Dollars	DS	2
BP Share Price	US Dollars	DS	2
Conoco Phillips Share Price	US Dollars	DS	2
Royal Dutch Shell Share Price		DS	2
Chevron Share Price	US Dollars	DS	2
US 3 month treasury bill		DS	2
US-DS Oil & Gas	Price Index	DS	2

DAX 30 Performance	Price Index	DS	2
US dollar to GB Pound	Exchange Rate	DS	2
UK Industrial Production	Index	DS	2
Retail price of electricity	$/MWh	EIA	2
Cost of Coal Receipts at Electric Generating Plants	Dollars per Million Btu, Including Taxes	EIA	2
Cost of Natural Gas Receipts at Electric Generating Plants	Dollars per Million Btu, Including Taxes	EIA	2
Crude Oil and Natural Gas Rotary Rigs in Operation, Onshore	Number of Rigs	EIA	2
Crude Oil and Natural Gas Rotary Rigs in Operation, Offshore	Number of Rigs	EIA	2
Crude Oil and Natural Gas Rotary Rigs in Operation, Total	Number of Rigs	EIA	2
Active Well Service Rig Count	Number of Rigs	EIA	2
Coal Consumption for Electricity Generation and Useful Thermal Output, Electric Power Sector	Thousand Short Tons	EIA	1
Distillate Fuel Oil Consumption for Electricity Generation and Useful Thermal Output, Electric Power Sector	Thousand Barrels	EIA	0
Residual Fuel Oil Consumption for Electricity Generation and Useful Thermal Output, Electric Power Sector	Thousand Barrels	EIA	0
Petroleum Coke Consumption for Electricity Generation and Useful Thermal Output, Electric Power Sector	Thousand Short Tons	EIA	2
Total Petroleum Consumption for Electricity Generation and Useful Thermal Output, Electric Power Sector	Thousand Barrels	EIA	0
Natural Gas Consumption for Electricity Generation and Useful Thermal Output, Electric Power Sector	Billion Cubic Feet	EIA	2
Wood Consumption for Electricity Generation and Useful Thermal Output, Electric Power Sector	Trillion Btu	EIA	2

Waste Consumption for Electricity Generation and Useful Thermal Output, Electric Power Sector	Trillion Btu	EIA	2
Electricity Retail Sales to the Residential Sector	Million kWh	EIA	2
Electricity Retail Sales to the Commercial Sector	Million kWh	EIA	1
Electricity Retail Sales to the Industrial Sector	Million kWh	EIA	2
Electricity Retail Sales to the Transportation Sector	Million kWh	EIA	2
Electricity Retail Sales, Total	Million kWh	EIA	2
Electricity End Use, Total	Million kWh	EIA	2
Nuclear Electricity Net Generation	Million kWh	EIA	2
Nuclear Share of Electricity Net Generation	Percent	EIA	3
Nuclear Generating Units, Capacity Factor	Percent	EIA	3
Crude Oil Domestic First Purchase Price	Dollars per Barrel	EIA	2
Free on Board Cost of Crude Oil Imports	Dollars per Barrel	EIA	2
Landed Cost of Crude Oil Imports	Dollars per Barrel	EIA	2
Refiner Acquisition Cost of Crude Oil, Domestic	Dollars per Barrel	EIA	2
Refiner Acquisition Cost of Crude Oil, Imported	Dollars per Barrel	EIA	2
Refiner Acquisition Cost of Crude Oil, Composite	Dollars per Barrel	EIA	2
Total Biomass Energy Production	Trillion Btu	EIA	2
Total Renewable Energy Production	Trillion Btu	EIA	2
Hydroelectric Power Consumption	Trillion Btu	EIA	0
Geothermal Energy Consumption	Trillion Btu	EIA	1
Wood Energy Consumption	Trillion Btu	EIA	2
Waste Energy Consumption	Trillion Btu	EIA	2
Total Biomass Energy Consumption	Trillion Btu	EIA	2
Total Renewable Energy Consumption	Trillion Btu	EIA	2
Crude Oil Stocks, SPR	Million Barrels	EIA	0
Crude Oil Stocks, Non-SPR	Million Barrels	EIA	2
Crude Oil Stocks, Total	Million Barrels	EIA	1
Distillate Fuel Oil Stocks	Million Barrels	EIA	0

Jet Fuel Stocks	Million Barrels	EIA	1
Propane/Propylene Stocks	Million Barrels	EIA	2
Liquefied Petroleum Gases Stocks	Million Barrels	EIA	2
Motor Gasoline Stocks (Including Blending Components and Gasohol)	Million Barrels	EIA	2
Residual Fuel Oil Stocks	Million Barrels	EIA	2
Other Petroleum Products Stocks	Million Barrels	EIA	2
Total Petroleum Stocks	Million Barrels	EIA	2
Primary Energy Consumed by the Residential Sector	Trillion Btu	EIA	2
Total Energy Consumed by the Residential Sector	Trillion Btu	EIA	2
Primary Energy Consumed by the Commercial Sector	Trillion Btu	EIA	2
Total Energy Consumed by the Commercial Sector	Trillion Btu	EIA	2
Primary Energy Consumed by the Industrial Sector	Trillion Btu	EIA	2
Total Energy Consumed by the Industrial Sector	Trillion Btu	EIA	2
Primary Energy Consumed by the Transportation Sector	Trillion Btu	EIA	2
Total Energy Consumed by the Transportation Sector	Trillion Btu	EIA	2
Primary Energy Consumed by the Electric Power Sector	Trillion Btu	EIA	2
Energy Consumption Balancing Item	Trillion Btu	EIA	0
Primary Energy Consumption Total	Trillion Btu	EIA	2

EIA: U.S. Energy Information Administration (2015a)
DS: Datastream (2015)
FRED: FRED Database Federal Reserve Bank of St. Louis Economic Research (2015)
[a]Corresponds to the following transformation:
0: Levels
1: Natural Logarithm
2: First Difference of Natural Logarithm
3: First Difference of Levels