

T.R.
GEBZE TECHICAL UNIVERSITY
INSTITUTE OF SOCIAL SCIENCES

**THE EFFECTS OF NATURAL GAS AND COAL FUTURES PRICES ON
ELECTRICITY SPOT PRICES IN USA
COINTEGRATION ANALYSIS**

EMRE ÖZÇAKMAK
MASTER THESIS
DEPARTMENT OF ECONOMICS

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GTÜ Sosyal Bilimler Enstitüsü Yönetim Kurulu'nun tarih ve sayılı kararıyla oluşturulan jüri tarafından 08/07/2015 tarihinde tez savunma sınavı yapılan Emre ÖZÇAKMAK'ın tez çalışması İktisat Anabilim Dalında YÜKSEK LİSANS tezi olarak kabul edilmiştir.

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İMZA/MÜHÜR

ÖZET

Elektrik piyasalarındaki liberalleşme düzenlemelerinden sonra, bu piyasada istikrarlı bir işleyiş sağlayabilmek için yüksek fiyat değişkenliğini yönetebilmek en önemli konu olmuştur. Yeniden yapılandırılmış bu piyasada elektrik fiyat riski talep, meteorolojideki belirsizlik, şebeke kayıp kaçakları ve bunun gibi birçok sorundan kaynaklanmakta, piyasa katılımcıları için birçok zorluk ve fırsata neden olmaktadır.

Bu yüzden bu kaçınılmaz risklerin bertarafı direk olarak finansal yönetim performansına bağlı olmakta, bu da girdi yakıt fiyatları ile çıktı elektrik fiyatları arasındaki finansal ve köklü ilişkiyi anlayabilmeyi gerektirmektedir.

Kointegrasyon dalgalanan fiyatlarda verimli risk yönetimi sağlamanın önemli bir aşamasıdır. Kömür ve doğalgaz elektrik üretiminde kullanılmakta ve bu girdilerin future sözleşmeleri mevsimsel fiyat dalgalanmalarında maliyet avantajı sağlamaktadır.

Araştırmamızda 10/10/2006 – 7/12/2013 dönemi arasında ABD enerji piyasasındaki kömür ve doğalgaz gibi iki ana fosil yakıtın future fiyatları ile spot elektrik fiyatları arasındaki uzun ve kısa dönemde dinamik ilişkisini incelemeye çalıştık.

Anahtar Kelimeler: Kömür Future Fiyatları, Doğalgaz Future Fiyatları, Elektrik Spot Fiyatları, Kointegrasyon Analizi

SUMMARY

Managing high price volatility is the most important issue for sustaining business operations smoothly and viable after the deregulation of power markets. In restructured and liberalised electric power markets price risk arises from wide spread reasons like demand and weather uncertainty and load migration, presents major challenges and opportunities for market participants.

Therefore, disposal of these inevitable risks is directly linked with financial management performance, which requires financial understanding the fundamentals of price relationship among various kind of fuel input with electricity output.

Co-integration is an important aspect to take into account for effective risk management of price fluctuations. Coal and natural gas is used to produce electricity by power generating companies so futures derivatives of natural gas and coal offset seasonal cost by the "spark spread" advantage; resulted because of the different seasonal prices of the two input fuel.

We researched the long-run relation and short-run dynamics within and between spot electricity prices and main fossil fuel prices – coal and natural gas – for the period 10/10/2006 – 7/12/2013 in USA energy market.

Key Words: Coal Future Prices, Natural Gas Future Prices, Electricity Spot Prices, Cointegration Analysis

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TABLE OF CONTENTS

	<u>Page</u>
ÖZET	i
SUMMARY	ii
ACKNOWLEDGEMENTS	iii
TABLE OF CONTENTS	iv
LIST OF ABBREVIATIONS	vi
LIST OF TABLES	vii
1. INTRODUCTION	1
2. ENERGY MARKETS	2
2.1. Deregulation of Electricity Markets	2
2.2. Energy Price Risk	3
2.3. Spot and Derivative Energy Markets	5
2.3.1. Spot Energy Markets	5
2.3.2. Derivative Energy Markets and Derivative Instruments	5
2.3.3. Relation between Spot and Derivatives Prospects for Energy Derivatives	6
2.3.4. Application of Derivatives into the Market	7
3. LITERATURE REVIEW	9
3.1. Energy Price Risk Management and Market Risk Management	9
3.2. Cointegration / Energy Price Relationship	10
4. METHODOLOGY	13
4.1. Stationary	13
4.2. Two types of non-stationarity	14
4.3. Testing for a unit root	15
4.3.1. Phillips–Perron (PP) tests	16
4.3.2. Dickey – Fuller (1979) Test	16
4.3.3. Augmented Dickey – Fuller (1981) Test	16
4.3.4. The Perron (1989) Procedure	17
4.3.5. Criticisms of Dickey–Fuller and Phillips–Perron-type Tests	18
4.4. Autocorrelation	18
4.5. Cointegration	19

4.5.1. Definition of cointegration (Engle and Granger, 1987)	20
4.5.2. Examples of General Cointegrating Relationships in Finance	21
4.6. Vector Autoregression (VAR) Analysis	21
4.6.1. Equilibrium Correction or Error Correction Models	22
4.6.2. The Engle–Granger 2-step Method	22
4.7. Vector Error Correction Model (VECM)	23
5. EMPIRICAL RESULTS	26
6. RESULTS	72
7. CURRICULUM VITAE	77

LIST OF ABBREVIATIONS

<u>Abbreviations</u>	<u>Description</u>
acf	: Autocorrelation Function
ADF	: Partial Autocorrelation Function
AR	: Autoregressive
CO ₂	: Carbon dioxide
COB	: California-Oregon border
DF	: Dickey - Fuller
EWMA	: Equally Weighed Moving Averages
FPE	: Final Prediction Error
GARCH	: Generalized AutoRegressive Conditional Heteroskedasticity
IND	: Indiana Hub
LHS	: Left Hand Side
MA	: Moving Average
MASS	: New England Region Electricity Hub
MgW	: Megawatt
MID-C	: Northwest Region Electricity Hub
MPR	: Market Price Risk
NBP	: National Balancing Point
NP	: Northern California Region Electricity Hub
NYMEX	: New York Mercantile Exchange
OLS	: Ordinary Least Squares
pacf	: Partial Autocorrelation Function
PJM	: PJM Interconnection Region Electricity Hub
PVERDE	: Palo Verde Southwest Region Electricity Hub
SP-15	: Southern California Region Electricity Hub
TTF	: Title Transfer Facility
VaR	: Value at Risk

LIST OF TABLES

<u>Table:</u>	<u>Page</u>
1.1: Spot Market Price Volatility for Selected Commodities	4
5.1: Augmented Dickey-Fuller Unit-Root Test Results for SP-15 HUB	26
5.2: Augmented Dickey-Fuller Unit-Root Test Results for PJM HUB	27
5-3: Augmented Dickey-Fuller Unit-Root Test Results for Pablo Verde HUB	27
5-4: Augmented Dickey-Fuller Unit-Root Test Results for NP HUB	28
5.5 Augmented Dickey-Fuller Unit-Root Test Results for MID-C HU	29
5.6 Augmented Dickey-Fuller Unit-Root Test Results for MASS HUB	29
5.7 Augmented Dickey-Fuller Unit-Root Test Results for IND HUB	30
5.8 Augmented Engle-Granger Cointegration Test Between SP-15 D-A Average Price and CA Coal Future Settlement Price	31
5.9 Augmented Engle-Granger Cointegration Test Between PJM D-A Average Price and CA Coal Future Settlement Price	31
5.10 Augmented Engle-Granger Cointegration Test Between PVERDE D-A Average Price and CA Coal Future Settlement Price	31
5.11 Augmented Engle-Granger Cointegration Test Between NP D-A Average Price and CA Coal Future Settlement Price	32
5.12 Augmented Engle-Granger Cointegration Test Between MIDC D-A Average Price and CA Coal Future Settlement Price	32
5.13 Augmented Engle-Granger Cointegration Test Between MASS D-A Average Price and CA Coal Future Settlement Price	32
5.14 Augmented Engle-Granger Cointegration Test Between IND D-A Average Price and CA Coal Future Settlement Price	33
5.15 Augmented Engle-Granger Cointegration Test Between SP-15 D-A Average Price and Natural Gas Future Settlement Price	33
5.16 Augmented Engle-Granger Cointegration Test Between PJM D-A Average Price and Natural Gas Future Settlement Price	34
5.17 Augmented Engle-Granger Cointegration Test Between PVERDE D-A Average Price and Natural Gas Future Settlement Price	34

5.18 Augmented Engle-Granger Cointegration Test Between NP D-A Average Price and Natural Gas Future Settlement Price	34
5.19 Augmented Engle-Granger Cointegration Test Between MIDC D-A Average Price and Natural Gas Future Settlement Price	35
5.20 Augmented Engle-Granger Cointegration Test Between MASS D-A Average Price and Natural Gas Future Settlement Price	35
5.21 Augmented Engle-Granger Cointegration Test Between IND D-A Average Price and Natural Gas Future Settlement Price	36
5.22 Lag Selection for VEC Model Between SP-15 D-A Average Price and CA Coal Future Settlement Price	36
5.23 Lag Selection for VEC Model Between PJM D-A Average Price and CA Coal Future Settlement Price	37
5.24 Lag Selection for VEC Model Between PVERDE D-A Average Price and CA Coal Future Settlement Price	37
5.25 Lag Selection for VEC Model Between NP D-A Average Price and CA Coal Future Settlement Price	38
5.26 Lag Selection for VEC Model Between MIDC D-A Average Price and CA Coal Future Settlement Price	38
5.27 Lag Selection for VEC Model Between MASS D-A Average Price and CA Coal Future Settlement Price	39
5.28 Lag Selection for VEC Model Between IND D-A Average Price and CA Coal Future Settlement Price	39
5.29 Lag Selection for VEC Model Between SP-15 D-A Average Price and Natural Gas Future Settlement Price	40
5.30 Lag Selection for VEC Model Between PJM D-A Average Price and Natural Gas Future Settlement Price	40
5.31 Lag Selection for VEC Model Between PVERDE D-A Average Price and Natural Gas Future Settlement Price	41
5.32 Lag Selection for VEC Model Between NP D-A Average Price and Natural Gas Future Settlement Price	41
5.33 Lag Selection for VEC Model Between MIDC D-A Average Price and Natural Gas Future Settlement Price	42
5.34 Lag Selection for VEC Model Between MASS D-A Average Price and Natural Gas Future Settlement Price	42

5.35 Lag Selection for VEC Model Between IND D-A Average Price and Natural Gas Future Settlement Price	43
5.36 VEC Model Between SP-15 D-A Av. Price and CA Coal Future Settlement Price	45
5.37 VEC Model Between PJM D-A Average Price and CA Coal Future Settlement Price	47
5.38 VEC Model Between PVERDE D-A Average Price and CA Coal Future Settlement Price	49
5.39 VEC Model Between NP D-A Average Price and CA Coal Future Settlement Price	51
5.40 VEC Model Between MIDC D-A Average Price and CA Coal Future Settlement Price	53
5.41 VEC Model Between MASS D-A Average Price and CA Coal Future Settlement Price	55
5.42 VEC Model Between IND D-A Average Price and CA Coal Future Settlement Price	57
5.43 VEC Model Between SP-15 D-A Av. Price and Natural Gas Future Settlement Price	59
5.44 VEC Model Between PJM D-A Average Price and Natural Gas Future Settlement Price	61
5.45 VEC Model Between PVERDE D-A Average Price and Natural Gas Future Settlement Price	63
5.46 VEC Model Between NP D-A Average Price and Natural Gas Future Settlement Price	65
5.47 VEC Model Between MIDC D-A Average Price and Natural Gas Future Settlement Price	67
5.48 VEC Model Between MASS D-A Average Price and Natural Gas Future Settlement Price	69
5.49 VEC Model Between IND D-A Average Price and Natural Gas Future Settlement Price	71

1. INTRODUCTION

After the deregulation of power markets, it is the most important issue managing high price volatility for sustaining business operations smoothly and viable for market participant such as power producers, operators of system the end users of the electricity markets.

Emerging price risk is in restructured and liberalised electric power industries, arises from wide spread reasons like demand and weather uncertainty and load migration, presents major challenges and opportunities for market participants.

Therefore, disposal of these inevitable risks is directly linked with financial performance of not only participants of electricity industry but also beneficial for whole country economy and for energy supply security.

Literature both in academic and business perspective is rich for financial tools investigating the financial and operational management mechanisms to facilitate market operations and enhance market efficiency in the restructured electricity industry.

Co-integration is an important aspect to take into account for effective risk management of spread positions. Coal and natural gas is used to produce electricity by power generating companies so futures derivatives of natural gas and coal offset seasonal cost by the "spark spread" advantage; resulted because of the different seasonal prices of the two input fuel.¹

We researched the long-run relation and short-run dynamics within and between spot electricity prices and main fossil fuel prices – coal and natural gas – for the period 10/10/2006 – 7/12/2013.

The results show the following:

- I. Directions and Long-run relations between electricity, natural gas and coal within US.
- II. Stationarity and Cointegration of the prices.

¹ <http://www.eia.gov/coal/nymex/>

2. ENERGY MARKETS

2.1 Deregulation of Electricity Markets

Restructuring and deregulation in electricity market has accelerated in worldwide and resulted electricity trade as a financial instrument can be stated as 'commoditization process'. This marketization of electricity after 1980's markets experienced the implementation of a variety of deregulatory reforms in the U.S. electricity sector. Wholesale electricity markets were under a transition from a strictly regulated system through local deregulated markets

This initiated a transition period from a single body which held all economic decision and physical electricity flow from a central structure to a multi actor body which let the decision to be taken by all market players, and flow of physical electricity is managed by system operator. This continuing transition is being evaluated with several experiences has been confrontation with multifaced problems all over the world and is still in development process.

Main steps of this reformization are through liberalisation, deregulation, re-regulation and privatisation. Most of these steps has been achieved in USA (as an early deregulated market) and in many other countries. Model improvisations have been developed for further processes of technical complexity.

Moreover, electricity represents uniquely different and much more complex structure then the other commodities depending on its own character of specifications. While pricing all other commodities, physical equilibrium/balance is not considered as a factor rather then electricity. Thus electricity may be the only commodity, in which physical balances are considered in stage of pricing.

Because of following reasons; price volatility and significant price increase are observed much more extremely rather then the other commodities;

- I. Electricity is a commodity which should be consumed simultaneously when it is generated ; this requires a system operator, that observes the supply and demand instantly , which is responsible to sustain the equilibrium.

II. Electricity as a commodity have an extremely low elasticity of demand. Household electricity demand elasticity is in between -0,15 and -0,25 (Hope 2005, 34).

III. While electricity is an extremely non-susbtitutional commodity for consumers and specially for retail householders, they should not be affected by the extreme real time price volatility of the electricity.

IV. Because of the transmission lines and distribution grids have a capacity for flow; overloading of the transmission can violate the balance of the system resulting failure of hole system.

V. Capacity limitations also can result different prices in different regions which means additional price risk both for consumers and producers.

Thus Commoditization of Electricity, in order to creating a competitive electricity market design will be as unique as being crucial for a efficiently operating market .These market risk and price volatility needs to be managed and disposed by this restructured market in favor of all participants of the market.

2.2 Energy Price Risk

Price volatilities are drastically more significant and higher in Energy markets than the other commodities markets. Price spreads induces cash and credit management complexity and this effects the financial decisions of prospective energy investments. Historical data is clear to reflect this extreme volatility condition of physical and derivative energy prices.

Despite of the significant patterns in other spot prices, in energy commodity markets spot and derivative prices do not follow recognizable trends. Natural gas spot price peaks periodically without any sign. Midwest, Pennsylvania-Maryland-New Jersey (PJM) regions, California-Oregon border (COB), and at Palo Verde, Wholesale electricity prices always waves over large “spikes” during summers. Also, on the West Coast wholesale electricity prices are extremely volatile in some winter months.

Natural gas and electricity are swinging in large ratios becuase of the demand interactions with weather conditions. Inventories provide limited stability against price spikes, because there are not enough large natural gas users inventories on site,

and the options for electricity storage are expensive. Physical arbitrage from low-cost supplies to places with high prices is impossible because of limited shipping or transporting capability. As a result of lack of physical network for transportation and limited storage capacity, prices oftenly soar when the demand suddenly increases.

Table 1. Spot Market Price Volatility for Selected Commodities

Commodity	Average Annual Volatility (Percent)	Market	Period
Electricity			
California-Oregon Border	309.9	Spot-Peak	1996-2001
Cinergy	435.7	Spot-Peak	1996-2001
Palo Verde	304.5	Spot-Peak	1996-2001
PJM.	389.1	Spot-Peak	1996-2001
Natural Gas and Petroleum			
Light Sweet Crude Oil, LLS.	38.3	Spot	1989-2001
Motor Gasoline, NYH	39.1	Spot	1989-2001
Heating Oil, NYH.	38.5	Spot	1989-2001
Natural Gas.	78.0	Spot	1992-2001
Financial			
Federal Funds Rate	85.7	Spot	1989-2001
Stock Index, S&P 500.	15.1	Spot	1989-2001
Treasury Bonds, 30 Year	12.6	Spot	1989-2001
Metals			
Copper, LME Grade A	32.3	Spot	January 1989-August 2001
Gold Bar, Handy & Harman, NY	12.0	Spot	1989-2001
Silver Bar, Handy & Harman, NY	20.2	Spot	January 1989-August 2001
Platinum, Producers	22.6	Spot	January 1989-August 2001
Agriculture			
Coffee, BH OM Arabic	37.3	Spot	January 1989-August 2001
Sugar, World Spot.	99.0	Spot	January 1989-August 2001
Corn, N. Illinois River	37.7	Spot	1994-2001
Soybeans, N. Illinois River	23.8	Spot	1994-2001
Cotton, East TX & OK.	76.2	Spot	January 1989-August 2001
FCOJ, Florida Citrus Mutual	20.3	Spot	September 1998-December 2001
Meat			
Cattle, Amarillo	13.3	Spot	January 1989-August 2001
Pork Bellies.	71.8	Spot	January 1989-August 1999

Sources: Data from Commodity Futures Trading Commission. Calculations by Energy Information

Administration staff.

Table 1.1 indicates the annual price volatility average of various commodities between years 1992 and 2001. According to the historical data; while financial commodities showing the lowest volatility, the electricity commodities represent the highest volatility.

2.3 Spot and Derivative Energy Markets

2.3.1. Spot Energy Markets

Spot markets are generally consists of trade of physical form of the commodities and processes are mostly a step of retail part of the supply chain. Commodities can be exchanged directly or indirectly within the interferences of a broker or a dialer institution (Chatnani 2010, 4-5). Spot markets are aimed to development of physical trade, but within the advancement of related technologies, have gained a financial aspect. Thus spot markets are in an incessant interaction with financial commodity markets.

There is a confusion in description of Electricity Spot Markets where electricity trade is occurred same as the other commodity spot markets. According to Bouissoleau (2004, 61) for Europe spot electricity market marks day-ahead electricity market, while for USA it marks real time spot market.

2.3.2. Derivative Energy Markets and Derivative Instruments

Derivative markets are the place for forward looking trade of commodities being transacted today. Fundamental of this market is to define price and other physical aspects of a commodity by contract for a future date to be physically traded. Derivatives as a financial instrument contracts, does not provide possessory benefit over the physical commodity to its holder. This transaction of exchanging derivatives provides opportunities for preventing prospect risk like volatilities, named Hedging. This aspect of derivative markets lets hedging of risks by exchange of future contracts so called as financial commodities market.

Forward contracts are simple extension of cash or cash-and-carry transactions. Whereas in a standard cash transaction the transfer of ownership and possession of the commodity occur in the present, delivery under a forward contract is delayed to the future. In energy markets, an oil refiner may enter into forward contracts to secure crude oil for future operations, thereby avoiding both volatility in spot oil prices and the need to store oil for extended periods.

Forward contracts are as varied as the parties using them, but they all tend to

deal with the same aspects of a forward sale. All forward contracts specify the type, quality, and quantity of commodity to be delivered as well as when and where delivery will take place. In addition, forward contracts set a price or pricing formula. The simplest forward contract sets a fixed (firm) price. More elaborate price-setting mechanisms include floors, ceilings, and inflation escalators. By setting such a price, the buyer and seller are able to reduce or eliminate uncertainty with respect to the sale price of the commodity in the future. Knowing such prices with certainty may allow forward contract users to better plan their commercial activity. Finally, the contract may contain miscellaneous terms or conditions, such as establishing the responsibilities of the parties under circumstances where one party fails to perform in an acceptable manner (lack of delivery, late delivery, poor quality, etc.). Overall, forward contracts are designed to be flexible so as to match the commercial merchandising needs of the parties entering into them.

Today; scope of derivatives are enlarged with some subsequent and similar versions of existing ones. Derivatives consist of following instruments;

Electricity swaps; are established for a constant quantity of power referenced to a variable spot price in order to enable their holders to pay a fixed price for underlying electricity, being independent of the floating electricity price, over the contracted short- to medium-term time period.

Electricity options; are financial options which can be created in the domain of electricity options by replacing the underlying of a financial option with electricity call options; put options; cap options; floor option; collar options and Spark spread options are subform of the options.

Financial Transmission Rights allow market participants to hedge related price risk of delivering electricity to the grid.

2.3.3 Relation between Spot and Derivatives Prospects for Energy Derivatives

Spot commodity markets and derivatives commodity markets are described as differentiating from each other; but they are in an incessant interaction and there are certain casual relationship between the price of a commodity in spot and derivative market.

In deregulated electricity market, electricity derivatives are important for providing ,

- I. signals of price,
- II. forecast for price,
- III. simplifying risk management,
- IV. increasing investments in capacity of transmission and generation,
- V. formation of the capital.

Energy derivatives as financial instruments helps maintain certainty in energy prices, hedging opportunities against volumetric risk, synthesize transmission and generation operations.

Evaluation of electricity derivatives market into a more active and effective market is strictly concerned with restructuring of the industry. As S.J. Deng and S.S. Oren stated in 2006, “prospects for electricity derivatives will remain limited until the electricity spot markets work fairly and properly.”

2.3.4 Application of Derivatives in to the Market

As the enormous demand can not to be met by a single fuel source generation it will cause to switch other plants that use the alternate fuel. The price of the input fuel used by generators assigns the price of electricity. So if coal prices are higher then the natural gas, gas input generators will process generating electricity.

Coal fired installations will be used to supply the excess electricity demand. If the price of natural gas approximates coal prices, this increase also pulls up the electricity prices. In contrast, if gas prices arise over the coal prices, this will increase electricity prices. Thus generation capacity will burn the cheapest fuel near capacity.

This fundamental facts reveal the positive correlation between natural gas and coal, the prices increase in one of this fuel cause generators to demand more of the other fuel, results increase the second fuel's price. Because of the main input fuel sources are coal and natural gas, generator operator's choices will be between this fuels. Risk occurs as the input price exceeds the output price. Two aspect of this price relationship is as follows;

The difference between the price of electricity and the price of natural gas is “spark spread”. Spark Spread is an effective measurement tool for the relation

between main input fuel the natural gas and the output electricity. The other measurement tool is the “dark spread”, which measures the relation between price of electricity and the price of coal.

These spreads are indicators of profitable position buying gas or coal and instead of selling electricity when it is positive, and vice versa.

3. LITERATURE REVIEW

3.1 Energy Price Risk Management and Market Risk Management

Livo Vehvilainen and Jussi Keppo (2001) utilizes financial risk management tools in order to define estimated value of the spot price that is directly captured from the futures quotations focusing on deregulated electricity market of Scandinavia. The analytical results found to be reasonable when compared with the corresponding results from the financial market. The deregulation of the electricity markets inevitably leads to a competitive market thus as the paper suggest if the unique properties of the electricity market are considered, financial methods can be utilized to analyze risk arising in the market and management of the risks.

Min Liu - Felix F. Wu (2007) offers a model which reckons on the multi-market environment of a competitive electricity market, in order to maximize participant's benefits and minimizing the risks, provided with an appropriate risk management scheme according to relevant analyzes and specifications of electricity trading. Results show that utilization of VaR is said to be beneficial for optimal portfolio to trade between multiple energy markets in order to reduce risks.

Sergey P. Kolos, Ehud I. Ronn try to estimate the the massiveness and direction of the commodity "market price of risk" (MPR) which has been performed in commodity and financial energy markets. According to results, upward or downward directions of forward prices are forecast indicators for future spot prices, so this directions can be evaluated as risk premiums in order to giving optimum hedging decisions. Negative MPR occurs in short term and positive MPR occurs in lon term. In Day-Ahead prices MPR is observed as moving simultaneously with short-term future prices.

Larsson Nossman, (2011) suggested a general multivariate model for co-integrated futures electric, natural gas, coal prices and lately CO2 prices. For the commodities with strong price interrelations as a result of alternatively being used to generate electricity a second different model without co-integration on different data sets are calculated for different spread positions of Value-at-Risk. Consequences implies taking account of co-integration is necessary for effective risk management of spread positions.

3.2 Cointegration / Energy Price Relationship

The dynamic nature of electricity markets provides many possibilities for understanding the relationship between input and output prices in a non- static environment. Cointegration analysis is employed to test and analyze this relationship. Cointegration analyzes used in the related literature were mostly focused on spot prices. Motivation of this thesis is to determine the existence and direction of the relation between forward natural gas and coal prices and day-ahead electricity prices in USA energy market to reach a better understanding of USA power market behavior to provide useful information and reliable insight for various aspects from risk management to investment decision and electricity generation fuel switch decisions for market participants.

Carol Alexander (1999) reviews the different approaches to measure energy correlations and examines their applications to energy markets using the natural gas and crude oil markets for illustration. Statistical measures of correlation are outlined, and equally weighed moving averages, EWMA and GARCH model are described. Some applications of correlation are considered and the ways in which correlations affect spreads, hedging and multi-asset options are highlighted. The concept of cointegration is introduced, and the use of cointegration to study trends in multivariate time series, the cointegration of spot and futures prices, and cointegration analysis are discussed. Panels give details of the correlation between natural gas spot and prompt future, correlation in the crude oil term structure, and cointegration and error correction in crude oil prices.

Emery and Liu investigates the relationship between electricity and natural-gas futures prices for the NYMEX's two longest-running futures contracts of California Oregon Border and Palo Verde; over period 1996 -2000. They found that electricity and futures prices are co-integrated and the character of the relationship is shaped by the seasonality on consumed electricity and preference of source used in generated electricity.

Cyriel de Jong and Stefan Schneider studies how cointegration can be applied to intercept the complex behaviour of energy spot prices of the TTF, Zeebrugge and NBP markets during the period 2004-2008. Cointegration between the gas spot prices of TTF, Zeebrugge and NBP markets is exposed only in 'forward time scale'.

The historical data indicates that the markets are shaped by bilateral interactions in price movements stemming from various reasons as like physical connections of energy source transportation to weather and other economic conditions.

Victor Moutinho, Joel Vieira, Antonio Carrizo Moreira (2011); analyze the long-term and short-term dynamics between electricity prices and commodity prices, using data between 2001 and 2009 from the Spanish electricity market. In this study, the short-run tests doesn't provide any descriptive comment, but according to the co-integration bivariate tests on long-term, gas and fuel prices behaves contradicting with the crude oil price.

Nakajima and Hamori (2013) employ lag-augmented vector autoregression method to examine the Granger-causal relationships over wholesale crude oil, electricity and natural gas prices. Moreover, cross-correlation function approach also used to examine the causality in variance between the variables. Gas prices Granger-cause electricity prices are in mean, according to both tests.

Alexis N. Imler investigates the effect of natural gas and oil, carbon dioxide emissions, energy intensity, on prices of spot coal between the years 1980 - 2007 while oil and natural gas prices were higher than the prices of coal. According to the findings of the study the relationship among spot coal and oil prices is negative, in contrast spot coal and natural gas prices has a positive relationship resulting the condition of a decrease in energy efficiency creating greater demand for coal and increasing the price.

In Mjelde and Bessler (2009) investigates the electricity wholesale spot prices and the crude oil, coal, natural gas and uranium prices in perspective of its dynamic interrelationships from diverse Mid-Columbia and PJM market, in years between 2001-2008. This study is the first one considering uranium prices and integrating to time series analyzes. According to the study in the long-run, the eight price series are cointegrated. With condition of some phases with less than $n-1$ cointegrating vectors indicates weak integration and absence of a single trend. Peak electricity prices effect natural gas prices in contemporaneous time, thus effecting oil prices indirectly at the end. In the long-run the crude oil, coal, natural gas are stable when disequilibrium occurs, electricity and uranium prices move towards the equilibrium.

Mohammadi (2009) investigated both the long and short-run dynamic relationship among main fossil fuels like coal, natural gas and crude oil and electricity prices and in the U.S. for the years between 1960 – 2007. He found that

electricity prices in the U.S are not being defined only by fuel prices. The results proposes, a steady, Bi-directional causality relationship between coal and electricity spot prices additionally a trivial relationship between crude oil and/or natural gas prices and electricity prices in the long-run. He suggests policies aiming to affect the industries of natural gas and/or crude oil have limited influence on the flow of electricity prices on the long-run.

Veysel Demir investigates both the long and short-run relationship among two fossil fuel prices – coal and natural gas – prices with day-ahead electricity prices and between the years of 2008 and 2011 in German, Netherland and Dutch energy markets. Thesis for the Msc degree, he set sights on electricity, natural gas and coal price relationship inside the of all countries, the electricity prices relationship among all countries and the interrelationship in Germany just before deactivation of seven nuclear power plants in the country. According to the results in the long-run, existence of a relation of co-integration among natural gas, coal and electricity price has been determined. In the short-run there is causality from base and peak electricity prices towards coal prices.

Our study, is an attempt to analyze cointegration relationship between spot electricity and natural gas, coal fossil fuel prices using panel data methods, in order to make contribution to previous empirical analysis and valuable findings. We take into account both the spot and future prices of commodities in seven hubs, SP-15 hub of Southern California Region, PJM Hub of PJM West Region; Palo Verde hub of Southwest Region; NP-15 hub of Northern California Region; Mid-C hub for Northwest Region; Mass Hub of New England Region and Indiana Hub of Midwest Region.

4. METHODOLOGY

4.1. Stationary

As one of the stochastic processes, the stationary process has been widely examined and inspected by time series analysts. Broadly, if a process variance and mean is not changed with time and the covariance rate of two time periods is based solely on the gap among time periods but not the exact time at which the covariance is enumerated, then we can assume that it is a stationary process (Gujarati, 2003:797). Constrains in time periods are as follows:

$$E[y_t] = \mu$$

$$Var[y_t] = \sigma^2$$

$$Cov[y_t, y_{t+n}] = Cov[y_t, y_{t+m}]$$

If a non-stationary series, y_t must be differenced d times before it gets to be stationary, then it is said to be integrated of order d . This would be composed $y_t \sim I(d)$. So if $y_t \sim I(d)$ then $\Delta y_t \sim I(0)$. This last wording expresses that applying the difference denote /operator, Δ , d times, prompts an $I(0)$ process, i.e. a procedure with no unit roots. Truth be told, applying the distinction administrator more than d times to an $I(d)$ procedure will even now bring about a stationary arrangement (however with a MA blunder structure). An $I(0)$ arrangement is a stationary arrangement, while an $I(1)$ arrangement contains one unit root. Case in point, consider the walk

$$y_t = y_{t-1} + u_t$$

To observe what types of data generating process could lead to an $I(2)$ series, take account the equation ;

$$y_t = 2y_{t-1} - y_{t-2} + u_t$$

An explicit example of the stationarity process is White Noise with zero average.

If all autocovariances and the mean are nonaffected by the alteration of time origin, than it means that the time series is weakly stationary. Another situation for weakly stationary processes is covariance stationary.

4.2. Two Types of Non-Stationarity

The models specified below is generally used to state the non-stationarity (the randomwalk) model;

$$y_t = \mu + y_{t-1} + u_t$$

additionally, there is a linear trend named as stationary process

$$y_t = \alpha + \beta_t + u_t$$

For each models, u_t is a white noise term. This model could be put together the model according to u_t where is described as an unstable process

$$y_t = \mu + \phi y_{t-1} + u_t$$

The usage of non-stationary data could result spurious regressions. Two stationary variables may be composed as autonomous random series. In this situation, one of those variables is regressed on the another variable. As a result, the estimation of R^2 is expected to be low and the t-ratio on the slope coefficient is not be necessarily different from zero.

This appears evident, for the variables are not identified with each other. In any case, if two variables are trending over the long term, a relapse of one on the other could have a high R^2 regardless of the fact that the two are completely unrelated. Thus, if standard regression methods are applied to non-stationary data, the result could be a regression that seems similar standard measures (significant coefficient

estimates and a high R^2), however which is truly valueless. This model termed as a 'spurious regression'.

4.3. Testing For a Unit Root

If series is described by unit root, applying the acf / pacf is imposible to spot them. Also, results of the tests for a given sample process is stationary if data generating process for y_t contains a unit root.

Initial research about testing for a unit root was made by Dickey and Fuller. Examining the null hypothesis that $\phi = 1$ is the main goal of the test

$$\Delta y_t = \phi y_{t-1} + u_t$$

against the one-sided alternative $\phi < 1$. Thus the hypotheses of interest are H_0 : series contains a unit root versus H_1 : series is stationary.

The regression specified below is easier than for computation and interpretation

$$\Delta y_t = \phi y_{t-1} + u_t$$

so that a test of $\phi = 1$ is equivalent to a test of $\psi = 0$ (since $\phi - 1 = \psi$).

Dickey–Fuller (DF) tests are also known as τ -tests, and can be conducted to enable for an intercept and deterministic trend, or may not be enable for both of them, in the test regression.

Dickey–Fuller (DF) tests are called t -tests, and can be directed taking into consideration a capture, or a capture and deterministic pattern, or not one or the other, in the test regression. The model for the unit root test for every lap is;

$$\Delta y_t = \phi y_{t-1} + \mu + \lambda_t + u_t$$

The tests can also be stated, by subtracting y_{t-1} from each side of the equation, as ;

$$\Delta y_t = \psi y_{t-1} + \mu + \lambda t + u_t$$

To ensure that it is autocorrelated or not, the range of Δy_t includes dynamic structure displayed in the dependent variable. As before, the test is sample of augmented Dickey–Fuller (ADF) test and is conducted on ψ .

4.3.1. Phillips–Perron (PP) tests

Phillips and Perron have added to a more complete hypothesis than ADF tests. The tests usually give the similar results and experience the same essential impediments as, the ADF tests.

4.3.2. Dickey – Fuller (1979) Test

Dickey- Fuller suggests three equations to test the existence of a unit root. The test can be applied in three types, meaning it can be tested with three different null hypothesis.(Gujarati, 2003:815):

$$\Delta y_t = \delta \Delta Y_{t-1} + u_t$$

$$\Delta y_t = \beta_1 + \delta \Delta Y_{t-1} + u_t$$

$$\Delta y_t = \beta_1 + \beta_1 t + \delta \Delta Y_{t-1} + u_t$$

At the first equation, series is a random walk without drift; at the second it is a random walk with drift and at the last equation is a random walk with drift around a stochastic trend. There is a unit root, if $\delta=0$ all equation. The series are stationary if $\delta<0$. For each three equations, critical values of the t test for testing the null hypothesis are different.

4.3.3. Augmented Dickey – Fuller (1981) Test

Dickey – Fuller (1979) test is a crucial point in estimating of integrated order, but it excludes the autocorrelation of error terms. The test will be invalid if the error term, u_t , is correlated. To prevent this, Dickey and Fuller (1981) used lagged value of dependent variable to approximate the autocorrelation. ADF-Augmented Dickey-

Fuller test is the commonly used and proved to be efficient for estimating integration order.

The of ADF test equation of Dickey – Fuller (1979) test) is denoted as ;

$$\Delta y_t = \beta_1 + \beta_1 t + \delta \Delta Y_{t-1} + \alpha_i \sum_{t=1}^m \Delta y_{t-1} + \varepsilon_t$$

ε_t is known as term of white noise error,

$$\Delta y_{t-1} = (y_{t-1} - y_{t-2}), \Delta y_{t-2} = (y_{t-2} - y_{t-3})$$

etc , m is denoted as the lag number.

In ADF test also we test if $\delta=0$. If hull hypothesis is rejected against alternative hypothesis, $\delta<0$, it shows stationarity of Δy_t series and $y_t \sim I(1)$. It is important to determine the lag number (m) and lag number must be comparatively small for having enough degrees of freedom; at the same time must be wide enough for not causing autocorrelation in error term.

4.3.4. The Perron (1989) Procedure

He argues that most financial time series are portrayed by broken trend stationary process, where the information producing procedure is a deterministic pattern yet with a basic break around 1929 that forever changed the levels(i.e. the captures) of the series.

$$\Delta y_t = \psi y_{t-1} + \mu p + \lambda t + \alpha_i \Delta y_{t-i} + u_t$$

The main he terms an "crash" model that permits a break in the level (i.e. the intercept) of the series; the second is an ' changing growth ' model that takes into consideration a break in the growth rate (i.e. the slope) of the series; the last model takes into account both sorts of break to happen in the same time, changing both the intercept and the incline of the trend the general equation for the third type of test is;

$$\Delta y_t = \psi y_{t-1} + \mu + \alpha_1 D_1 + \alpha_2 (t - T_b) D_t + \lambda t + \sum_{i=1}^p \alpha_i + \Delta y_{t-i} + u_t$$

For the crack only model, set $\alpha_2 = 0$, while for the changing growth only model, set $\alpha_1 = 0$. In each of the three cases, there is a unit root with a structural break at T_b under the invalid null hypothesis and an series that is a stationary process with a break under the option

4.3.5. Criticisms of Dickey Fuller And Phillips Perron Type Tests

The most critical evaluation which was focused at unit root tests; if the procedure is stationary however with a root near to the non-stationary limit, then descriptive potential is weak. For instance, consider an AR(1) data creating process with coefficient 0.95. If the genuine data producing process is $y_t = 0.95y_{t-1} + u_t$

This implies that an inability to reject the null hypothesis could happen because of the fact that the null was correct, or that there is inadequate data in the example to empower rejection. One approach to get around this case is to utilize a stationarity test and additionally a unit root test.

4.4. Autocorrelation

During the analysis of time series, serial independence assumption is usually disregarded. There may be a correlation between errors in time periods. This feature is known as serial autocorrelation or autocorrelation. The errors can be caused by many different sources like, measurement error, determining wrong model, omitting parameters, overpassing nonlinearities and random incalculable effects. Some of these effects can result in serially correlated errors.

The OLS estimations are impartial and dependable under the LS estimations. Therefore, OLS estimations are dependable if the error terms are serially correlated. Problem arise when attempting to minimize the variance of linear combination. While minimizing the variance of linear combination of $\sum a_t \varepsilon_t$,

$$Var\left(\sum a_t \varepsilon_t\right) = \sum a_t^2 \sigma^2 + \sum_{t \neq k} \sum a_t a_k Cov(\varepsilon_t, \varepsilon_k)$$

for efficiency.

If $Cov(\varepsilon_t, \varepsilon_k) \neq 0$, the second term of the right part is not disappeared, then it is not going to be as same as minimizing a normal OLS equation, $\sum a_t^2 \sigma^2$ and OLS equation will not be efficient. Notice that the autocorrelation will cause to inconsistency if the lagged dependent parameters are counted as explanatory variables. The calculated regression coefficient variance would be inconsistent; therefore the test must be count as invalid.

The estimated residual variance is an underestimate and R^2 is an overestimate, if the serial correlation is positive and increasing with time. In addition to this, t-statistics will be more significant than its actual value (Gujarati, 2003).

4.5. Cointegration

Most of the macroeconomic time series include trend and as mentioned before, and presence of nonstationarity in time series in econometric analyses may cause serious problems. The time series, which include stochastic or deterministic trend, can give spurious regression results which causes test statistics to be invalid.

By taking their differences for d times we can make non-stationary parameters stationary. But even so, cointegrating may occur, that is, the combination of two non-stationary parameters might be stationary.

Engle and Granger designated a linear combination of two or more series might be stationary (Engle and Granger, 1987:251). The stationarity combination may be described as the equilibrium relationship between the variables or as cointegration.

The combination of a set of variables $X_{i,t}$ with differing orders of integration will have an order of integration equal to the largest.

If $x_{i,t} \sim I(d_i)$ for $i = 1, 2, 3, \dots, k$ so that there are k variables each integrated of order d_i , and letting;

$$z_t = \sum_{n=1}^{\infty} \alpha_n x_{n,t}$$

Then $z_t \sim I(\max d_i)$. z_t in this context is simply a linear combination of the k variables X_i ;

$$x_{i,t} = \beta_i x_{i,t} + z_i$$

As a additional statement, take account the following regression model composed of variables y_t, x_{2t}, x_{3t} which are all $I(1)$

$$y_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + u_t$$

Taking all combiners except the residuals to the LHS;

$$y_t - \beta_1 - \beta_2 x_{2t} - \beta_3 x_{3t} = u_t$$

Linear combination of $I(1)$ variables will be $I(0)$, that means it is stationary, if the variables are cointegrated.

4.5.1. Definition of cointegration (Engle and Granger, 1987)

Assume that w_t is a $k \times 1$ vector of variables, then the elements of w_t are integrated of order (d, b) if:

- I. All variables of w_t are $I(d)$
- II. There is at least one vector f coefficients α such that

$$\alpha' w_t \sim I(d - b)$$

In reality, most of the financial data and variables contains at least one unit root, in this context, if a linear combination of variables is defined as stationary, association of them is described as cointegrated. Generally time series are non-stationary but ‘move together’ over trend because of that, there are influences on the series which express that the two series are associated by some integration in the long term.

Besides their integration would occur in the long term, a cointegrating relationship may also be witnessed as cointegrating variables deviating from their relationship in the short term.

4.5.2. Examples of general cointegrating relationships in finance

Financial theory must propose where two or more variables would be expected to carry some long-run relationship with a different one. There are many examples in finance of where cointegration might be expected to hold, including following areas :

- I. Spot and futures prices of a commodity or asset
- II. Relative prices ratio and Exchange rates
- III. Equity prices

4.6. Vector Autoregression (VAR) Analysis

VAR analysis considers every parameter in a systematic integrity. They are usually used for dynamic effect of random shocks to system of variables and for estimating the relation between macroeconomic variables. It also used for stationary parameters on same level.

To get the feedback of present and past values of the parameters, we can use VAR model. Theoretically there is no obstacle for taking several variables into the model in VAR analysis. Each additional variable for the model decreases the degrees of freedom. A careful analysis for theoretical model helps to choose the set of variables.

The VAR model is showed as ,

$$x_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + e_t$$

where

c is a $k \times 1$ vector of constants,

A_i is a $k \times k$ matrix (for every $i=1,\dots,p$),

e_t is a $k \times 1$ vector of error terms.

We have to keep in mind that there have to be causality among variables. With respect to the economic data and theory that has taken into consideration, the variables must have an economic influence on each other. Careful lag length selection is necessary because it may cause same problems if it is selected too short or too long.

Instead of parameter measurement, this analysis focuses on interrelationship between the economic time series. Interaction of the previous variables appears as a residual correlation in VAR models.

4.6.1. Equilibrium correction or error correction models

While this methodology is measurably substantial, it has the issue that first difference models have no long-run solution. For instance, consider two series, y_t and x_t , that are both $I(1)$. The model that one may consider assumption is,

$$\Delta y_t = \beta \Delta x_t + u_t$$

Hence all the difference terms will be zero in, i.e. $\Delta y_t = 0$; $\Delta x_t = 0$, and thus everything in the equation cancels.

Model has no long-run arrangement and it consequently has nothing to say in regards to whether x and y have a balance relationship.

But there is a class of models that can conquer this issue by utilizing mixes of initially differenced and lagged levels of cointegrated variables ; as in the following equation.

$$\Delta y_t = \beta_1 \Delta x_t + \beta_2 (y_{t-1} - \gamma x_{t-1}) + u_t$$

This is known as an error correction model or an equilibrium correction model, and $(y_{t-1} - \gamma x_{t-1})$ is known as the error correction term. y_t and x_t are cointegrated with cointegrating coefficient γ , then $(y_{t-1} - \gamma x_{t-1})$ will be $I(0)$ even though the constituents are $I(1)$.

4.6.2. The Engle–Granger 2-step method

Engle-Granger's single equation technique; Two-Step Modelling Method of estimating a long-run equation conducted as follows:

In Step 1, dynamics are ignored and the long-run equation is estimated:

$$y_t = \beta X_t + u_t$$

In order for y_t and X_t to be cointegrated, the estimated residuals from equation must be stationary. In this case the cointegration regression is said to be sufficient. As the variables are nonstationary, we can face the spurious regression problem. Therefore, R^2 and DW must be carefully inspected. If all indicators are satisfactory, we can proceed to the next step.

In Step 2; the second step includes estimating of a short-run model. In the short-run there may be disequilibrium. Sargan (1984) and Engle Granger suggest a theorem inclusion of error term into the equation as "equilibrium error" (Gujarati, 2003:824). According to the theorem two variables Y and X are cointegrated, the relationship between the variables can be expressed as Error Correction Mechanism (ECM) (Engle and Granger, 1987:255). ECM for equation is as follows:

$$\Delta y_t = \alpha_0 + \alpha_1 \Delta X_t + \alpha_2 u_{t-1} + \varepsilon_t$$

Δ indicates the first difference, ε_t is an error/equilibrium term and u_{t-1} is the cointegration regression's lagged value error term.

The Engle–Granger 2-step method causes some problems;

- I. The usual finite sample problem of a lack of power in unit root and cointegration tests.
- II. There could be simultaneous equations bias if the causality between y and x runs in both directions.

4.7. Vector Error Correction Model (VECM)

A VECM is a variation of VAR model. It is a restricted version of it that allows short run dynamics by restricting the long run behavior of the endogenous variables. The long run equilibrium effects the short run dynamics of the parameters in an ECM. ECM allows us to investigate the short-run dynamics in the relationship between x and y (Woolridge, 2003:592).

We can apply this approach to VAR models. We are also going to use a new version of Granger–Johansen representation theorem to determine the magnitude of the initial condition.

If we think the p -dimensional VAR model where y_t and x_t are $I(1)$ processes and not cointegrated;

$$y_t = A_1 y_{t-1} + \dots + A_k y_{t-k} + \beta X_t + \varepsilon_t$$

the errors are independent and exactly distributed (0) and x_t are the deterministic terms. If we write the model in error correction style:

$$\Delta Y_t = \Pi_1 Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \beta X_t + \varepsilon_t$$

$$\Pi = \sum_{i=1}^p A_{i-1} \text{ and } \Gamma_i = -\sum_{j=i+1}^p A_j$$

where Δ is the difference operator. Granger's theorem implies that when the coefficient matrix π reduces rank $r < k$ ($k \times r$ matrices exist and each with rank r such that $\pi = \alpha\beta$ and β is stationary. Each column of β is the cointegrating vector and r represents the number of cointegration correlations. The factors of α are taken as the adjustment coefficients. Johansen's method computes the matrix in an unrestricted form. After, it checks whether restrictions can be rejected by reducing rank of n or not (Verbeek, 2008). The lag length was selected by utilizing the Akaike information criterion (AIC) for cointegration tests.

The Trace statistic tests the null hypothesis of r cointegrating correlations against the modifying of k cointegrating relations. Here, k demonstrates the endogenous variables. The trace statistic for the null hypothesis of r cointegrating correlations has been written as;

$$\lambda_{trace} = T \sum_{i=r+1}^k \log(1-\lambda_i)$$

λ_i shows the biggest eigenvalue of the Π in the VAR equation. The maximum eigenvalue statistic (λ_{max}) tests the null hypothesis of r cointegrating correlations versus the alternative $r+1$ cointegrating correlations (Verbeek, 2008). The test statistic is computed as:

$$\lambda_{max} = -T \log(1 - \lambda_{r+1})$$

To estimate the lag length for VAR model, Akaike Information Criteria (AIC) is used. Engle and Granger's two step error correction method might be used in a multivariate context while the Johansen's (1990) Vector Error Correction Model (VECM) brings much more effective estimators of co integrating vectors. Because VECM bears good information maximum likelihood estimation model that commissions for applying co integration in a whole system of equations at once. The VECM can be written:

$$\Delta Y_t = \Gamma_1 \sum \Delta Y_{t-1} + \Gamma_{k-1} \Delta Y_{t-k-1} + \Pi Y_{t-k} + \mu_t$$

Where Δ presents first differences,

$$\Gamma_1 = -(I - A - \dots - A_i), (I = I, \dots, k-1), \Pi = -(I - A_1 - \dots - A_{ik})..$$

The short run and long run adjustments to Y is highlighted by the Γ and Π . $\Pi = \alpha\beta$ denotes the speed of the adjustment to disequilibrium and represents the matrix of the long-term coefficients (Verbeek, 2008).

5. EMPIRICAL RESULTS

We applied Augmented Dickey-Fuller Unit-Root Test on Our Data in order to examine the presence of unit root. Goal of this test is indicate whether average level of Day – Ahead Electricity prices has unit root at different HUBs.

According to the table 5.1; there is no unit root in first differentiation on average level of Day – Ahead Electricity prices at SP-15 HUB. The day Ahead electricity price at SP-15 HUB has integration of order 1/(1).

Investigations in Central Appalachian Coal Future at settlement Price level indicates presence of Unit Root but first differentiation of this settlement price has no unit root it has integration of order 1/I(1).

Unit root test are positive at Natural Gas Future settlement prices level (modified as equal to 1 Billion MgW/Hour energy exposure) .As the other series differentiation of Natural Gas Future settlement prices doesn't have unit root.Briefly Natural Gas Future settlement prices has integration of order 1/I(1).

Table 5.1: Augmented Dickey-Fuller Unit-Root Test Results for SP-15 HUB

Variable	Test Statistic	%1 Critical Value	%5 Critical Value	%10 Critical Value
SP-15 D-A Av. Price	-1.435	-2.58	-1.95	-1.62
Δ SP-15 D-A Av. Price	-19.51	-2.58	-1.95	-1.62
CA Coal Fut. Sett. Price	-2.232	-3.96	-3.41	-3.12
Δ CA Coal Fut. Sett. Price	-14.144	-3.96	-3.41	-3.12
Natural Gas Fut. Sett. Price	-2.434	-3.96	-3.41	-3.12
Δ Natural Gas Fut. Sett. Price	-12.129	-3.96	-3.41	-3.12

According to the table 5.1; there is no unit root in first differentiation on average level of Day – Ahead Electricity prices at PJM HUB. The day Ahead electricity price at PJM HUB has integration of order 1/(1).

Investigations in Central Appalachian Coal Future at settlement Price level indicates presence of Unit Root but first differentiation of this settlement price has no unit root it has integration of order 1/I(1).

Unit root test are positive at Natural Gas Future settlement prices level(modified as equal to 1 Billion MgW/Hour energy exposure). As the other series

differentiation of Natural Gas Future Settlement Prices doesn't have unit root. Briefly Natural Gas Future settlement prices has integration of order 1/I(1).

Table 5.2: Augmented Dickey-Fuller Unit-Root Test Results for PJM HUB

Variable	Test Statistic	%1 Critical Value	%5 Critical Value	%10 Critical Value
PJM D-A Av. Price	-1.746	-2.580	-1.950	-1.620
ΔPJM D-A Av. Price	-21.266	-2.580	-1.950	-1.620
CA Coal Fut. Sett. Price	-2.277	-3.960	-3.410	-3.120
ΔCA Coal Fut. Sett. Price	-14.442	-3.960	-3.410	-3.120
Natural Gas Fut. Sett. Price	-2.477	-3.960	-3.410	-3.120
ΔNatural Gas Fut. Sett. Price	-12.890	-3.960	-3.410	-3.120

According to the table 5-3; there is no unit root in first differentiation on average level of Day – Ahead Electricity prices at Pablo Verde HUB. The day Ahead electricity price at Pablo Verde HUB has integration of order 1/(1).

Investigations in Central Appalachian Coal Future at settlement Price level indicates presence of Unit Root but first differentiation of this settlement price has no unit root it has integration of order 1/I(1).

Unit root test are positive at Natural Gas Future settlement prices level (modified as equal to 1 Billion MgW/Hour energy exposure) .As the other series differentiation of Natural Gas Future settlement prices doesn't have unit root.Briefly Natural Gas Future settlement prices has integration of order 1/I(1).

Table 5-3 Augmented Dickey-Fuller Unit-Root Test Results for Pablo Verde HUB

Variable	Test Statistic	%1 Critical Value	%5 Critical Value	%10 Critical Value
PVERDE D-A Av. Price	-1.537	-2.580	-1.950	-1.620
ΔPVERDE D-A Av. Price	-14.348	-3.960	-3.410	-3.120
CA Coal Fut. Sett. Price	-2.253	-3.960	-3.410	-3.120
ΔCA Coal Fut. Sett. Price	-12.340	-3.960	-3.410	-3.120
Natural Gas Fut. Sett. Price	-2.437	-3.960	-3.410	-3.120
ΔNatural Gas Fut. Sett. Price	-12.340	-3.960	-3.410	-3.120

According to the table 5-4; there is no unit root in first differentiation on average level of Day – Ahead Electricity prices at NP HUB. The day Ahead electricity price at NP HUB has integration of order 1/(1).

Investigations in Central Appalachian Coal Future at settlement Price level indicates presence of Unit Root but first differentiation of this settlement price has no unit root it has integration of order 1/I(1).

Unit root test are positive at Natural Gas Future settlement prices level (modified as equal to 1 Billion MgW/Hour energy exposure) .As the other series differentiation of Natural Gas Future settlement prices doesn't have unit root.Briefly Natural Gas Future settlement prices has integration of order 1/I(1).

Table 5-4 Augmented Dickey-Fuller Unit-Root Test Results for NP HUB

Variable	Test Statistic	%1 Critical Value	%5 Critical Value	%10 Critical Value
NP D-A Av. Price	-0.307	-2.580	-1.950	-1.620
Δ NP D-A Av. Price	-12.804	-2.580	-1.950	-1.620
CA Coal Fut. Sett. Price	-1.691	-3.960	-3.410	-3.120
Δ CA Coal Fut. Sett. Price	-9.823	-3.960	-3.410	-3.120
Natural Gas Fut. Sett. Price	-2.526	-3.960	-3.410	-3.120
Δ Natural Gas Fut. Sett. Price	-9.083	-3.960	-3.410	-3.120

According to the table 5.5; there is no unit root in first differentiation on average level of Day – Ahead Electricity prices at MID-C HUB. The day Ahead electricity price at MID-C HUB has integration of order 1/(1).

Investigations in Central Appalachian Coal Future at settlement Price level indicates presence of Unit Root but first differentiation of this settlement price has no unit root it has integration of order 1/I(1).

Unit root test are positive at Natural Gas Future settlement prices level (modified as equal to 1 Billion MgW/Hour energy exposure). As the other series differentiation of Natural Gas Future settlement prices doesn't have unit root.Briefly Natural Gas Future settlement prices has integration of order 1/I(1).

Table 5.5 Augmented Dickey-Fuller Unit-Root Test Results for MID-C HUB

Variable	Test Statistic	%1 Critical Value	%5 Critical Value	%10 Critical Value
MIDC D-A Av. Price	-1.859	-2.580	-1.950	-1.620
ΔMIDC D-A Av. Price	-17.321	-2.580	-1.950	-1.620
CA Coal Fut. Sett. Price	-2.253	-3.960	-3.410	-3.120
ΔCA Coal Fut. Sett. Price	-14.348	-3.960	-3.410	-3.120
Natural Gas Fut. Sett. Price	-2.437	-3.960	-3.410	-3.120
ΔNatural Gas Fut. Sett. Price	-12.340	-3.960	-3.410	-3.120

According to the table 5.6; there is no unit root in first differentiation on average level of Day – Ahead Electricity prices at MASS HUB. The day Ahead electricity price at MASS HUB has integration of order $1/I(1)$.

Investigations in Central Appalachian Coal Future at settlement Price level indicates presence of Unit Root but first differentiation of this settlement price has no unit root it has integration of order $1/I(1)$.

Unit root test are positive at Natural Gas Future settlement prices level (modified as equal to 1 Billion MgW/Hour energy exposure) .As the other series differentiation of Natural Gas Future settlement prices doesn't have unit root.Briefly Natural Gas Future settlement prices has integration of order $1/I(1)$.

Table 5.6: Augmented Dickey-Fuller Unit-Root Test Results for MASS HUB

Variable	Test Statistic	%1 Critical Value	%5 Critical Value	%10 Critical Value
MASS D-A Av. Price	-1.417	-2.580	-1.950	-1.620
ΔMASS D-A Av. Price	-20.100	-2.580	-1.950	-1.620
CA Coal Fut. Sett. Price	-2.262	-3.960	-3.410	-3.120
ΔCA Coal Fut. Sett. Price	-14.519	-3.960	-3.410	-3.120
Natural Gas Fut. Sett. Price	-2.494	-3.960	-3.410	-3.120
ΔNatural Gas Fut. Sett. Price	-12.237	-3.960	-3.410	-3.120

According to the Table 5.7; there is no unit root in first differentiation on average level of Day – Ahead Electricity prices at IND HUB. The day Ahead electricity price at IND HUB has integration of order 1/(1).

Investigations in Central Appalachian Coal Future at settlement price level indicates presence of Unit Root but first differentiation of this settlement price has no unit root it has integration of order 1/I(1).

Unit root test are positive at Natural Gas Future settlement prices level (modified as equal to 1 Billion MgW/Hour energy exposure) .As the other series differentiation of Natural Gas Future settlement prices doesn't have unit root. Briefly Natural Gas Future settlement prices has integration of order 1/I(1).

Table 5.7 Augmented Dickey-Fuller Unit-Root Test Results for IND HUB

Variable	Test Statistic	%1 Critical Value	%5 Critical Value	%10 Critical Value
IND D-A Av. Price	-2.259	-3.960	-3.410	-3.120
ΔIND D-A Av. Price	-14.321	-3.960	-3.410	-3.120
CA Coal Fut. Sett. Price	-2.259	-3.960	-3.410	-3.120
ΔCA Coal Fut. Sett. Price	-14.321	-3.960	-3.410	-3.120
Natural Gas Fut. Sett. Price	-2.481	-3.960	-3.410	-3.120
ΔNatural Gas Fut. Sett. Price	-12.605	-3.960	-3.410	-3.120

Presence of cointegration relation between Electricity prices and Central Appalachian Coal Future settlement prices at SP-15 HUB; are investigated Augmented Engle-Granger Cointegration test. In place of Engle Granger 2 way test, Augmented Engle-Granger Cointegration test is employed in order to achieve AR(1), AR(2), AR(3) process results which has higher autoregressive processes. In this test $H_0: \rho=1$ (no correlation) is tested versus $H_1: \rho < 1$ correlation.

In all AR processes presence of cointegration is obvious as Table 5.8. Specially results of t – test of AR(0) a strong cointegration is evident and t values decrease with higher degree autoregressive processes. Briefly t-test values at table 5.8 illustrates presence of co-integration relation between Electricity prices and Central Appalachian Coal Future settlement prices at SP-15 HUB at high levels. Results at table-5.1 supports the findings at table-5.7 indicating the relation between two series namely I(1).

Table 5.8 : Augmented Engle-Granger Cointegration Test Between SP-15 D-A Average Price and CA Coal Future Settlement Price

Cointegration Test	Test Value	Probability
t Test AR(0)	-12.0696	0
t Test AR(1)	-9.718	0
t Test AR(2)	-7.8379	0
t Test AR(3)	-6.7906	0

In all AR processes presence of Co-integration is shown at Table 5.9. Results of t – test of AR(0) and Specially AR(1) showing the strong cointegration and t values decreases with higher degree autoregressive processes.

Table 5.9 Augmented Engle-Granger Cointegration Test Between PJM D-A Average Price and CA Coal Future Settlement Price

Cointegration Test	Test Value	Probability
t Test AR(0)	-14,0637	0
t Test AR(1)	-15,2267	0
t Test AR(2)	-12,0669	0
t Test AR(3)	-10,6069	0

In all AR processes presence of Co-integration is shown at Table 5.10. Results of t – test of AR(0) showing the strong cointegration and t values decreases with higher degree autoregressive processes.

Table 5.10 Augmented Engle-Granger Cointegration Test Between PVERDE D-A Average Price and CA Coal Future Settlement Price

Cointegration Test	Test Value	Probability
t Test AR(0)	-11,1161	0
t Test AR(1)	-9,1108	0
t Test AR(2)	-7,4499	0
t Test AR(3)	-6,5663	0

In all AR processes , presence of Co-integration is shown at Table 5-11. Results of t – test of AR(1) showing the strongest cointegration and t values decreases with higher degree autoregressive processes.

Table 5.11 Augmented Engle-Granger Cointegration Test Between NP D-A Average Price and CA Coal Future Settlement Price

Cointegration Test	Test Value	Probability
t Test AR(0)	-7,8078	0
t Test AR(1)	-8,0294	0
t Test AR(2)	-6,6595	0
t Test AR(3)	-6,1093	0

In all AR processes , presence of Co-integration is shown at Table 5.12. Results of t – test of AR(0) showing the strongest cointegration and t values decreases with higher degree autoregressive processes.

Table 5.12 Augmented Engle-Granger Cointegration Test Between MIDC D-A Average Price and CA Coal Future Settlement Price

Cointegration Test	Test Value	Probability
t Test AR(0)	-9,2910	0
t Test AR(1)	-8,5160	0
t Test AR(2)	-7,0867	0
t Test AR(3)	-6,2862	0

In all AR processes , presence of Co-integration is shown at Table 5.13. Results of t – test of AR(1) showing the strongest cointegration and t values decreases with higher degree autoregressive processes.

Table 5.13 : Augmented Engle-Granger Cointegration Test Between MASS D-A Average Price and CA Coal Future Settlement Price

Cointegration Test	Test Value	Probability
t Test AR(0)	-11,3612	0
t Test AR(1)	-12,5695	0
t Test AR(2)	-10,1847	0
t Test AR(3)	-9,1924	0

In all AR processes , presence of Co-integration is shown at Table 5.14. Results of t – test of AR(1) showing the strongest cointegration and t values decreases with higher degree autoregressive processes.

Table 5.14 Augmented Engle-Granger Cointegration Test Between IND D-A Average Price and CA Coal Future Settlement Price

Cointegration Test	Test Value	Probability
t Test AR(0)	-10,7775	0
t Test AR(1)	-11,5420	0
t Test AR(2)	-9,5629	0
t Test AR(3)	-8,2600	0

Another series which we will investigate is the relation between electricity prices at SP-15 HUB and Natural Gas Future settlement prices .This relation is also investigated with Augmented Engle-Granger Cointegration test , AR(0), AR(1), AR(2), ve AR(3) proseses are considered.Co-integration test results as shown at table-3, strong co-integration relations are found according to the AR(0), AR(1), AR(2), ve AR(3) proseses.

As shown on Table 5.15 a decrease in co-integration relation is evident at higher order autoregressive proseses but strong relation is also present between I(1) electricity prices and Natural Gas Future settlement prices at SP-15 HUB.T values are also remain high despite of a little decrease and still indicates a presence of co-integration at %1 mean.

Table 5.15 Augmented Engle-Granger Cointegration Test Between SP-15 D-A Average Price and Natural Gas Future Settlement Price

Cointegration Test	Test Value	Probability
t Test AR(0)	-19.5052	0
t Test AR(1)	-16.328	0
t Test AR(2)	-13.5027	0
t Test AR(3)	-11.9654	0

As shown on Table 5.15 a decrease in co-integration relation is evident at higher order autoregressive proseses but strong relation is also present between I(1) electricity prices and Natural Gas Future settlement prices specially at AR(1) at PJM HUB.T values are also remain high despite of a little decrease and still indicates a presence of co-integration at %1 mean.

Table 5.16 Augmented Engle-Granger Cointegration Test Between PJM D-A Average Price and Natural Gas Future Settlement Price

Cointegration Test	Test Value	Probability
t Test AR(0)	-17,7273	0,0000
t Test AR(1)	-19,8938	0,0000
t Test AR(2)	-16,0427	0,0000
t Test AR(3)	-14,4530	0,0000

As shown on Table 5.16 a decrease in co-integration relation is evident at higher order autoregressive processes but strong relation is also present between I(1) electricity prices and Natural Gas Future settlement prices specially at AR(0) at PVERDE HUB.T values are also remain high despite of a little decrease and still indicates a presence of co-integration at %1 mean.

Table 5.17 Augmented Engle-Granger Cointegration Test Between PVERDE D-A Average Price and Natural Gas Future Settlement Price

Cointegration Test	Test Value	Probability
t Test AR(0)	-18,4157	0,0000
t Test AR(1)	-15,6460	0,0000
t Test AR(2)	-13,0607	0,0000
t Test AR(3)	-11,7820	0,0000

Table 5.17 a decrease in co-integration relation is evident at higher order autoregressive processes but strong relation is also present between I(1) electricity prices and Natural Gas Future settlement prices specially at AR(1) at NP HUB.T values are also remain high despite of a little decrease and still indicates a presence of co-integration at %1 mean.

Table 5.18 Augmented Engle-Granger Cointegration Test Between NP D-A Average Price and Natural Gas Future Settlement Price

Cointegration Test	Test Value	Probability
t Test AR(0)	-9,1437	0,0000
t Test AR(1)	-9,2554	0,0000
t Test AR(2)	-7,7146	0,0000
t Test AR(3)	-7,0910	0,0000

A decrease in co-integration relation is evident at higher order autoregressive processes but strong relation is also present between I(1) electricity prices and Natural Gas Future settlement prices specially at AR(0) at MIDC HUB.T values are also remain high despite of a little decrease and still indicates a presence of co-integration at %1 mean.

Table 5.19 Augmented Engle-Granger Cointegration Test Between MIDC D-A Average Price and Natural Gas Future Settlement Price

Cointegration Test	Test Value	Probability
t Test AR(0)	-12,5577	0,0000
t Test AR(1)	-11,6454	0,0000
t Test AR(2)	-9,8113	0,0000
t Test AR(3)	-8,7966	0,0000

Table 5.19 a decrease in co-integration relation is evident at higher order autoregressive processes but strong relation is also present between I(1) electricity prices and Natural Gas Future settlement prices specially at AR(1) at MASS HUB.T values are also remain high despite of a little decrease and still indicates a presence of co-integration at %1 mean.

Table 5.20 Augmented Engle-Granger Cointegration Test Between MASS D-A Average Price and Natural Gas Future Settlement Price

Cointegration Test	Test Value	Probability
t Test AR(0)	-13,8152	0,0000
t Test AR(1)	-15,6066	0,0000
t Test AR(2)	-12,7734	0,0000
t Test AR(3)	-11,6530	0,0000

Table 5.20 a decrease in co-integration relation is evident at higher order autoregressive processes but strong relation is also present between I(1) electricity prices and Natural Gas Future settlement prices specially at AR(1) at IND HUB.T values are also remain high despite of a little decrease and still indicates a presence of co-integration at %1 mean.

Table 5.21 Augmented Engle-Granger Cointegration Test Between IND D-A Average Price and Natural Gas Future Settlement Price

Cointegration Test	Test Value	Probability
t Test AR(0)	-15,5844	0,0000
t Test AR(1)	-17,2351	0,0000
t Test AR(2)	-14,7807	0,0000
t Test AR(3)	-12,9582	0,0000

We aimed to implementing a VEM model which considers maximum one week period because of existing data frequency is in Daily base. Thus as a result of our investigations on with higher lag numbered alternative models , we decided to considering maximum one week long period in length. Following tables illustrates the Lags with four selection criteria as maximum 4 lag numbers.

Final prediction error (FPE) , Akaike, Hannan-Quinn, Schwarz Bayesian criterias indicates the avaiability and suitiblity of implementation of a 4 Lag model between electricity prices and Central Appalachian coal futures settlement prices at SP-15 HUB. Also VEC analisys will be applied between electricity prices and Central Appalachian coal futures settlement prices as in 4 Lags.

Table 5.22 Lag Selection for VEC Model Between SP-15 D-A Average Price and CA Coal Future Settlement Price

Number of Lags	FPE Criteria	Akaike Criteria	Hannan-Quinn Criteria	Schwarz Bayesian Criteria
0	228.521	11.1074	11.1138	11.1247
1	216.722	11.0544	11.065	11.0833
2	209.043	11.0183	11.0332	11.0588
3	206.224	11.0047	11.0239	11.0568
4	199.374*	10.9709*	10.9943*	11.0346*

Final prediction error (FPE) , Akaike, Hannan-Quinn, Schwarz Bayesian criterias indicates the avaiability and suitiblity of implementation of a 4 Lag model between electricity prices and Central Appalachian coal futures settlement prices at PJM HUB. Also VEC analisys will be applied between electricity prices and Central Appalachian coal futures settlement prices as in 4 Lags.

Table 5.23 Lag Selection for VEC Model Between PJM D-A Average Price and CA Coal Future Settlement Price

Number of Lags	FPE Criteria	Akaike Criteria	Hannan-Quinn Criteria	Schwarz Bayesian Criteria
0	399.628,0000	11,6663	11,6725	11,6831
1	392.783,0000	11,6490	11,6593	11,6771
2	381.525,0000	11,6199	11,6344	11,6592
3	379.18	11,6138	11,6323	11,6643
4	371.005*	11,592*	11,6146*	11,6537*

Final prediction error (FPE) , Akaike, Hannan-Quinn, Schwarz Bayesian criterias indicates the availability and suitability of implementation of a 4 Lag model between electricity prices and Central Appalachian coal futures settlement prices at PVERDE HUB. Also VEC analysis will be applied between electricity prices and Central Appalachian coal futures settlement prices as in 4 Lags.

Table 5.24 Lag Selection for VEC Model Between PVERDE D-A Average Price and CA Coal Future Settlement Price

Number of Lags	FPE Criteria	Akaike Criteria	Hannan-Quinn Criteria	Schwarz Bayesian Criteria
0	212.312,0000	11,0338	11,0401	11,0509
1	206.75	11,0073	11,0178	11,0358
2	199.957,0000	10,9739	10,9885	11,0138
3	197.813,0000	10,9631	10,9820	11,0144
4	192.739*	10.9371*	10.9602*	10.9999*

Final prediction error (FPE) , Akaike, Hannan-Quinn, Schwarz Bayesian criterias indicates the availability and suitability of implementation of a 4 Lag model between electricity prices and Central Appalachian coal futures settlement prices at NP HUB. Also VEC analysis will be applied between electricity prices and Central Appalachian coal futures settlement prices as in 4 Lags.

Table 5.25 Lag Selection for VEC Model Between NP D-A Average Price and CA Coal Future Settlement Price

Number of Lags	FPE Criteria	Akaike Criteria	Hannan-Quinn Criteria	Schwarz Bayesian Criteria
0	12,1536	8,1734	8,1847	8,20309*
1	12,0379	8,1638	8,1827	8,2133
2	11,8657	8,1494	8,17576*	8,2187
3	11,8336*	8,14669*	8,1806	8,2358
4	11,8634	8,1492	8,1906	8,2581

Final prediction error (FPE) , Akaike, Hannan-Quinn, Schwarz Bayesian criterias indicates the availability and suitability of implementation of a 4 Lag model between electricity prices and Central Appalachian coal futures settlement prices at MIDC HUB. Also VEC analysis will be applied between electricity prices and Central Appalachian coal futures settlement prices as in 4 Lags.

Table 5.26 Lag Selection for VEC Model Between MIDC D-A Average Price and CA Coal Future Settlement Price

Number of Lags	FPE Criteria	Akaike Criteria	Hannan-Quinn Criteria	Schwarz Bayesian Criteria
0	143,3730	10,6412	10,6475	10,6583
1	142,7890	10,6371	10,6476	10,6657
2	139,1430	10,6113	10,6259	10,6512*
3	137,9390	10,6026	10,6214	10,6539
4	136.27*	10.5904*	10.6135*	10,6532

Final prediction error (FPE) , Akaike, Hannan-Quinn, Schwarz Bayesian criterias indicates the availability and suitability of implementation of a 4 Lag model between electricity prices and Central Appalachian coal futures settlement prices at MASS HUB. Also VEC analysis will be applied between electricity prices and Central Appalachian coal futures settlement prices as in 4 Lags.

Table 5.27 Lag Selection for VEC Model Between MASS D-A Average Price and CA Coal Future Settlement Price

Number of Lags	FPE Criteria	Akaike Criteria	Hannan-Quinn Criteria	Schwarz Bayesian Criteria
0	453,7190	11,7932	11,7996	11,8104
1	445,9870	11,7760	11,7866	11,8047
2	435,1750	11,7515	11,7663	11.7917*
3	434,5120	27,6990	11,7690	11,8016
4	427.785*	11.7344*	11.7576*	11,7975

Final prediction error (FPE) , Akaike, Hannan-Quinn, Schwarz Bayesian criterias indicates the availability and suitability of implementation of a 4 Lag model between electricity prices and Central Appalachian coal futures settlement prices at IND HUB. Also VEC analysis will be applied between electricity prices and Central Appalachian coal futures settlement prices as in 4 Lags.

Table 5.28 Lag Selection for VEC Model Between IND D-A Average Price and CA Coal Future Settlement Price

Number of Lags	FPE Criteria	Akaike Criteria	Hannan-Quinn Criteria	Schwarz Bayesian Criteria
0	140,1550	10,6185	10,6248	10,6356
1	138,7200	10,6082	10,6187	10,6367
2	135,7040	10,5862	10,6009	10,6261
3	133,9080	10,5729	10,5918	10,6242
4	131,707*	10,5563*	10,5794*	10,619*

Table 5.28 indicates Lagged selection test for the VEC Model that will be implemented between electricity prices and Central Appalachian coal futures settlement prices at SP-15 HUB. Final prediction error (FPE) , Akaike, ve Hannan-Quinn criterias indicates the suitability of a 4 Lagged model while Schwarz Bayesian indicates a model with out a Lag. Because of more criterias are suggesting a 4 Lagged model, in VEC framework; a 4 Lagged model will be employed in order to investigate the relation between electricity prices and Central Appalachian coal futures settlement prices at SP-15.

Table 5.29 Lag Selection for VEC Model Between SP-15 D-A Average Price and Natural Gas Future Settlement Price

Number of Lags	FPE Criteria	Akaike Criteria	Hannan-Quinn Criteria	Schwarz Bayesian Criteria
0	38.7365	9.33254	9.33892	9.34989*
1	38.3085	9.32142	9.33207	9.35035
2	37.8773	9.31011	9.325	9.3506
3	37.7159	9.30584	9.32499	9.3579
4	37.2729*	9.29402*	9.31743*	9.35765

Table 5.29 Lagged selection test for the VEC Model that will be implemented between electricity prices and Central Appalachian coal futures settlement prices at PJM HUB. Final prediction error (FPE) , Akaike, ve Hannan-Quinn criteras indicates the suitability of a 4 Lagged model while Schwarz Bayesian indicates a model with out a Lag. Because of more criterias are suggesting a 4 Lagged model, in VEC framework; a 4 Lagged model will be employed in order to investigate the relation between electricity prices and Central Appalachian coal futures settlement prices at PJM.

Table 5.30 Lag Selection for VEC Model Between PJM D-A Average Price and Natural Gas Future Settlement Price

Number of Lags	FPE Criteria	Akaike Criteria	Hannan-Quinn Criteria	Schwarz Bayesian Criteria
0	59,0994	9,7549800	9,7611600	9,7718100
1	57,0843	9,7202800	9,7305900	9,7483500
2	56,4251	9,7086700	9,72309*	9,74795*
3	56,4619	9,7093200	9,7278700	9,7598300
4	56,0123	9,70132*	9,7240000	9,7630600

Table 5.30 Lagged selection test for the VEC Model that will be implemented between electricity prices and Central Appalachian coal futures settlement prices at PVERDE HUB. Final prediction error (FPE), Akaike, ve Hannan-Quinn criteras indicates the suitability of a 4 Lagged model while Schwarz Bayesian indicates a model with out a Lag. Because of more criterias are suggesting a 4 Lagged model, in VEC framework; a 4 Lagged model will be employed in order to investigate the relation between electricity prices and Central Appalachian coal futures settlement prices at PVERDE.

Table 5.31 Lag Selection for VEC Model Between PVERDE D-A Average Price and Natural Gas Future Settlement Price

Number of Lags	FPE Criteria	Akaike Criteria	Hannan-Quinn Criteria	Schwarz Bayesian Criteria
0	29,786400	9,069800	9,076100	9,08692*
1	29,488700	9,059760	9,070250	9,088290
2	29,181500	9,049290	9,063970	9,089230
3	29,114600	9,046990	9,065870	9,098350
4	28,88*	9,0389*	9,06198*	9,101670

Table 5.31 Lagged selection test for the VEC Model that will be implemented between electricity prices and Central Appalachian coal futures settlement prices at NP HUB. Final prediction error (FPE), Akaike, ve Hannan-Quinn criteras indicates the suitability of a 4 Lagged model while Schwarz Bayesian indicates a model with out a Lag. Because of more criterias are suggesting a 4 Lagged model, in VEC framework; a 4 Lagged model will be employed in order to investigate the relation between electricity prices and Central Appalachian coal futures settlement prices at NP.

Table 5.32 Lag Selection for VEC Model Between NP D-A Average Price and Natural Gas Future Settlement Price

Number of Lags	FPE Criteria	Akaike Criteria	Hannan-Quinn Criteria	Schwarz Bayesian Criteria
0	2,91337	6,74507	6,75636	6,77477
1	2,85349	6,72430	6,74313	6,77381*
2	2,81926*	6,71223*	6,73859*	6,78155
3	2,82310	6,71359	6,74748	6,80271
4	2,83468	6,71768	6,75910	6,82661

Table 5.32 Lagged selection test for the VEC Model that will be implemented between electricity prices and Central Appalachian coal futures settlement prices at MIDC HUB. Final prediction error (FPE), Akaike, ve Hannan-Quinn criteras indicates the suitability of a 4 Lagged model while Schwarz Bayesian indicates a model with out a Lag. Because of more criterias are suggesting a 4 Lagged model, in VEC framework; a 4 Lagged model will be employed in order to investigate the relation between electricity prices and Central Appalachian coal futures settlement prices at MIDC.

Table 5.33 Lag Selection for VEC Model Between MIDC D-A Average Price and Natural Gas Future Settlement Price

Number of Lags	FPE Criteria	Akaike Criteria	Hannan-Quinn Criteria	Schwarz Bayesian Criteria
0	21,56650	8,74689	8,75319	8,76401*
1	21,50670	8,74412	8,75461	8,77265
2	21,16510	8,72811	8,74279	8,76805
3	21,02580	8,72151	8,74039*	8,77286
4	20,9519*	8.71798*	8,74106	8,78075

Table 5.33 Lagged selection test for the VEC Model that will be implemented between electricity prices and Central Appalachian coal futures settlement prices at MASS HUB. Final prediction error (FPE), Akaike, ve Hannan-Quinn criteras indicates the suitability of a 4 Lagged model while Schwarz Bayesian indicates a model with out a Lag. Because of more criteras are suggesting a 4 Lagged model, in VEC framework; a 4 Lagged model will be employed in order to investigate the relation between electricity prices and Central Appalachian coal futures settlement prices at MASS.

Table 5.34 Lag Selection for VEC Model Between MASS D-A Average Price and Natural Gas Future Settlement Price

Number of Lags	FPE Criteria	Akaike Criteria	Hannan-Quinn Criteria	Schwarz Bayesian Criteria
0	68,23690	9,89874	9,90507	9,91595
1	66,14580	9,86762	9,87817	9,89631
2	65,20650	9,85331	9,86808*	9,89348*
3	65,23690	9,85378	9,87277	9,90542
4	64,8762*	9,84823*	9,87144	9,91135

Table 5.34 Lagged selection test for the VEC Model that will be implemented between electricity prices and Central Appalachian coal futures settlement prices at IND HUB. Final prediction error (FPE) , Akaike, ve Hannan-Quinn criteras indicates the suitability of a 4 Lagged model while Schwarz Bayesian indicates a model with out a Lag. Because of more criteras are suggesting a 4 Lagged model, in VEC framework; a 4 Lagged model will be employed in order to investigate the relation between electricity prices and Central Appalachian coal futures settlement prices at IND.

Table 5.35 Lag Selection for VEC Model Between IND D-A Average Price and Natural Gas Future Settlement Price

Number of Lags	FPE Criteria	Akaike Criteria	Hannan-Quinn Criteria	Schwarz Bayesian Criteria
0	20,650400	8,703490	8,709770	8,720580
1	20,135400	8,678230	8,688700	8,70672*
2	20,046900	8,673830	8,688490	8,713710
3	19,940900	8,668530	8,68737*	8,719800
4	19,8811*	8,66553*	8,688560	8,728190

Table 5.36 shows the result of the VEC Model implemented on the relation between day-ahead electricity average prices and Central Appalachian Coal Futures Settlement prices.

Dependent variable on left panel of the table is the first difference of average day-ahead electricity price at SP-15 hub. There exist long term effects of coal futures settlement prices on average day-ahead electricity prices. The coefficient on adjustment parameter is statistically significant at 1% level and also. At the same time short term effects and corrections on electricity prices are also evident. Specially 1st, 2nd, 3rd and 4th lags of first differences of electricity prices are negative and statistically significant. Only fourth lag of the first difference of coal future settlement prices is statistically significant with a positive coefficient. The model's R square is %17.03 on the left panel of Table 5.36.

Dependent variable on right panel of Table 5.36 is the first difference of Central Appalachian coal future prices. Adjustment parameter is positive and shows long term effect of average day ahead electricity prices on coal futures settlement prices. In other words, prices tend to reach equilibrium via a long term process. In the short term, 1. lag of the first difference of electricity prices has statistically significant effect at %5 level. The first difference of coal future settlement prices has positive effect on dependent variable only at the 1st and 4th lags. R square of this model is %3.91 on the right panel of Table 5.36.

As we consider whole VEC model given on Table 5.36, two way relation is observed among coal futures and day ahead average electricity prices at SP-15 hub. Short term corrections are present from day ahead electricity prices to Central Appalachian coal futures prices and vice versa.

Lagrange Multiplier Test is applied for the detection of autocorrelation and we reject the existence of first order autocorrelation process.

Table 5.36 VEC Model Between SP-15 D-A Av. Price and CA Coal Fut. Sett. Price

Dependent Variable: Δ SP-15 D-A Av. Price				Dependent Variable: Δ CA Coal Fut. Sett. Price			
Variable	Coefficient	Z Value	Prob.	Variable	Coefficient	Z Value	Prob.
Constant	-0.000028	0	1	Constant	-0.0005345	-0.02	0.987
Adjustment Parameter	-0.0677055	-5.61	0	Adjustment Parameter	0.0035432	2.03	0.043
Δ SP-15 D-A Av. Price _{t-1}	-0.3066065	-12.82	0	Δ SP-15 D-A Av. Price _{t-1}	-0.0046391	-2.64	0.008
Δ SP-15 D-A Av. Price _{t-2}	-0.2852059	-11.77	0	Δ SP-15 D-A Av. Price _{t-2}	-0.0092729	-1.34	0.181
Δ SP-15 D-A Av. Price _{t-3}	-0.1870263	-7.86	0	Δ SP-15 D-A Av. Price _{t-3}	-0.0031774	-0.92	0.357
Δ SP-15 D-A Av. Price _{t-4}	-0.1610658	-7.12	0	Δ SP-15 D-A Av. Price _{t-4}	0.0000629	0.02	0.985
Δ CA Coal Fut. Sett. Price _{t-1}	0.1122646	0.72	0.474	Δ CA Coal Fut. Sett. Price _{t-1}	0.155782	6.85	0
Δ CA Coal Fut. Sett. Price _{t-2}	0.0392843	0.25	0.805	Δ CA Coal Fut. Sett. Price _{t-2}	-0.0027426	-0.12	0.905
Δ CA Coal Fut. Sett. Price _{t-3}	0.0946507	0.6	0.551	Δ CA Coal Fut. Sett. Price _{t-3}	-0.0322418	-1.4	0.161
Δ CA Coal Fut. Sett. Price _{t-4}	0.2725457	1.74	0.082	Δ CA Coal Fut. Sett. Price _{t-4}	0.1005675	4.43	0
R Square: 17.03%				R Square: 3.91%			
Lagrange Multiplier Test Lag 1 Probability: 0.16840							
Lagrange Multiplier Test Lag 2 Probability: 0.01904							

Table 5.37 shows the result of the VEC Model implemented on the relation between day-ahead electricity average prices and Central Appalachian Coal Futures Settlement prices.

Dependent variable on left panel of the table is the first difference of average day-ahead electricity price at PJM hub. There exist long term effects of coal futures settlement prices on average day-ahead electricity prices. The coefficient on adjustment parameter is statistically significant at 1% level and also. At the same time short term effects and corrections on electricity prices are also evident. Specially 1st, 2nd, 3rd and 4th lags of first differences of electricity prices are negative and statistically significant. Only fourth lag of the first difference of coal future settlement prices is statistically significant with a positive coefficient. The model's R square is %15,56 on the left panel of Table 5.37.

Dependent variable on right panel of Table 5.37 is the first difference of Central Appalachian coal future prices. Adjustment parameter is positive and shows long term effect of average day ahead electricity prices on coal futures settlement prices. In other words, prices tend to reach equilibrium via a long term process. In the short term, 1. lag of the first difference of electricity prices has statistically significant effect at %5 level. The first difference of coal future settlement prices has positive effect on dependent variable only at the 1st and 4th lags. R square of this model is %1.55 on the right panel of Table 5.37.

As we consider whole VEC model given on Table 5.37, two way relation is observed among coal futures and day ahead average electricity prices at PJM hub. Short term corrections are present from day ahead electricity prices to Central Appalachian coal futures prices and vice versa.

Lagrange Multiplier Test is applied for the detection of autocorrelation and we reject the existence of first order autocorrelation process.

Table 5.37 VEC Model Between PJM D-A Average Price and CA Coal Future Settlement Price

Dependent Variable: Δ PJM D-A Av. Price				Dependent Variable: ΔCA Coal Fut. Sett. Price			
Variable	Coefficient	Z Value	Probability	Variable	Coefficient	Z Value	Probability
Constant	-0,000125	0	1	Constant	0,0004697	0,01	0,989
Adjustment Parameter	-0,130204	-8.92	0	Adjustment Parameter	0, 0034719	1,88	0,061
ΔPJM D-A Av. Price _{t-1}	0,502258	2,13	0	ΔPJM D-A Av. Price _{t-1}	0,0003408	1.11	0,909
ΔPJM D-A Av. Price _{t-2}	-0,228842	-9,92	0	ΔPJM D-A Av. Price _{t-2}	-0,0045879	-1,57	0,117
ΔPJM D-A Av. Price _{t-3}	-0.0987767	-4,45	0	ΔPJM D-A Av. Price _{t-3}	-0, 0027643	0.98	0,326
ΔPJM D-A Av. Price _{t-4}	-0,135192	-6,07	0	ΔPJM D-A Av. Price _{t-4}	-0, 0047631	-1,69	0,092
ΔCA Coal Fut. Sett. Price _{t-1}	0,147765	0,84	0,402	ΔCA Coal Fut. Sett. Price _{t-1}	0, 0712962	3,19	0,001
ΔCA Coal Fut. Sett. Price _{t-2}	-0,010427	-0,06	0,953	ΔCA Coal Fut. Sett. Price _{t-2}	-0, 0077395	0,35	0,729
ΔCA Coal Fut. Sett. Price _{t-3}	0,18807	1,07	0,287	ΔCA Coal Fut. Sett. Price _{t-3}	-0, 0373398	-1,67	0,095
ΔCA Coal Fut. Sett. Price _{t-4}	0,102246	0,58	0,562	ΔCA Coal Fut. Sett. Price _{t-4}	0, 0741065	3,32	0,001
R Square: 15,56%				R Square: 1,55%			
Lagrange Multplier Test Lag 1 Probability: 0,00098							
Lagrange Multplier Test Lag 2 Probability: 0,00007							

Table 5.38 shows the result of the VEC Model implemented on the relation between day-ahead electricity average prices and Central Appalachian Coal Futures Settlement prices.

Dependent variable on left panel of the table is the first difference of average day-ahead electricity price at PVERDE hub. There exist long term effects of coal futures settlement prices on average day-ahead electricity prices. The coefficient on adjustment parameter is statistically significant at 1% level and also. At the same time short term effects and corrections on electricity prices are also evident. Specially 1st, 2nd, 3rd and 4th lags of first differences of electricity prices are negative and statistically significant. Only fourth lag of the first difference of coal future settlement prices is statistically significant with a positive coefficient. The model's R square is %14,84 on the left panel of Table 5.38.

Dependent variable on right panel of Table 5.38 is the first difference of Central Appalachian coal future prices. Adjustment parameter is positive and shows long term effect of average day ahead electricity prices on coal futures settlement prices. In other words, prices tend to reach equilibrium via a long term process. In the short term, 1. lag of the first difference of electricity prices has statistically significant effect at %5 level. The first difference of coal future settlement prices has positive effect on dependent variable only at the 1st and 4th lags. R square of this model is %1.40 on the right panel of Table 5.38.

As we consider whole VEC model given on Table 5.38, two way relation is observed among coal futures and day ahead average electricity prices at PVERDE hub. Short term corrections are present from day ahead electricity prices to Central Applachian coal futures prices and vice versa.

Lagrange Multiplier Test is applied for the detection of autocorrelation and we reject the existence of first order autocorrelation process.

Table 5.38 VEC Model Between PVERDE D-A Average Price and CA Coal Future Settlement Price

Dependent Variable: Δ PVERDE-15 D-A Av. Price				Dependent Variable: Δ CA Coal Fut. Sett. Price			
Variable	Coefficient	Z Value	Probability	Variable	Coefficient	Z Value	Probability
Constant	-0,0000509	0	1	Constant	-0,0008017	-0,02	0,982
Adjustment Parameter	-0,060805	-5,52	0	Adjustment Parameter	0,0033837	1,92	0,054
Δ PVERDE D-A Av. Price _{t-1}	-0,2725263	-11,61	0	Δ PVERDE D-A Av. Price _{t-1}	-0,0033837	-0,79	0,429
Δ PVERDE D-A Av. Price _{t-2}	-0,2596543	-10,93	0	Δ PVERDE D-A Av. Price _{t-2}	-0,0114311	-2,64	0,008
Δ PVERDE D-A Av. Price _{t-3}	-0,1624042	-6,94	0	Δ PVERDE D-A Av. Price _{t-3}	-0,0052035	-1,22	0,222
Δ PVERDE D-A Av. Price _{t-4}	-0,1486505	-6,62	0	Δ PVERDE D-A Av. Price _{t-4}	0,0017325	0,42	0,672
Δ CA Coal Fut. Sett. Price _{t-1}	0,1031151	0,83	0,406	Δ CA Coal Fut. Sett. Price _{t-1}	0,0465032	2,06	0,040
Δ CA Coal Fut. Sett. Price _{t-2}	0,1031151	1,08	0,282	Δ CA Coal Fut. Sett. Price _{t-2}	0,025662	1,13	0,256
Δ CA Coal Fut. Sett. Price _{t-3}	0,0736429	0,59	0,553	Δ CA Coal Fut. Sett. Price _{t-3}	-0,0319772	-1,41	0,157
Δ CA Coal Fut. Sett. Price _{t-4}	0,2951982	2,38	0,017	Δ CA Coal Fut. Sett. Price _{t-4}	0,0707174	3,13	0,002
R Square: 14,84%				R Square: 1,40%			
Lagrange Multplier Test Lag 1 Probability: 0.29670							
Lagrange Multplier Test Lag 2 Probability: 0.00685							

Table 5.39 shows the result of the VEC Model implemented on the relation between day-ahead electricity average prices and Central Appalachian Coal Futures Settlement prices.

Dependent variable on left panel of the table is the first difference of average day-ahead electricity price at NP hub. There exist long term effects of coal futures settlement prices on average day-ahead electricity prices. The coefficient on adjustment parameter is statistically significant at 1% level and also. At the same time short term effects and corrections on electricity prices are also evident. Specially 2nd and 3rd lags of first differences of electricity prices are negative and statistically significant. Only fourth lag of the first difference of coal future settlement prices is statistically significant with a positive coefficient. The model's R square is %10,37 on the left panel of Table 5.39.

Dependent variable on right panel of Table 5.39 is the first difference of Central Appalachian coal future prices. Adjustment parameter is positive and shows long term effect of average day ahead electricity prices on coal futures settlement prices. In other words, prices tend to reach equilibrium via a long term process. In the short term, 1st lag of the first difference of electricity prices has statistically significant effect at %5 level. The first difference of coal future settlement prices has positive effect on dependent variable only at the 1st, 2nd and 3rd lags. R square of this model is %1.75 on the right panel of Table 5.39.

As we consider whole VEC model given on Table 5.39, two way relation is observed among coal futures and day ahead average electricity prices at NP hub. Short term corrections are present from day ahead electricity prices to Central Appalachian coal futures prices and vice versa.

Lagrange Multiplier Test is applied for the detection of autocorrelation and we reject the existence of first order autocorrelation process.

Table 5.39 VEC Model Between NP D-A Average Price and CA Coal Future Settlement Price

Dependent Variable: Δ NP-15 D-A Av. Price				Dependent Variable: Δ CA Coal Fut. Sett. Price			
Variable	Coefficient	Z Value	Probability	Variable	Coefficient	Z Value	Probability
Constant	-0,000019	-0,00	1,00	Constant	0,009921	0,35	0,729
Adjustment Parameter	-0,09946	-6,28	0,00	Adjustment Parameter	-0,00019	-0,05	0,96
Δ NP D-A Av. Price _{t-1}	0,024708	0,76	0,446	Δ NP D-A Av. Price _{t-1}	-0,004409	-0,57	0,569
Δ NP D-A Av. Price _{t-2}	-0,156479	-4,98	0	Δ NP D-A Av. Price _{t-2}	-0,003633	-0,48	0,628
Δ NP D-A Av. Price _{t-3}	-0,064805	-2,05	0,041	Δ NP D-A Av. Price _{t-3}	-0,007486	-0,99	0,322
Δ CA Coal Fut. Sett. Price _{t-1}	0,35295	2,63	0,0008	Δ CA Coal Fut. Sett. Price _{t-1}	0,085944	2,69	0,007
Δ CA Coal Fut. Sett. Price _{t-2}	-0,059514	-0,44	0,659	Δ CA Coal Fut. Sett. Price _{t-2}	0,01356	0,42	0,673
Δ CA Coal Fut. Sett. Price _{t-3}	0,317038	2,36	0,018	Δ CA Coal Fut. Sett. Price _{t-3}	0,013814	0,43	0,667
R Square: 9,68 %				R Square: 0,94 %			
Lagrange Multiplier Test Lag 1 Probability: 0,21455							
Lagrange Multiplier Test Lag 2 Probability: 0,41271							

Table 5.40 shows the result of the VEC Model implemented on the relation between day-ahead electricity average prices and Central Appalachian Coal Futures Settlement prices.

Dependent variable on left panel of the table is the first difference of average day-ahead electricity price at MIDC hub. There exist long term effects of coal futures settlement prices on average day-ahead electricity prices. The coefficient on adjustment parameter is statistically significant at 1% level and also. At the same time short term effects and corrections on electricity prices are also evident. Specially; 1st, 2nd, 3rd and 4th lags of first differences of electricity prices are negative and statistically significant. Only fourth lag of the first difference of coal future settlement prices is statistically significant with a positive coefficient. The model's R square is %9,4 on the left panel of Table 5.40.

Dependent variable on right panel of Table 5.40 is the first difference of Central Appalachian coal future prices. Adjustment parameter is positive and shows long term effect of average day ahead electricity prices on coal futures settlement prices. In other words, prices tend to reach equilibrium via a long term process. In the short term, 1. lag of the first difference of electricity prices has statistically significant effect at %5 level. The first difference of coal future settlement prices has positive effect on dependent variable only at the 1st lag. R square of this model is %1.18 on the right panel of Table 5.40.

As we consider whole VEC model given on Table 5.40, two way relation is observed among coal futures and day ahead average electricity prices at MIDC hub. Short term corrections are present from day ahead electricity prices to Central Applachian coal futures prices and vice versa.

Lagrange Multiplier Test is applied for the detection of autocorrelation and we reject the existence of first order autocorrelation process.

Table 5.40 VEC Model Between MIDC D-A Average Price and CA Coal Future Settlement Price

Dependent Variable: ΔMIDC-15 D-A Av. Price				Dependent Variable: ΔCA Coal Fut. Sett. Price			
Variable	Coefficient	Z Value	Probability	Variable	Coefficient	Z Value	Probability
Constant	1,110006	0	1,00	Constant	0,0000232	0	0,999
Adjustment Parameter	-0,052737	-5,6	0,00	Adjustment Parameter	0,0025211	1,23	0,217
ΔMIDC D-A Av. Price _{t-1}	-0.1327978	-5,73	0,446	ΔMIDC D-A Av. Price _{t-1}	-0,0090363	-1,79	0,073
ΔMIDC D-A Av. Price _{t-2}	-0,207305	-9	0,00	ΔMIDC D-A Av. Price _{t-2}	-0,009869	-0,60	0,049
ΔMIDC D-A Av. Price _{t-3}	-0,127427	-5,59	0,00	ΔMIDC D-A Av. Price _{t-3}	-0,0029891	-0,36	0,546
ΔMIDC D-A Av. Price _{t-4}	-0,102973	-4,56	0,00	ΔMIDC D-A Av. Price _{t-4}	-0,0017686	-3,69	0,718
ΔCA Coal Fut. Sett. Price _{t-1}	0.0875005	0,84	0,401	ΔCA Coal Fut. Sett. Price _{t-1}	0,0469448	2,08	0,038
ΔCA Coal Fut. Sett. Price _{t-2}	0,067751	0,65	0,516	ΔCA Coal Fut. Sett. Price _{t-2}	-0,0246581	1,09	0,276
ΔCA Coal Fut. Sett. Price _{t-3}	0,0165503	0,16	0,874	ΔCA Coal Fut. Sett. Price _{t-3}	-0.0316715	-1,40	0,162
ΔCA Coal Fut. Sett. Price _{t-4}	0,0889722	0,85	0,393	ΔCA Coal Fut. Sett. Price _{t-4}	-0.0713768	3,16	0,002
R Square: 9,4 %				R Square: 1,18%			
Lagrange Multplier Test Lag 1 Probability: 0.63496							
Lagrange Multplier Test Lag 2 Probability: 0.15871							

Table 5.41 shows the result of the VEC Model implemented on the relation between day-ahead electricity average prices and Central Appalachian Coal Futures Settlement prices.

Dependent variable on left panel of the table is the first difference of average day-ahead electricity price at MASS hub. There exist long term effects of coal futures settlement prices on average day-ahead electricity prices. The coefficient on adjustment parameter is statistically significant at 1% level and also. At the same time short term effects and corrections on electricity prices are also evident. Specially; 2nd, 3rd and 4th lags of first differences of electricity prices are negative and statistically significant. Only fourth lag of the first difference of coal future settlement prices is statistically significant with a positive coefficient. The model's R square is %12 on the left panel of Table 5.41.

Dependent variable on right panel of Table 5.41 is the first difference of Central Appalachian coal future prices. Adjustment parameter is positive and shows long term effect of average day ahead electricity prices on coal futures settlement prices. In other words, prices tend to reach equilibrium via a long term process. In the short term, 1. lag of the first difference of electricity prices has statistically significant effect at %5 level. The first difference of coal future settlement prices has positive effect on dependent variable only at the 1st and 2nd lags. R square of this model is %1.13 on the right panel of Table 5.41.

As we consider whole VEC model given on Table 5.41, two way relation is observed among coal futures and day ahead average electricity prices at MASS hub. Short term corrections are present from day ahead electricity prices to Central Applachian coal futures prices and vice versa.

Lagrange Multiplier Test is applied for the detection of autocorrelation and we reject the existence of first order autocorrelation process.

Table 5.41 VEC Model Between MASS D-A Average Price and CA Coal Future Settlement Price

Dependent Variable: Δ MASS-15 D-A Av. Price				Dependent Variable: Δ CA Coal Fut. Sett. Price			
Variable	Coefficient	Z Value	Probability	Variable	Coefficient	Z Value	Probability
Constant	0,0000788	0,00	1,00	Constant	0,0027305	0,08	0,940
Adjustment Parameter	-0,0989053	-7,89	0,00	Adjustment Parameter	-0,0028547	1,86	0,063
Δ MASS D-A Av. Price _{t-1}	0.0839354	3,57	0,00	Δ MASS D-A Av. Price _{t-1}	0,1534925	-0,55	0,579
Δ MASS D-A Av. Price _{t-2}	-0.1989056	-8,52	0,00	Δ MASS D-A Av. Price _{t-2}	-0,1309993	-1,56	0,118
Δ MASS D-A Av. Price _{t-3}	-0.0748427	-3,29	0,001	Δ MASS D-A Av. Price _{t-3}	0,0027946	-0,61	0,141
Δ MASS D-A Av. Price _{t-4}	-0.1140381	-5,00	0,00	Δ MASS D-A Av. Price _{t-4}	-0,0041138	-1,47	0,141
Δ CA Coal Fut. Sett. Price _{t-1}	0.1302841	0,70	0,482	Δ CA Coal Fut. Sett. Price _{t-1}	0,0620307	2,74	0,006
Δ CA Coal Fut. Sett. Price _{t-2}	-0.0825344	-0,45	0,656	Δ CA Coal Fut. Sett. Price _{t-2}	0,0120741	0,53	0,595
Δ CA Coal Fut. Sett. Price _{t-3}	0.0375373	0,20	0,84	Δ CA Coal Fut. Sett. Price _{t-3}	-0,0233612	-1,03	0,304
Δ CA Coal Fut. Sett. Price _{t-4}	0.2837446	1,53	0,125	Δ CA Coal Fut. Sett. Price _{t-4}	0,0646693	2,85	0,004
R Square: 12 %				R Square: 1,13 %			
Lagrange Multiplier Test Lag 1 Probability: 0,05664							
Lagrange Multiplier Test Lag 2 Probability: 0,02729							

Table 5.42 shows the result of the VEC Model implemented on the relation between day-ahead electricity average prices and Central Appalachian Coal Futures Settlement prices.

Dependent variable on left panel of the table is the first difference of average day-ahead electricity price at IND hub. There exist long term effects of coal futures settlement prices on average day-ahead electricity prices. The coefficient on adjustment parameter is statistically significant at 1% level and also. At the same time short term effects and corrections on electricity prices are also evident. Specially; 2nd and 3rd lags of first differences of electricity prices are negative and statistically significant. Only fourth lag of the first difference of coal future settlement prices is statistically significant with a positive coefficient. The model's R square is %0,1021 on the left panel of Table 5.42.

Dependent variable on right panel of Table 5.42 is the first difference of Central Appalachian coal future prices. Adjustment parameter is positive and shows long term effect of average day ahead electricity prices on coal futures settlement prices. In other words, prices tend to reach equilibrium via a long term process. In the short term, 1. lag of the first difference of electricity prices has statistically significant effect at %5 level. The first difference of coal future settlement prices has positive effect on dependent variable only at the 1st, 2nd, 3rd and 4th lags. R square of this model is %0,0079 on the right panel of Table 5.42.

As we consider whole VEC model given on Table 5.42, two way relation is observed among coal futures and day ahead average electricity prices at IND hub. Short term corrections are present from day ahead electricity prices to Central Applachian coal futures prices and vice versa.

Lagrange Multiplier Test is applied for the detection of autocorrelation and we reject the existence of first order autocorrelation process.

Table 5.42 VEC Model Between IND D-A Average Price and CA Coal Future Settlement Price

Dependent Variable: Δ IND-15 D-A Av. Price				Dependent Variable: ΔCA Coal Fut. Sett. Price			
Variable	Coefficient	Z Value	Probability	Variable	Coefficient	Z Value	Probability
Constant	0,0000285	0	1	Constant	0,0005993	0,02	0,987
Adjustment Parameter	-0,0904589	-8,19	0	Adjustment Parameter	0,0043096	1,81	0,070
Δ IND D-A Av. Price _{t-1}	0,0615551	2,69	0,007	Δ IND D-A Av. Price _{t-1}	0,0007232	0,15	0,883
Δ IND D-A Av. Price _{t-2}	-0,1539182	-6,93	0	Δ IND D-A Av. Price _{t-2}	-0,0051993	-1,09	0,277
Δ IND D-A Av. Price _{t-3}	-0,123444	-5,5	0	Δ IND D-A Av. Price _{t-3}	-0,0027166	-0,56	0,574
ΔCA Coal Fut. Sett. Price _{t-1}	-0,0772626	-0,74	0,462	ΔCA Coal Fut. Sett. Price _{t-1}	0,0662147	2,93	0,003
ΔCA Coal Fut. Sett. Price _{t-2}	0,2146096	2,04	0,041	ΔCA Coal Fut. Sett. Price _{t-2}	0,0116541	0,51	0,607
ΔCA Coal Fut. Sett. Price _{t-3}	0,1564046	1,49	0,137	ΔCA Coal Fut. Sett. Price _{t-3}	-0,0342886	-1,51	0,130
R Square: 10,21 %				R Square: 0,79 %			
Lagrange Multiplier Test Lag 1 Probability: 0.00000							
Lagrange Multiplier Test Lag 2 Probability: 0,00002							

Table 5.43 shows the result of the VEC Model implemented on the relation between day-ahead electricity average prices and natural gas futures settlement prices.

Dependent variable on left panel of the table is the first difference of average day-ahead electricity price at SP-15 hub. There exist long term effects of natural gas futures settlement prices on average day-ahead electricity prices. The coefficient on adjustment parameter is statistically significant at 1% level and also. At the same time short term effects and corrections on electricity prices are also evident. Specially; 1st , 2nd , 3rd and 4th lags of first differences of electricity prices are negative and statistically significant. Only fourth lag of the first difference of natural gas future settlement prices is statistically significant with a positive coefficient. The model's R square is %20,29 on the left panel of Table 5.43.

Dependent variable on right panel of Table 5.43 is the first difference of natural gas future prices. Adjustment parameter is positive and shows long term effect of average day ahead electricity prices on natural gas futures settlement prices. In other words, prices tend to reach equilibrium via a long term process. In the short term, 1. lag of the first difference of electricity prices has statistically significant effect at %5 level. The first difference of natural gas future settlement prices has positive effect on dependent variable only at the 2nd lag. R square of this model is %1,06 on the right panel of Table 5.43.

As we consider whole VEC model given on Table 5.43, two way relation is observed among natural gas futures and day ahead average electricity prices at SP hub. Short term corrections are present from day ahead electricity prices to natural gas futures prices and vice versa.

Lagrange Multiplier Test is applied for the detection of autocorrelation and we reject the existence of first order autocorrelation process.

Table 5.43 VEC Model Between SP-15 D-A Av. Price and Natural Gas Future Settlement Price

Dependent Variable: ΔSP-15 D-A Av. Price				Dependent Variable: ΔNatural Gas Fut. Sett. Price			
Variable	Coefficient	Z Value	Prob.	Variable	Coefficient	Z Value	Prob.
Constant	-0.0001259	0	1	Constant	-0.0099455	-0.69	0.490
Adjustment Parameter	-0.2111115	-10.04	0	Adjustment Parameter	0.0026724	1.94	0.052
ΔSP-15 D-A Av. Price _{t-1}	-0.2110774	-7.92	0	ΔSP-15 D-A Av. Price _{t-1}	-0.0059637	-3.42	0.001
ΔSP-15 D-A Av. Price _{t-2}	-0.203191	-7.83	0	ΔSP-15 D-A Av. Price _{t-2}	-0.0029189	-1.72	0.085
ΔSP-15 D-A Av. Price _{t-3}	-0.1281487	-5.21	0	ΔSP-15 D-A Av. Price _{t-3}	-0.0038594	-2.40	0.016
ΔSP-15 D-A Av. Price _{t-4}	-0.118097	-5.18	0	ΔSP-15 D-A Av. Price _{t-4}	-0.0032744	-2.20	0.028
ΔNatural Gas Fut. Sett. Price _{t-1}	0.9031207	2.57	0.01	ΔNatural Gas Fut. Sett. Price _{t-1}	-0.0342708	-1.49	0.135
ΔNatural Gas Fut. Sett. Price _{t-2}	0.3126703	0.89	0.374	ΔNatural Gas Fut. Sett. Price _{t-2}	0.0126575	0.55	0.582
ΔNatural Gas Fut. Sett. Price _{t-3}	0.1389026	0.4	0.692	ΔNatural Gas Fut. Sett. Price _{t-3}	-0.0267493	-1.17	0.243
ΔNatural Gas Fut. Sett. Price _{t-4}	-0.0991413	-0.28	0.777	ΔNatural Gas Fut. Sett. Price _{t-4}	-0.0051113	-0.22	0.823
R Square: 20.29%				R Square: 1.06%			
Lagrange Multplier Test Lag 1 Probability: 0.09736							
Lagrange Multplier Test Lag 2 Probability: 0.54343							

Table 5.44 PJM shows the result of the VEC Model implemented on the relation between day-ahead electricity average prices and natural gas futures settlement prices.

Dependent variable on left panel of the table is the first difference of average day-ahead electricity price at PJM hub. There exist long term effects of natural gas futures settlement prices on average day-ahead electricity prices. The coefficient on adjustment parameter is statistically significant at 1% level and also. At the same time short term effects and corrections on electricity prices are also evident. Specially; 2nd and 4th lags of first differences of electricity prices are negative and statistically significant. Only fourth lag of the first difference of natural gas future settlement prices is statistically significant with a positive coefficient. The model's R square is %18,10 on the left panel of Table 5.44.

Dependent variable on right panel of Table 5.44 is the first difference of natural gas future prices. Adjustment parameter is positive and shows long term effect of average day ahead electricity prices on natural gas futures settlement prices. In other words, prices tend to reach equilibrium via a long term process. In the short term, 1. lag of the first difference of electricity prices has statistically significant effect at %5 level. The first difference of natural gas future settlement prices has positive effect on dependent variable only at the 2nd lag. R square of this model is %0,55 on the right panel of Table 5.44.

As we consider whole VEC model given on Table 5.44, two way relation is observed among natural gas futures and day ahead average electricity prices at PJM hub. Short term corrections are present from day ahead electricity prices to natural gas futures prices and vice versa.

Lagrange Multiplier Test is applied for the detection of autocorrelation and we reject the existence of first order autocorrelation process.

Table 5.44 VEC Model Between PJM D-A Average Price and Natural Gas Future Settlement Price

Dependent Variable: ΔPJM D-A Av. Price				Dependent Variable: ΔNatural Gas Fut. Sett. Price			
Variable	Coefficient	Z Value	Prob.	Variable	Coefficient	Z Value	Prob.
Constant	0,000038	0,00	1,00	Constant	-0,0092614	-0,67	0,504
Adjustment Parameter	-0,2827338	-16,06	0,00	Adjustment Parameter	-0,0011593	-1,28	0,199
Δ PJM D-A Av. Price _{t-1}	0,1660302	7,53	0.00	Δ PJM D-A Av. Price _{t-1}	-0,0017623	-1.56	0.119
Δ PJM D-A Av. Price _{t-2}	-0,1208492	-5,44	0.00	Δ PJM D-A Av. Price _{t-2}	0,0005617	0.49	0.622
ΔNatural Gas Fut. Sett. Price _{t-1}	0,1507126	0,34	0.731	ΔNatural Gas Fut. Sett. Price _{t-1}	-0,0416311	-1.86	0.063
ΔNatural Gas Fut. Sett. Price _{t-2}	0,6881028	1,58	0.115	ΔNatural Gas Fut. Sett. Price _{t-2}	0,0140139	0.63	0.531
R Square: 18,10%				R Square: 0,55%			
Lagrange Multiplier Test Lag 1 Probability: 0,16540							
Lagrange Multiplier Test Lag 2 Probability: 0,43832							

Table 5.45 shows the result of the VEC Model implemented on the relation between day-ahead electricity average prices and natural gas futures settlement prices.

Dependent variable on left panel of the table is the first difference of average day-ahead electricity price at PVERDE hub. There exist long term effects of natural gas futures settlement prices on average day-ahead electricity prices. The coefficient on adjustment parameter is statistically significant at 1% level and also. At the same time short term effects and corrections on electricity prices are also evident. Specially; 1st, 2nd and 3rd lags of first differences of electricity prices are negative and statistically significant. Only fourth lag of the first difference of natural gas future settlement prices is statistically significant with a positive coefficient. The model's R square is %18,31 on the left panel of Table 5.45.

Dependent variable on right panel of Table 5.45 is the first difference of natural gas future prices. Adjustment parameter is positive and shows long term effect of average day ahead electricity prices on natural gas futures settlement prices. In other words, prices tend to reach equilibrium via a long term process. In the short term, 1. lag of the first difference of electricity prices has statistically significant effect at %5 level. The first difference of natural gas future settlement prices has positive effect on dependent variable only at the 2nd lag. R square of this model is %0,76 on the right panel of Table 5.45.

As we consider whole VEC model given on Table 5.45, two way relation is observed among natural gas futures and day ahead average electricity prices at PVERDE hub. Short term corrections are present from day ahead electricity prices to natural gas futures prices and vice versa.

Lagrange Multiplier Test is applied for the detection of autocorrelation and we reject the existence of first order autocorrelation process.

Table 5.45 VEC Model Between PVERDE D-A Average Price and Natural Gas Future Settlement Price

Dependent Variable: ΔPVERDE D-A Av. Price				Dependent Variable: ΔNatural Gas Fut. Sett. Price			
Variable	Coefficient	Z Value	Prob.	Variable	Coefficient	Z Value	Prob.
Constant	-0,0000607	-0,00	1,00	Constant	-0,009782	-0,69	0,492
Adjustment Parameter	-0,1977719	-10,13	0,00	Adjustment Parameter	0,0012264	0,85	0,394
ΔPVERDE D-A Av. Price _{t-1}	-0,1853478	-7,18	0,00	ΔPVERDE D-A Av. Price _{t-1}	0,0048561	-2.55	0.011
ΔPVERDE D-A Av. Price _{t-2}	-0,1814275	-7,19	0,00	ΔPVERDE D-A Av. Price _{t-2}	0,0016128	-0.87	0.386
ΔPVERDE D-A Av. Price _{t-3}	-0,1055812	-4,39	0,00	ΔPVERDE D-A Av. Price _{t-3}	0,0032748	-1.85	0.065
ΔPVERDE D-A Av. Price _{t-4}	-0,1067369	-4,73	0,00	ΔPVERDE D-A Av. Price _{t-4}	0,0014512	-0.87	0.383
ΔNatural Gas Fut. Sett. Price _{t-1}	0,8914517	2,88	0,004	ΔNatural Gas Fut. Sett. Price _{t-1}	-0,035974	-1.58	0.115
ΔNatural Gas Fut. Sett. Price _{t-2}	0,3875102	1,25	0,212	ΔNatural Gas Fut. Sett. Price _{t-2}	0,0133966	0.59	0.558
ΔNatural Gas Fut. Sett. Price _{t-3}	-0,0003139	-0,00	0,999	ΔNatural Gas Fut. Sett. Price _{t-3}	-0.0240943	-1.06	0.290
ΔNatural Gas Fut. Sett. Price _{t-4}	-0,1044361	-0,34	0,735	ΔNatural Gas Fut. Sett. Price _{t-4}	-0.0162581	-0.72	0.474
R Square: 18,31%				R Square: 0,76%			
Lagrange Multiplier Test Lag 1 Probability: 0,05459							
Lagrange Multiplier Test Lag 2 Probability: 0,29329							

Table 5.46 shows the result of the VEC Model implemented on the relation between day-ahead electricity average prices and natural gas futures settlement prices.

Dependent variable on left panel of the table is the first difference of average day-ahead electricity price at NP hub. There exist long term effects of natural gas futures settlement prices on average day-ahead electricity prices. The coefficient on adjustment parameter is statistically significant at 1% level and also. At the same time short term effects and corrections on electricity prices are also evident. Specially; 1st, 2nd, 3rd and 4th lags of first differences of electricity prices are negative and statistically significant. Only fourth lag of the first difference of natural gas future settlement prices is statistically significant with a positive coefficient. The model's R square is %10,37 on the left panel of Table 5.46.

Dependent variable on right panel of Table 5.46 is the first difference of natural gas future prices. Adjustment parameter is positive and shows long term effect of average day ahead electricity prices on natural gas futures settlement prices. In other words, prices tend to reach equilibrium via a long term process. In the short term, 1. lag of the first difference of electricity prices has statistically significant effect at %5 level. The first difference of natural gas future settlement prices has positive effect on dependent variable only at the 2nd lag. R square of this model is %1,75 on the right panel of Table 5.46.

As we consider whole VEC model given on Table 7-d, two way relation is observed among natural gas futures and day ahead average electricity prices at NP hub. Short term corrections are present from day ahead electricity prices to natural gas futures prices and vice versa.

Lagrange Multiplier Test is applied for the detection of autocorrelation and we reject the existence of first order autocorrelation process.

Table 5.46 VEC Model Between NP D-A Average Price and Natural Gas Future Settlement Price

Dependent Variable: ΔNP D-A Av. Price				Dependent Variable: ΔNatural Gas Fut. Sett. Price			
Variable	Coefficient	Z Value	Prob.	Variable	Coefficient	Z Value	Prob.
Constant	0,0000349	0,00	1,000	Constant	0,0026739	0,19	0,850
Adjustment Parameter	-0,1377841	-7,59	0,000	Adjustment Parameter	0,001796	0,84	0,403
ΔNP D-A Av. Price _{t-1}	0,0517618	1,63	0.103	ΔNP D-A Av. Price _{t-1}	-0.0000219	-0.01	0.995
ΔNP D-A Av. Price _{t-2}	-0,1343419	-4.26	0.000	ΔNP D-A Av. Price _{t-2}	0.0034815	0.93	0.350
				ΔNP D-A Av. Price _{t-3}			
				ΔNP D-A Av. Price _{t-4}			
ΔNatural Gas Fut. Sett. Price _{t-1}	0,8096957	3,00	0,003	ΔNatural Gas Fut. Sett. Price _{t-1}	-0.1206869	-3.78	0.000
ΔNatural Gas Fut. Sett. Price _{t-2}	0,1443843	0,53	0,595	ΔNatural Gas Fut. Sett. Price _{t-2}	0.0106221	0.33	0.741
				ΔNatural Gas Fut. Sett. Price _{t-3}			
				ΔNatural Gas Fut. Sett. Price _{t-4}			
R Square: 10,37%				R Square: 1,75%			
Lagrange Multplier Test Lag 1 Probability: 0,13740							
Lagrange Multplier Test Lag 2 Probability: 0,55847							

Table 5.47 shows the result of the VEC Model implemented on the relation between day-ahead electricity average prices and natural gas futures settlement prices.

Dependent variable on left panel of the table is the first difference of average day-ahead electricity price at MID-C hub. There exist long term effects of natural gas futures settlement prices on average day-ahead electricity prices. The coefficient on adjustment parameter is statistically significant at 1% level and also. At the same time short term effects and corrections on electricity prices are also evident. Specially; 1st, 3rd and 4th lags of first differences of electricity prices are negative and statistically significant. Only fourth lag of the first difference of natural gas future settlement prices is statistically significant with a positive coefficient. The model's R square is %11.04 on the left panel of Table 5.47.

Dependent variable on right panel of Table 5.47 is the first difference of natural gas future prices. Adjustment parameter is positive and shows long term effect of average day ahead electricity prices on natural gas futures settlement prices. In other words, prices tend to reach equilibrium via a long term process. In the short term, 1. lag of the first difference of electricity prices has statistically significant effect at %5 level. The first difference of natural gas future settlement prices has positive effect on dependent variable only at the 2nd lag. R square of this model is %0,68 on the right panel of Table 5.47.

As we consider whole VEC model given on Table 5.47, two way relation is observed among natural gas futures and day ahead average electricity prices at MID-C hub. Short term corrections are present from day ahead electricity prices to natural gas futures prices and vice versa.

Lagrange Multiplier Test is applied for the detection of autocorrelation and we reject the existence of first order autocorrelation process.

Table 5.47 VEC Model Between MIDC D-A Average Price and Natural Gas Future Settlement Price

Dependent Variable: ΔMIDC D-A Av. Price				Dependent Variable: ΔNatural Gas Fut. Sett. Price			
Variable	Coefficient	Z Value	Prob.	Variable	Coefficient	Z Value	Prob.
Constant	-0,0000932	-0,00	1,000	Constant	-0,009888	-0,69	0,487
Adjustment Parameter	0,0130819	-7,88	0,000	Adjustment Parameter	0,000972	0,86	0,392
ΔMIDC D-A Av. Price _{t-1}	-0,1004287	-4,22	0,000	ΔMIDC D-A Av. Price _{t-1}	-0,004422	-2.14	0.032
ΔMIDC D-A Av. Price _{t-2}	-0,1759495	-7,49	0,000	ΔMIDC D-A Av. Price _{t-2}	-0,000712	-0.35	0.727
ΔMIDC D-A Av. Price _{t-3}	-0,1071388	-4,67	0,000	ΔMIDC D-A Av. Price _{t-3}	-0,003891	-1.95	0.051
ΔMIDC D-A Av. Price _{t-4}	-0,0834884	-3,69	0,000	ΔMIDC D-A Av. Price _{t-4}	-0,001532	-0.78	0.435
ΔNatural Gas Fut. Sett. Price _{t-1}	0,562637	2,15	0,032	ΔNatural Gas Fut. Sett. Price _{t-1}	-0,038970	-1.71	0.086
ΔNatural Gas Fut. Sett. Price _{t-2}	-0,2021022	-0,77	0,441	ΔNatural Gas Fut. Sett. Price _{t-2}	0,0106246	0.47	0.641
ΔNatural Gas Fut. Sett. Price _{t-3}	-0,0195644	-0,07	0,940	ΔNatural Gas Fut. Sett. Price _{t-3}	-0,027477	-1.21	0.225
ΔNatural Gas Fut. Sett. Price _{t-4}	-0,1030253	-0,40	0,693	ΔNatural Gas Fut. Sett. Price _{t-4}	-0,016789	-0.74	0.458
R Square: 11,04%				R Square: 0,68%			
Lagrange Multiplier Test Lag 1 Probability: 0,70624							
Lagrange Multiplier Test Lag 2 Probability: 0,41776							

Table 5.48 shows the result of the VEC Model implemented on the relation between day-ahead electricity average prices and natural gas futures settlement prices.

Dependent variable on left panel of the table is the first difference of average day-ahead electricity price at MASS hub. There exist long term effects of natural gas futures settlement prices on average day-ahead electricity prices. The coefficient on adjustment parameter is statistically significant at 1% level and also. At the same time short term effects and corrections on electricity prices are also evident. Specially; 1st, 2nd, 3rd and 4th lags of first differences of electricity prices are negative and statistically significant. Only fourth lag of the first difference of natural gas future settlement prices is statistically significant with a positive coefficient. The model's R square is %13,35 on the left panel of Table 5.48.

Dependent variable on right panel of Table 5.48 is the first difference of natural gas future prices. Adjustment parameter is positive and shows long term effect of average day ahead electricity prices on natural gas futures settlement prices. In other words, prices tend to reach equilibrium via a long term process. In the short term, 1. lag of the first difference of electricity prices has statistically significant effect at %5 level. The first difference of natural gas future settlement prices has positive effect on dependent variable only at the 2nd lag. R square of this model is %0,73 on the right panel of Table 5.48.

As we consider whole VEC model given on Table 5.48, two way relation is observed among natural gas futures and day ahead average electricity prices at MASS hub. Short term corrections are present from day ahead electricity prices to natural gas futures prices and vice versa.

Lagrange Multiplier Test is applied for the detection of autocorrelation and we reject the existence of first order autocorrelation process.

Table 5.48 VEC Model Between MASS D-A Average Price and Natural Gas Future Settlement Price

Dependent Variable: ΔMASS D-A Av. Price				Dependent Variable: ΔNatural Gas Fut. Sett. Price			
Variable	Coefficient	Z Value	Prob.	Variable	Coefficient	Z Value	Prob.
Constant	0,000038	0,000	1,000	Constant	-0,009731	-0,68	0,494
Adjustment Parameter	-0,1890949	-12,76	0,000	Adjustment Parameter	-0,000738	-1,02	0,308
ΔMASS D-A Av. Price _{t-1}	0,1534925	6,83	0,000	ΔMASS D-A Av. Price _{t-1}	-0,0020024	-1.82	0.068
ΔMASS D-A Av. Price _{t-2}	-0,1309993	-5,76	0,000	ΔMASS D-A Av. Price _{t-2}	-0,0000549	-0.05	0.961
ΔNatural Gas Fut. Sett. Price _{t-1}	0,8723236	1,87	0.062	ΔNatural Gas Fut. Sett. Price _{t-1}	-0,0508624	-2.23	0.026
ΔNatural Gas Fut. Sett. Price _{t-2}	0,6043195	1,30	0.194	ΔNatural Gas Fut. Sett. Price _{t-2}	0,0335084	1,47	0.140
R Square: 13,35 %				R Square: 0,73 %			
Lagrange Multiplier Test Lag 1 Probability: 0,08755							
Lagrange Multiplier Test Lag 2 Probability: 0,22240							

Table 5.49 shows the result of the VEC Model implemented on the relation between day-ahead electricity average prices and natural gas futures settlement prices.

Dependent variable on left panel of the table is the first difference of average day-ahead electricity price at IND hub. There exist long term effects of natural gas futures settlement prices on average day-ahead electricity prices. The coefficient on adjustment parameter is statistically significant at 1% level and also. At the same time short term effects and corrections on electricity prices are also evident. Specially; 2nd and 3rd lags of first differences of electricity prices are negative and statistically significant. Only fourth lag of the first difference of natural gas future settlement prices is statistically significant with a positive coefficient. The model's R square is %15,63 on the left panel of Table 5.49.

Dependent variable on right panel of Table 5.49 is the first difference of natural gas future prices. Adjustment parameter is positive and shows long term effect of average day ahead electricity prices on natural gas futures settlement prices. In other words, prices tend to reach equilibrium via a long term process. In the short term, 1. lag of the first difference of electricity prices has statistically significant effect at %5 level. The first difference of natural gas future settlement prices has positive effect on dependent variable only at the 2nd lag. R square of this model is %0,47 on the right panel of Table 5.49.

As we consider whole VEC model given on Table 5.49, two way relation is observed among natural gas futures and day ahead average electricity prices at IND hub. Short term corrections are present from day ahead electricity prices to natural gas futures prices and vice versa.

Lagrange Multiplier Test is applied for the detection of autocorrelation and we reject the existence of first order autocorrelation process.

Table 5.49 VEC Model Between IND D-A Average Price and Natural Gas Future Settlement Price

Dependent Variable: Δ IND D-A Average Price				Dependent Variable: Δ Natural Gas Future Settlement Price			
Variable	Coefficient	Z Value	Prob.	Variable	Coefficient	Z Value	Prob.
Constant	0,0000471	0,000	1,000	Constant	-0,0095779	-0.68	0,499
Adjustment Parameter	-0,1988371	-11,56	0,000	Adjustment Parameter	0,000978	-0,64	0,520
ΔIND D-A Av. Price _{t-1}	0,1008369	4.15	0,000	ΔIND D-A Av. Price _{t-1}	-0,0017938	-0.84	0.403
ΔIND D-A Av. Price _{t-2}	-0,1212576	-5,16	0,000	ΔIND D-A Av. Price _{t-2}	-0,0013294	-0.64	0.522
ΔIND D-A Av. Price _{t-3}	-0,0826933	-3,66	0,000	ΔIND D-A Av. Price _{t-3}	0,0002388	0.12	0.905
ΔIND D-A Av. Price _{t-4}	-0,0727767	-3,23	0,001	ΔIND D-A Av. Price _{t-4}	0,0004491	0.23	0.821
ΔNatural Gas Fut. Sett. Price _{t-1}	0,0777261	0,30	0.764	ΔNatural Gas Fut. Sett. Price _{t-1}	-0,0426127	-1.87	0.062
ΔNatural Gas Fut. Sett. Price _{t-2}	0,0116541	1,28	0.199	ΔNatural Gas Fut. Sett. Price _{t-2}	0,0131713	0.58	0.564
ΔNatural Gas Fut. Sett. Price _{t-3}	-0,0342886	2,94	0.003	ΔNatural Gas Fut. Sett. Price _{t-3}	-0,0207458	-0.91	0.363
ΔNatural Gas Fut. Sett. Price _{t-4}	0,4860929	1,89	0,059	ΔNatural Gas Fut. Sett. Price _{t-4}	-0,0179181	-0.79	0.431
R Square: 15,63 %				R Square: 0,47 %			
Lagrange Multiplier Test Lag 1 Probability: 0,36318							
Lagrange Multiplier Test Lag 2 Probability: 0,01436							

6. RESULTS

By implementing the daily price data for the period 10-10-2008 till 07-12-2011 for USA, in this paper examined the short and long-run dynamics among and between electricity, natural gas and coal prices in seven different regions.

We applied Augmented Dickey-Fuller Unit-Root Test on our data in order to examine the presence of unit root to indicate whether average level of day – ahead electricity, coal and natural gas future prices has unit root at different HUBs. Results mainly indicated that there is no unit root at seven hubs.

Presence of cointegration relation between Electricity prices and Coal and Natural Gas Futures prices are investigated at all hubs. Augmented Engle-Granger Cointegration test is employed in order to achieve AR(1), AR(2), AR(3), AR(4) process results which has higher autoregressive processes. In all AR processes presence of cointegration is obvious and a strong cointegration is evident and t values decreases with higher degree autoregressive processes between energy prices.

Unit root tests and cointegration tests resulted in slightly different coefficients but the same level of significance. Likewise error correction models also show different coefficients and in some cases differences in significance occur.

We aimed to implementing a VECM model which considers maximum one week period with Final prediction error (FPE) , Akaike, Hannan-Quinn, Schwarz Bayesian criterias indicates with four lag model between electricity prices, coal and natural gas futures settlement prices at all hubs. Results indicates positive results between the prices.

Lastly we examined both long and short term effects of natural gas and coal futures settlement prices on average day-ahead electricity prices and vice versa. According to the coefficient on adjustment parameters results are statistically significant with a positive coefficient. Also Lagrange Multiplier Test is applied for the detection of autocorrelation and we reject the existence autocorrelation process.

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CURRICULUM VITAE

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