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THE REGIONAL GREENHOUSE GAS INITIATIVE AND U.S. ENERGY MARKETS

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THE REGIONAL GREENHOUSE GAS INITIATIVE AND U.S. ENERGY MARKETS

by

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ABSTRACT

The Regional Greenhouse Gas Initiative and U.S. Energy Markets

by

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There have been numerous studies in relation to carbon permit prices in the greenhouse gas (GHG) emissions trading market and energy markets. Most previous studies have focused on the European Union Emissions Trading Scheme (EU ETS) since its creation in 2005. Notable findings are 1) the carbon permit price in the EU ETS and energy prices are closely interrelated, and 2) crude oil and electricity prices are the main drivers of the carbon permit price. Our attention moves to another emissions trading market in the U.S., the Regional Greenhouse Gas Initiative (RGGI), which began in 2009 for nine northeastern US states. The RGGI is the first regulatory carbon cap-and-trade system in the U.S. To my best knowledge, there is no rigorous empirical study about the RGGI.

A primary research objective is to investigate a mutual relationship among the RGGI carbon permit price and energy prices in the northeastern U.S. I have applied the Lag Augmented Vector Autoregression (LA-VAR) model to capture the mutual relationship among the RGGI, electricity, natural gas, and coal prices. Impulse response function (IRF) results suggest that an interrelation between the RGGI carbon permit price and electricity market exists, although it is weak and statistically insignificant. This implies that both markets are not closely attached. IRF also suggests that the natural gas price has positive impacts on the RGGI carbon permit price but the natural gas price is not influenced by the RGGI market. In addition, IRF tells us that the RGGI price and coal price are negatively related each other.

Key findings designate that, unlike the EU ETS, the RGGI market and electricity market in the RGGI region are not tied closely, and the natural gas is the main driver of the system in the RGGI region. The loose relationship between the two markets can be explained by recent weak carbon credit demand, which stems from low GHG emissions. The recent low natural gas prices have led to increased fuel switching, which reduces GHG emissions as power companies switch from coal to natural gas sources.

(64 pages)

PUBLIC ABSTRACT

The Regional Greenhouse Gas Initiative and Energy Markets in the U.S.

Kangil Lee

The dynamic mutual relationship between the Regional Greenhouse Gas Initiative (RGGI) carbon permit price and energy prices in the U.S. is examined. Results show that the RGGI and electricity markets are not closely linked, although the carbon permit price is usually closely interrelated with energy prices. The loose relationship between the RGGI and electricity markets can be explained by the recent low carbon credit demand which stems from the low greenhouse gas (GHG) emissions existent in the particular area covered by the RGGI. The low GHG emissions result from fuel switching due to recent low natural gas prices. Unlike the European Union Emissions Trading Scheme, natural gas is the key driver of the RGGI system.

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CONTENTS

LIST OF TABLES

Table Page

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1. Background

1.1.1. Climate Change and International Efforts

The Kyoto Protocol was signed in 1997, indicating possible adverse impacts caused by global climate change. The Kyoto Protocol is the first international agreement to reduce the emissions of greenhouse gases (GHG)[1] by setting binding obligations. The Protocol was adopted by Parties to the United Nations Framework Convention on Climate Change (UNFCCC) and entered into force in 2005. The U.S. has not ratified the Kyoto Protocol but has been trying to reduce its GHG emissions. The first period of emission reduction commitments in the Kyoto Protocol expired on December 31, 2012.

A new treaty to limit GHG emissions was established in the 2011 United Nations Climate Change Conference held in Durban, South Africa, called the Durban Platform. Negotiators agreed to be part of a legally binding treaty to address climate change. The terms of the future treaty are to be defined by 2015 and become effective in 2020. The Durban platform is notable insofar as it marks the first time developing countries such as China and India have made an obligation to reduce GHG emissions.

1.1.2. Emissions Trading

Various policy options have been introduced to achieve emission goals in the Kyoto protocol and the Durban Platform. Emissions trading, or cap and trade, is the most widely

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[1] The United Nations Framework Convention on Climate Change (UNFCCC) stipulates seven GHGs in the Kyoto Protocol: CO_2, NH_4, N_2O, HFC, PFC, and SF_6. In this study, GHG or carbon refer to CO_2, without other specific mention.

accepted policy option in many countries and regions. Emissions trading is a market-based approach to control GHG emission by providing economic incentives. A central authority (usually a governmental body) sets a limit or cap on the amount of emissions of GHG.

The limit or cap is allocated or sold in the form of auction to firms, which represents the right to emit GHG. Firms with lower abatement costs will reduce GHG emissions below the cap and sell their surplus (permit supply) in the emissions trading market. On the other hand, companies with high abatement costs will buy emissions permits (permit demand) from the firms who sell the permit in the emissions trading market. The supply and demand will be cleared and permit prices will be determined. Through these processes emission targets are achieved at the minimum cost.

The European Union (EU) launched the European Emissions Trading Scheme (EU ETS) in 2005 to implement their GHG reduction obligations. As of 2013 the EU ETS covers more than 11,000 factories, power stations, and other installations in all 28 EU member states plus Iceland, Norway, and Liechtenstein (European Commission 2013).[2] The installations regulated by the EU ETS are collectively responsible for close to half of the EU's emissions of carbon dioxide (CO_2) and 40% of its total GHG. The trading volume of the GHG emission permits has grown for the last several years.

Although the U.S. has not ratified the Kyoto protocol, there are three GHG emissions trading markets: the Chicago Climate Exchange (CCX), the Regional Greenhouse Gas Initiative (RGGI) and California's Cap and Trade Program. The CCX has been defunct since the end of 2010 (Bern 2011) due to low carbon prices. The nine northeastern states in the U.S. started a mandatory program to abate GHG emissions in 2009, the RGGI. California started the enforceable emissions trading market in 2013.

[2] http://ec.europa.eu/clima/policies/ets/index_en.htm

1.1.3. Regional Greenhouse Gas Initiative (RGGI)

The RGGI, a regional initiative, is the first regulatory GHG cap and trade system in the U.S. Nine states (Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont) are now participating. The GHG emissions of that region account for about 10% of total US emissions. Power plants with 25 MW or more capacity have a carbon reduction obligation under the RGGI. The first permit auction was held in September 2008, and the first three-year compliance period began on January 1, 2009. The RGGI is a relatively small, local market. The amount of total trading volume was 249 million USD in 2011,[3] less than 1% of the trading volume in the EU ETS (World Bank 2012).

1.2. Motivation of Research

There has been much debate surrounding the relationship between carbon permit prices in the GHG emissions trading market and energy markets for electricity, crude oil, coal, and natural gas. Most previous studies have focused on the EU ETS since its creation in 2005. These previous studies could be categorized into three groups; 1) studies recognizing factors influencing a carbon price in the emissions trading market, 2) studies testing the efficiency of the emissions trading market, and 3) studies investigating mutual interactions between the carbon price and energy prices. Notable findings are that carbon price in the EU ETS and energy prices are closely interrelated, and crude oil price and electricity price are the main drivers of the carbon price in the EU ETS.

Our attention moves naturally to another emissions trading market in the U.S., the RGGI. To my best knowledge, there is surprisingly no rigorous empirical study to analyze the interrelationship between the RGGI market and the energy markets. As mentioned, most

[3] The amount of transaction volume was 120 million tCO_2e in 2011. The tCO_2e refers to tonnes of carbon dioxide equivalent.

researchers have paid attention to the EU ETS because the EU ETS is the largest and most influential carbon trading market in the world. Also it has amassed the largest volume of transaction data including historical carbon prices and trading volumes. On the other hand, the RGGI is a small and regional market which has relatively sparse transaction data. One of key contributions of this research is to fill this research gap by investigating the dynamic interaction between the RGGI and energy markets. In doing so, I identify the main driver(s) of the carbon price in the RGGI and characterize the price dynamics in the RGGI and energy markets in the region.

On the other hand, there are voices of concern for the low carbon prices in the EU ETS (The Economist 2013; The Guardian 2013). The carbon price plummeted in the fourth quarter of 2011 in the EU ETS. The current carbon price is less than \$5/tCO_2e (as of December, 2013), whereas the former price stayed between \$19~\$26/tCO_2e until around mid-2011. One of the reasons for the recent low carbon price is the chronic oversupply of carbon permits (The Economist 2013). The EU has been seeking a structural reform of the carbon market, named “back-loading,” which would take 900 million tons of carbon allowances off the market now and reintroduce it later, to prevent further decline of carbon price (Financial Times 2013).

The RGGI also has been reporting a low carbon price of around \$3.30/tCO_2e (as of December, 2013) (The RGGI CO_2 Allowance Tracking System). The low carbon price in the RGGI is a result of different reasons from those of the EU ETS. A leading cause for low carbon prices in the RGGI region is a low carbon credit demand. The low carbon credit demand has stemmed from the low GHG emissions in the RGGI states. The current GHG emissions are already 34% below the emission cap (Figure 1). Stavins (2012) and Environment Northeast (2012) point out that a low GHG emission in the RGGI states has originated from three sources: 1) fuel switching from coal to natural gas in electricity generation, 2) the economic recession in 2008, and 3) weak electricity demand due to moderate weather conditions in the region.

The low carbon credit demand weakens the relationship between the RGGI market and electricity market, unlike the EU ETS where the carbon trading market is tightly attached to energy markets. In sum, this paper has two research goals: 1) investigating the mutual relationship between carbon price and energy prices in the northeastern U.S. by discovering the main driver of these markets, and in doing so 2) examining whether the RGGI market and other energy markets are closely interrelated.

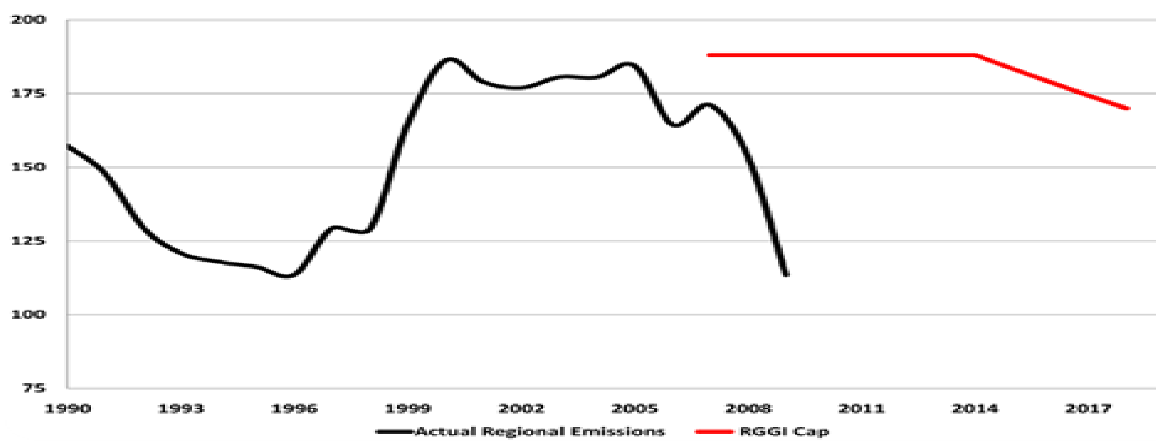

Figure 1. Historical CO_2 Emissions in the RGGI Region (Unit: Millions of tons)

Source: Reproduce Figure 2 in Woods Hole Research Center (WHRC) Addressing greenhouse gas emissions through the Regional Greenhouse Gas Initiative, available at http://www.whrc.org/policy/rggi.html

1.3. Research Question

Two main research objectives are established.

1.3.1. Mutual Relationship among Carbon Price and Energy Prices

The first goal of the study is to examine the mutual relationship among carbon price and energy prices. Specific research questions are as follows:

- *Does the RGGI carbon price interact with other energy prices?*
- *If so, how do they interact with each other?*

1.3.2. Differences between EU ETS and RGGI

The second goal of this research is how the RGGI differs from the EU ETS:

- *What makes the RGGI and the EU ETS different if the patterns of interrelationship among carbon and energy prices are different?*

1.4. Organization of the Research

This study is structured as follows. Chapter 1 provides a general introduction and research questions. Chapter 2 explains background information. In particular, I explore the cost effectiveness of the emissions trading and discuss the RGGI. Chapter 2 also reviews previous studies on the GHG emissions trading market. Chapter 3 introduces key variables and the research methodology. Chapter 4 discusses the empirical results. Finally, Chapter 5 concludes this study and outlines possible further studies.

CHAPTER 2

EMISSIONS TRADING AND LITERATURE REVIEW

2.1. Emissions Trading and the RGGI

2.1.1. Emissions Trading

Emissions trading is a market-based approach to control pollution, such as GHG emissions, by providing economic incentives to emitters. If pollution emitters exchange their emission permits in a market, the emission goal that government sets is achieved at the minimum cost. Firms with lower abatement costs will reduce pollutants emissions below their allowance and sell their surplus in the emissions trading market. Companies with high abatement cost will buy emission permits in the market instead of reducing their emissions by themselves. These emission permits will be cleared when permit price is determined by equal market demand.

2.1.1.1. Theoretical Background of Emissions Trading

In this section, we will examine the cost effectiveness of emissions trading from a theoretical perspective. Crocker (1966) and Dales (1968) developed the idea of emissions trading to allocate the emission reduction burden among emitters, and Montgomery (1972) provided a proof that emissions trading could be a cost effective way to control pollutants and emissions. Consider the following minimization problem based on Tietenberg (2006):

(1) $min_x \sum_i C_i(x_i),$

(2) s. t. $\alpha + \sum(e_i - x_i) \leq \bar{A}$

(3) and $x_i \geq 0$

where i refers to emitters, or firms, C_i is the abatement cost, x_i is the abatement of emissions of the emitter i. $C_i' > 0$ and $C_i'' > 0$. α in equation (2) is emissions from other sources including natural sources, e_i is uncontrolled emissions from firm i, and thus $\sum(e_i - x_i)$ is the total emissions from the all emitters. $\bar{A}$ in equation (2) is the target level of emission or emission goal. The first constraint (2) means that the amount of total emissions should be less than the emission target level.

The Lagrangian of this minimization problem is:

(4) $$L = \sum C_i(x_i) + \lambda(\bar{A} - \alpha - \sum(e_i - x_i)),$$

and Kuhn-Tucker conditions are:

(5) $$C_i{}'(x_i) - \lambda \geq 0 \text{ and } x_i[C_i{}'(x_i) - \lambda] = 0$$

(6) $$\alpha + \sum(e_i - x_i) \leq \bar{A} \text{ and } \lambda[\alpha + \sum(e_i - x_i) - \bar{A}] = 0$$

(7) $$x_i \geq 0;\ \lambda \geq 0 \quad i = 1, \cdots, n$$

Lagrange multiplier, λ, in equation (5) is the shadow price of the pollution constraint, and this is positive value when the pollution constraint is binding. All the marginal abatement costs (MACs) of regulated companies have to be equal to λ.

Suppose that this outcome is achieved through an emissions trading market. In this case, the amount of emission permit supply will be $\bar{E} = \sum(e_i - x_i)$. Suppose the amount of initial allocation for individual companies is e_i^0. Then, the total amount of each allocation for all companies will be matched with $\bar{E}$, that is, $\bar{E} = \sum e_i^0$. The representative company has the following cost minimization problem:

(8) $$min_{x_i}\, C_i(x_i) + p\left(e_i - x_i - e_i^0\right),$$

where p is an initial permit price. Then the KT conditions are as follows:

(9) $$C_i{}'(x_i) - p \geq 0 \text{ and } x_i[C_i{}'(x_i) - p] = 0,$$

(10) $$x_i \geq 0.$$

Comparing equations (5) and (9), the lowest cost solution will be reproduced when p and λ are equal.

2.1.1.2. Elements of Emissions Trading

The fundamental elements of emissions trading are the emissions target, allocation methods, and penalty. An emissions target or a cap, $\bar{A}$ in equation (2), is essential to the effective operation of emissions trading. The emissions target can be set by the control authority (usually a governmental or inter-governmental body); however, it can also be set by a private sector group. This is the case in a voluntary system like the Chicago Climate Exchange (CCX).

After setting the emissions target, the control authority determines how many allowances are distributed to firms. The control authority needs to consider equity and cost effectiveness as well as individual firms' capacity when they distribute the allowance. There are two allocation methods, grandfathering and auction. Grandfathering refers to free allocation. More specifically, when grandfathering is applied, the amount of allowance is allocated freely based on firm's historical emissions records. Considering the economic impact and adaptation period, most carbon emissions trading systems allocate their allowances using grandfathering in early stages. In addition to grandfathering, allowances can be distributed by auction. An auction is not a free allocation. Emitters participate in an auction[4] and bid to acquire a given volume of allowances at a specified price (European Union 2010). Emitters do not prefer auctions because they have to pay to get the allowances. In the case of the EU ETS, all the allowances were allocated with

[4] Emitters do not participate directly in an auction in the EU ETS. Agents bid on behalf of their clients to acquire a given volume of allowances at a specified price.

grandfathering in the pilot period, and more than 40% of allowances were allocated through auction starting in 2013 (European Commission 2013).[5]

Both allocation methods have pros and cons. The grandfathering method could act as a barrier to new companies entering the market (OECD and IEA 2002); however, when the emissions trading is newly introduced, this free allocation method (grandfathering) is commonly applied to reduce the impact in the industrial sector. On the other hand, an auction is a burden to emitters in comparison to a free allocation method, although if an auction is applied, regulators can get additional funds from the auction.

Penalties are an essential element that makes emissions trading work properly. In the EU ETS, a penalty was \$40/tCO_2e in the pilot period,[6] and it was increased to \$100/tCO_2e in Phase II. This penalty will be adjusted with the EU consumer price index in Phase III.[7]

2.1.1.3. Emissions Trading Markets in the World

Emissions trading has a short history, even though it was proposed in late 1960s by Crocker (1966) and Dales (1968). The first emissions trading market was introduced in the U.S. to reduce lead in the gasoline refinery industry in 1982 (Ellerman, Joskow, and Harrison 2003). In 1995 Nitro Oxide (NO_x) and Sulfur Dioxide (SO_2) emissions trading programs started under the Acid Rain Program (ARP) to abate NO_x and SO_2 emissions from power plants. For GHG emissions, the EU ETS is the first and the largest system. Although several voluntary GHG

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[5] The share of the auction allocation is different according to sectors and time. For example, the share of an auction in the manufacturing industry is 20% in 2013; however, this will increase by up to 70% by 2020. On the other hand, only 15% of aviation allowances will be auctioned during the 2013-2020 period (IETA 2013).

[6] The penalty is imposed when firms emit more than their allocated emission cap. It is imposed annually: the penalty is imposed on 30 April each year for the regulated party's annual emissions made in the previous year (European Union 2010).

[7] Phase I of the EU ETS, between 2005 and 2007, is a pilot period, and Phase II of the EU ETS began in 2008 and finished in 2012. Phase III will be continued until 2020.

emissions trading markets were introduced, they are small and local. In addition to the EU, six other countries (Australia, China, India, Kazakhstan, New Zealand, and Switzerland) and four regions in North America (Alberta, California, the RGGI states, and Quebec) are now operating GHG emissions trading (International Emissions Trading Association (IETA) fact sheet in http://www.ieta.org/worldscarbonmarkets). Emissions trading in South Korea will begin in 2015. Table 1 contains emissions trading markets at present around the world. The majority of the transactions are being delivered through the EU ETS (World Bank 2012).

Table 1. GHG Emissions Trading in the World

	Time table	Target	Coverage
EU	2005-2020	20% below 1990 levels by 2020	11,500 Installations 40% of Total Emissions
Alberta	2007-Present	Annual intensity reduction of 12% below baseline	All industrial facilities
New Zealand	2008-2020	10-20% below 1990 levels by 2020	Forestry; Energy Fuels and industrial; and Waste and Synthetic
RGGI	2009-2018	10% below 2014 levels by 2018	Power Sector
India	2012-2015	20-25% intensity reduction below 2005 levels by 2020	Power, thermal, iron and steel, fertilizers, textiles, aluminum, pulp and paper, chlor-alkali
California	2013-2020	Reach 1990 levels by 2020	Energy; Industrial Sources; Oil and Gas
Québec	2013-2020	20% below 1990 levels by 2020	Energy; Industrial Sources; Oil and Gas
Australia	2013-2020	5% below 2000 levels by 2020	Energy, Industrial Process, Commercial Transport.
China	2015-2020 (National from 2015)	Intensity reduction of 40-45% below by 2020	Differs between pilots; National coverage unclear
Kazakhstan	2013-2020	7% below 1990 levels by 2020	Oil and gas; power; Mining and Metals; Chemicals; others being considered
Switzerland	2013-2020	20% below 1990 levels by 2021	950 companies across multiple sectors
Tokyo	2013-2019	25% below 2020 levels by 2020	1400 Facilities, 20% of Total Emissions
Korea	2015-2026	30% below BAU by 2020	490 Emitters, 60% of Total Emissions

Source: Table reproduced from IETA factsheet, available at http://www.ieta.org/worldscarbonmarkets

The U.S. has three GHG emissions trading market: The CCX, the Regional Greenhouse Gas Initiative (RGGI), and California's Cap and Trade Program. Among these markets, the CCX, which was a voluntary GHG emissions trading market, discontinued operations at the end of 2010 (Bern 2011). The RGGI and California's cap and trade program are mandatory markets.

2.1.2. Regional Greenhouse Gas Initiative

2.1.2.1. What Is RGGI?

The Regional Greenhouse Gas Initiative (RGGI) is the first regulatory GHG cap and trade system in the U.S. for nine northeastern states. Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont are now participating.[8] Figure 2 shows the geographical location of the RGGI. Grey circles in the map on right show the locations of the power plants in the RGGI states.

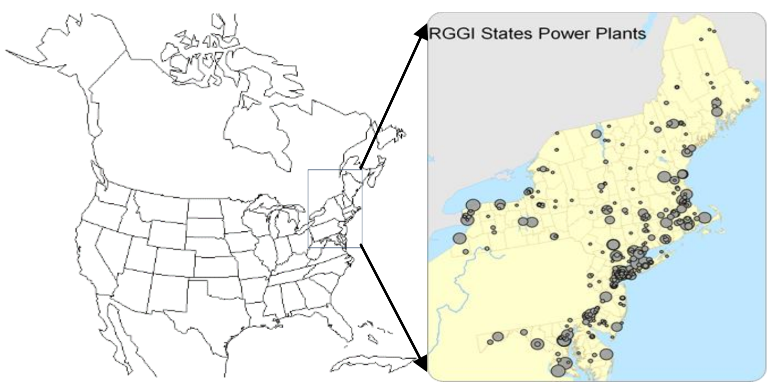

Figure 2. Geographical Area of the RGGI

Source: The Woods Hole Research Center (WHRC) (http://www.whrc.org/policy/rggi.html)
Note: Grey circles in the map show the locations of the power plants in the RGGI states

The GHG emissions of the RGGI region accounts for about 10% of total US emissions. Currently, fossil fuel power plants with 25 MW or more capacity in electricity generation are

[8] New Jersey participated at the beginning, but it withdrew from the RGGI in 2011.

regulated. Besides purchasing allowances, power plants can use up to a 3.3% allowance through CO_2 Offset to meet their CO_2 compliance obligation.[9] The first permit auction was held in September 2008, and the first three-year compliance period began in January 2009 and ended in December 2011.

The scale of the cap was 188 million tCO_2e per year during 2009-2011. During the 2012-2014 period, the cap is 165 million tCO_2e per year. The size of the RGGI is relatively small in terms of carbon trading volume, with only $249 million worth of transactions in 2011, just 0.2% of the EU ETS trading volume (Figure 3). The RGGI trading volume peaked in 2009 and has continually decreased since that point, whereas the trading volume in the EU ETS keeps growing. Current emissions are already 34% below the emission cap (Environment Northeast 2012). Because of the ineffectiveness of this prior emission cap, a new cap will be applied beginning in 2015. According to RGGI Inc. (2013) the emission cap will be 91 million tCO_2e in 2014, and will decrease by 2.5% per year for the years 2015 through 2020.

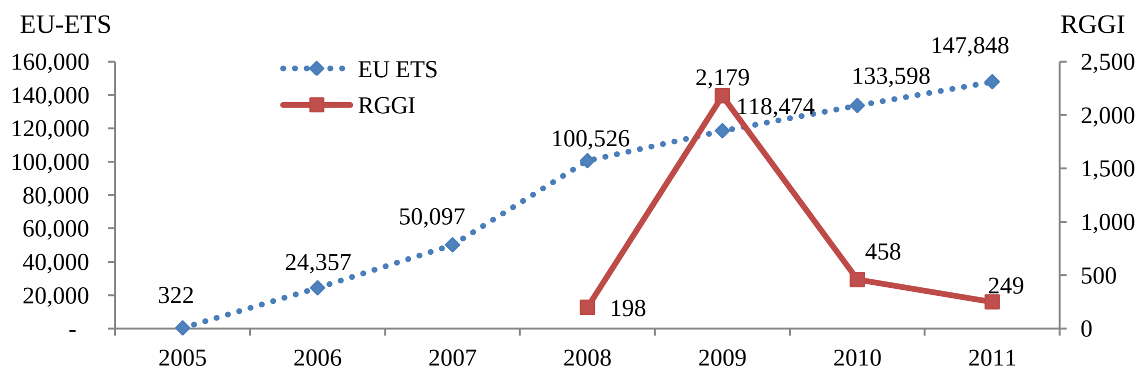

Figure 3. Market Sizes between EU ETS and RGGI (Unit: Million USD)

Source: World Bank (2012)

[9] Five eligible offset project categories follow: 1) Capture or destroy CH_4 from landfills; 2) Reduce emissions of SF_6 from electricity transmission and distribution equipment; 3) Sequester CO_2 through afforestation; 4) Reduce emissions of CO_2 through non-electric end-use energy efficiency in buildings; and 5) Avoid CH_4 emissions through agricultural manure management operations.

2.1.2.2. Electricity Generation in RGGI Region

In nine RGGI states, four fuel sources (natural gas, nuclear, hydroelectric conventional, and coal) account for more than 95% of the total electricity generation in 2012 (Figure 4). Among these sources, natural gas is the largest source since 2006. Around 45% of electricity in the RGGI states is generated by natural gas. The share of coal has been decreasing from 20% in 2001 to less than 10% in 2012. Nuclear and hydroelectric conventional energy sources constitute about 40% of the electricity generation. The share of the electricity generation by petroleum is below 1% since 2010 (Figure 4).

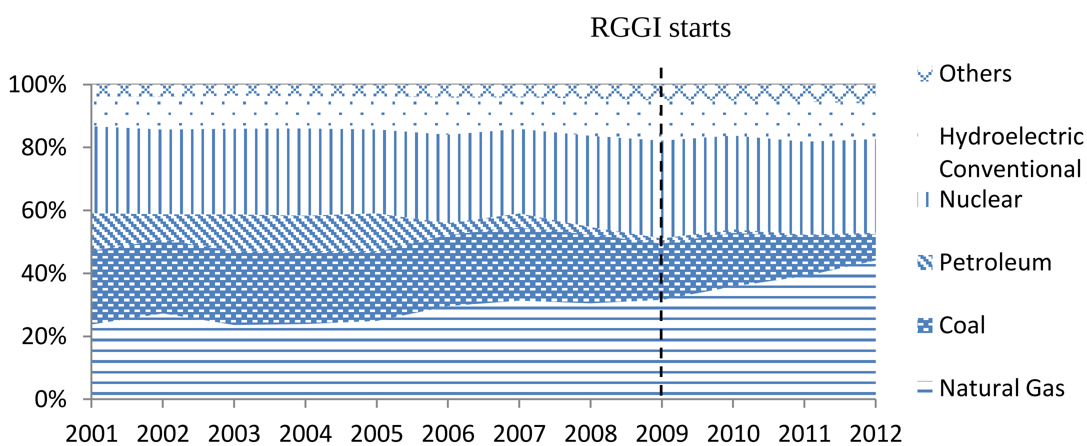

Figure 4. Fuel Sources for Electricity Generation in RGGI states

Source: Calculated by the author based on EIA data

2.1.2.3. Fuel Switching

The most prominent observation in Figure 4 derives from fuel switching, which implies that natural gas replaces coal. Fuel switching has continually accelerated in the region since the introduction of the RGGI in 2009 (Table 2). The share of natural gas increased by 13% from 2009-2012, and the share of coal decreased by 9% in the RGGI states from 2009-2012.

Table 2. Share of Natural Gas and Coal in Electricity Generation in RGGI States (Unit: %)

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Gas[1]	23.8	27.3	23.6	23.9	24.9	29.6	31.4	30.5	31.6	35.9	39.1	44.2
Coal[2]	23.5	23.4	23.5	22.9	21.9	22.7	23.2	21.9	17.9	17.1	12.5	8.4

Note: [1] Percentage share of natural gas in electricity generation in the RGGI region;
[2] Percentage share of coal in electricity generation in the RGGI region

There are various reasons for this fuel switching. A recent low natural gas price caused by shale gas development is one of the main reasons. There is an incentive for electricity producers to switch their fuel from coal to natural gas. The Acid Rain Program (ARP) may be another reason. The ARP requires electricity producers to reduce SO_2 and NO_x emissions. Natural gas emits much lesser SO_2 and NO_x than coal (Table 3).

Table 3. Pollution Emission by Fuel Types at Power Plant in the U.S.

Fuel type	Carbon dioxide (CO_2)	Sulfur dioxide (SO_2)	Nitrogen oxides (NO_x)
Natural Gas	1,135 lbs/MWh	0.1 lbs/MWh	1.7 lbs/MWh
Oil	1,672 lbs/MWh	12 lbs/MWh	4 lbs/MWh
Coal	2,249 lbs/MWh	13 lbs/MWh	6 lbs/MWh

Source: EPA website (http://www.epa.gov/cleanenergy/energy-and-you/affect/air-emissions.html)

2.2. Literature Review

As transaction data for carbon trading accumulates, a number of empirical studies on emissions trading markets have been published, mostly on the EU ETS. Recent studies can be categorized into three groups: 1) testing (cap-and-trade) market efficiency (e.g. Montagnoli and de Vries 2010; Conrad, Rittler, and Rotfuß 2012), 2) examining determinants of the carbon price (e.g. Mansanet-Bataller, Pardo, and Valor 2007; Alberola, Chevallier, and Chèze 2008; Aatola, Ollikainen, and Toppinen 2013), and 3) analyzing dynamic interactions between the carbon market and energy markets (e.g. Fezzi and Bunn 2009; Kirat and Ahamada 2011; Reboredo 2013). Among these three categories, two groups (2 and 3) are relevant to this research.

2.2.1. Market Efficiency Test

The market is said to be efficient when one cannot consistently obtain returns above the market average, especially in finance markets, given the information available at the time the investment is made (Fama 1970, 1998).

Because of the EU ETS's short history, the market is relatively immature (Montagnoli and de Vries 2010). Therefore, there is a necessity to examine the market efficiency test for the EU ETS. Montagnoli and de Vries (2010) test the efficient market hypothesis in the market for carbon permits in Phase I and Phase II of the EU ETS. The results indicate that Phase I, the trial and learning period, was inefficient, whereas the first period under Phase II showed signs of restoring market efficiency. The result of this study tells us that as both market participants and policymakers learned from the implementation of the EU ETS during the pilot period, the market matured in later phases.

Conrad, Rittler, and Rotfuß (2012) show the EU Allowance (EUA) price reacts to EU National Allocation Plan (NAP) announcements by applying the Generalized Autoregressive Conditional Heteroscedastic (GARCH) model. In addition, immediate EUA price reactions are observed in response to German and U.S. macroeconomic announcements on future economic development as well as current economic conditions. This result consistently supports the results of Montagnoli and de Vries (2010). From these studies, we discover that the EU ETS is an efficient market.

2.2.2. Determinants of Carbon Price

In general the key drivers of the carbon price in an emissions market are energy prices such as crude oil, natural gas, coal, and electricity. Weather conditions and policy options, such as the emissions target, are also the determinants of the carbon price in the emissions market (Chevallier 2012).

Mansanet-Bataller, Pardo, and Valor (2007) examine which factors might explain daily carbon price changes in the EU ETS in 2005. Theirs was the first study considering weather factors in an analysis regarding the determinants of carbon price. They applied the Multivariate Least Squares Regression model, and their findings denote energy prices for Brent crude oil and natural gas were the most decisive elements among carbon price determinants. In addition to these energy prices, an unusual temperature event (extremely low temperature) in Germany increased the carbon permit price.

Alberola, Chevallier, and Chèze (2008) extend the Mansanet-Bataller, Pardo, and Valor (2007) study with additional observations of the EU ETS through April 2007. The result shows that the EU ETS carbon price reacts to energy prices and unexpected temperature changes in the winter, which coincides with the results of Mansanet-Bataller, Pardo, and Valor (2007). They also found two structural changes (April, 2006 and October, 2006) during Phase I. The two structural changes were due to the disclosure of 2005 official emissions data (April, 2006) and the European Commission announcement of stricter allocations in Phase II (October, 2006).

Creti, Jouvetb, and Mignonc (2012) also discuss determinants of the carbon price in the EU ETS. Although the purpose of the Creti, Jouvetb, and Mignonc (2012) study is conceptually identical to both Mansanet-Bataller, Pardo, and Valor (2007) and Alberola, Chevallier, and Chèze (2008), it extends the time period to include Phases II. In particular, this study tests whether the carbon price drivers from Phase I still hold in Phase II. They consider energy prices and institutional factors as carbon price determinants. They show the continuation of carbon price determinants from Phase I in Phase II using cointegration techniques.

Aatola, Ollikainen, and Toppinen (2013) also examine carbon price determinants in the EU ETS from 2005-2010. This study considers more variables: EUA (the EU ETS allowance forward price), electricity price (used in markets such as EEX, German power exchange, and Nord Pool), commodities price (i.e. mineral, steel, and paper), the UK gas price, two stock variables related with electricity price (a water reservoir in the Nord Pool and UK gas storage data), and the economic growth indicator (London stock market index). Their results also show that carbon price determinants, such as energy prices, in Phase I continue in Phase II in the EU ETS. Through Ordinary Least Squares (OLS) and Vector Autoregression (VAR) methods, they conclude that around 40% of the carbon price in the EU ETS can be explained by gas prices, coal prices, and Germany's electricity prices. Among these factors, Germany's electricity price is the most crucial element in the carbon price.

In sum, various studies have examined price drivers in the EU ETS. According to these studies, factors such as energy prices, weather conditions, and institutional factors such as policy announcements affect the EU ETS market.

2.2.3. Dynamic Interactions between Carbon and Energy Markets

The final vein of empirical studies on carbon emissions trading is an analysis regarding interactions between the carbon market and energy markets. These studies have paid more attention to the dynamic interrelation between carbon price, energy prices and electricity price.

Fezzi and Bunn (2009) examine the mutual interaction among three market prices (the EUA price, the UK electricity price, and the UK natural gas price) through the Vector Error Correction Model (VECM). The time frame for this study is restricted to Phase I of the EU ETS.

Results show that the UK electricity price increases the EUA price instantly and considerably. In turn, the carbon price increases the UK electricity price with a few days lag. This result shows that the EU ETS is mutually and strongly related to the electricity market.

Another research question examines whether or not the EU ETS provides appropriate economic incentives. In answer to this query, Kirat and Ahamada (2011) investigate the relationship between carbon price in the Phase I of the EU ETS and electricity contracts in France and Germany. They applied the multivariate GARCH model. Their results indicate that the electricity industry in both France and Germany weakly respond to the EU ETS, with Germany having a stronger interdependence. They explain that the reason for this weak response is due to the excess allocation of allowances during Phase I.

Chevallier (2011) constructs a carbon pricing model that considers macroeconomic factors, such as the aggregated EU industrial production index. Energy prices (Brent crude oil, natural gas, and coal prices) are also considered as main carbon price drivers. Through the Markov-switching VAR model,[10] the interactions between the macroeconomic index and energy prices are captured. The result shows that industrial production positively affects the EUA price in an economic expansion period (Phase I) and negatively in an economic recession period (Phase II). This result is consistent with general intuition, which implies that an increased production level brings more CO_2 emissions. As a result, this leads to a strong carbon credit demand.

Reboredo (2013) examines the interdependence between the EUA price and Brent crude oil price during the Phase II period. This study applies copula models[11] to measure dependence between these two markets. The results show that the EU ETS price and Brent crude oil price are

[10] The Markov switching VAR model involves multiple structures that can characterize time series behaviors in different settings. By permitting switching between these structures, this model is able to capture more complex dynamic patterns (Kim and Nelson 1999)

[11] The copula model measures the dependence among random variables (Schweizer and Wolff 1981).

positively related. Additionally, Reboredo (2013) showed that when an investment portfolio contains both EU ETS allowances and crude oil, the portfolio reduces risk, making it a useful option whereby investors can hedge against that risk.

Many studies have examined the relationships between the carbon market and energy markets. According to these studies, the price of carbon can be explained by the prices of energy commodities such as natural gas, oil, coal, and electricity. In addition, the carbon market and the electricity market interact with each other, but the magnitude varies depending on the country under consideration (the UK has a strongly correlated relationship whereas France and Germany are relatively weak).

Unfortunately, all literature exclusively deals with the EU ETS. As far as I know, there is no empirical study on the RGGI. As we discussed in the previous Chapter, the RGGI has different characteristics from the EU ETS. As a result, the relationship between the RGGI and U.S. energy markets might indicate trends that differ from the EU ETS. Therefore, there is a necessity for rigorous study which tests how the RGGI interacts with energy markets. This is the primary research question of this study.

CHAPTER 3

DATA AND METHODOLOGY

Based on the discussion in chapter 2, four variables—RGGI carbon prices, electricity prices, natural gas prices, and coal prices—are selected to investigate the relationships between the RGGI and energy markets.

3.1. Key Variables and Data Collection

Natural gas and coal are the main fuel sources used to generate electricity in nine RGGI states. Both natural gas and coal accounted for 52% of the total electricity generation in 2012 (natural gas 44%, and coal 8%). Thus, I include the prices of natural gas and coal as the fuel sources in this model. Electricity price is another important variable used to investigate this dynamic interrelationship. Oil accounted for less than 1% of the electricity generated in 2012, thus it is excluded from the model.

3.1.1. RGGI Price

The RGGI price data has been obtained through the RGGI CO_2 Allowance Tracking System (RGGI COATS). The first allowance auction was held on September 30, 2008, and RGGI COATS data starts on that date.[12] Transactions have occurred irregularly, however. The total number of carbon price observations is 204, although carbon allowances had been traded over three years.

Figure 5 shows RGGI carbon prices from September, 2008, to January, 2012. The RGGI price stayed around 2-3\$/tCO_2e. In the early stage of the RGGI, the carbon price was over 3\$/tCO_2e. This price has decreased over time, and after 2010 it leveled out at around 2\$/ tCO_2e.

[12] The first compliance period began on January 1, 2009.

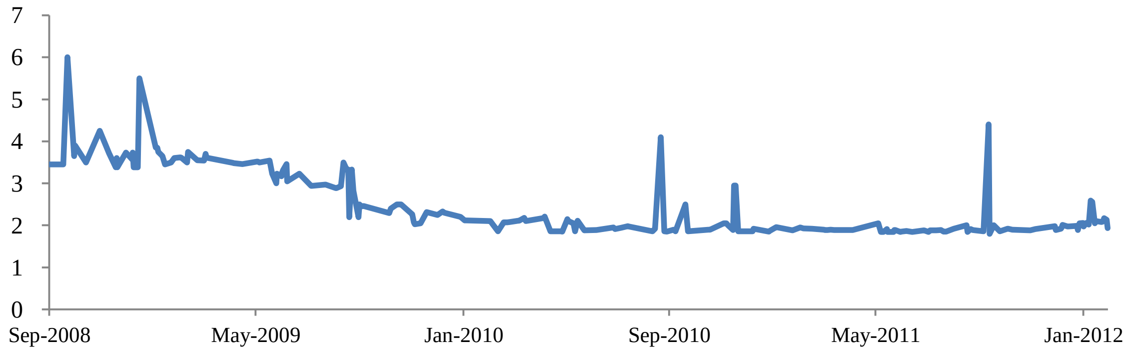

Figure 5. RGGI Allowance Price (Unit: $/$CO_2$ ton)

3.1.2. Electricity Price

The U.S. high-voltage electricity system is operated and distributed by individual utilities, such as independent system operators (ISO's) or regional transmission organizations (RTO's), and their power pools. ISOs and RTOs are organizations formed under the direction of the Federal Energy Regulatory Commission (FERC). They coordinate, control, and monitor the operation of the electrical power system. In North America, nine ISOs and RTOs distribute electricity, and these ISOs and RTOs serve two-thirds of electricity consumers in the U.S. and more than 50 % of Canada's population (Figure 6).

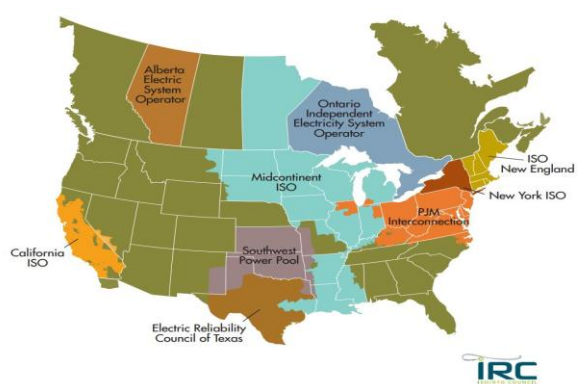

Figure 6. RTOs & ISOs in North America
Source: Reproduced from the ISO/RTO Council (IRC)

Three of these systems (one RTO—PJM and two ISOs—ISO-NE and NYISO) distribute electricity in the RGGI region (see Figure 6). PJM covers Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia, and the District of Columbia. ISO New England (ISO-NE) serves Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont. The New York Independent System Operator (NYISO) covers New York State. The electricity prices in these three electric transmission systems move together, as shown in Figure 7.

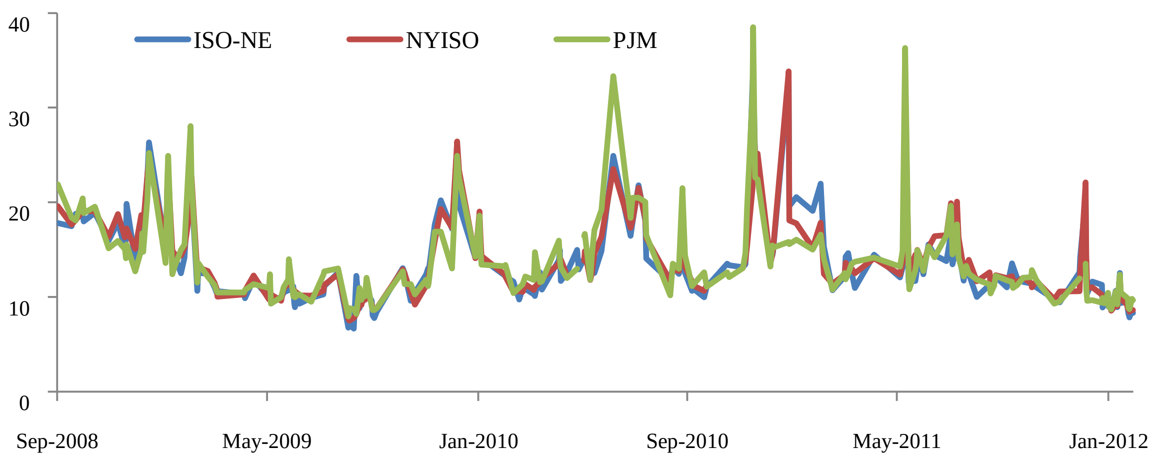

Figure 7. Electricity Prices in the Three Regions (Unit: $/MMBTU)

Note: Three electricity distribution systems in the RGGI region are PJM, ISO-NE, and NYISO. PJM covers Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia. ISO New England (ISO-NE) serves Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont. The New York Independent System Operator (NYISO) covers New York State

The electricity price data for PJM, ISO-NE, and NYISO were collected from the FERC database. Electricity price data reflects a Day-Ahead market price.[13] Due to the irregularity of the

[13] The Day-Ahead Market price is a forward market price for the next operating day, and it is calculated based on the generation offers, demand bids, and scheduled bilateral transactions (http://www.pjm.com/markets-and-operations/energy/day-ahead.aspx).

RGGI transaction data, these daily wholesale prices are adjusted to the corresponding transaction date of the allowance trade in the RGGI. The electricity price series is the simple average of these three electric transmission systems, ISO-NE, NYISO, and PJM. Note that some of the data in PJM is excluded because some regions in PJM system are located outside of the RGGI region (e.g. Commonwealth Edison covers Illinois while Dominion covers Virginia and North Carolina). Electricity prices fluctuate due to seasonality caused mainly by cooling demand in the summer and heating demand in the winter (Figure 8).

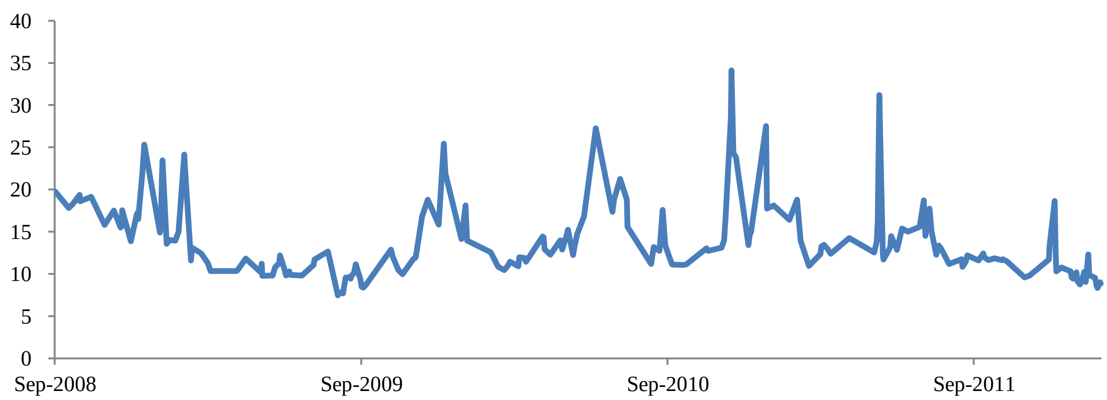

Figure 8. Electricity Price (Unit: $/MMBTU)

Note: Simple average of three electricity Day-Ahead prices in ISO-NE, NYISO, and PJM.

3.1.3. Natural Gas and Coal Prices

The natural gas price is the daily futures price of Henry Hub Gulf Coast in the New York Mercantile Exchange (NYMEX). Natural gas price data is compiled from the Center for Agricultural and Rural Development at Iowa State University (CARD). Dates of the natural gas price are adjusted to correspond with the transaction dates of the RGGI (Figure 9).

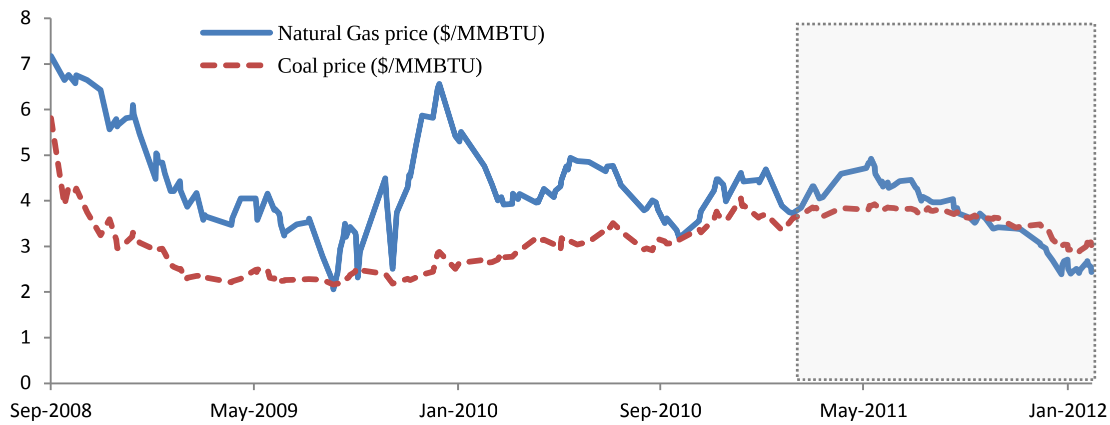

Figure 9. Natural Gas and Coal Price (Unit: $/MMBTU)

The coal price is the daily futures price of Central Appalachian, which is also traded through NYMEX. Coal price data was compiled by the U.S. Energy Information Agency (EIA). Coal prices are adjusted to correspond with the transaction dates of the RGGI (Figure 9). As illustrated in Figure 9, the natural gas price has been historically higher than that of coal; however, (grey boxed area in Figure 9) the price gap between natural gas and coal has recently narrowed and even reversed.

Table 4 contains basic data statistics, specifications, and their sources. The unit of electricity price is $/MWh, coal $/short ton, and natural gas $/MMBTU.[14] Those three different units are converted to $/MMBTU. As shown in Figure 5, Figure 8, and Figure 9, electricity price, natural gas price, and coal price move together.

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[14] MMBTU stands for million British thermal unit. The BTU (or Btu) is a traditional unit of energy equal to about 1,055 joules.

Table 4: Data Statistics, Specification, and Sources

	RGGI price ($/ton of CO_2)	Electricity price ($/MMBTU)	Natural Gas price ($/MMBTU)	Coal price ($/MMBTU)
Observations	204	204	204	204
Mean	2.49	13.76	4.09	3.10
Std. Dev.	0.78	4.44	1.01	0.60
Minimum	1.80	7.44	2.06	2.17
Maximum	6.00	34.11	7.17	5.81
Time Period	September 30, 2008 ~ February 28, 2012			
Specification	RGGI allowance price data	Day-Ahead Prices in the RGGI region: ISO-NE, NYISO, and PJM	Futures price of the nearby contracts from NYMEX	Futures price of Central Appalachian, nearby contracts from NYMEX
Data source	RGGI COATS	Federal Energy Regulatory Commission	Center for Agricultural and Rural Development – Iowa State University	U.S. Energy Information Agency

3.2. Methodology

A Vector Autoregression (VAR) and an Error Correction Model (ECM) are commonly applied in previous literature to analyze the vector of time series and capture the dynamic interrelationship among the variables considered. In this study, the Lag Augmented Vector Autoregression (LA-VAR), which is a modified version of the VAR model introduced by Toda and Yamamoto (1995), is applied to perform the econometric analysis.

There are two reasons why the LA-VAR model is applied instead of the VAR or the ECM model. Firstly, the LA-VAR captures the dynamic interrelationship between variables considered regardless of their stationarity (Kurozumi and Yamamoto 2000). Secondly, the LA-VAR has better size stability than ECM (Dolado and Lutkepohl 1996; Zapata and Rambaldi 1997; Giles and Mirza 1999; Giles 2002). In other words, the LA-VAR captures the dynamic interrelationship between variables better than ECM in a small sample.

3.2.1. Multivariate Time-Series Model: VAR

A VAR model was introduced by Sims (1980). The model describes the evolution of a set of k variables over the sample period as a linear function of only their past values. A VAR (p), with k variables, can be written as follows:

$$\text{(11)} \qquad \mathbf{y}_t = \mathbf{A}_0 + \mathbf{A}_1\mathbf{y}_{t-1} + \mathbf{A}_2\mathbf{y}_{t-2} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{e}_t ,$$

where $\mathbf{y}_t$ is a $k \times 1$ column vector, $\mathbf{A}_0$ is a $k \times 1$ vector of constants, $\mathbf{A}_i$ is a collection of $k \times k$ matrices of parameters, and $\mathbf{e}_t$ is a $k \times 1$ error term (also called innovation). The optimal lag length, p, can be determined using information criteria, such as the Akaike Information Criteria (AIC).

3.2.2. Stationary Test[15]

Stationarity is an essential underlying concept for time-series econometric analysis. If a time-series' data is not stationary, consistent estimators cannot be obtained. The time-series data, y_t, is stationary if its first two moments are finite and constant over time, meaning that neither the mean nor the autocovariance depend on the date t (Hamilton 1994). Mathematically, $\mathrm{E}(y_t) = \mu$ and $\gamma_j = \mathrm{E}[(y_t - \mu)(y_{t+j} - \mu)]$ for all t and j, where γ_j is the autocovariance between y_t and y_{t+j}.

Stationarity of the time-series data is important because estimates are not consistent with non-stationary series. A property of a stationary process is mean-reverting, indicating it will fluctuate around its mean, estimates remaining consistent. In addition, a non-stationary series causes a spurious regression problem. If two variables are trending over time, a regression of one on the other could have a high R^2 value even if the two series are unrelated.

[15] The theoretical background in this section is referenced from Gujarati (2003).

To test whether the time-series data is stationary, the unit root test is widely used. Equation (12) is the random walk model:

(12) $y_t = \rho y_{t-1} + u_t, \quad -1 \le \rho \le 1,$

where u_t is a white noise error term. When ρ =1, implying the existence of a unit root, becomes a random walk model without drift, indicating a non-stationary stochastic process. If we regress y_t on its lagged value y_{t-1} and the estimated ρ is not statistically different from 1, then y_t is non-stationary.

The Dickey-Fuller (DF) and the Phillips-Perron (PP) tests are well-known and commonly applied methods to test for the unit root. In these tests, the null hypothesis is that the series has a unit root, i.e., H_0: $\rho = 1$. If the null hypothesis is rejected, then the data series is stationary. The DF test is based on estimating the equation (12) by ordinary least squares, and thus it may suffer from a serial correlation problem. The Augmented DF test adds the lagged difference terms of the regressand to adjust for the serial correlation. The PP test uses an alternative method to account for the serial correlation problem. The PP test uses Newey–West (1987) standard errors to deal with serial correlation problem in the innovation term.[16] The lag length (or bandwidth) for the PP test is determined using the formula $4(T/100)^{2/9}$ where T is the sample size as suggested in Newey and West (1994), which is 4 for the variables. However, choosing the lag length this way is not necessarily optimal (Hoechle 2007). In this study the PP test is implemented for the unit root test through STATA software. Results are reported in Table 5. The PP adjusted τ test statistic of natural gas is given by -2.527 (fail to reject) and it implies that natural gas is non stationary.

[16] When we have serial correlation problem, we can use New-West standard error to make robust serial correlation standard error. Newey-West standard error is constructed by
$X'\hat{\Omega}X = X'\hat{\Omega}_0X + \frac{n}{n-k}\sum_{l=1}^{m}(1-\frac{l}{m+1})\sum_{t=l+1}^{n}\hat{e}_t\hat{e}_{t-l}(X_t'X_{t-l} + X_{t-l}'X_t)$, and $X'\hat{\Omega}_0X = \frac{n}{n-k}\sum_i \hat{e}_i^2 X_i'X_i$,
where $\hat{e}_i = y_i - X_i\hat{\beta}_{OLS}$, X_i is the ith row of the X matrix, n is the number of observations, k is the number of predictors, m is the lag length, and $X'\hat{\Omega}_0X$ is the White formulation and this White formulation can only take care of heteroskedasticity.

Null hypotheses for RGGI and ELEC are rejected at 1% significance level, and null hypothesis for COAL is rejected at 5% significance level. In sum, RGGI carbon price, electricity prices, and coal prices are stationary, but natural gas prices are non-stationary.

Table 5. Results of Phillips-Perron Tests

	RGGI	ELEC	GAS	COAL
Z(rho)	-21.418	-44.731	-11.336	-11.809
Z(t)	-3.563***	-5.070***	-2.527	-3.418**
10% Critical Value	-2.573	-2.573	-2.573	-2.573
5% Critical Value	-2.883	-2.883	-2.883	-2.883
MacKinnon approximate p-value for Z(t)	0.007	0.000	0.109	0.010
No. of Lags	4	4	4	4
No. of Obs.	204	204	204	204

Note: *** 1%, ** 5%, and * 10% significance levels

1. Z(rho) is the Phillips-Perron ρ test statistic, and Z(t) is the Phillips-Perron adjusted τ test statistic for the coefficient of ρ in the equation (12). These statistics are calculated as following formulas: $Z_\rho = n(\hat{\rho}_n - 1) - \frac{1}{2}\frac{n^2\hat{\sigma}^2}{s_n^2}(\hat{\lambda}_n^2 - \hat{\gamma}_{0,n}), Z_\tau = \sqrt{\frac{\hat{\gamma}_{0,n}}{\hat{\lambda}_n^2}}\frac{\hat{\rho}_n - 1}{\hat{\sigma}} - \frac{1}{2}(\hat{\lambda}_n^2 - \hat{\gamma}_{0,n})\frac{1}{\hat{\lambda}_n}\frac{n\hat{\sigma}}{s_n}$, $\hat{\gamma}_{j,n} = \frac{1}{n}\sum_{i=j+1}^{n}\hat{u}_i\hat{u}_{i-j}$, $\hat{\lambda}_n^2 = \hat{\gamma}_{0,n} + 2\sum_{j=1}^{q}(1 - \frac{j}{q+1})\hat{\gamma}_{j,n}$, $s_n^2 = \frac{1}{n-k}\sum_{i=1}^{n}\hat{u}_i^2$,where u_i is the OLS residual, k is the number of covariates in the regression, q is the number of Newey-West lags to use in calculating $\hat{\lambda}_n^2$, and $\hat{\sigma}$ is the OLS standard error of $\hat{\rho}$.

2. P-values are based on the MacKinnon approximate for Z(t). There was no standard asymptotic distribution to test a unit root. MacKinnon (1994) calculated asymptotic distribution function, and with the result of the study, *P*-value can be applied.

3. If null hypothesis is rejected, then the series is stationary.

3.2.3. Lag Augmented Vector Autoregression (LA-VAR)

Although a VAR model has been applied abundantly in many studies, it has some limitations. A VAR model cannot capture dynamic interrelationships when a data series is not stationary. An Error Correction Model (ECM) or LA-VAR then needs to be applied to test a dynamic interrelationship for a non-stationary data series. In the LA-VAR model, additional lag is added to the VAR model. For this reason, before implementing the LA-VAR model, optimal lag length has to be determined.

3.2.4. Deciding Optimal Lag Length

Toda and Yamamoto (1995) involves the estimation of an LA-VAR (p + d_{max}) model where p is the optimal lag length of the VAR system and d_{max} is the maximal order of integration of the variables in the system. The order of integration is the minimum number of times a series must be differenced to make it stationary. To decide the lag length of the LA-VAR model, we need to find p and d_{max}.

When too many lags are applied, the error in the forecasts will be bigger. On the contrary, if too few lags are applied, this could leave out relevant information. Therefore, applying optimal lag length is important. The optimal lag length, p, can be determined by minimizing the following information criteria: Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and the Hannan-Quinn Criterion (HQIC). These information criteria contain both the goodness of fit of the model and the complexity of the model. Each of the information criterions are defined as follows:

$$\text{AIC} = -2\left(\frac{LL}{T}\right) + \frac{2t_p}{T} \tag{13}$$

$$\text{SIC} = -2\left(\frac{LL}{T}\right) + \frac{\ln(T)}{T} t_p \tag{14}$$

$$\text{HQIC} = -2\left(\frac{LL}{T}\right) + \frac{2\ln\{\ln(T)\}}{T} t_p \tag{15}$$

where t_p is the total number of parameters in the model, LL is the value of the log likelihood function, and T is the number of observations. For the equations (13) - (15), the first term, -2(LL/T) indicates an estimate of the deviance of the fit of the model, and the second term of each equation indicates the degree to which the number of model parameters is being penalized. The optimal lag length, *p*, is chosen to minimize these information criteria. The results of those information criteria values, which were obtained by using STATA, are in Table 6.

There is a confliction in these results: HQIC and SIC indicate one lag is the optimal lag length, whereas AIC tells us three is optimal. According to Koop (2006), this confliction occurs often in practice, and there is no specific rule to select optimal lag length with such confliction in the information criteria values. Two out of the three information criteria in Table 6 suggest that the optimal lag length of the VAR is to be one.[17]

Table 6. Information Criteria Values for Lag Order Selection in VAR

Lag	AIC	HQIC	SIC
0	-1.36	-1.34	-1.30
1	-7.44	**-7.31***	**-7.11***
2	-7.51	-7.27	-6.92
3	**-7.62***	-7.27	-6.76
4	-7.56	-7.10	-6.43
5	-7.56	-7.00	-6.17

Note: The minimum values of AIC, HQIC, and SIC determine the optimal lag length of the VAR system. Those minimum values are indicated by * in this table.

The natural gas price series is non-stationary, as shown in section 3.2.2. The first differenced natural gas price is stationary based on the PP test result. The maximal order of integration of the natural gas price, therefore, is one. Thus, the optimal lag length of the LA-VAR model is two.

[17] According to Lütkepohl (2005), AIC often shows inconsistent results with the other information criteria and unnecesarily extends the length of lag.

3.2.5. Final Model

Let $\mathbf{y}_t$ represent a vector of energy prices at time t, as follows: $\mathbf{y}'_t = [\boldsymbol{y}_{rggi,t}, \boldsymbol{y}_{elec,t}, \boldsymbol{y}_{gas,t}, \boldsymbol{y}_{coal,t}]$, where $\boldsymbol{y}_{rggi}$ is the RGGI carbon allowance price, $\boldsymbol{y}_{elec}$ stands for the electricity price, $\boldsymbol{y}_{gas}$ is the natural gas price, and $\boldsymbol{y}_{coal}$ is the coal price, respectively. The LA-VAR with the two time lags is then given by the following:

(16) $$\mathbf{y}_t = \mathbf{A}_0 + \mathbf{A}_1\mathbf{y}_{t-1} + \mathbf{A}_2\mathbf{y}_{t-2} + \mathbf{e}_t ,$$

where $\mathbf{A}_0$, $\mathbf{A}_1$, and $\mathbf{A}_2$ are the corresponding coefficients vectors, and $\mathbf{e}_t$ is a vector of innovations.

CHAPTER 4

RESULTS AND DISCUSSION

4.1. Empirical Results

4.1.1. Estimation Results

The estimation results of the LA-VAR are presented in Appendix A. The individual estimated coefficients of the LA-VAR are not easy to interpret. Impulse response functions (IRF) are used to interpret these results (Gujarati 2003, p. 853). A Granger causality test is another way to interpret results.

4.1.2. Granger Causality

A variable y_1 Granger causes a variable y_2 if past values of y_1 are useful for predicting y_2 (Granger, 1969). A common method for testing Granger causality is to regress y_2 on its own lagged values and on lagged values of y_1 to test the null hypothesis that the estimated coefficients on the lagged values of y_1 are jointly zero. Rejecting the null hypothesis means y_1 Granger causes y_2. Table 7 presents pair-wise Granger causality tests results obtained by STATA software.

Consider the results of the four tests for the first equation in Table 7. The first is a Wald test[18] wherein the coefficients of the ELEC that appear in the equation for RGGI are jointly zero. The null hypothesis that ELEC does not Granger cause RGGI cannot be rejected. Similarly, we cannot reject the null hypothesis that the coefficients of the GAS in the equation for RGGI are jointly zero, so we cannot reject the hypothesis that GAS does not Granger cause RGGI. We can reject the null hypothesis of the third test that the coefficients of the COAL in the equation for

[18] The Wald test, which is asymptotic version of F-test, is a way regarding testing the significance of specific dependent variables in a model. If Wald test is significant for a particular explanatory variable, then we would conclude that the parameters associated with these variables are not zero, so that the variables should be included in the model (Kyngäs and Rissanen 2001).

RGGI are jointly zero. Therefore, COAL Granger causes RGGI. The fourth test is with respect to the null hypothesis that the coefficients of all the other endogenous variables are jointly zero. Because this can be rejected, we can reject the null hypothesis that ELEC, GAS, and COAL do not Granger cause RGGI.

The other test results in Table 7 can be interpreted in a similar way. In sum, the results show that the RGGI allowance price and coal price Granger cause bilaterally, and natural gas price Granger causes electricity price.

Table 7. The Result of Granger Causality Wald Tests

Equation	Excluded	chi2	df	Prob > chi2
RGGI	ELEC	3.576	2	0.167
RGGI	GAS	1.075	2	0.584
RGGI	**COAL**	**18.422**	**2**	**0.000**
ELEC	RGGI	1.248	2	0.536
ELEC	**GAS**	**29.031**	**2**	**0.000**
ELEC	COAL	3.580	2	0.167
GAS	RGGI	2.868	2	0.238
GAS	ELEC	0.148	2	0.929
GAS	COAL	0.289	2	0.865
COAL	**RGGI**	**8.039**	**2**	**0.018**
COAL	ELEC	0.320	2	0.852
COAL	GAS	0.741	2	0.690

Note: Null hypothesis “excluded” does not cause “equation.”

4.1.3. Impulse Response Function

An Impulse Response Function (IRF) shows responses of variables to a one-time only shock to the innovation of a variable holding all other innovations constant. A one-time only shock is a positive shock of magnitude equal to one standard deviation of the innovation applied in the contemporaneous period (Hamilton 1994, p. 318). Suggested by Swanson and Granger

(1997), the moving average representation (MA) is derived from the estimated LA-VAR in equation (16) such that $\mathbf{y}_t = \sum_{i=0}^{\infty} \mathbf{\Theta}_i \mathbf{e}_{t-i}$. The IRF is defined as $\partial \mathbf{y}_{t+h} / \partial \mathbf{e}_t$.[19] The IRF results were obtained by using STATA software.

4.1.3.1. Impact on RGGI

The IRF for the impulse on RGGI to energy markets are presented in Figure 10. Solid lines are impulse responses and dotted lines are 95% confidence intervals. If there is a positive external shock in the RGGI (in other words, an increase in permit price), then coal price will decrease. When permits become expensive, there is an incentive for power companies to reduce carbon emissions. There might be two choices: reducing electricity generation or switching fuel to a cleaner energy source (natural gas). In either case, the coal demand becomes weak and coal prices decrease.

It is not clear how demand for natural gas reacts to an external shock in the RGGI price. Due to fuel switching, natural gas demand may become strong, indicating expectations for a subsequent rise in natural gas prices. On the other hand, the companies who have used natural gas to generate electricity will reduce their natural gas consumption and lower their carbon emissions as permits become more expensive. The IRF in Figure 10 suggests that the gas price will increase, but not in a statistically significant manner.

[19] Many previous empirical studies have used an arbitrary ordering of variables in $\mathbf{\Theta}_i$ to perform IRF, based on theory, expert opinions, or Choleski decomposition. The ordering of the variables in this study is RGGI, ELEC, GAS, and COAL.

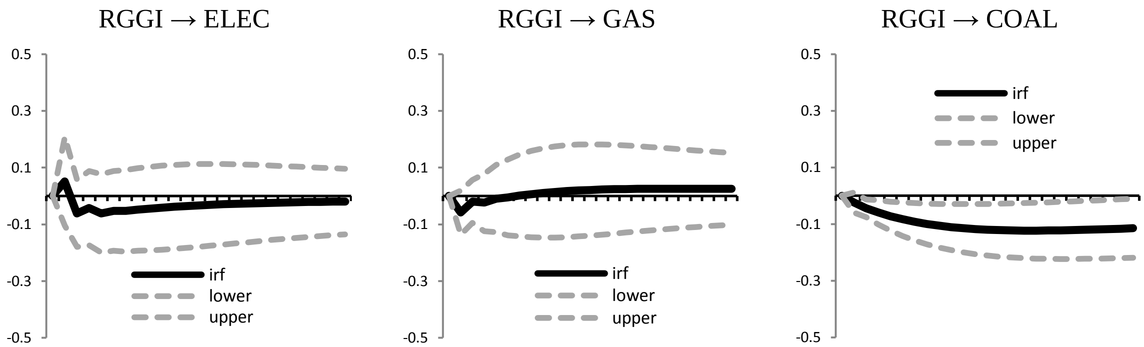

Figure 10. Impulse Response Functions (Impulse from RGGI Price to other Energy Markets)

When permit prices increase, power companies have two choices: reducing electricity generation to avoid the extra burden of buying another permit, or raising electricity prices to pass the burden on to consumers. Either case increases electricity price; however, the result of IRF shows that the electricity price will increase in the short term, but it will soon decrease, although this result is not statistically significant.

4.1.3.2. Impact on Energy Markets

The results for how the RGGI price reacts to an external shock on energy prices are presented in Figure 11. If the electricity price increases, permit prices in the RGGI market also increase, but this effect goes away quickly. By intuition we can conjecture that when electricity price goes up, power companies generate more electricity and emit more carbon. This leads to higher permit prices due to strong permit demand. Note that this is different from the results for the EU ETS discussed earlier.

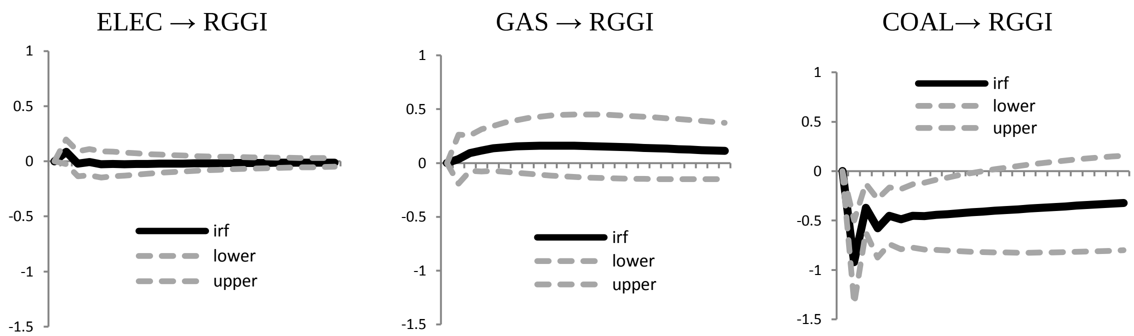

Figure 11. Impulse Response Functions (Impulse from Energy Prices to RGGI Prices)

With increases in the natural gas price, permit prices in the RGGI will also increase. In this case, electricity producers may use more coal than natural gas. This leads to an increase in carbon emissions and leads to high permit demand. Electricity producers purchase more permits in such a situation.

Lastly, if there is a positive external shock in the coal price (if the coal price rises for some reason), then permit prices in the RGGI will decrease. This is because electricity producers may substitute coal with natural gas, which is relatively cheaper. Natural gas includes far less carbon, so carbon emissions will be reduced. In turn, it weakens the demand for carbon permits, and permit prices in the RGGI will subsequently decrease.

4.1.3.3. Impact on Other Markets

The other IRF results are presented in Appendix B. Interpretations are as follows:

- Coal price increases both electricity price and natural gas price (second and third IRF in the first row in B-1 in Appendix B.)
- Increased natural gas price leads to increase electricity price (second IRF in the third row in B-1in Appendix B.)

- Coal price does not respond to any changes in RGGI natural gas and electricity prices (the first column in B-1in Appendix B.)
- A positive shock in electricity price does not affect either coal price or natural gas price (first and third IRFs in the second row in B-1in Appendix B.)

4.2. Discussion

The RGGI carbon price and electricity price are not closely related, as shown in Figure 10 and Figure 11. This is against our intuition because GHG regulation causes the additional cost burden on electricity generation, and, therefore, electricity price should rise. This unexpected discrepancy could be explained by fuel switching. In the RGGI states, natural gas is the largest fuel source to generate electricity in the time period 2005-2006, and its consumption keeps growing. In the same time period, coal consumption was decreasing (Figure 12). The main reason to switch fuel is that natural gas is relatively cheap. After the introduction of the RGGI in 2009, this fuel switching was accelerated because the RGGI carbon policy made natural gas more attractive. This is obvious when we plot the Dark Spark Spread (DSS) and Clean Spark Spread (CSS) as shown in Figure 13.

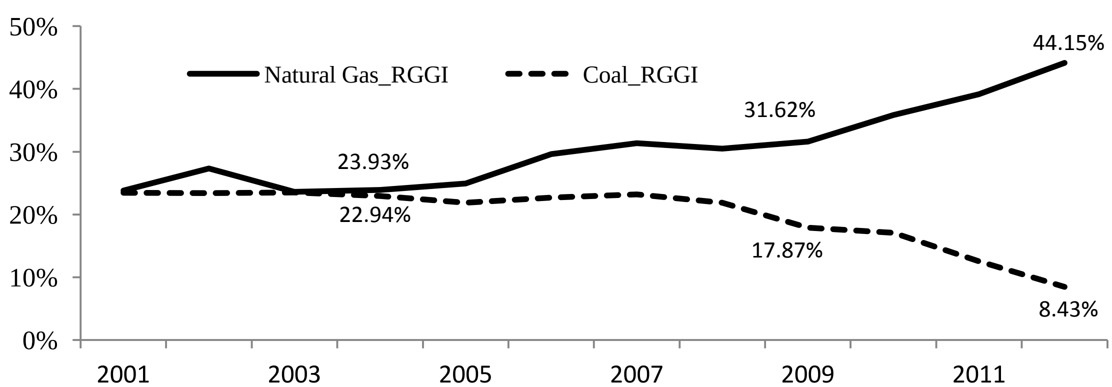

Figure 12. Share of Coal and Natural Gas in Electricity Generation in RGGI States

The spark spread is a measure of a power plant's profitability from selling a unit of electricity (Alberola, Chevallier, and Chèze 2008). The DSS is the gross margin of a coal-fired power plant, and the CSS is the gross margin of a gas-fired power plant (Alberola, Chevallier, and Chèze 2008). Spark spread is defined as follows:

$$(17) \qquad \text{spark spread} = \boldsymbol{P}_{elec} - \left(\frac{\boldsymbol{P}_{fuel}}{\boldsymbol{\rho}_{fuel}} + \boldsymbol{P}_{carbon}\boldsymbol{E}_{fuel}\right),$$

where ρ_{fuel} is the efficiency of fuels (or the heat rate) and E_{fuel} is the emission coefficient (U.S. Energy Information Agency 2013).

Power plants will tend to choose the higher spark spread of two options, and natural gas has a higher spark spread than coal since September 2008. Fuel switching implies low GHG emissions, especially regarding CO_2, without burdening electricity generation. This is because natural gas has a lower emission coefficient and, in turn, generates a weak carbon credit demand in the RGGI. In fact, RGGI emissions fell an average of 34% below the cap during 2009 - 2011. A loose relationship between the RGGI and the electricity market could occur due to the recent dominant occurrence of fuel switching in RGGI region.[20] The power industry in the RGGI region responds to energy markets, especially the natural gas market; however, it does not respond strongly to the RGGI market, and these relationships are logically acceptable.

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[20] There are three options for transitioning from existing coal-fired boilers to natural gas (B & W Power Generation Group 2010). First, the power industry could switch the fuel by modification of an existing boiler. This option implies the partial modification of existing boilers in addition to some operational changes such as sootblowing schedule changes. Second, they could add a gas turbine to the existing boiler cycle. This option involves the addition of another gas turbine to an existing plant. The last option is to construct a new plant to replace an existing coal plant. This last option appears to be the most probable method because 73% of the U.S. coal-fired plants currently have exceeded their expected life span (30 year). In fact, U.S. Energy Information Agency (2014) projects roughly 20% (a total of 60 GW of capacity) of coal-fired power plants will be retired by 2020. Natural gas generating plants can be constructed more quickly than coal-fired generation plants. The specifics of construction time are as follows: simple cycle plants can typically be constructed in 18 to 30 months. Combined cycle plants can be constructed in about 36 months. These lead times are less than the average for coal plants, which take about 72 months to construct.

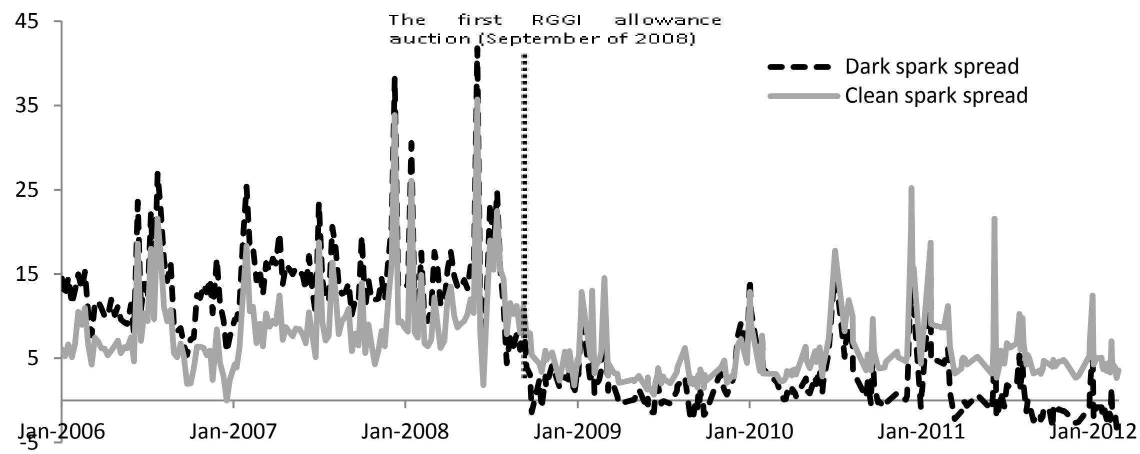

Figure 13. Dark and Clean Spark Spread

Note: The spark spread is a measure of a power plant's profitability from selling a unit of electricity. The Dark Spark Spread (DSS) is the gross margin of a coal-fired power plant, and the Clean Spark Spread (CSS) is the gross margin of a gas-fired power plant. The power plant will choose the higher spark spread.

To distinguish the low gas price effect and the positive carbon permit price effect in fuel switching, a simple regression model was run. The regression model is as follows:

(18) $$\boldsymbol{Share_{gas,t} = \beta_0 + \beta_1 P_{gas,t} + \beta_2 RGGI + \beta_3 P_{gas,t} \cdot RGGI + \beta_4 Summer + u_t},$$

where $Share_{gas}$ refers to the share of natural gas in electricity generation in the RGGI region, P_{gas} refers to the natural gas price, *RGGI* refers to the RGGI dummy, $P_{gas} \cdot RGGI$ refers to an interaction term, and *Summer* is the seasonal trend dummy (for June – August). To this regression analysis, monthly data was applied for the period March 2005 – December 2012, and the number of observations was 94.

OLS estimates are no longer efficient when we have a serial correlation problem, i. e. $\mathrm{Cov}(u_t, u_s) \neq 0, t \neq s$. To test the existence of a serial correlation problem, the Durbin-Watson *d* Test statistic was calculated using STATA software. The equation for the Durbin-Watson *d* Test statistic is as follows:

(19) $$d = \frac{\sum_2^T (u_t - u_{t-1})^2}{\sum_1^T u_t^2},$$

where T refers to the number of time periods and $\boldsymbol{u_t}$ refers to residuals. The Durbin-Watson d Test statistic value was 0.760. This result implies that positive serial correlation exists. When we have positive serial correlation, estimates of the standard errors are smaller than the true standard errors. This serial correlation problem was fixed by regression with the Newey-West Standard Error.[21] The result is presented in Table 8.

Table 8. Results of Regression Model to Test Fuel Switching

$Share_{gas}$	Coef.		Newey-West Std. Err.	T-stat
Constant	35.369***		3.133	11.290
P_{gas}	-0.948 **		0.390	-2.430
RGGI	18.342***		4.300	4.270
$P_{gas} \cdot RGGI$	-3.647***		0.808	-4.510
Summer	5.828***		1.236	4.710
R^2	0.641			
F	39.670	Prob > F = 0.000		
No. of Obs.	94			

*** 1%, ** 5%, and * 10% significance levels

[1] The standard errors are biased when serial correlation is present. Test for serial correlation: Durbin-Watson d-statistic = 0.760. To fix this serial correlation problem, Newey-West standard errors was applied.

[2] $Share_{gas}$ refers to the share of natural gas in electricity generation in the RGGI region, P_{gas} refers to the natural gas price, *RGGI* refers to the RGGI dummy, $P_{gas} \cdot RGGI$ refers to an interaction term, and *Summer* is the seasonal trend dummy.

The dummy variables for the RGGI and trend during summer season have a positive and statistically significant effect on the share of natural gas in electricity generation in the RGGI region. In other words, after the introduction of the RGGI and during the summer season (June – August), the share of natural gas in electricity generation in the RGGI region increased. P_{gas} has a negative effect on the share of natural gas in electricity generation in the RGGI region. This result is obvious: when natural gas price increases, then natural gas demand weakens. When we

[21] As we discussed in the previous chapter, we can use Newey-West standard error to make robust standard error when we have serial correlation problem.

consider the interaction term effect, the absolute number of the coefficient increases by 3.65. This indicates that the RGGI has accelerated fuel switching.

To see more detail on the elasticity of the linear combination term, elasticity at the means before and after the RGGI introduction is calculated as follows:

(20) Before the RGGI: $\frac{\partial Share_{gas}}{\partial P_{gas}} \cdot \frac{\overline{P_{gas}}}{\overline{Share_{gas}}} = \hat{\beta}_1 \cdot \frac{\overline{P_{gas}}}{\overline{Share_{gas}}}$

= - 0.17 (95% confidence interval: -0.30, -0.03),

(21) After the RGGI: $\frac{\partial Share_{gas}}{\partial P_{gas}} \cdot \frac{\overline{P_{gas}}}{\overline{Share_{gas}}} = (\hat{\beta}_1 + \hat{\beta}_3) \cdot \frac{\overline{P_{gas}}}{\overline{Share_{gas}}}$

= - 0.81 (95% confidence interval: -1.06, -0.57),

where β_1 is the estimated coefficient of natural gas price, and β_3 is the estimated coefficient of the interaction term.

Elasticity at the means changes from -0.17 to -0.81 after the introduction of the RGGI. The result of the calculation tells us that if natural gas price decreased by 10%, the share of natural gas electricity generation would increase by 1.7%. When the interaction term effect is considered, this situation changes. If natural gas price decreased by 10%, the share of natural gas electricity generation would increase by 8.1%. In other words, the share of natural gas more increases than without interaction term considered. The fact that accelerated fuel switching with the introduction of the RGGI is verified.

CHAPTER 5

CONCLUDING REMARKS AND FUTURE STUDIES

There have been numerous studies in relation to carbon permit prices in the greenhouse gas emissions trading market and energy markets such as electricity, natural gas, coal, and crude oil. Most previous studies have focused on the European Union Emissions Trading Scheme (EU ETS) since its creation in 2005. Notable findings indicate that the EU ETS carbon permit price and energy prices are closely interrelated, and crude oil and electricity prices are the main drivers of the carbon permit price. Our attention then moves to another emissions trading market in the U.S., the Regional Greenhouse Gas Initiative (RGGI), which began in January 2009 for nine northeastern U.S. states. The RGGI is the first regulatory carbon cap-and-trade system in the U.S. To my best knowledge, there has been no rigorous empirical study on the RGGI.

The primary research objective of this study is to investigate the mutual relationship between the RGGI carbon price and energy prices in the northeastern U.S. To capture the mutual relationship among the prices for the RGGI, electricity, natural gas, and coal markets, the Lag Augmented Vector Autoregression (LA-VAR) model is applied. The impulse response function results suggest that mutual relations between the RGGI allowance price and the electricity market exist, although they are weak (and statistically insignificant). This implies that these markets are not closely attached to each other. The impulse response function also suggests that the natural gas price has positive impacts on the RGGI price, but the RGGI market does not influence the natural gas price. In addition, it tells us that RGGI prices and coal prices negatively interact with each other.

The key findings of this study state that 1) the RGGI market and electricity market in the RGGI region are not closely tied, unlike the EU ETS. This loose relationship between the two markets can be explained by the recent weak carbon credit demand stemming from low GHG emissions. These low GHG emissions result from fuel switching from coal to natural gas due to recent low natural gas prices. 2) Natural gas is the main driver of the RGGI system.

Based on the findings of this study, we discover the following two policy implications. First, there have been concerns as to whether the RGGI market actually works. Despite these concerns, the RGGI has been working to reduce GHG emissions through fuel switching. The RGGI has accelerated fuel switching. Second, the newly reduced emission cap, which will apply starting in 2015, might make the relationship between the RGGI and energy markets stronger. Further fuel switching, however, might make the relationship between the RGGI and electricity markets weaker. Therefore, when we consider the possibility of these conflicting effects in the second policy implication, the relationship between the RGGI and electricity markets warrants future study.

Regrettably, this empirical work has some limitations. First of all, transaction periods in the RGGI market were irregular. Usually, transforming the data into an evenly spaced series through the use of interpolation can solve an unevenly spaced time series problem. Unfortunately, because the sample size of RGGI transaction data is limited, it cannot be fixed by this kind of revision. Thus, the unevenly spaced time series data was applied. Another limitation of this work is the omission of the ARP allowance price. As discussed in a previous chapter, natural gas emits much smaller levels of SO_2 and NO_x than coal; therefore, adding this variable can perhaps better explain the relationships between the RGGI and energy markets. Lastly, external effects including electricity import from neighbor states are not considered in this study. The RGGI imposes a GHG abatement duty only on the power plants in the RGGI region. This regulation of the power industry might expedite the movement of power plants to other regions. In addition, the electricity imported from nearby states could increase. This kind of impact, however, was not considered in this study.

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APPENDICES

Appendix A The Completes Result of the VAR Estimation

VAR estimation results are presented in Table A-1.

Table A-1. VAR Estimation Results

Vector autoregression

Sample: Sep, 2008- Jan, 2012		No. of obs	= 202
Log likelihood	= 790.124	AIC	= -7.467
FPE	= 6.72e-09	HQIC	= -7.228
Det(Sigma_ml)	= 4.71e-09	SBIC	= -6.877

Equation	Parms	RMSE	R-sq	chi2	P>chi2
Ln_RGGI	9	0.136	0.767	664.228	0
Ln_ELEC	9	0.175	0.632	347.286	0
Ln_GAS	9	0.088	0.876	1420.99	0
Ln_COAL	9	0.040	0.958	4558.729	0

RGGI Equation

		Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Ln_RGGI							
	Ln_RGGI						
	L1.	0.456	0.062	7.360	0.000	0.335	0.578
	L2.	0.372	0.062	5.970	0.000	0.250	0.494
	Ln_ELEC						
	L1.	0.086	0.057	1.520	0.129	-0.025	0.197
	L2.	-0.097	0.056	-1.730	0.084	-0.207	0.013
	Ln_GAS						
	L1.	0.035	0.116	0.300	0.762	-0.193	0.263
	L2.	0.027	0.121	0.230	0.820	-0.210	0.265
	Ln_COAL						
	L1.	-0.920	0.215	-4.280	0.000	-1.340	-0.499
	L2.	0.807	0.203	3.980	0.000	0.409	1.204
	_cons	0.210	0.108	1.930	0.053	-0.003	0.422

ELEC Equation

		Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Ln_ELEC							
	Ln_RGGI						
	L1.	0.051	0.080	0.640	0.520	-0.105	0.208
	L2.	-0.087	0.080	-1.090	0.276	-0.244	0.070
	Ln_ELEC						
	L1.	0.503	0.073	6.900	0.000	0.360	0.646
	L2.	-0.017	0.072	-0.240	0.813	-0.158	0.124
	Ln_GAS						
	L1.	0.479	0.150	3.200	0.001	0.186	0.772
	L2.	-0.099	0.156	-0.640	0.524	-0.404	0.206
	Ln_COAL						
	L1.	-0.206	0.276	-0.740	0.456	-0.747	0.336
	L2.	0.326	0.261	1.250	0.212	-0.185	0.837
	_cons	0.696	0.140	4.990	0.000	0.423	0.970

GAS Equation

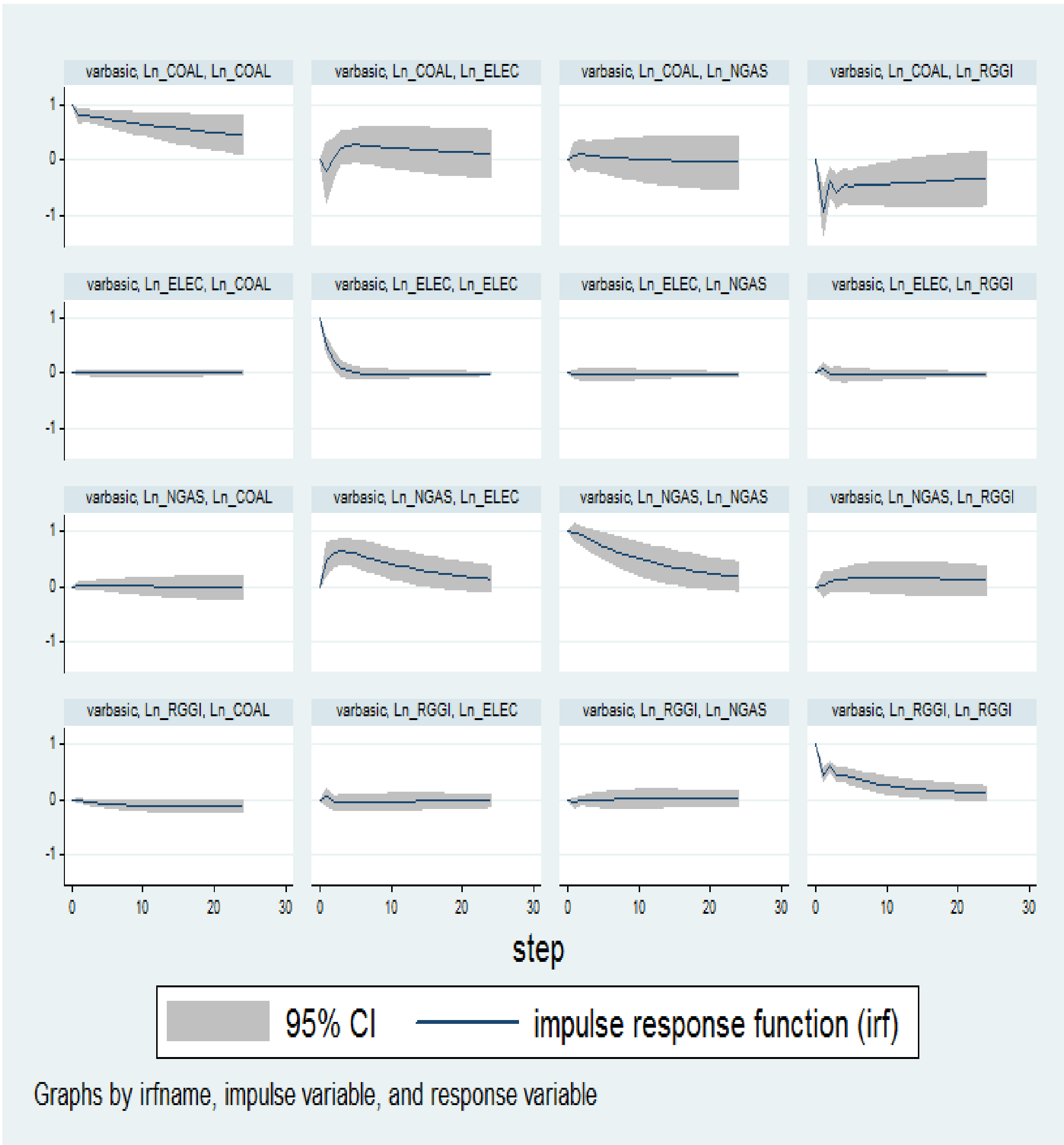
		Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Ln_GAS							
	Ln_RGGI						
	L1.	-0.059	0.040	-1.470	0.142	-0.137	0.020
	L2.	0.066	0.040	1.660	0.098	-0.012	0.145
	Ln_ELEC						
	L1.	-0.008	0.036	-0.220	0.829	-0.079	0.064
	L2.	-0.006	0.036	-0.170	0.864	-0.077	0.065
	Ln_GAS						
	L1.	0.970	0.075	12.960	0.000	0.824	1.117
	L2.	-0.029	0.078	-0.380	0.705	-0.182	0.123
	Ln_COAL						
	L1.	0.074	0.138	0.530	0.594	-0.197	0.345
	L2.	-0.069	0.131	-0.530	0.598	-0.325	0.187
	_cons	0.101	0.070	1.440	0.149	-0.036	0.238

COAL Equation

		Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Ln_COAL							
	Ln_RGGI						
	L1.	-0.024	0.018	-1.340	0.180	-0.060	0.011
	L2.	-0.012	0.018	-0.670	0.501	-0.048	0.023
	Ln_ELEC						
	L1.	0.009	0.017	0.550	0.586	-0.023	0.041
	L2.	-0.002	0.016	-0.140	0.891	-0.034	0.030
	Ln_GAS						
	L1.	0.029	0.034	0.860	0.391	-0.037	0.096
	L2.	-0.027	0.035	-0.780	0.436	-0.097	0.042
	Ln_COAL						
	L1.	0.809	0.063	12.920	0.000	0.686	0.932
	L2.	0.136	0.059	2.290	0.022	0.020	0.251
	_cons	0.072	0.032	2.280	0.023	0.010	0.134

Appendix B Impulse Response Function

Full impulse response function results are presented in B-1.



B-1. Impulse Response Functions Results

Note: [1] The IRFs illustrate how individual data series respond to a positive shock (an increase in price) in each of the variables over time.
[2] RGGI represents the RGGI allowance price; ELEC represents the electricity price; GAS represents the natural gas price; and COAL represents the coal price.
[3] Grey areas are 95% confidence intervals.