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Dynamic Interactions between Carbon and Energy Prices in the U.S. Regional Greenhouse Gas Initiative[1]

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ABSTRACT

Numerous studies have investigated the dynamic interrelationship between carbon emission trading market and energy markets. Previous studies focused on the European Union emissions trading scheme (EU-ETS) ascertain that carbon market and energy markets are closely attached, and find that electricity market is the main driver of the system. Our research on U.S. Regional Greenhouse Gas Initiative (RGGI) using lag augmented vector autoregression reveals that the RGGI market and electricity market in the region are tied but not strongly, unlike the EU-ETS. This loose relationship between the two markets might be explained by the recent weak carbon credit demand stemming from fuel switching and low electricity demand. Another finding is that natural gas is the main driver of the RGGI system, which is possibly due to from the recent shale gas boom.

Keywords: Carbon Emission Trading, Lag Augmented Vector Autoregression, Regional Greenhouse Gas Initiative
JEL Classifications: C32, Q52, Q53

1. INTRODUCTION

There have been numerous researches and debates regarding relationships among carbon emission trading market and energy markets, especially their prices. As transaction data in the carbon trading markets, e.g. the European Union emission trading scheme (EU-ETS), are accumulated, a number of empirical studies on emissions trading market have been published. Recent studies might be categorized into two groups (i) examining determinants of the carbon price, e.g. Mansanet-Bataller et al., (2007); Alberola et al., (2008), and Aatola et al., (2013), and (ii) analyzing dynamic interactions among carbon market and energy markets, e.g. Fezzi and Bunn (2009); Oberndorfer (2009), Kirat and Ahamada (2011); Reboredo (2013). Notable findings in these studies are (i) the EU-ETS carbon price and energy prices (in the EU) are closely attached, and (ii) electricity price is the main driver of the carbon price (in the EU-ETS).

Our eyes move naturally to another emission trading market in the U.S., the Regional Greenhouse Gas (GHG) Initiative (RGGI), which began on January 1, 2009 for the nine northeastern US states. To the best of our knowledge, there is no rigorous and ad hoc empirical study to analyze the interrelationship between the RGGI market and energy markets in the U.S. most of researchers have paid attention to the EU-ETS possibly because the EU-ETS is the largest and most influential carbon trading market and also it has amassed the large volume of transaction data including historical carbon prices and trading volumes. The RGGI is a small, regional and non-Kyoto protocol compliance market which has accumulated relatively small and sparse transaction data. One of the key contributions of this article is to fill this research gap by investigating dynamic interactions between the RGGI and energy markets in the RGGI region. In doing so, we identify the main driver(s), if any, of the carbon price in the RGGI and characterize the price dynamics in the RGGI region.

Meanwhile there are voices concerning low carbon prices in the EU-ETS. The carbon price plummeted in the fourth quarter of 2011 in the EU-ETS. The current carbon price in the EU-ETS is <$5/ton of CO_2 (as of December, 2013), which were maintained at around

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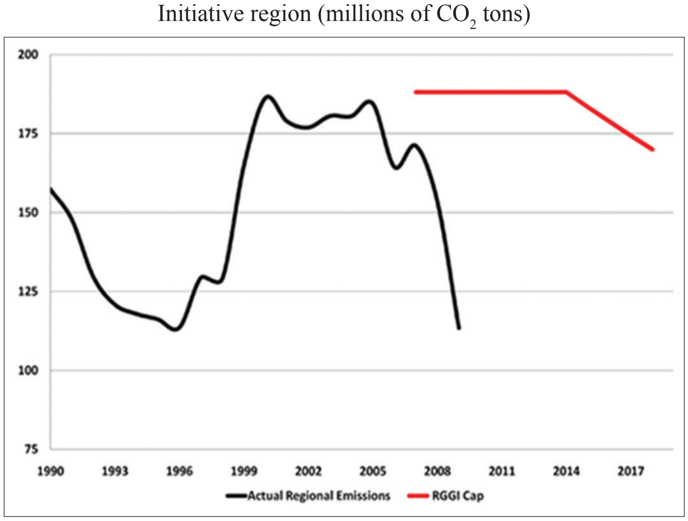
\$19~\$26/ton of CO_2 until around mid-2011. A chronic oversupply of carbon permits is one of the reasons for the recent low carbon price. The EU has been seeking a structural reform of the carbon market, named "back-loading," which would take 900 million tons of carbon allowances off the market now and reintroduce it later, to prevent further decline of carbon price (Reed, 2013).

The RGGI also has been reporting a low carbon price of around \$3.30/ton of CO_2 (as of December, 2013) (RGGI CO_2 allowance tracking system). The low carbon price in the RGGI is caused by a low carbon credit demand which has stemmed from low GHG emissions in the RGGI states (Stavins, 2012; Murray et al., 2014). The current GHG emissions are already 34% below the emission cap (Figure 1). Stavins (2012); Ramseur (2014) and Murray et al., (2014) point out that the low GHG emissions in the RGGI region has originated from two sources (i) Fuel switching from coal to cleaner natural gas in electricity generation, (ii) weak electricity demand due to the economic recession in 2008 and the moderate weather condition in the region. The low carbon credit demand stemmed from fuel switching in the RGGI region would make the relationship between the RGGI and electricity market loose and, in turn, it causes low carbon prices. In addition, fuel switching and the weak connection between the RGGI and electricity market make the RGGI and other energy markets loose, too.

Many researchers and policy makers have worried about whether the RGGI fails[1] because of the recent low carbon prices. The low carbon prices, however, does not indicate the failure of the RGGI rather the RGGI system have flaws (Stavins, 2012). We will verify that the RGGI actually works, i.e. to show existence of the mutual relationship between RGGI carbon price and energy prices. In sum, this paper aims to investigate a mutual relationship among RGGI carbon price and energy prices in the northeastern U.S., specifically investigate whether the RGGI interact with other energy markets.

1 The article posted on September 9, 2011 on the New Jersey Watchdog (2011) says "the RGGI nears brink of failure …"

Figure 1: Historical CO_2 emissions in the Regional Greenhouse Gas Initiative region (millions of CO_2 tons)



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

We expect that the RGGI and energy markets are not strongly attached but have a statistically significant relationship.

2. LITERATURE REVIEW

In general, key drivers of the carbon price in the emission trading market are energy prices such as crude oil, natural gas, coal, and electricity. Weather condition and policy options such as the emission target, are also key determinants of the carbon price (Chevallier, 2012). Mansanet-Bataller et al., (2007) examine which factors explain the carbon price in the EU-ETS in 2005, applying the multivariate least squares regression model. Results show that the energy prices such as Brent crude oil and natural gas were the most decisive elements among carbon price determinants.

Alberola et al., (2008) extend Mansanet-Bataller et al., (2007) study with additional observations of the EU-ETS through April of 2007. The result shows that the EU-ETS carbon price reacts to the energy prices and unexpected temperature change in winter which coincides with the results of Mansanet-Bataller et al., (2007). They also find two structural changes (April 2006 and October 2006) during Phase I.[2] The two structural changes were due to the disclosure of 2005 official emission data in April 2006 and the European Commission announcement of stricter allocations in Phase II in October 2006. Creti et al., (2012) also discuss determinants of the carbon price in the EU-ETS. Although the purpose of the study is conceptually identical to both Mansanet-Bataller et al., (2007) and Alberola et al., (2008), it extends the time period to include Phase II and show that carbon price determinants in Phase I have maintained in Phase II in the EU-ETS using the cointegration technique. Aatola et al., (2013) also examine carbon price determinants in the EU-ETS between 2005 and 2010 and conclude that the electricity price in Germany and natural gas and coal prices are the key factors. In sum, various studies have examined carbon price drivers in the EU-ETS. Factors such as energy prices, weather conditions and institutional factors such as policy announcements affect the EU-ETS market.

The other 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 markets, the EU-ETS, UK electricity market, and UK natural gas market using vector error correction model (VECM). Results show that the UK electricity price increases the EU-ETS carbon price instantly and considerably and the carbon price increases the UK electricity price with a few days lag. It indicates that the EU-ETS is mutually and strongly related to the electricity market.

Kirat and Ahamada (2011) investigate the relationship between the carbon price in the EU-ETS and electricity contracts in France and Germany using the generalized autoregressive conditional

2 Phase I of the EU-ETS, between 2005 and 2007, is a pilot period, and the EU-ETS began in earnest in Phase II, between 2008 and 2012. Phase III will be continued up until 2020.

heteroscedastic model. The result tells us that the electricity industry in both France and Germany weakly respond to the EU-ETS, with Germany having a stronger interdependence. This is because of 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 are also considered as main carbon price drivers. Using the Markov-switching VAR model (Kim and Nelson, 1999), the interactions between the macroeconomic index and energy prices are captured. The result shows that industrial production positively affects the EU-ETS 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 GHG emissions. As a result this reads to a strong carbon credit demand. Reboredo (2013) examines the interdependence between the EU-ETS price and Brent crude oil price during Phase II period using the copula model[3] which measures dependence between the EU-ETS and energy markets. The result indicates that the EU-ETS price and Brent crude oil price are positively related. Additionally, Reboredo (2013) shows that when an investment portfolio contains both EU-ETS allowances and crude oil, the portfolio reduces financial risk of the power plants.

In sum, according to studies listed above, 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. Unfortunately, all literature exclusively deals with the EU-ETS. As far as we know, there is no empirical study on the RGGI that may have different characteristics from the EU-ETS.

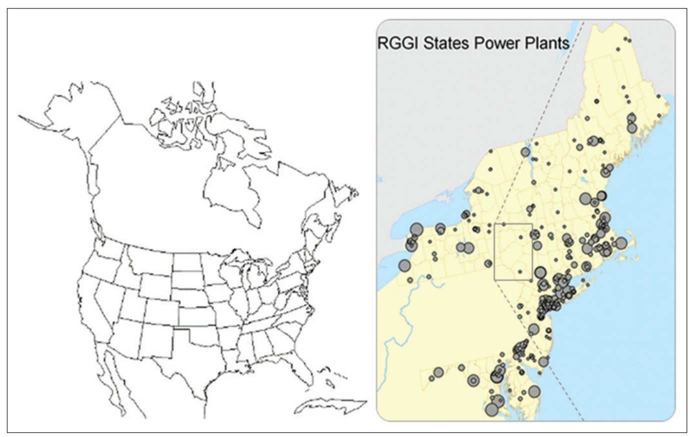
3. RGGI

The RGGI is the first regulatory GHG cap-and-trade system in the U.S. in nine northeastern states.[4] Figure 2 shows the RGGI states and its coverage, locations and size of power plants. Currently, fossil fuel-fired power plants with 25 MW or more capacity in electricity generation are participating the program.

GHG emissions of the RGGI region accounts for about 10% of total US GHG emissions. Power plants can use CO_2 offset[5] to meet their CO_2 compliance obligation besides purchasing carbon permits from the RGGI. The first permit auction was held in September 2008, and the first 3 years compliance period began in January 2009 that ended in December 2011. The emission cap was 188 million CO_2 tons/year during 2009-2011. During 2012-2014, the cap of the program is 165 million CO_2 tons/year. Because of the ineffectiveness of this prior emission cap in the RGGI region, a new cap of 91 million CO_2 tons/year will be applied beginning in 2015. The size of the RGGI is relatively small in terms of carbon trading volume of $249 million 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.

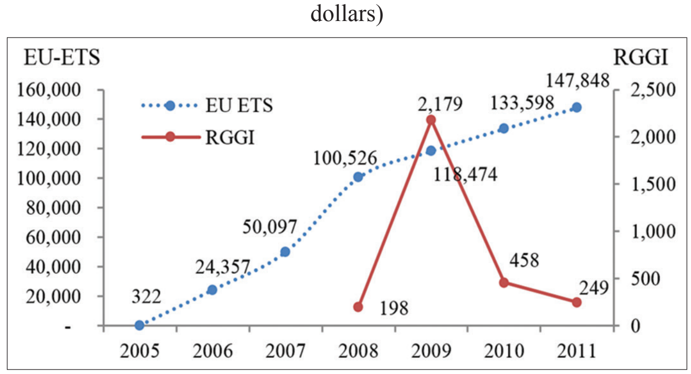
The RGGI achieved its emissions reduction goal already, 34% below its cap (Figure 1). However, the RGGI "was not binding" (Stavins, 2012), which means that the emission reduction goal is achieved through the external conditions, e.g. less GHG emissions due to fuel switching and the weak electricity demand due to the economic recession in 2008 and the moderate weather condition in the region. Experts, e.g. Stavins (2012) and Ramseur (2014), however, argue that it doesn't mean the design of the RGGI system has a defect. According to Ramseur (2014), although the RGGI did not directly reduce carbon emission, the profits from allowance

Figure 2: Regional Greenhouse Gas Initiative (RGGI) coverage - power plants in the nine RGGI states



Note: Grey circles in the right side of map show the location of the power plants in the RGGI states.
Source: The map for RGGI states power plants is obtained and reproduced from Woods Hole Research Center (WHRC) (http//www.whrc.org/policy/rggi.html)

Figure 3: Market size comparison between Regional Greenhouse Gas Initiative and European Union emission trading scheme (million dollars)



Source: World Bank (2012)

3 The copula model, a multivariate probability distribution for which the marginal probability distribution of each variable is uniform, measures the dependence among random variables (Schweizer and Wolff, 1981).

4 Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont.

5 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.

auctions contributed to support for clean energy projects such as energy efficiency and renewable energy. In addition, Ramseur (2014) claims the program promotes other states' or federal level's GHG reduction activity.

4. METHODOLOGY AND DATA

4.1. Lag Augmented Vector Autoregression (LA-VAR)

An *ad-hoc* approach is applied to investigate the mutual relationships between carbon price and energy prices. The VAR or the VECM are commonly applied to analyze vector of time series data and capture the dynamic interrelationship among variables. In this study, however, the LA-VAR (Toda and Yamamoto, 1995; Yamada and Toda, 1998) is applied to perform the econometric analysis. The LA-VAR overcomes the problem of pretest bias from applying the standard approach of testing the hypotheses, which is conditioned on testing for unit roots and co-integration to apply either a VAR or VECM (Yamada and Toda, 1998; Emirmahmutoglu and Kose, 2011). The LA-VAR is appealing because it remains applicable regardless of whether the VAR process is stationary or has any order of integration (Toda and Yamamoto, 1995; Kurozumi and Yamamoto, 2000) and thus the LA-VAR does not require the pretests for cointegrating rank. Secondly, the LA-VAR has better size stability than VECM (Yamada and Toda, 1998; Henriques and Sadorksy, 2008). In other words, the LA-VAR captures the dynamic interrelationship between variables better than VECM in a small sample, which is applicable well to our data set.

Let p_t be a vector of the carbon and the energy prices at time t, $p_t' = \left[p_{rggi}, p_{elec}, p_{gas}, p_{coal}\right]_t$, where p_{rggi} is the RGGI carbon price, p_{elec} stands for the electricity price, p_{gas} is the natural gas price, and p_{coal} is the coal price, respectively. The LA-VAR with the two lags[6] is then given by

$$P_t = \beta_0 + \beta_1 p_{t-1} + \beta_2 p_{t-2} + e_t \quad (1)$$

Where β_0, β_1, and β_2 are the corresponding coefficients matrices, and is a vector of innovations (residuals).

The estimated coefficients in equation (1) are not easily interpreted due to the complexity of the system. Usually an impulse response function (IRF) is used to illustrate the dynamic relationship among variables. Suggested by Swanson and Granger (1997), the moving average representation (MA) is derived from the estimated LA-VAR, $p_t = \sum_{i=0}^{\infty} \Theta_i v_{t-i}$ where Θ_i is the moving average coefficient matrix and v_t is orthogonalized innovations. The IRF is defined as $\partial p_{t+h} / \partial v_t$

6 Toda and Yamamoto (1995) suggest the estimation of the LA-VAR($k+d_{max}$) model where is the optimal lag length of the VAR system and is the maximal order of integration of the variables in the system. The optimal lag length of the VAR is determined as 1 using information criterions such as Hanna-Quinn Information Criterion and Schwarz Information Criterion. The maximal order of integration of the variables is found to be 1 using the Phillips-Perron test, i.e., p_{reggi}, p_{elec}, and p_{coal} are stationary, and p_{gas} is non-stationary order of 1. All of the test results are not reported here to save space but available upon request. Also estimates of equation (1) are not reported either but available upon request.

Since e_t from the LA-VAR in equation (1) may include off-orthogonal contemporaneous correlations, we transform e_t to orthogonal price innovations v_t such that

$$v_t = Ge_t \quad (2)$$

Where the 4´4 matrix G contains the contemporaneous causal structure among orthogonal innovations v_t, which is identified[7] through direct acyclic graphs (DAG) (Pearl, 2000). DAG is the data-induced method to determine the ordering in the innovations (Park et al., 2006 and 2008) from the VAR model has been suggested as an alternative to the widely used Choleski factorization (Swanson and Granger, 1997; Bessler et al., 2003). Note that the causal flow from the DAG should not be interpreted as the evidence of true causalities among variables, especially without any analytical framework for the identification. We use the DAG only for ordering the variables to perform IRF analysis in the later sections.

4.2. Data

The RGGI carbon prices are archived through the RGGI CO_2 allowance tracking system (COATS) (https//rggi-coats.org/eats/rggi). The first allowance auction was held in September 2008 and COATS data starts on September 30 of 2008. Transactions have occurred irregularly since then, however. The total number of carbon price observations is 204, although carbon allowances had been traded over 3 years.[8] The average price is \$2.49/ton of CO_2 and standard deviation is \$0.78/ton of CO_2 (Table 1). As shown in Panel A in Figure 4, the RGGI price stayed around \$2-3/ton of CO_2. In the early stage of the RGGI, the carbon price was over \$3/ton of CO_2. This price has decreased over time and after 2010 it leveled out at around \$2/ton of CO_2 with a price spike from time to time.

Electricity price is compiled from three wholesale electricity markets that cover the RGGI states, i.e. ISO-NE, NYISO and PJM.[9] Price data outside of the RGGI region are excluded. The average of electricity prices are computed over a number of markets within three wholesale markets and matched them to the corresponding dates for the carbon allowance transaction from the COATS transaction log. As shown in Table 1, the mean electricity price is \$13.76/MMBTU[10] and the standard deviation is \$4.44/MMBTU.

7 The Cholesky factorization may be used here; however, it has significant shortcomings since it allows for arbitrarily choosing one causal case over many others (Bernanke, 1986; Demirap and Hoover, 2003). Thus the selection may not reflect the actual contemporaneous causal ordering among the variables. The DAGs represents the contemporaneous causal structure based on data and also it represents an improvement over the conventional method.

8 Authors acknowledge that a robust empirical analysis is difficult due to illiquid data than the more mature EU-ETS data then one should be careful on drawing conclusions on the RGGI. As the RGGI is a new and young market, this is a problem not to be avoided, however.

9 ISO-NE: Independent System Operators New England that serves Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont, NYISO: New York Independent System Operator that covers New York state, PJM: Pennsylvania New Jersey Maryland Interconnection that is a Regional Transmission Organization serves all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia.

10 1 MMBTU ≈ 293 kWh

The volatility of the electricity price is relatively large as shown in Panel B in Figure 4. As expected its movement is similar to those of natural gas and coal prices in Panels B and C in Figure 4.

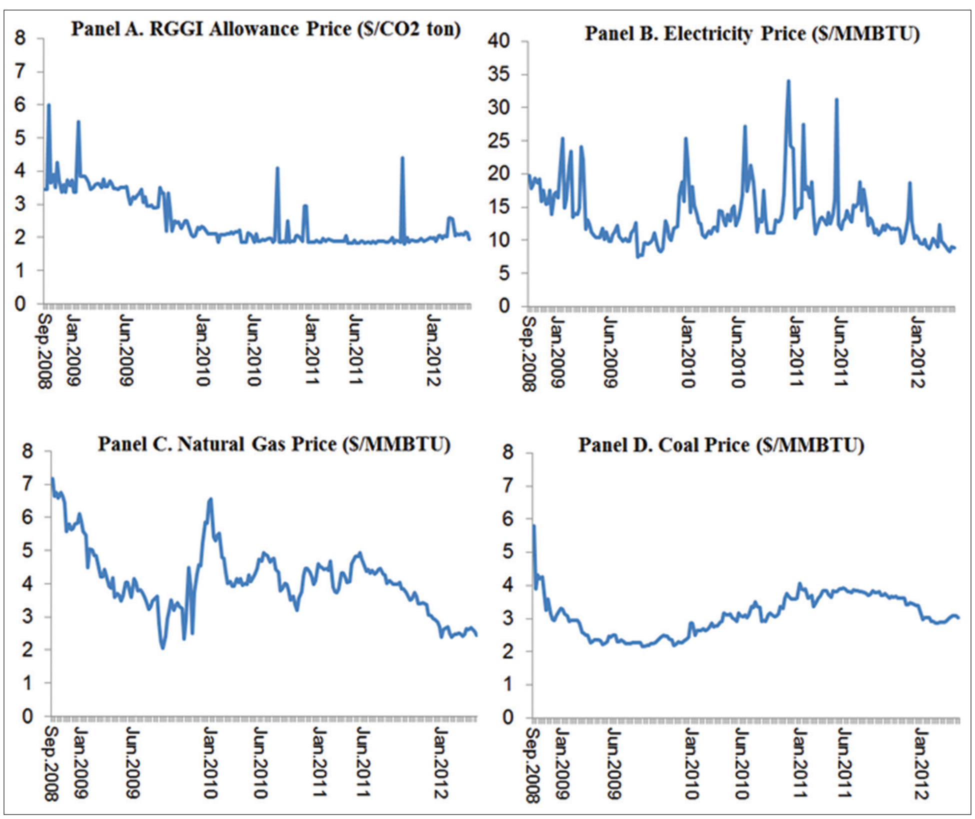
Natural gas and coal are main fuel sources to generate electricity in the nine RGGI states. Both natural gas and coal account for 52% of the total electricity generation in 2012, while nuclear account for 30% and hydro power 11% of the total generation, respectively. Thus, natural gas and coal prices are included in the system. Oil accounts for <1% of the electricity generation in 2012 in the RGGI region and thus it is excluded from the model. 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 4). Also, coal price is the daily futures price of nearby contract for Central Appalachian from the NYMEX and are compiled from the Energy Information Agency. The average natural gas price is $4.09/MMBTU and the average coal

Table 1: Data statistics, specification and sources

Data	RGGI price ($/ton of CO_2)	Electricity price* ($/MMBTU)	Natural gas price ($/MMBTU)	Coal price ($/MMBTU)
Observation	204	204	204	204
Mean	2.49	13.76	4.09	3.10
Standard deviation	0.78	4.44	1.01	0.60
CV (%)	31.19	32.28	24.59	19.34
Minimum	1.80	7.44	2.06	2.17
Maximum	6.00	34.11	7.17	5.81
Specification	RGGI allowance price data	Forward price of electricity wholesale in ISO-NE, NYISO, and part of PJM	Futures price of the nearby contracts from NYMEX	Futures price of Central Appalachian, nearby contracts from NYMEX
Data source	RGGI COATS	FERC	Center for Agricultural and Rural Development – Iowa State University	EIA

*Average of the three electric transmission systems, ISO-NE, NYISO, and PJM; All of ISO-NE (Connecticut, NEMass/Boston, New Hampshire, Maine, Mass Hub) and NYISO (Capital, Hudson Valley, Long Island, New York City, North, West) electricity prices are included. Some electricity prices outside the RGGI region in PJM transmission system are excluded. FERC: Federal Energy Regulatory Commission, EIA: Energy Information Agency, RGGI: Regional Greenhouse Gas Initiative, CV: Coefficient of variation

Figure 4: Plot of variables (September 2008-December 2012), Panel A RGGI allowance price (S/CO_2 ton), Panel B Electricity price (S/MMBTU), Panel C Natural gas price (S/MMBTU), Panel D Coal price (S/MMBTU)



Sources: Regional Greenhouse Gas Initiative (RGGI) price from RGGI COATS; electricity price from Energy Information Agency (EIA); natural gas price from Center for Agricultural and Rural Development – Iowa State University; coal price from EIA.

price is $3.10/MMBTU. As shown in Figure 4, natural gas has been more expensive than coal during 2008-2010. After 2011 the price gap between natural gas and coal has narrowed and even reversed.

5. EMPIRICAL RESULTS AND DISCUSSION

5.1. Contemporaneous Causal Structure

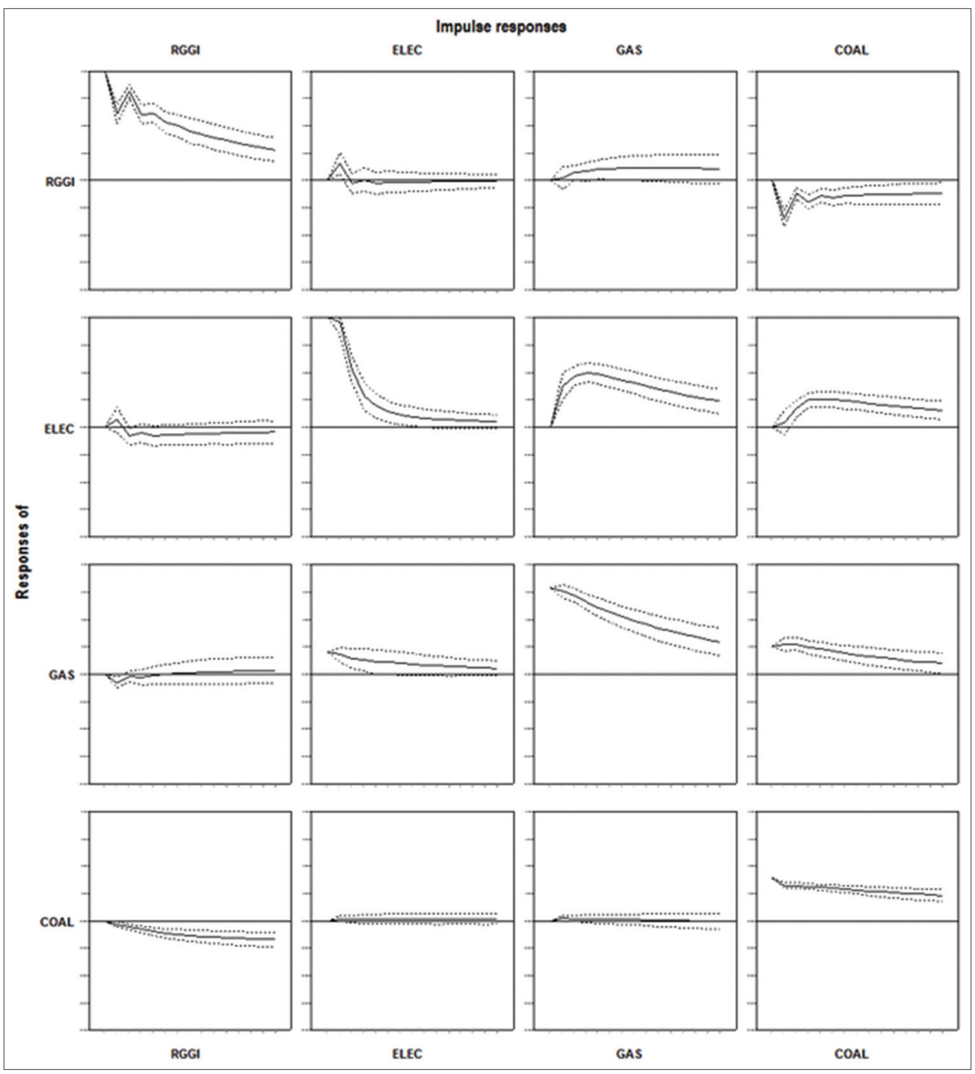
The matrix G in the MA representation contains the contemporaneous causal structure among orthogonal innovations as in equation (2), which is identified through the DAG. The DAG approach identifies the causal relationship among non-experimental data based on a conditional independence (Pearl, 2000; Spirtes et al., 2000; Scheines et al. 1994). The PC algorithm marketed as TETRAD IV (http//www.phil.cmu.edu/projects/tetrad/) is used to specify the directed acyclic graph. See Kalisch and Buhlmann (2007) for more about DAG and the PC-algorithm.

DAG result is shown in Figure 5. It shows the contemporaneous causal relationships among the variables in equation (1). As shown in Figure 6 both electricity price and coal price directly cause natural gas price. Interestingly the RGGI price is not linked with others contemporaneously. Note that the causal flow in Figure 6 should not be interpreted as the evidence of true causalities among variables. We use the DAG result to order the variables to perform IRF analysis. Also note that the causal structure in Figure 6 only shows the direction of causal flows among the variables and does not say anything about the magnitude or the sign of the effect. These are determined by the IRF.

5.2. Impulse-Response Analysis

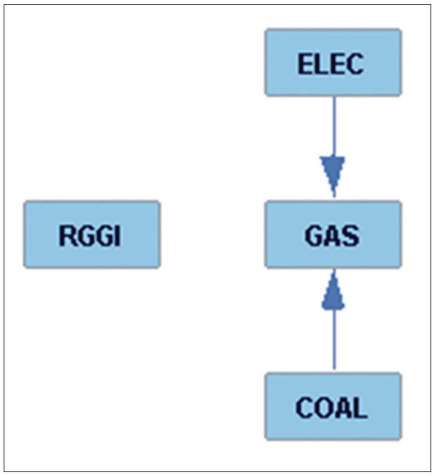
Based on the MA representation and the contemporaneous causal pattern from DAG in Figure 5, normalized IRFs are generated to explore the long-run relationship among variables in the model (Figure 5). The IRFs illustrate how individual series responds to a positive shock, increase in price, in each of the variables over time. Solid lines in Figure 5 are impulse responses and dotted lines are 95% confidence intervals of impulse responses.

Figure 5: Impulse response functions



Notes: (1) The impulse response functions illustrate how individual data series responds to a positive shock, increase in price, in each of the variables over time, (2) Regional Greenhouse Gas Initiative (RGGI) represents for RGGI allowance price; ELEC represents for electricity price; GAS represents for natural gas price; and COAL represents for coal price, (3) dotted lines are 95% confidence bands.

Figure 6: Contemporaneous causal structure using PC algorithm in TETRAD IV



Notes: Regional Greenhouse Gas Initiative (RGGI) represents for RGGI carbon permit price; ELEC represents for electricity price; GAS represents for natural gas price; and COAL represents for coal price. Arrows indicates the contemporaneous causal flow. The causal flow should not be interpreted as the evidence of true causalities among variables without the analytical framework of identification. We use this result to order the variables when we conduct impulse response function analysis

First column of IRFs in Figure 5 shows the RGGI impacts on energy markets in response to a one-time-only shock to the RGGI price. The RGGI has negative impact on electricity and coal prices while no impact on natural gas price. Electricity price increases initially as expected but decreases in subsequent periods, which is not consistent with our intuition (IRF in first column and second row of Figure 5). When the carbon permit price (RGGI price) increases, power companies may have two choices, reducing electricity generation to avoid extra burden to buy permits or raising electricity price to pass the burden to consumers. Either of case, electricity price may increase. Authors believe this is because of fuel switching, coal to cleaner and cheaper natural gas to generate electricity after shale boom. Even so, note that there exist statistically significant relationship between two prices, which is opposite to our initial expectation. In sum, the relationship between RGGI price and electricity price is not strong but statistically significant.

It is not sure how the natural gas market reacts to the change in RGGI price. Due to the fuel switching, natural gas demand may become strong when the RGGI price increase. Natural gas price is expected to rise. However, the companies who has been used natural gas to generate electricity will reduce the natural gas consumption and carbon emission, because permit becomes expensive. The IRF in Figure 5 shows that the gas price will decrease in a short term and slightly increase soon, but statistically not significant.

Coal price decreases in response to the RGGI price change. When permit becomes expensive, there is an incentive for power companies to reduce carbon emission. There might be two choices, to reduce electricity generation or to switch fuel to cleaner one, natural gas. Either case, the coal demand becomes weak which contains much carbon in it.

If electricity price is increased, permit price in the RGGI will increase slightly for a short-term (IRF in second column and first row). When electricity price goes up, power companies generate more electricity and emit more carbon. It leads higher permit price. However, as shown in IRF, the magnitude is relatively small and the impact goes away quickly, which is different from the results for the EU-ETS.

With increases in natural gas price, permit price in the RGGI will increase. In this case, electricity producers may use more coal than natural gas. This leads to increase in carbon emission and makes permit demand strong. Electricity producer buy more permit in such situation.

Lastly, if there is a positive external shock in the coal market, then permit price in the RGGI will decrease. It is because, the electricity producers may substitute coal with natural gas, which is relatively cheaper. Natural gas includes much less carbon, so carbon emissions will be reduced. In turn, it makes carbon permit demand weak, therefore, permit price in the RGGI will decrease.

In short, we have three observations from the IRF

i. The mutual relations between the RGGI and electricity market exist. Electricity market responses negatively to the change in RGGI market. The RGGI reacts positively to electricity market but in a short time of period.
ii. Natural gas price has positive impact on the RGGI carbon price but natural gas price is not influenced by the RGGI, and
iii. The RGGI carbon price and coal price are negatively related each other.

6. CONCLUDING REMARK

There have been numerous studies in relation to carbon permit prices in the GHG emissions trading market and energy markets. Most of previous studies have focused on the EU-ETS since its creation in 2005. Notable findings indicate that the EU-ETS carbon price and energy prices are closely interrelated, and electricity price has been the main driver of the carbon price. Our attention then moves to the RGGI, which began in January 2009 for nine northeastern U.S. states. The primary research objective 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 LA-VAR model (Toda and Yamamoto, 1995; Kurozumi and Yamamoto, 2000) is adopted.

The key findings are (i) the RGGI market and electricity market in the RGGI region are tied but not strongly, unlike the EU-ETS. This loose relationship between the two markets might be explained by the recent weak carbon credit demand stemming from fuel switching and low electricity demand, and (ii) natural gas is the main driver of the RGGI system, which is possibly due to from the recent shale gas boom. Based on these findings, 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 worked, in other words, maintain the mutual relationship (even if it is weak). Second, the newly adjusted emission cap, i.e. carbon permit demand will be strong, which will be effective in 2015, may tie the RGGI and energy markets stronger in the future. Due to the expected further fuel switching, however, the emission cap should be much lower than the current level to work otherwise the RGGI price would maintain low.

Regrettably, this empirical work has some limitations. First of all, a robust empirical analysis is difficult due to illiquid and irregular transaction data then one should be careful on drawing conclusions on the RGGI and energy markets. As the RGGI is a new and young market, this is a problem not to be avoided, however. Second, electricity import/export from/to neighboring states outside RGGI region are not considered explicitly. Only GHG emissions in the RGGI states are regulated and thus the RGGI might expedite the movement of power plants to other regions. Also, it is plausible to import electricity from nearby states (leakage).

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