INFLUENCE OF RENEWABLE ENERGY ON CARBON PRICES IN THE USA

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ABSTRACT

INFLUENCE OF RENEWABLE ENERGY ON CARBON PRICES IN THE USA

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In this study, the decrease in carbon prices is explained with increasing incentives to renewable energy sources and with economic growth, energy prices and carbon permits. For this purpose, we analyze the carbon market prices in the US for energy markets. Carbon prices are low in the US compared to other countries. The reason behind the low price can be increasing incentives to renewable energy resources in the USA. To explore the reasons and justifications, we employ econometric methods on real life data from USA. In this context, linear regression, VEC model and panel data analysis are performed according to their applicability and use. As a result, a significant and negative relationship is observed between CO2 prices and renewable portfolio standards and carbon allowances in the US CO2 market. Also, there is a significant and positive relationship between CO2 prices and industrial production. Finally, oil and natural gas prices have a negative effect on CO2 price while coal price has a positive effect on CO2 price.

Keywords: US Carbon Prices, Renewable Portfolio Standards (RPS), Regional Greenhouse Gas Initiative (RGGI), VEC (Vector Error Correction Model), Energy Prices, Panel Data, Industrial Production, Carbon Permits, USA.

ÖZ

YENİLENEBİLİR ENERJİNİN ABD'DEKİ KARBON FİYATLARINA ETKİSİ

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Bu çalışmada, yenilenebilir enerji kaynaklarına artan teşvikler ile ekonomik büyüme, enerji fiyatları ve karbon kullanma izinleri ile karbon fiyatlarındaki düşüş açıklanmaya çalışılmıştır. Bu çalışma, ABD'deki enerji piyasası için karbon piyasası fiyatlarını incelemeyi amaçlamaktadır. ABD'de karbon fiyatlarının diğer ülkelere göre düşük olduğu görülmektedir. Düşük CO2 fiyatının arkasındaki neden ABD'de yenilenebilir enerji kaynaklarına yönelik teşviklerin artmasından kaynaklanabilmektedir. Bu durumun sebelerini anlayabilmek için ABD verileri ekonometrik yöntemlerle incelenmiştir. Bu bağlamda doğrusal regresyon, VEC modeli ve panel veri analizi yapılmıştır. Sonuç olarak, ABD CO2 pazarında CO2 fiyatları ile yenilenebilir portföy standartları ve karbon ödenekleri arasında anlamlı ve negatif bir ilişki olduğu gözlemlenmektedir. Ayrıca, CO2 fiyatları ile sanayi üretimi arasında anlamlı ve pozitif bir ilişki vardır. Son olarak, petrol ve doğal gaz fiyatlarının CO2 fiyatı üzerinde negatif etkisi olurken, kömür fiyatının CO2 fiyatı üzerinde pozitif bir etkisi bulunmaktadır.

Anahtar Kelimeler: Yenilenebilir Portföy Standartları (RPS), Bölgesel Sera Gazı Girişimi (RGGI), VEC (Vektör Hata Düzeltme Modeli),Panel Veri,Enerji, Endüstriyel Üretim, Karbon İzinleri, ABD.

To my family

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TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

CHAPTER 1

INTRODUCTION

Climate change caused by human-made greenhouse gas increases; is extremely important for the natural ecosystems, the socio-economic structure, and the lives. Due to the various gases in the atmosphere, the heating and insulation effect in the atmosphere called the greenhouse effect. Apart from the natural process, some of the gases are generated by human activities like economic growth, population growth, a decrease in agricultural land and forests, an increase in transportation and of environmental wastes, change of consumption habits of people, increase in non-renewable energy production and consumption. They increase the number of greenhouse gases in the atmosphere and cause the natural greenhouse effect to become dangerous. Increasing the greenhouse effect leads to an increase in global warming, deterioration of the ecological system and a change in the climate. It is foreseen that climate change due to global warming can cause the melting of the glaciers, the rise of the sea level, the occurrence of severe weather events, etc. and significant consequences that may directly or indirectly affect human life and health, socioeconomic sectors and ecological systems (IPCC-Intergovernmental Panel on Climate Change, 2013 [4]).

Assessments by the Intergovernmental Panel on Climate Change (IPCC) show that the Earth's climate heats up to 0.85C degrees (1.53 degrees Fahrenheit) between 1880 and 2012, and human activities affecting the atmosphere are probably an important factor. The Fifth Assessment Report (Summary for Policy Makers) of the IPCC states, "In warming the atmosphere, human influence has been detected. (EIA, 2018) [9].

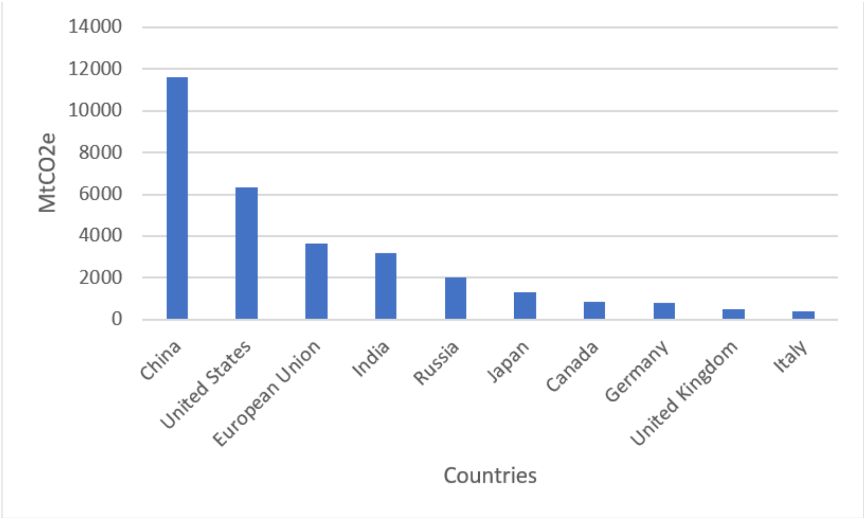

Figure 1.1: Total Emission in 2014 by country.[8]

From Figure 1.1, it can be seen that US emissions (6,319 MtCO2e) are the world's second-largest (after China which has the largest emission level as 11,601 MtCO2e in 2014). Some of the consequences of the increasing CO2 emission can be listed as; a) decrease in the yields in agriculture, b) increase in the forest fires c) increase in disasters such as drought, erosion and desertification, d) reduction in living areas and species, e) increase in the deaths due to heatwaves, f) thirst as a result of decrease in freshwater resources g) inundated coastal countries islands as a result of the increase in sea and ocean levels.

The global effort for climate change has begun with the negotiation of the United Nations Framework Convention on Climate Change (UNFCCC). UNFCCC, whose aim is to stop the atmospheric greenhouse gas accumulation at a level that will prevent the dangerous human-induced impact on the climate system, is entered into force on 21 March 1994. The UNFCCC, which is the most important international step in climate change, includes 195 countries, including the European Union (EU) (UNFCCC, 2015a) [7]. On 11 December 1997, the Kyoto Protocol (KP) was implemented on 16 February 2005 to achieve the goal of the UNFCCC and increase its effectiveness. 192 countries, including the EU, are members of the Protocol (UNFCCC, 2015b) [7]. As in the first commitment period of the KP (Kyoto Protocol), the elasticity mechanisms (Joint Implementation-JI, Clean Development Mechanism-CDM, and Emission Trading) are established to achieve greenhouse gas decrease targets in the second commitment period, and their activities continue between 2013-2020.

As of 2015, 42 emission-trading systems operate in the scope of Emissions Trading. Markets are concentrated in these regions in parallel with the US, Canada, EU, Australia, New Zealand, China and Japan, the main players in climate change negotiations.

1.1 Trading Scheme- Cap and Trade Program

Reducing greenhouse gas emissions from human activities that cause climate change at minimum cost has been the main target of regulations of governments. However, the cost of unit reduction of greenhouse gas emissions varies by country. With the flexibility mechanisms recognized in the KP, countries will be able to benefit from low costs. The flexibility mechanisms defined in the Protocol are the technical and economic tools to help their countries fulfill their obligations. One of them is the emission trading (carbon market) mechanism. The carbon market refers to the market in which carbon credits, in other words, carbon certificates obtained within defined exchange rates and standards, are purchased and sold to prevent or reduce greenhouse gases causing global climate change, especially carbon dioxide.

The carbon market is seen as an important tool in reducing emissions if it operates following market rules. This market penalizes those who emit more than the limit set to reduce emissions, while those that emit less are rewarding to ensure that the available resources are used at the lowest cost. Besides, the carbon market makes it possible to trade carbon all over the world by converting the pollution units it charges into ownership rights. Thus, it encourages enterprises to use clean technology by encouraging less greenhouse gas emissions. The emission trading system (ETS) sets a limit (or upper limit) for greenhouse gas emissions arising from the facilities covered by the system. Since the upper limit directly limits greenhouse gas emissions, this tool provides policymakers with certainty about the number of emissions that will take place over a period. This upper limit shall be gradually reduced over time by the emission reduction objective of a jurisdiction.

The facilities under the ETS are obliged to use their appropriations to meet the total greenhouse gas emissions caused by the release. These allocations are distributed free of charge or through an auction process. Allocations can also be obtained by trade between other third parties, which determines the market price of all allocations. Since there is a cost associated with greenhouse gas emissions under the ETS, there is an incentive to reduce the emissions of plants. The theory of economics (unlike command and control emission reduction policies), which is the basis of the emissions trade, is to offer the option to trade despite the investments aimed at reducing, and thus the lowest cost options for emission reduction by the market.

Cap and trade system consist of two parts. In the first part, the government determines the maximum amount of emissions. The government sells, or exports permits for greenhouse gas to emitters and each emitter needs a permit for each ton of greenhouse gas they emit. In the second part, emitters can trade carbon permits among themselves and create a price for permits in this market. This encourages everyone who is facing with carbon price to reduce their CO2 emissions.

For the first time, ETS was able to limit greenhouse gas emissions. Since the implementation in the EU in 2005, the number of ETSs has increased (Kossoy, Peszko, 2015) [32].

The Regional Greenhouse Gas Initiative (RGGI) is the first mandatory market-based cap and trade program to reduce CO2 emissions from electricity generation in the Northeastern US states. The RGGI framework is discussed in detail in Chapter 2.

1.2 Renewable Energy Mechanism

Increasing the use of renewable energy is one of the most accurate solutions to reduce carbon emissions [13]. Because these energy sources are a renewable and less polluting energy system which do not contain CO2 like fossil sources. Solar, wind, biomass, geothermal and hydro energies are the main types of renewable energy sources. The main advantage of them is that they can be found anywhere in the world depending on their geographical and geopolitical situation. That means they are natural energy sources. That is why, countries do not need to import them, these sources alleviate the problem of energy dependency.

The level of atmospheric carbon dioxide has been constantly increasing since the beginning of the industrial revolution and is predicted to increase even faster as the global economy grows. Significant climate changes are associated with an increase in the atmospheric density of certain gases, particularly CO2.

Renewable energy technologies produce very low or close to zero greenhouse gas emissions compared to fossil fuels. They include hydro, wind, solar, geothermal waste energy and biomass energy.

The International Energy Agency expects a %70 increase in oil demand and a %130 increase in carbon emissions by 2050 [11].

Most of the carbon dioxide emissions resulting in greenhouse effects are caused by using fossil fuels in energy production and consumption. Therefore, a tax policy that encourages the reduction of fossil fuel use and the use of renewable energy sources that do not harm the environment instead of fossil resources will contribute to the reduction of environmental externalities [28].

The main contributions of this research are to investigate the relationship between the main drivers of the carbon price in the RGGI and to explain the relationship between CO2 price and renewable energy policy. In our study, we use 3 econometric models which are linear regression model, Vector Error Correction model, and Panel data analysis. We anticipate observing a negative and statistically significant relationship between CO2 prices and renewable energy portfolio targets for RGGI states (that is the parameter we measured the renewable energy incentives in the US in RGGI states). Also, we try to find a significant relationship between energy prices like coal, oil and natural gas prices and CO2 prices. In addition, we try to find a significant and negative impact of allowance quantity in the market (supply of CO2 permits) and CO2 prices. Finally, we expect to find a strong and positive relationship between CO2 price and industrial production (or economic activity in the region). In our study, we use Stata 14.2 as our statistical analysis program.

1.3 Literature Survey

There is extensive research to investigate the carbon pricing mechanism literature, solely on the EU. Many studies show that energy prices (oil, natural gas, coal and electricity prices) are the main drivers of the carbon price in the allowance market. Also, weather conditions (cold-warm temperature), policy options like the emission target, renewable energy subsidies are the main determinants of EU-ETS carbon price (Chevallier, 2012) [20]. In that respect, some authors such as Mansanet-Bataller et al. (2007) [33], Aatola et al. (2013) [14], Reboredo (2013) [39] explain the determinants of EU-ETS carbon price as energy prices like oil, natural gas, coal, electricity. In addition to energy prices, Rickels et al. (2007) [40], Alberola et al., (2008) Rickels, et al. (2010) [41] find a significant additional effect of weather conditions like unexpected temperature change on the EU-ETS carbon price.

Regarding some studies, Koch et al. (2014) [35] find the economic condition in the country as an important factor that affects the EU-ETS carbon price. Moreover, Hintermann (2010) [17] Bergh et. al. (2013) [21] Abrell – Weigt (2008) [15] also research the relationship between renewable energy deployment (like availability of hydroelectric power or RES-E injections) and the carbon price in EU ETS; they observe that using renewable energy in the electricity production decreases EU-ETS carbon prices.

In summary, various studies examining the carbon price drivers in the EU-ETS, factors like energy prices, weather conditions and policy instruments such as renewable energy incentives affect EU-ETS allowance prices. Kim and Koo (2010) [30] examine the factors affecting the US carbon allowance market. They observe that the coal price is a key factor affecting the carbon allowance trading volume. The changes in the crude oil and natural gas prices and the coal price have significant effects on the carbon allowance market. Besides, there is evidence that the temperature and economic crisis in the US have significant impact on the carbon allowance trade volume.

Kim and Lee (2014) [31] investigate the relationship among the RGGI carbon price and energy prices in the Northeastern USA, they find that the price of natural gas has a positive effect on the carbon price of RGGI, but the price of natural gas is not affected by RGGI, and the price of carbon and the price of coal are negatively related.

We depict from the literature that economic activity, energy prices like coal, natural gas and renewable energy impacts are the main drivers for carbon prices. To our knowledge, early all literature entirely pay attention to the carbon allowance market in the EU, since EU-ETS is the biggest and most important carbon trade market. However, when we look at the US carbon allowance market, we see it as a small, regional and non-Kyoto protocol market, and it has made relatively small and few realizations. (Kim and Lee, 2015) [31].

Therefore, we question how the relationship between CO2 price and renewable energy incentives in the USA is.

1.4 Aim of the Study

The main contributions of this research are to investigate the relationship between the main drivers of the carbon price in the US- RGGI and to explain the relationship between CO2 price and renewable energy policy. Here, we choose to investigate US market mainly because;
a) It is non-Kyoto CO2 market so it shows a unique market for our study,
b) Relative to the consumption, CO2 price is lower compared with other ETS markets,
c) There is limited literature related with US allowance market,
d) CO2 market price regulations are clear,
e) Pioneer in renewable energy source improvements.

The main components to analyze the study are carbon dioxide price and renewable portfolio standards to measure the impact of incentives on CO2 price. Moreover, we obtain renewable energy production to calculate the weighted average of renewable energy targets of states. Besides, initial permit quantity (quantity offered to RGGI states) is used to quantify the supply effect of permits on CO2 price. Coal, natural and oil spot prices data are used to represent energy prices. Lastly, to measure economic activity, we look at the industrial production index. Econometric models are employed using Stata 14.2 as software.

We anticipate observing a negative and statistically significant relationship between CO2 prices and renewable energy portfolio targets for RGGI states (that is the parameter we measured the renewable energy incentives in the US in RGGI states). Also, we aim to find a significant relationship between energy prices like coal, oil and natural gas prices and CO2 prices. Besides, we search a significant and negative impact of allowance quantity in the market (supply of CO2 permits) and CO2 prices. Finally, we expect to find a strong and positive relationship between CO2 price and industrial production (or economic activity in the region).

The outcomes of this thesis can be useful for policymakers in determination related to complementary environmental policies in reducing carbon emission in the US allowance market.

The organization of the thesis is as follows; Chapter 1 provides background information about climate change and gives information about the emission trading scheme. Moreover, we explain the hypothesis of the thesis, previous work on this subject and overview of the thesis. In Chapter 2, we give background information about the Regional Greenhouse Gas Initiative (RGGI). In Chapter 3, we explain the methods used briefly. The empirical analysis, the results and findings are presented in Chapter 4. The conclusion and comments are given in Chapter 5.

CHAPTER 2

THE RGGI PROGRAM - US EMISSION TRADING SCHEME

2.1 History of CO2 Prices in US Market

RGGI begin on January 1, 2009, for ten northeastern US states. As seen from the Figure 2.1, these states are Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, Vermont, and New Jersey. In 2012, New Jersey withdrew from the program.

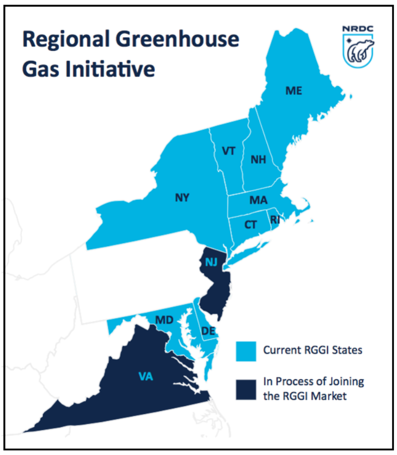

Figure 2.1: RGGI States Map [29]

Compared with carbon allowance prices, for instance in EU ETS, the carbon allowance price for the year 2018 is $17.80 while it is $4.94 for the same year in RGGI states. Figure 2.2. shows the CO2 price based on different trading systems. The most expensive price is observed in Alberta CCIR, followed by Korea ETS, whereas the minimum occurred in Guangdong pilot ETS.

The reasons behind low CO2 price in the US compared with other ETS system are:

a) RGGI is not an economy-wide system.

b) It implements only to carbon dioxide (CO2) emissions from electric power plants with capacities to generate 25 megawatts or more- approximately to 168 facilities (Ramseur, 2017) [38]. This is less compared with other ETS markets.

c) It has limited scope, only executed in 9 states.

d) It is a voluntary market.

Voluntary carbon markets are carried out voluntarily, regardless of the policies and objectives set by the governments. Organizations that want to be carbon neutral buy carbon certificates that are generated as a result of emission reductions provided by a voluntary standard to reduce and offset their emissions by calculating their carbon footprints. Regional Greenhouse Gases Initiative and RGGI Market are one of the voluntary carbon markets.

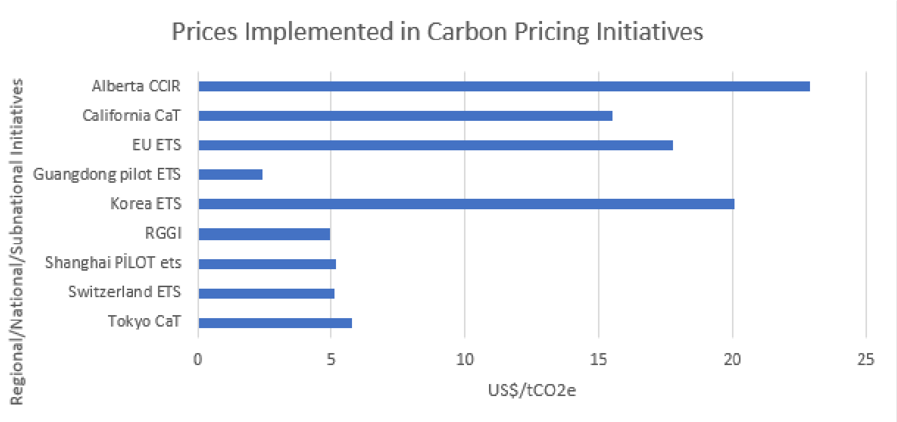

Figure 2.2: CO2 market prices in different carbon trading systems [32].

We can see from Figure 2.3 that carbon price is low (around \$2) between 2009 and 2012. Because in several auctions during these years, some allowances were left unsold. After 2012, RGGI announced a 45 percent cap reduction yielding the demand for CO2 allowances rise and carbon prices start to increase up to \$8 per short ton towards 2016. Following the publication of the Clean Energy Plan in 2015, bids were offered more than three times the total number of RGGI amount of allowances. This situation increases allowance prices. After 2016, the downward trend starts at allowance price.

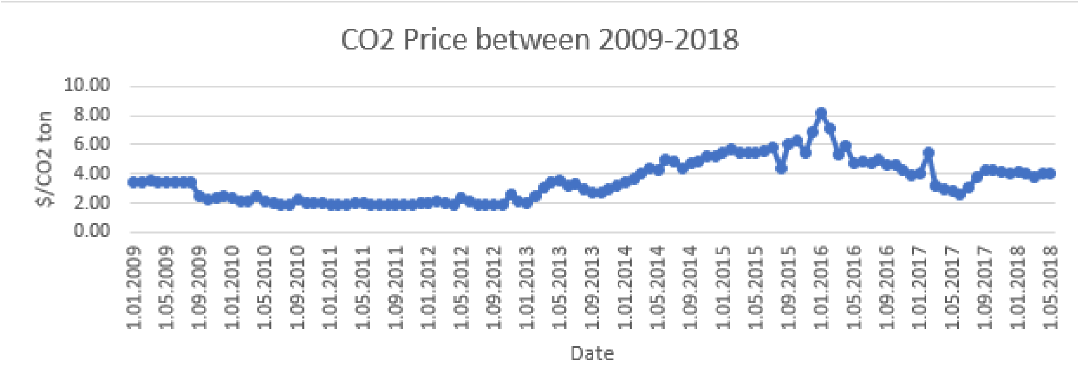

Figure 2.3: CO2 price in US between 2009 and 2018 [6].

The aim of the RGGI program is to cap and reduce carbon dioxide (CO2) emissions from the energy sector. The cap and trade program is projected to support the states to decrease annual CO2 emissions of the power sector under 2005 levels by 2020.

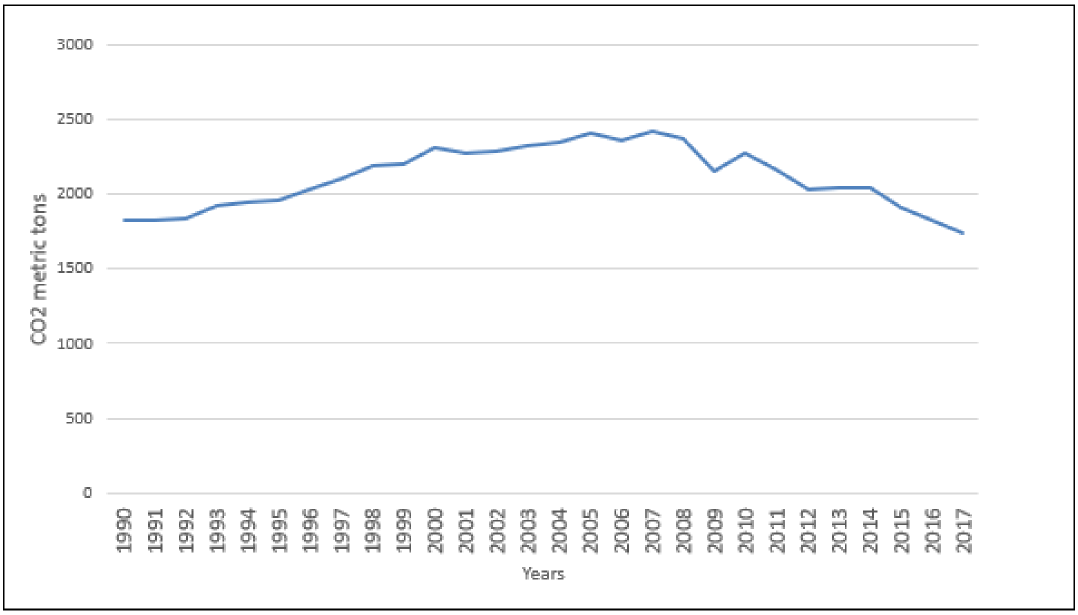

Figure 2.4: CO2 emissions for total electric power industry for years between 1990-2017 for all energy sources [10]

From Figure 2.4, it is seen that the emission in nine RGGI states decreases around 30 percent in 2009 which is the starting date of RGGI. After 2009, we see that the carbon emission level starts to decrease. This is because of the transition from coal and oil to natural gas, nuclear power, and renewables which are less emitting or zero-emitting resources. Theoretically, Figure 2.4 shows the effect of the cap and trade system on CO2 price. Furthermore, it shows the impact of policy instruments like renewable energy incentives on carbon price.

The complementary policies like renewable energy incentives can realize significant emission reductions (Heindl and Löschel, 2012) [27]. However, they cause a surplus of the number of allowances in the ETS market, which leads to downward pressure on the carbon allowance prices.

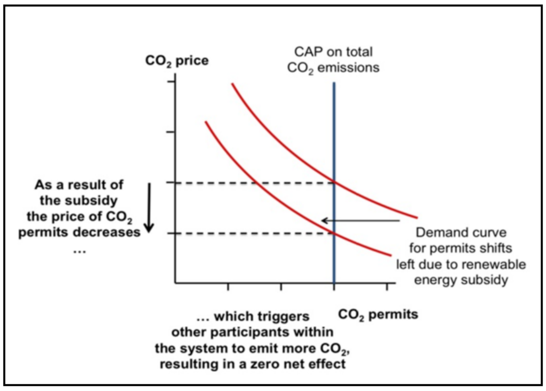

Figure 2.5: Relation between carbon emission prices and renewable energy subsidy [44]

To achieve emissions reductions, a cap and trading system is the most effective program. Nevertheless, when a government combines the cap and trade system with other policy measures, this efficiency can change severely [23].

For instance, when a government prepares a subsidy program to promote production through renewable resources, the direct effect of these subsidies is the replacement of electricity produced by fossil fuel power plants with electricity produced by renewable techniques. Consequently, CO2 emissions decrease. For this reason, electricity producers save the CO2 permits they can sell in the permit market. As a result, the price of CO2 permits decreases. External changes in emissions in Figure 2.5 result from policies that complement the RGGI cap and trade programs. Some examples that can cause to exogenous shifts in emission are:

i) Renewable portfolio standards (RPS) found in all 10 original RGGI states. RPS entails a certain part of the state energy to come from non-renewable sources such as wind, solar, geothermal and biomass and thus creates emission reduction and MAC (it measures the cost of reducing one more unit of pollution) curve shifts (marginal cost of additional decreases in pollution). This mechanism imposes an obligation on electricity supply companies to generate a certain amount of electricity from a renewable energy source.

ii) Also, The RGGI program includes emission limits, such as the use of RGGI auction revenues for energy efficiency, as well as additional measures to reduce emissions. This means that the auction revenues in the RGGI program are used for energy efficiency. RGGI states (collectively) allocate the auction revenues as 64 percent for energy efficiency, 10 percent for electricity bill assistance, 4 percent for GHG abatement, 16 percent for clean and renewable energy, 6 percent for administration, and 1 percent for RGGI, Inc. in 2015.

iii) All the regulations of the Federal Clean Air Act on air pollutants such as sulfur dioxide (SO2), nitrogen oxide (NOx) and mercury (Hg) introduces legal requirements for coal-fueled production, which opts to replace appropriate alternatives such as natural gas and nuclear energy with renewable energy sources. These policies are applied in these RGGI states.

In short, the decrease in the CO2 price can be due to policies that are complementary to the RGGI cap-and-trade programs, such as Renewable portfolio standards (RPS), RGGI program supplementary measures or Federal Clean Air Act, which exist in all the ten original RGGI states. In the framework of this study, we consider Renewable portfolio standards (RPS) of seven states (except New York and Vermont) in the USA. We use Connecticut [CT], Maine [ME], Rhode Island [RI], Massachusetts [MA], New Hampshire [NH], Maryland [ML] and Delaware [DE] as a representation of renewable energy incentives. Since these are the only states whose RPS parameters are published and accessible. We expect that RPS requirements are strongly correlated across states. Therefore, RPS requirements for one state should serve as a good instrument for the RPS requirement for other states.

Figure 2.6 shows the Renewable Portfolio Targets across 7 states. All the targets of the states except New Hampshire are increasing continuously. The reason behind the

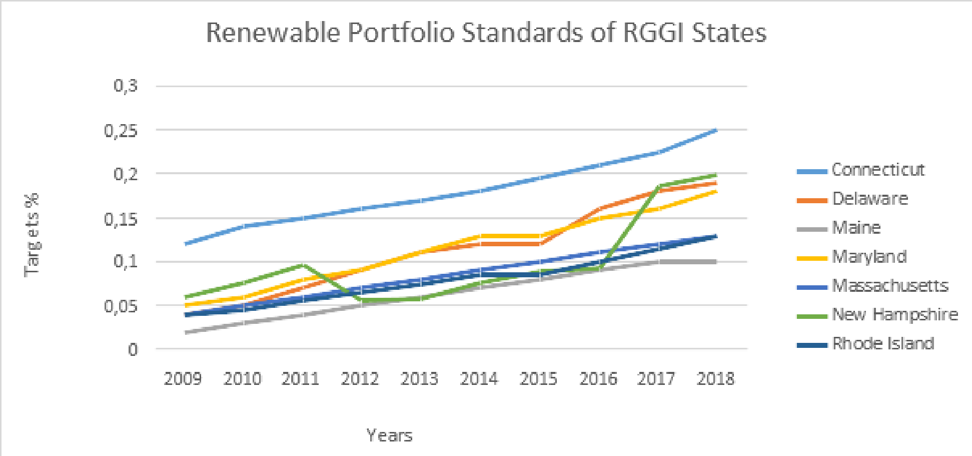

Figure 2.6: RPS targets across 7 RGGI states [8]

decrease in the target of New Hampshire is because the renewable energy requirement of each class of energy for the state is modified.

Table 2.1: Correlations of RPS Targets Between States

Correlation	CT	DE	ME	ML	MA	NH
Connecticut [CT]	1.00					
Delaware [DE]	0.99	1.00				
Maine [ME]	0.99	1.00	1.00			
Maryland [ML]	0.98	0.99	0.99	1.00		
Massachusetts [MA]	0.99	1.00	1.00	0.99	1.00	
New Hampshire [NH]	0.71	0.66	0.66	0.6	0.65	1.00
Rhode Island [RI]	0.99	0.99	0.99	0.99	0.99	0.7

We can see from Table 2.1 that during 2009 and 2018, those percentage targets are highly correlated ($\rho > 0.60$) between states. It is remarkable also that there are perfect positive correlation between some states such as (ME,DE), (MA,DE) and (MA,ME). This is mainly because percent targets yearly by each state increase at the same rate.

CHAPTER 3

METHODOLOGY

In this chapter, we summarize the methodology used in the empirical analysis. Most of the studies in energy prices consider linear and non-linear models to capture the influence of exogenous variables on the price.

3.1 Linear Regression Model

Multiple regression is the statistical procedure used to estimate the values of a response (dependent) variable from a collection of predictive (independent) variable values (Wooldridge, 2012) [41].

The general multiple linear regression model (also called the multiple regression model) can be written in the population as

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_k x_k + u \tag{3.1}$$

where β_0 is the intercept, β_i is the parameter associated with x_i, x_i=*1,... k*. Since there are k independent variables and an intercept, equation (3.1) contains *k +1* (unknown) population parameters. Just as in simple regression, the variable u is the error term or disturbance. It contains factors other than $x_1, x_2, \ldots, x_k$ that affect *y*. No matter how many explanatory variables we include in our model, there will always be factors we cannot include, and these are collectively contained in *u* (Wooldridge, 2012) [43].

The assumptions of multivariate regression analysis is the normal distribution, linearity, freedom from extreme values and the absence of multiple bonds between independent variables (Büyüköztürk, 2012) [18]. It is of great importance that the random error, u satisfy the properties:

i) $E\left(u\right)=0$

ii) σ_u^2 is constant

iii) u_i's are independent identically normally distributed.

3.2 Time Series Analysis

A time series is a set of sequential data points, typically measured at successive times. Let mathematical representation $x(t)$ be the vector $t = 0, 1, 2, 3......n$ represents the time elapsed. A time series containing records of a single variable is called univariate. However, if the records of multiple variables are considered, they are called multivariable. In a continuous-time series, observations are measured continuous in time, whereas a discrete-time series includes observations measured at specific time points. In the stationary time series, the covariance is independent of t for each h,

$$\gamma_x(X_t, X_{t-h}) = E[(X_t - \mu)(X_{t-h} - \mu)]. \tag{3.2}$$

The mean is independent of t,

$$E\left(X_t\right) = \mu. \tag{3.3}$$

Stationary time series have the best linear predictor.

Stationary Models are classified as;

1. Auto Regressive (AR)

$$X_t = \phi_t X_{t-1} + ... + \phi_{p-1} X_{t-1} + Z_t. \tag{3.4}$$

$$Z_t \sim WN(0, \sigma_2). \quad (3.5)$$

The equation 3.4 is the white noise.

2. Moving Average (MA)

   Moving average model uses past forecast errors in a regression model;

$$X_t = c + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + ... + \theta_q \epsilon_{t-q}. \quad (3.6)$$

   where ϵ_t is white noise. MA(q) model is a moving average model of order q.

3. ARMA
   X_t is an $ARMA(p, q)$ process if X_t is stationary and if for every t

$$X_t - \phi_1 X_{t-1} - ... - \phi_p X_{t-p} = Z_t + \theta_1 Z_{t-1} + ... + \theta_q Z_{t-q} \quad (3.7)$$

   where $Z_t \sim WN(0, \sigma^2)$ and the polynomials $(1 - \phi_1 z - ... - \phi_p z^p)$ and $(1 + \phi_1 z + ... + \phi_p z^p)$ have no common factors.

3.2.1 Vector Autoregression Model (VAR)

Vector autoregression (VAR) is a model for two or more time series in which each variable is modeled as a linear function of the historical values of all variables, and also includes disturbances with zero means given in all historical values of the observed variables. It is often used to estimate the systems of interrelated time series and to analyze the dynamic effect of random distortions on the system of variables. We can write a static, k-dimensional VAR (p) operation as follows:

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + C x_t + u_t \quad (3.8)$$

where, $y_t = (y_{1t}, y_{2t}, ..., y_{Kt})'$ is a *k x 1* vector of endogenous variables; $x_t = (x_{1t}, x_{2t}, ..., x_{Kt})'$ is a *d x 1* vector of exogenous variables. The coefficients, $A_1, A_2, ..., A_p$ are a *k x k* matrices of lag coefficients to be estimated; C denotes exogenous variable coefficient and $u_t = (u_{1t}, u_{2t}, ..., u_{Kt})'$ is a *k x 1* white noise innovation process, with the properties $E(u_t) = 0$, and $E(u_t u_s') = 0$.

3.2.2 Vector Error Correction Model

A vector error correction (VEC) model is a limited VAR that is modeled to be used with non-stationary arrays that are known to be cointegrated and have co-integration constraints in the specification. The VEC specification limits the long-term movement of endogenous variables in approaching cointegration relationships while allowing a wide variety of short-term dynamics. The term cointegration is acknowledged as the error correction term since the deviation from the long-term equilibrium is gradually adjusted by a series of partial short-term adjustments. For example, assume the two-variable system with a cointegration equation that does not have a delayed difference term:

$$y_{2,t} = \beta y_{1,t} \tag{3.9}$$

and the corresponding VEC is

$$\Delta y_{1,t} = \gamma_1 (y_{2,t-1} - \beta y_{1,t-1}) + \varepsilon_{1,t} \tag{3.10}$$

$$\Delta y_{2,t} = \gamma_2 (y_{2,t-1} - \beta y_{1,t-1}) + \varepsilon_{2,t}. \tag{3.11}$$

In this simple model, the only right side variable is the error correction term. In the long term equilibrium, this term is zero. However, if y_1 and y_2 deviate from the long term equilibrium of the previous period, the error correction term is not zero, and each variable is set to partially restore the equilibrium relationship. The coefficients γ_1 and γ_2 measure the speed of adjustment. If the two endogenous variables have no trend and the cointegrating equations have an intercept, the VEC has the form

$$\Delta y_{1,t} = \gamma_1 (y_{2,t-1} - \mu - \beta y_{1,t-1}) + \varepsilon_{1,t} \tag{3.12}$$

$$\Delta y_{2,t} = \gamma_2 (y_{2,t-1} - \mu - \beta y_{1,t-1}) + \varepsilon_{2,t}. \tag{3.13}$$

Another VEC specification assumes that there are linear trends in the series and a constant in the cointegrating equations so that it has the form

$$\Delta y_{1,t} = \delta_1 + \gamma_1(y_{2,t-1} - \mu - \beta y_{1,t-1}) + \varepsilon_{1,t} \tag{3.14}$$

$$\Delta y_{2,t} = \delta_2 + \gamma_2(y_{2,t-1} - \mu - \beta y_{1,t-1}) + \varepsilon_{2,t} \tag{3.15}$$

Similarly, there may be a trend in the cointegration equation, but there is no separate trend in the two VEC equations.

3.3 Panel Data Analysis

Panel data analysis is a method of reviewing a subject within multiple dimensions that is periodically observed over a defined period of time. The panel data includes two dimensions: cross-sectional and time series, so a regression model for panel data is different from an OLS regression because it provides information about both dimensions, i.e. individuals and time. The general model of panel data can be defined as:

$$y_{it} = \alpha_i + \sum_{k=1}^{K} x_{it} * \beta_{kit} + u_{it} \tag{3.16}$$

where $i = 1, \ldots, N$, N is the number of cross-sectional dimension (or individuals), T is the number of time dimensions (or periods), K is the number of independent variables. There are many types of panel data models but the two most commonly analyzed models are the fixed effects model and the random effects model.

3.3.1 Fixed Effects Model (FE)

α_i's are individual intercepts (fixed for given N). x_{it} is the vector of parameters $[x_{1it} \ldots x_{Kit}]$, β is the vector $[\beta_1 \ldots \beta_K]$. Then,

$$y_{it} = \alpha_i + x'_{it} * \beta + u_{it}. \tag{3.17}$$

No overall intercept is (usually) included in the model. Under FE, consistency does not require that the individual intercepts (whose coefficients are the α_i's) and u_{it} are uncorrelated. Only $E(x_{it}u_{it}) = 0$ must hold. There are $N - 1$ additional parameters for capturing the individual heteroscedasticity. In our model we use, fixed effect in panel data analysis according to Hausman test result. The effects of timeinvariant variables with time invariant effects are controlled by fixed effects model.

3.3.2 Random Effect Model (RE)

Here, it is assumed that α_i's are independent and identical with mean zero and variance, σ^2_α .

The model becomes

$$y_{it} = \beta_0 + x'_{it}\beta + \alpha_i + u_{it}, u_{it} \sim iid\left(0, \sigma^2_u\right) \tag{3.18}$$

where α_i 's are random variables with the same variance. The value of α_i is specific for individual i. The α of the different individuals are independent, the mean is zero, and the overall mean is captured at β_0. α_i is homoscedastic and does not change over time between individuals.

CHAPTER 4

EMPIRICAL ANALYSIS

To determine the influence of renewable energy incentives on CO2 prices, we consider factors contributing to the price movements. Based on the nature of the research question raised in this thesis, we employ three methodological approach, mentioned in Chapter 3, to depict different aspects in the role of renewable energy on CO2 emission prices in selected states. The variables taken into account with their abbreviations are: CO2 Price (CO2), CO2 Allowance Quantity (ALQ), Industrial Production (IP), Crude Oil Price (CROP), Natural Gas Price (NGP), Coal Prices (COP), and Renewable Portfolio Standards (RSP).

As the first initiative, we use energy prices like oil prices, natural gas prices and coal prices as main drivers to observe their impact on the CO2 market. Here, we ignore electricity prices since natural gas, coal and oil prices are strongly linked to electricity price resulting in multicollinearity. We expect a negative and significant relationship between CO2 prices and energy prices. Also, we take CO2 allowance quantity which means CO2 emission permits us to observe how CO2 supply affects CO2 demand and consequently CO2 price. We expect a negative and strong relationship between CO2 price and quantity allowances. Additionally, we analyze the relationship between renewable energy incentives and CO2 prices using Renewable Energy Portfolio Standards' targets for RGGI states that is interrelated RE incentives for each state. We also expect a negative and strong relationship between RE incentives and CO2 prices since each states' individual RE targets have a positive influence on energy consumption and their energy consumption planning. We presume a decrease in the demand for CO2 emitting resources and incline in more renewable energy opportunities and investments. Finally, we measure the impact of economic activity on CO2 price. We employ the industrial production index in the US and expect a positive and significant

effect on CO_2 price.
Each of these analyses is performed using appropriate methodology due to the nature of the variables. We employ linear regression to estimate CO_2 prices in terms of its associated variables, VEC to capture the inter-related connection among variables with respect to time and panel data analysis to depict the influence of Renewable energy initiatives on the CO_2 prices. Each variable contains totally 115 monthly observations representing the occurrences between January 2009 and July 2018. The analyses are done using STATA (version 11) software.

4.1 Data

The variables considered in the framework of the analysis are, CO_2 price, CO_2 allowance, industrial production index, energy prices, renewable portfolio standards. To fit an appropriate model, it is vital to understand the dynamics of each variable. For this reason, country and variable specific characteristics are summarized.

i) CO_2 Price;

RGGI for each state is recorded by RGGI CO_2 allowance monitoring system (COATS) [5]. The RGGI CO_2 Allowance Tracking Program (RGGI COATS) is a platform on which each state archives and tracks data on the CO_2 Budget Trading Program. It also includes the transfer of CO_2 allowances purchased by winning bidders, which are open for sale by the states and won a quarterly auction (RGGI, 2019) [5]. The auction for the first allowance was made in September 2008 and the transactions were irregular since then.

CO_2 price changes year by year, having the first auction to be held in 2008 and by mid-2010 RGGI allowances were sold at nearly the price floor, or minimum allowable bid and the price have stayed at that level for more than two years. This is because of a decline in natural gas prices that were starting as far back as 2007. The decline in the natural gas price led to a decrease in CO_2 emissions because natural gas amount changes with coal amount, which was a generation fuel in the Northeast region. Between 2010 and 2012, some auction's allowances were not sold. Although the RGGI reduces its emissions cap, actual emissions stay under the cap. This causes an excess of allowances.

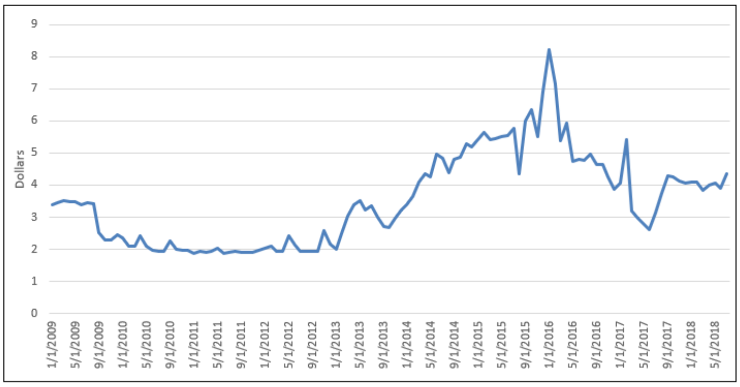

Figure 4.1: CO2 monthly price in US between 2009 and 2018 in RGGI states [5]

As seen from the Figure 4.1, in January 2013, RGGI stated its goal to reduce its CO2 emissions limit by 45 percent starting from 2014. Due to the declaration of the limit cut, CO2 prices rose above the base price, while CO2 prices traded above $4. In February 2013, the RGGI announced the Cost Environmental Protection Reserve (CCR). The CCR keeps the number of allowances until the allowance price reaches a determined level. The CCR trigger price used to be $4 and it was to increase annually by $2 (up to $10) by 2017, after that it would increase by 2.5 percent each year. For 2014, a limit of 5 million allowance limits and 10 million withdrawal limits were determined for all subsequent years. In 2015 August, the Clean Energy Plan was announced. Here, more than three times the total number of RGGI allowances offered provided. This increased allowance prices. Since the beginning of 2016, the downward trend in clearing prices shows a low demand for RGGI allowances.

Recently, for effectively determining the minimum allowance price adjustments, a reserve price was added to the RGGI program. For the year 2017, this reserve price was $2.15, which was higher than the $2.10 CO2 price in 2016. In March 2017, more than 14 million grants were sold with a clearing price of $ 3, the lowest CO2 price for more than three years. The March 2017 auction won $ 43.1 million and was used for many purposes, including supporting RGGI states' energy efficiency, renewable energy, direct energy bill assistance, and greenhouse gas reduction programs.

During the year of 2018, we see that CO2 allowance prices look constant except toward the middle of the year there exists a small increase in the price. Here, we use monthly data from January 2009 to July 2018. That equals 115 observations.

ii) CO2 Allowance;

CO2 allocations are provided by each RGGI state in the amount specified in the respective laws and/or regulations of each state. All CO2 allocations distributed by all RGGI states constitute the total limit of RGGI (the total cap). Most of the allowances distributed by an auction can only be retained by a certain amount in a given account and distributed according to government-specific programs (RGGI, 2019) [5]. Many of the CO2 allowances provided by each RGGI state are distributed quarterly through regional CO2 auctions (RGGI, 2019) [5].

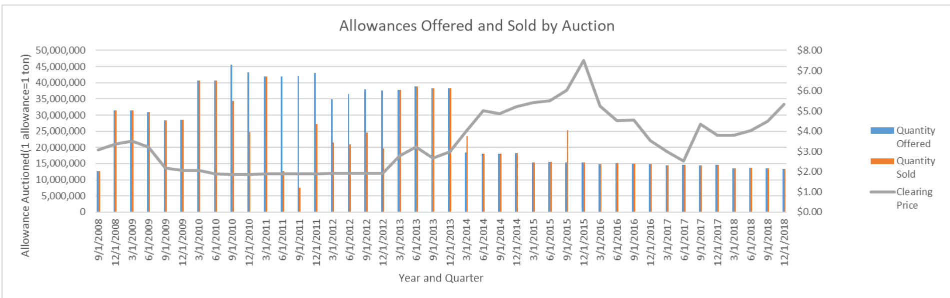

Figure 4.2: RGGI Allowances Offered, Sold, and Clearing Price between 2008-2018

Figure 4.2 shows the allowance offered and sold quarterly by auction. The left vertical axis is for allowance units and the right vertical axis shows the market price of allowances. At the beginning of the RGGI cap and trade program, all allowances that are offered were sold until the 3rd quarter of 2010. According to the graph, the market price (clearing price) started to decrease in 2009. In the third quarter of 2010, the price floor starts, and no allowances are sold at the floor price, which is less than $ 2. It was the end of the first RGGI program of 2012. Between 2009 and 2012, more than 169 million tons of allowances were not sold. This amount also equals 26 percent of the total allowance quantity in that interval.

Some states like Connecticut, Massachusetts, New York, Delaware, Rhode Island, and Vermont said in January 2012 that they will withdraw any allowances they could not sell in their auctions instead of keeping those excess allowances for the next compliance period. After a review of the RGGI program in 2012, because of the failure of the prior emission cap, 9 RGGI states dropped the emission cap to 91 million short tons which were a 45 percent decrease. This amount of decrease in this cap is divided into 2.5 percent decreases each year between 2015 and 2020. Because of these changes in the emission cap, an allowance shortage occurs; so, all the allowances can be traded in the auction and CO2 prices increased beyond the floor in 2013. The change in CO2 allowance quantity can also be seen in Figure 4.3.

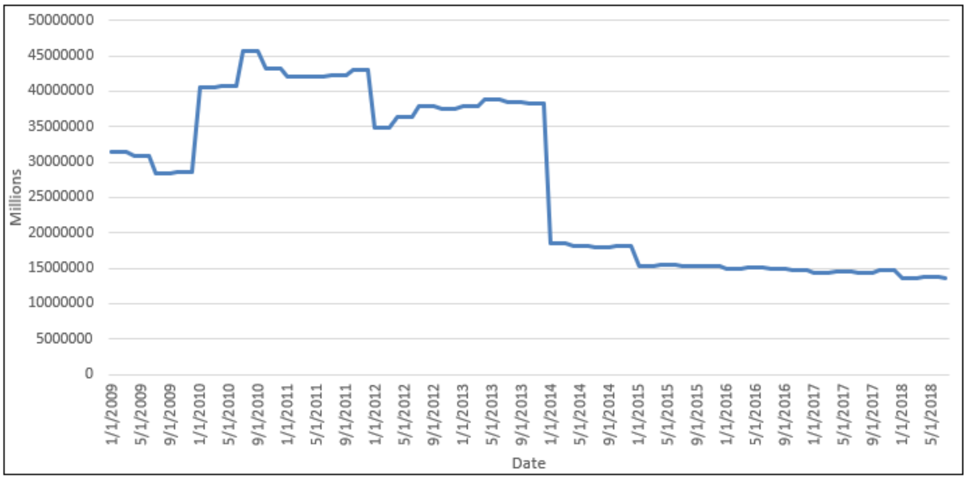

Figure 4.3: RGGI Allowance Quantity between 2009-2018 [5]

The first allowance auction was held in September 2008.

- 1st period (2009-11), the emission cap was 188 million CO2 tons/year.
- 2nd period (2012-14), the cap of the program is 165 million CO2 tons/year. Because of the ineffectiveness of this prior emission cap in the RGGI region,
- 3rd period (2015-17), a new cap of 91 million CO2 tons/year is applied by 2015.
- 4th period (2018-20), 78 million CO2 tons.

iii) Industrial Production Index;

As another indicator that affects the change in CO2 price, we look at the industrial production index in the US. The Industrial Production Index (IND PRO) is an economic indicator, which measures the actual output for all facilities in the USA, including those in manufacturing, mining, and electricity and gas facilities (except those in the US territories) [36]. The index was compiled monthly to draw attention to short-term changes in industrial production. It measures the movements in production and emphasizes the structural developments in the economy. Monthly growth in the production index is an indicator of the growth in the sector [36].

Since the INDP index does not exist for each state separately, we use the total industrial production index in the U.S.A. That's why the Industrial production index may be expected to be a weak explanatory factor in explaining CO2 prices in the 9 original RGGI states.

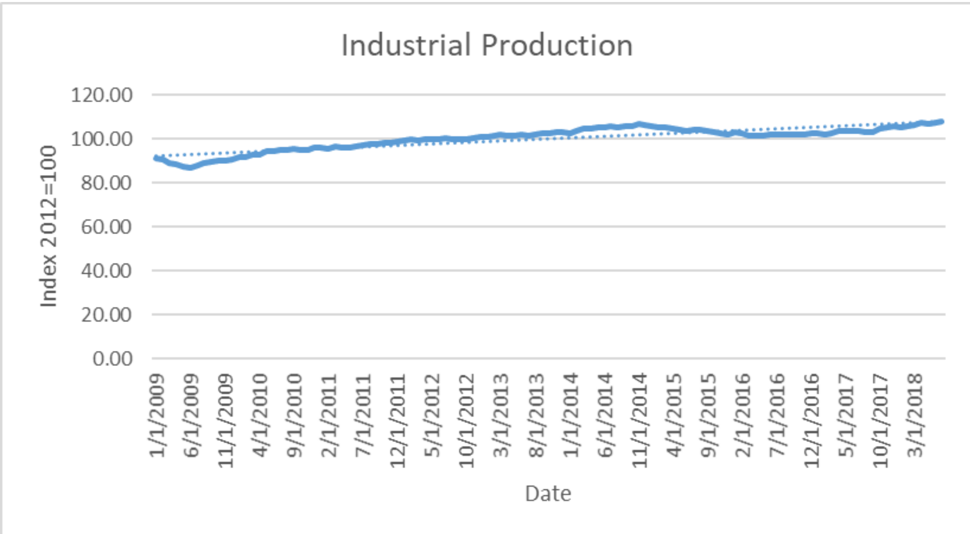

Figure 4.4: Montly industrial Production for years between 2009-2018 [3]

In Figure 4.4, between January 2009 and June 2009, we see a fall in the Industrial production index (87.49) which is the lowest index value of all the years. This is mainly due to the effect of the economic recession in the country and the RGGI states after 2008. This situation causes a decreasing in electricity production. Because decreasing economic activity brings about a fall in energy usage and this situation causes less consumption of CO2 and fewer emissions and reducing demand for carbon allowances in the market. After 2009, industrial production increases steadily until November 2014. After this date, it decreases significantly. Because of the serious winter weather over a great part of the country, manufacturing industrial production falls. After 2015, it begins to increase again.

iv) Energy Prices;

Here, we use monthly data from January 2009 to July 2018 which yields 115 observations. When we choose the energy prices of the states, we firstly look at the electricity production by different energy resources highly used and produced GHG emission in RGGI states. Secondly, when we choose energy prices of states, we look at the relevant literature.

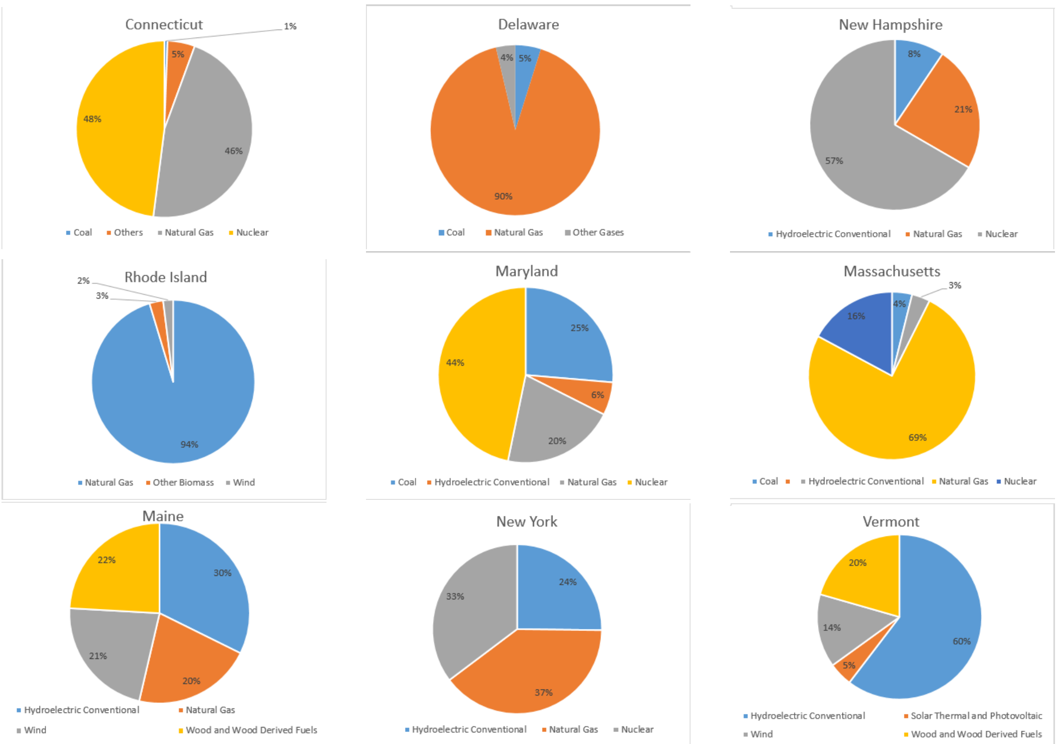

Figure 4.5: Electricity generation sources by States in 2017 [3]

A seen in the Figure 4.5, the electricity generation by each RGGI state in the year of 2017 is dominated by the natural gas source within RGGI states. In order to measure the effect of energy resources in RGGI states on CO2 price, we use natural gas price in our model.

As seen in Figure 4.6, we can notice that in 2008, it has higher production, but it has decreased over the years. Even if its share in overall energy production in 2017 is low, Coal production was an important resource in the energy market

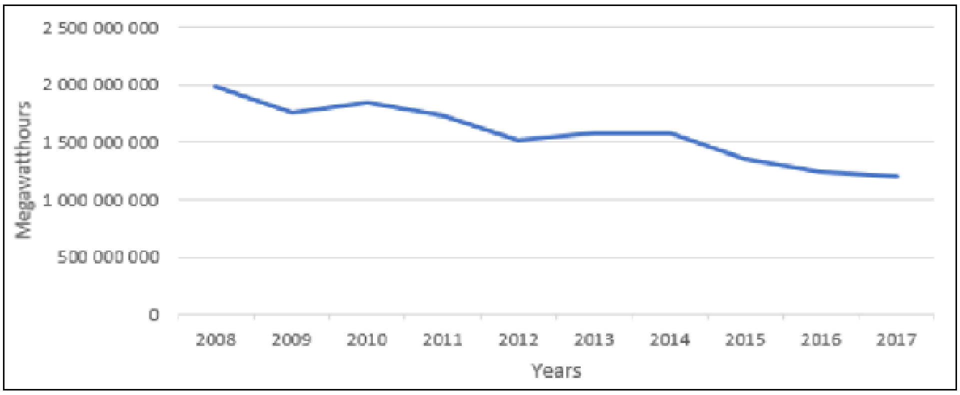

Figure 4.6: Annual Coal Generation in RGGI states [3].

during years, that's why we also include coal prices to our regression model to see its impact on CO2 price in the US market over the years.

We consider Natural Gas, Coal and Crude Oil spot prices monthly from January 2009 to July 2018. Mansanet-Bataller et al. (2007) [33] and Alberola et al. (2008a) [16] is the first to reveal the relationships between the economics of energy markets and the price of CO2. Based on data of spot and futures prices, authors determine that carbon prices in the EU ETS are dependent on the use of fossil fuels (eg. oil, gas, coal). Apart from the EU ETS market, we can see limited research in the US ETS market. Hammoudeh, Nguyen, and Sousa (2014) explain the impact of energy prices on CO2 emission allowance prices with a quantile regression approach in the US. They find a negative relationship between crude oil prices and CO2 prices, also a negative relationship between natural gas prices and CO2 prices when CO2 price is low. Finally, a negative impact of coal prices on carbon prices was found. In summary, since the increases in the energy prices cause a decrease in energy production and, consequently decrease in CO2 emission, the demand for allowance and hence allowance price decrease.

Depending on both the literature and the energy generation by sources by each RGGI states, we consider coal spot prices, natural gas spot prices and crude oil spot prices as our explanatory variables.

The relationship between energy prices depicts that crude oil price and the natural gas price has an inter-commodity spread. When one gets increasingly costly (hypothetically, assume oil price) on a historical basis, consumers have another option of changing, in other words, switching to the other (natural gas here), especially with regards to warming. It is usually related to the exploration and production of natural gas and crude oil. The release and capture of natural gas can happen during oil drilling. Oil, petroleum or hydrocarbon reserves are usually found in the depths of the earth's crust. Drilling oil wells usually release these natural gas reserves (Hecht, 2019) [26]. As relevant energy products, oil and natural gas prices have a definite historical price relationship. Nevertheless, this connection has altered in recent years due to the detection of new natural gas reserves in the United States.

The major natural gas reserves in the Marcellus and Utica regions of the USA have changed the price relationship between these two energy products. With the decline in crude oil prices at the end of 2014 and 2015, the price relationship between the two commodities reverted to the more normal historical levels that have been known in the last twenty-five years. In the figures of 4.7 and 4.8 both fuel energy sources, it is seen that there is mostly a negative relationship until 2014. While the crude oil price has an increasing trend between 2009 and 2014, natural gas price is decreasing in the beginning but at the beginning of 2010, it starts to increase. Between 2011 and 2012 it is decreasing again. After 2014, the crude oil price are increasing.

Figure 4.7: Crude Oil monthly spot prices between 2009-2018. [9]

The natural gas is the lowest fossil fuel that emits greenhouse gases, which accounts for about 47 percent of carbon dioxide per coal (Moomaw et al. 2011) [34]. In an assessment of the 2008 natural gas reserves in the USA, the Colorado Mineral School Potential Gas Committee has recorded a 40 percent increase in existing gas reserves since its previous calculation in 2006. This unprecedented improvement can be attributed to the detection of shale gas fields that were previously unreachable. Companies are now developing a method of hydraulic fracture where pressurized water, sand, and chemical mixtures are affected by a fracture in rocks and shale rocks releasing gas.

The sudden development of this natural gas supply provided a 46 percent drop in natural gas prices between 2005 and 2011, while the price of coal has increased. Natural gas has maintained a large supply and this situation together with the economic recession lowers its price. In 1990, natural gas is 12 percent of electricity generation in RGGI states. However, the market share rises to 40 percent until 2011. For the moment, the coal market share decreases by 11 percent in 2011, compared to 25 percent of total production in 1990.

Figure 4.8: Natural gas monthly spot prices between 2009-2018 [37]

As a last fuel variable, we use coal spot prices. From the different parts of US coal commodity regions which are Central Appalachia (CAP), Northern Appalachia (NAP) Illinois Basin (ILB), Powder River Basin (PRB), and Uinta Basin (UIB), we choose Northern Appalachia coal prices. Because this is the region closest coal-producing region to the 9 RGGI states. Between 2009-2010, we see a sharp decrease in the coal price in the Appalachian Region. After that, it starts to increase until September 2011. It has a decreasing trend during the years between 2012 and 2017. The price of Northern coal increased by 39 in 2018 due to strong international demand for both metallurgy and steam coal.

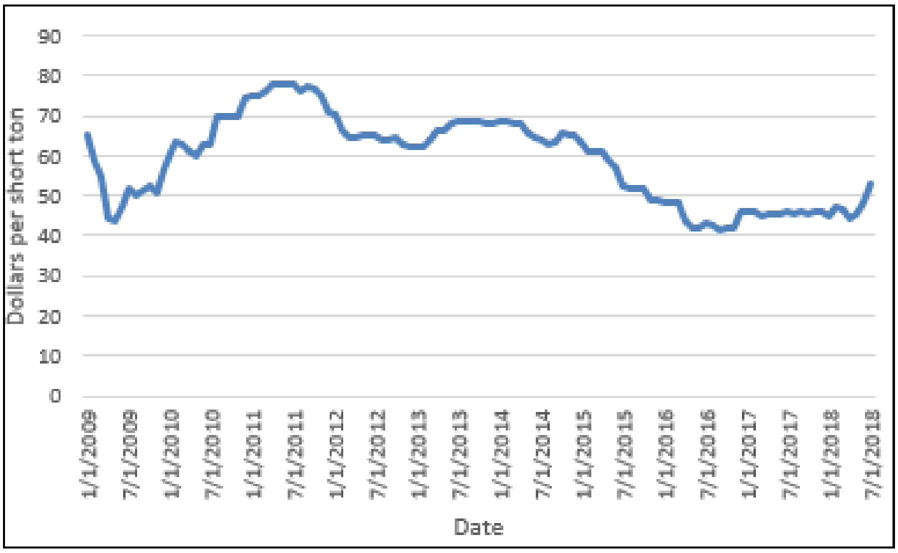

Figure 4.9: Average Monthly Coal Spot Price in Northern Appalachia(NAP) between 2009-2018 [2]

v) Renewable Portfolio Standard

The renewable portfolio standard (RPS) requires electricity services and other retail electricity providers to provide a percentage (or absolute quantity) of minimum customer demand, determined by appropriate renewable electricity sources. By March 2015, 29 states and Washington, D.C. constituted mandatory RPS requirements. The percentage increase of target by each states are represented in the Figure 4.10. Here, we use the weighted average of RPS targets of each 9 states. We give weight to the RPS in each state according to the monthly electricity generation capacity in each province.State RPS's are the drivers for renewable energy development in RGGI states (CRS, 2017) [12]. To calculate the weighted average of RPS, we firstly find electricity generation in 9 states in total electric power industry monthly. After that, we multiply monthly electricity generation in each state with RPS rate. Later, we sum all 9 states' weighted values and finally, we divide it by total electricity generation. Here, we do not add the weather as another variable to our model to prevent multicollinearity problems with RPS ratios. Because the price effects of extreme weather conditions are indirectly related to the impact of energy demand. It may be related in several ways. For example, cooling and heating of homes and supply of carbon-free energy (rainfall, hours of sunlight, wind speed). Using the renewable energy incentives provided to electricity producers, we achieve the supply/demand effects of the weather variable. Besides, Alberola et al. 2008a [16] do not include high endogenous variables, such as electricity prices and/or clean spark or dark sparks, as this could result in biased estimates of price variables in our model. In the study of Fezii and Bunn (2009) [22], carbon costs are often transferred to electricity prices in many countries, and vice versa.

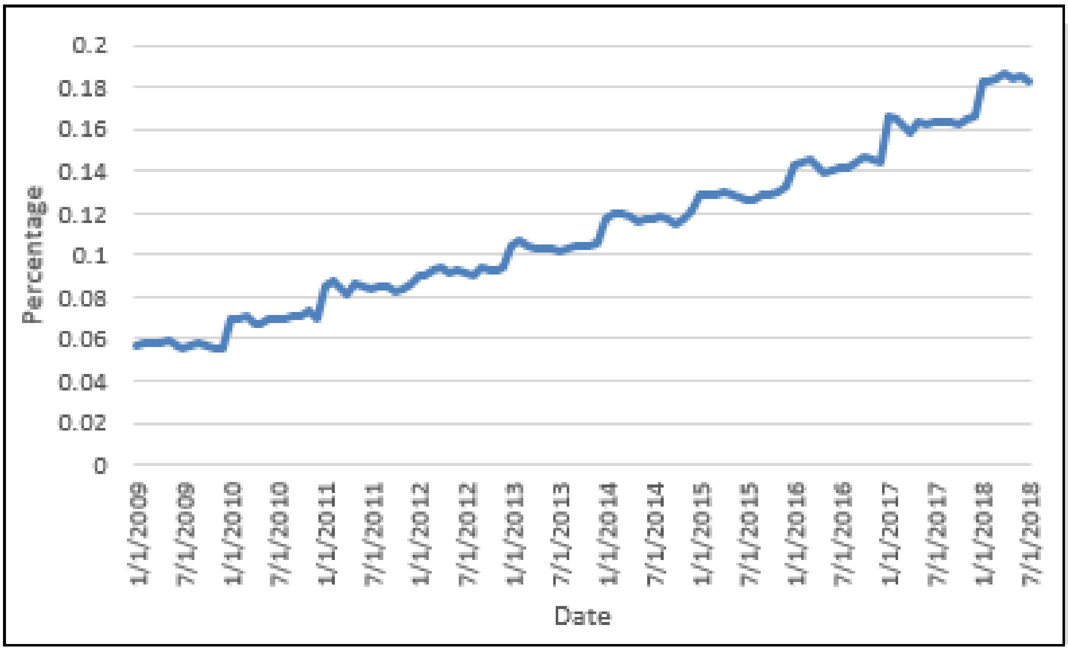

Figure 4.10: Renewable Portfolio Standards of 9 states monthly between 2009-2018 [1]

In our initial analyses, we employ OLS (ordinary least square) to estimate the relation between carbon prices and our explanatory variables (coal price, natural gas price, coal price, the number of allowances, industrial production, renewable energy incentives using multivariate regression model.

4.2 Descriptive Statistics

The descriptive statistics of the variables used in this study over the years are summarized in Table 4.1.

The the quantity of allowances (ALQ), crude oil price (CROP), natural gas price (NGP), coal price (COP), Industrial production index (IP), Weighted average of RPS of 9 RGGI states (WA) are yield the coefficients of variations are less than one. Although CO2 price, allowance quantity, natural gas price, and weighted average price have positive skewness value. None of them except COP is close to zero. On the other hand, coal prices, crude oil prices, and industrial production have negative skewness.

Table 4.1: Descriptive Statistics of the Variables

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	JB
CO2	3.52	1.42	1.88	8.22	0.69	2.92	0.00
ALQ	27.20	11.84	13.55	45.60	0.12	1.26	0.00
IP	100.15	5.23	87.07	107.79	-0.87	2.82	0.00
CROP	73.31	22.31	30.32	109.53	-0.12	1.63	0.00
NGP	3.45	0.87	1.73	6.00	0.44	3.00	0.13
COP	58.87	10.82	41.45	78.10	-0.04	1.76	0.00
WA	0.11	0.04	0.06	0.19	0.29	2.11	0.00

Table 4.2: Dependence Between Variables

Variable	CO2	ALQ	IP	CROP	NGP	COP
CO2	1					
ALQ	-0.8072	1				
IP	0.524	-0.6097	1			
CROP	-0.629	0.6618	-0.0922	1		
NGP	-0.4221	0.443	-0.3851	0.4661	1	
COP	-0.536	0.7451	-0.1694	0.7889	0.5147	1
WA	0.5818	-0.8026	0.8397	-0.45	-0.5049	-0.5795

From Table 4.2, we observe a negative and strong relationship between price and allowance quantity (-0.81). There is a strong negative relationship between crude oil price and CO2 price (- 0.62). The weighted average of RPS has a positive and strong correlation with the CO2 price (0.58). Both the coal price and the natural gas price have a negative correlation with CO2 price (-0.54) and (-0.42) respectively. The industrial production index has a positive correlation with the CO2 price (0.52). As the correlation coefficients are all greater than 0.50, we conclude that explanatory variables have a strong relationship with CO2 price. Contrary to all other variables, the weighted average of RPS and CO2 prices are shown in an unexpected association direction.

In our analysis, we derive out the size and importance of renewable energy subsidies on carbon prices. Therefore, we use 3 different methodologies to measure this effect. The first one is the linear regression model, we estimate at which the CO2 allowance price as a function of the allowance amount, energy prices, economic variable, and weighted average renewable energy targets. In our second model, we look at the time series model and finally, in the panel data model, we look at the magnitude and the significance of the effect of different renewable energy targets on CO2 price.

4.3 Linear Regression

In our first model, we test all the variables that may play a role in determining the explained variable. Our aim is to capture the information between price and other variables and obtain a prediction for CO2 Prices in terms of allowance quantity (ALQ), industrial production (IP), oil price (CROP), coal price [COP] and WA denoting RPS requirements expressed as a weighted average.

$$CO2_t = \beta_0 + \beta_1 * ALQ_t + \beta_2 * IP_t + \beta_3 * CROP_t + \beta_4 * NGP_t + \beta_5 * COP_t + \beta_6 * WA_t + u_t \tag{4.1}$$

In the Table 4.3, natural gas prices and coal prices are insignificant in our model. That is why we exclude those variables from the model and check at the normality of the residuals resulting from the new regression model.
The Skewness/Kurtosis tests for Normality, show that residuals of the regression are non-normal as illustrated in Table 4.4.

Table 4.3: Linear Regression Results.

Variables	Coef.	Std. Err.	t	P > t
CO2_full				
ALP	-0.0919	0.0137757	6.67	0
IP	0.1673997	0.039696	4.22	0
CROP	-0.0281162	0.0053376	5.27	0
NGP	-0.0876129	0.1012992	0.86	0.389
COP	0.0128669	0.0154512	0.83	0.407
WA	-27.69067	5.7612	4.81	0
_cons	-6.056427	3.105596	1.95	0.054
Number of obs	115			
Prob>F	0			
R-squared	0.77			
Adj R-squared	0.75			

Table 4.4: Skewness/Kurtosis tests for Normality of Residuals

Data	Obs.	Pr(Skewness)	Pr(Kurtosis) adj	chi2(2)	Prob>chi2
Original	115	0.0197	0.0006	14.04	0.0009

Table 4.5: Skewness/Kurtosis tests for Normality of Residuals

Data	Obs.	Pr(Skewness)	Pr(Kurtosis) adj	chi2(2)	Prob>chi2
Log-transformed	115	0.8748	0.5594	0.37	0.83149

In the Table 4.5, the log- transformed variables are fit into the regression model whose residuals with new transformed variables are normally distributed. Therefore, CO2 prices can be estimated with respect to the parameter estimates given in Table 4.6.

*: significant at 5 percent

The estimation results show us that there is a negative and statistically significant

Table 4.6: Linear Regression Results.

Variables	Coef.	Std. Err.	t	P > t
ln_CO2_full				
ln_ALP	-0.72993	0.086404	-8.45	0*
ln_IP	5.458575	0.953595	5.72	0*
ln_CROP	-0.40707	0.09046	-4.5	0*
ln_WA	-0.99197	0.173966	-5.7	0*
_cons	-22.12987	4.543216	-4.87	0*
Number of obs	115			
Prob>F	0.7862			
Adj R-squared	0.7785			

($p<0.05$) relationship between CO2 price and allowance quantity in the US. This is consistent with the cap and trade system in the research of Trick and Benz in 2010 [16]. The CO2 price in the cap and trade system is mainly affected by the supply of RGGI allowances. In our system, all the CO2 allowances issued by all the RGGI states compose the RGGI cap. If RGGI states decrease the total cap in the system or as a result of renewable energy incentives of the government in those states, a reduction in CO2 emission occurs, electricity producers or permit buyers try to sell the extra permits in the market. Because of this, the CO2 price decreases when allowance quantity increases. We can see from Table 4.6 that one short ton percent increase in ALQ leads to 0.7 percent dollars decrease in CO2 price.

When looking at the relationship between CO2 price and economic activity by using the industrial production index, it can be seen that it is significant and positively related to CO2 price. That is consistent with macroeconomic theory. When industrial production increases, related CO2 emissions rise, and therefore electricity producers in RGGI states need more CO2 allowances to cover their emissions. This economic logic brings about carbon price increases ceteris paribus (Chevallier, 2011) [19]. We can see from the table that a one percent increase in the IP will result in 5.4 percent dollars increase in the CO2 price. Also, we can see that this relationship is the most important influence in magnitude. IP will result in 5.4 percent dollars increase in the CO2 price. Also, we can see that this relationship is the most important influence in magnitude.

The energy prices depict a negative and significant relationship between crude oil prices and CO2 prices in our linear regression model. This is appropriate with the theory (Hammoudeh, 2014) [24]. If there is a 1 percent increase in the crude oil price, this causes an important drop in the CO2 price. We know that crude oil is the second biggest source of greenhouse gas emissions after coal. Especially, we notice that, when the latter is huge, a considerable drop of CO2 prices are brought about rises in crude oil prices. This may be due to the strong effects of high oil prices at the higher end of the carbon spectrum, but not substituting coal for oil (Hammoudeh, 2014) [25]. The reason behind the negative relationship between crude oil prices and CO2 prices may be the strong positive correlation between oil prices and natural gas prices. In other words, the oil price coefficient in the above equation may be measuring the impact of natural gas price on CO2 prices. One percent dollar per Btu increase in the crude oil price will cause a 0.40 percent dollar decrease in the CO2 price. Finally, there exists a significant and negative relationship between CO2 price and weighted average of RPS of 7 RGGI states. An increasing share in the renewable energy incentives in these 7 RGGI states appears to be related to decreasing CO2 allowance prices. With the increasing renewable incentives, some portion of state power will come from renewable energy resources like wind, solar, etc. This situation will cause a decrease in CO2 emission and energy companies will need fewer permits to produce electricity. In that way, the demand for CO2 permits will decrease and the CO2 price will fall.

We can see also from Table 4.6 that one-megawatt hours percent share increase in WA (weighted average of RPS) will result in 0.99 percent dollars decrease in the CO2 price.

In sum, firstly, we construct a linear regression model with the linear forms of the variables. Because of the non-normality of the variables, we transformed the variables by taking the logarithms. We find significant coefficients at 5 percent significance level.

To check the statistical availability of this model, we need to test the coefficients jointly and individually. Explanatory variables which are allowance quantity, industrial production, crude oil price, and weighted average are statistically significant at 0.05 level of significance. If we look at the collective significance of parameters, we can see that F statistics are lower than 0.05 that is the equation is jointly significant at a 5 percent level of significance. As a result, the regression has consistently estimated parameters.
Approximately 78 percent of the variations in CO2 prices are explained by allowance quantity, industrial production, crude oil price and weighted average of RPS rates of states ($R^2 = 0.78$). After theoretical reasoning and statistical significance tests, we can conclude that the linear model is a valid model. However, estimated parameters by using ordinary least squares may lead to inefficiency, biasedness, and inconsistency problems if Gauss Markov assumptions are violated. Also tests have the assumption of being identically and independent distributed. That means, if there is heteroscedasticity or autocorrelation in the model, parameters are not the best linear predictors. That's why firstly we need to check if there is a heteroscedasticity problem or not. After that, we will control whether there is an autocorrelation problem in our model.

Table 4.7: White's Heteroscedasticity test results

Source	**chi2**	**p-value**
Heteroskedasticity	38.45	0.0004
Skewness	11.07	0.2057
Kurtosis	0.12	0.7315
Total	49.65	0.0001
Chi2(1)	0.1	
Prob>chi2	0.7513	

The Table 4.7 indicate that there is heteroscedasticity in the residuals($p<0.001$). Because there is heteroscedasticity OLS will cause inefficient estimators. Furthermore, we use the Breusch-Godfrey Serial Correlation LM Test for autocorrelation which results in rejecting the null hypothesis on "no serial correlation" in the residuals as can be seen from Table 4.8.

Table 4.8: Breusch-Godfrey Serial Correlation LM Test.

lags(p)	**chi2**	**df**	**Prob > chi2**
1	58.191	1	0

To handle the autocorrelation problem, we use Newey-West standard errors regression in the scope of time series analysis.

Table 4.9: Newey-West Standard Errors

Variables	**Coef.**	**Std. Err.**	**P > t**
ln_CO2			
ln_ALQ	-0.7299	0.1371	0*
ln_IP	5.4585	1.2361	0*
ln_CROP	-0.4070	0.1247	0*
ln_WA	-0.9919	0.1908	0*
_cons	-22.1298	5.9156	0*
Number of Obs.	115		
f(4,110)	67.54		
Prob>F	0		

The Newey-West standard errors in the context of a time series are resistant to random autocorrelation (up to order of the chosen lag) and arbitrary heteroscedasticity. Standard errors that occur are called Heteroscedasticity and Autocorrelation Corrected (HAC) standard errors. We test our explanatory variables with Newey-West standard errors and find that all explanatory variables are significant at 5 percent level of significance.Also, when we look at the Skewness/Kurtosis test for Normality, the residuals of the regression are normally distributed, Prob> chi2 is 0.83 which is higher than the 5 percent significance level.

4.3.1 Stationarity Checks

The last sufficient condition for obtaining BLUE estimators is the stationarity of variables. We use the Augmented Dickey-Fuller Test to determine the integration order of variables

Table 4.10: Augmented DF Test for the Variables

Variables	**Level**	**Suppress Constant**	**First Difference**
CO2	0.3435	insignificant	0*
ALQ	0.8175	insignificant	0*
IP	0.8175	significant	0*
CROP	0.4455	insignificant	0*
WA	0.9629	significant	0*

*: significant at $p<0.001$

As seen from the Table 4.10, all variables of the regression except the industrial production index and the weighted average of RPS are found to have integration of order 1. Because of the nonstationary of variables, this model will not give BLUE estimators even if there is no heteroscedasticity or autocorrelation. The non-stationary variables may have a long term or short-term relationship. Therefore, these variables may be cointegrated. As a result, it can cause the estimation of the stationary relationship, we will look at the statistics results of the Johansen cointegration test with all variables in Vector Auto Regression (VAR). As a first step, we will look at the lag-order selection criteria.

As seen in Table 4.11, according to the number of lags we have different selection criteria like Final Prediction Error (FPE), Akaike Information Criterion (AIC), Hannan Quinn Information Parameters (HQIC) and Schwartz Information Parameters (HQIC) and Schwartz Information Parameters (SBIC) and Final Prediction Error (FPE).

Table 4.11: Lag- order selection statistics.

lag	**LL**	**LR**	**df**	**p**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	-973.774				36.8372	17.7959	17.8457	17.9186
1	-260.009	1427.5	25	0	.000134*	5.27289*	5.57161*	6.00938*
2	-238.153	43.712*	25	0.012	0.000143	5.33005	5.87771	6.68029
3	-226.617	23.072	25	0.573	0.000183	5.57485	6.37146	7.53884
4	-214.54	24.154	25	0.511	0.000235	5.80982	6.85536	8.38755
5	-203.169	22.742	25	0.593	0.000308	6.05762	7.3521	9.2491

To select parameters with optimal lags for VAR, we follow the "majority rule" among the criteria. That means according to AIC, FPE, HQIC and SBIC test statistics, we find the optimum lag as 1 as seen from the Table 4.11. As next step, we perform the Johansen cointegration test.

Here we apply Johansen cointegration with the maximum eigenvalue and the trace test. There are at least r cointegrating relationships and the maximum eigenvalue test telling us there are at most r cointegrating relationships.

As Table 4.12 above shows, at a maximum rank of zero, the trace statistic (86.91) is higher than the critical values (68.52). Therefore; the null hypothesis is rejected. We can say that there is cointegration between variables. Also, when we look at max statistics, the value 39.16 exceeds the critical value of 33.46 thus null hypothesis can be rejected. Thus, as per maximum rank 0, our variables are cointegrated. For maximum rank two, we see that the trace statistic (22.51) is not more than the critical value

Table 4.12: Johansen cointegration test results

maximum rank	parm	LL	eigenvalue	trace statistic	5% critical value
0	5	-314.6575		86.9145	68.52
1	14	-295.0768	0.29073	47.7531	47.21
2	21	-282.4568	0.19861	22.5131*	29.68
3	26	-274.0169	0.13763	5.6333	15.41
4	29	-271.2047	0.04814	0.0089	3.76
5	30	-271.2003	0.00008		

maximum rank	parm	LL	eigenvalue	max statistics	5% critical value
0	5	-314.6575		39.1614	33.46
1	14	-295.0768	0.29073	25.24	27.07
2	21	-282.4568	0.19861	16.8798	20.97
3	26	-274.0169	0.13763	5.6244	14.07
4	29	-271.2047	0.04814	0.0089	3.76
5	30	-271.2003	0.00008		

(29.68). Therefore, we cannot reject the null hypothesis. This proposes that there is one cointegration relationship among the variables in the regression equation. Also, for max statistics, the value 16.87 does not exceed the critical value of 20.97, thus null hypothesis cannot be rejected. Thus, as per maximum rank two, all variables are cointegrated into two-equation. When we look at from cointegration of equation 0 to cointegration of 4, vector error correction model (VECM) will be the appropriate model to apply because there exists cointegration of variables. If there is cointegration, the AR representation of the initial differences is no longer valid. However, the Engel-Granger representation theorem ensures that there is VECM representation The VECM model considers the dynamics of long-term and short-term causality.

4.4 Vector Error Correction Model Results

In the model of VECM, we take the first difference of the variables of CO2, ALQ, CROP, NGP, COP, IP, and WA. We use all the energy prices with linear forms contrary to linear regression model. Our aim is to capture time impact of the all variables

with each other.
In the regression equations, we take D_CO2 as both dependent and lagged and the rest as independent variables.
"ce1" and "ce2" show two cointegration equations. To understand the long-term relationship between the CO2 price and other variables, "ce1", "ce2", "ce4", "ce4", "ce5" and "ce6" should show a negative coefficient and a significant p-value.
As Table A.1 indicates(see Appendix A), only the ce1 equation has a negative coefficient and has a significant p-value of 0.031 at the 5 percent level of significance. The ce3 coefficient is positive and nearly significant at the 5 percent level. Moreover, ce4 is negative and very nearly significant at the 10 percent level. Thus, VECM does not show a long-term causality between CO2 price and the other six variables.

Also, to analyze the short-term causality between variables, we look at individual lag coefficients and p-values for each independent variable. Therefore, this describes the lagged values of the explanatory variables for the CO2 price. the only second lag of coal price ($p < 0.005$) is significant at 1 percent and the weighted average of RPS ($p < 0.032$) is significant at a 5 percent level of significance level. That means the only second lag of coal price and weighted average of RPS have a short-term relationship with CO2 price at the 5 percent level of significance.

When looking the relationship of the dependent variable related with supply of allowances which is the allowance quantity and rest of the variables as our explanatory variables, we see from Table A.1 (see Appendix A) that the only equation of ce2 has a negative coefficient and a significant p-value of 0.012. This VECM does not show long-term causality between allowance quantity and the other six variables. There is no short-term relation between allowance quantity and any of the other variables at the 5 percent level.

When we look at the other economic indices which is industrial production as dependent variable and the rest of the variables as our explanatory variables, we see from the Table A.2 (see Appendix A) that equations of ce3 and ce6 have a negative coefficient and have a significant p-value as 0 and 0.041 respectively. Since only two equations out of six satisfy the condition, this VECM does not show long-term causality between industrial production and the other six variables at the 5 percent level. Also, while only the 1st lag of industrial production (p-value of 0.034), and the weighted average of RPS (0.021) are significant at 5 percent, 1st lag of crude oil price (p-value of 0.002) is significant at 1 percent significance level. That means the only 1st lag of industrial production, crude oil price and weighted average of RPS have a short-term causality with industrial production at the 5 percent level.

In the results of first energy price which is crude oil price as the dependent variable and the rest of the variables as our explanatory variables, we see from the Table A.2 (see Appendix A) that none of them has a negative coefficient and has a significant p-value. That's why, VECM does not show long-term causality between crude oil prices and the other six variables. Also, 1st lag of allowance quantity (p-value of 0.000), is significant at 1 percent. That means the only 1st lag of allowance quantity has a short-term causality with the crude oil price at the 5 percent level.

In the results of the second energy price which is natural gas price as dependent variable and the rest of the variables as our explanatory variables, we see from the Table A.3 (see Appendix A) that the only equation of ce6 has a negative coefficient and has a significant p-value (0.010). That's why, VECM does not show a long-term causality between natural gas prices and the other six variables at the 5 percent level. Also, 1st lag of allowance quantity (p-value of 0.003), is significant at a 1 percent significance level. That means the only 1st lag of allowance quantity has a short-term causality with natural gas price at the 5 percent level.

In the results of the last energy price variable which is coal price as dependent variable and the rest of the variables as our explanatory variables, we see from the Table A.3 (see Apeendix A) that the only equation of ce6 has a negative coefficient and has a significant p-value (0.000). That's why, VECM does not show long-term causality between natural gas prices and the other six variables at the 5 percent level. Also, 2nd lag of industrial production (p-value of 0.014), and 3rd lag of natural gas price (p-value 0.048) are significant at a 5 percent significance level. That means the only 2nd lag of industrial production and 3rd lag of natural gas price have a short-term causality with coal price at the 5 percent level.

When we look at the renewable energy incentives which is the weighted average as dependent variable of RPS and the rest of the variables as our explanatory variables, we see from the Table A.4 (see Appendix A) that the only equation of ce4 has a negative coefficient and has a significant p-value (0.036). That's why, VECM does not show a long-term causality between natural gas prices and the other six variables at the 5 percent level. Also, 1st lag of industrial production (p-value of 0.003), 1st lag of natural gas price (p-value 0.007) and 3rd lag of weighted average of RPS (p-value 0.039) are significant at 5 percent significance level. That means the only 1st lag of industrial production and natural gas price and 3rd lag of weighted average of RPS have a short-term causality with a weighted average of RPS at the 5 percent level. Also, when we look at the Skewness/Kurtosis test for Normality, the residuals of the model are normally distributed, Prob> chi2 is 0.11 which is higher than the 5 percent significance level.

4.4.1 Granger Causality Test Result

Granger causality is a method to investigate causality between two variables in a time series. If X is affected by the delayed values of both X and Y, Y Granger causes X. Likewise, if the change in Y is affected by the delayed values of X, X Granger causes Y. When Y Granger causes X and X Granger causes Y, this bidirectional Granger is known as causality. If only one Granger causes another, it is called one-way causality (or one-way causality in the sense of Granger). If none of the variable Granger causes another, there is no causality.

The most important point here is the one-way relationship between the CO2 price and the weighted average of the RPS targets. In Table 4.13, there are seven sections separated by horizontal lines. Each section is identified by a different equation named under the first column. The first section (corresponding to the "CO2" equation) shows that the lagged values of the WA cause CO2 at a 5 percent significance level because the p-value of the WA is equal to 0.001, which is less than 0.05. In contrast, the last section (corresponding to the "WA" equation) shows that the lagged values of CO2 do not cause weight loss at a 5 percent significance level because the CO2 p-value is $0.614 > 0.05$. Therefore, at the 5 percent significance level, the causality direction is from WA to CO2. Causality is unidirectional because there is no grace in the opposite direction (from CO2 to WA) at a 5 percent significance level.

According to the Granger Causality test; CO2 price is affected from IP and WA while IP is effected from CROP, COP and WA . CROP and NGP are both significantly related with ALQ. COP is impacted by ALQ and itself. Finally, WA is effected from IP and CROP.

Table 4.13: Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
CO2	ALQ	6.4071	2	0.041
CO2	IP	15.812	2	0
CO2	CROP	2.988	2	0.224
CO2	NGP	0.83839	2	0.658
CO2	COP	2.8325	2	0.235
CO2	WA	14.467	2	0.001
CO2	ALL	34.264	12	0.001
ALQ	CO2	2.4052	2	0.3
ALQ	IP	2.478	2	0.29
ALQ	CROP	2.3574	2	0.308
ALQ	NGP	1.5163	2	0.469
ALQ	COP	4.3426	2	0.114
ALQ	WA	0.03946	2	0.98
ALQ	ALL	18.495	12	0.101
IP	CO2	0.13831	2	0.933
IP	ALQ	2.0373	2	0.361
IP	CROP	23.543	2	0
IP	NGP	0.55453	2	0.758
IP	COP	6.8478	2	0.033
IP	WA	12.935	2	0.002
IP	ALL	55.185	12	0
CROP	CO2	5.3815	2	0.068
CROP	ALQ	8.0894	2	0.018
CROP	IP	0.43665	2	0.804
CROP	NGP	2.9864	2	0.225
CROP	COP	0.84297	2	0.656
CROP	WA	0.51008	2	0.775
CROP	ALL	28.132	12	0.005
NGP	CO2	1.5676	2	0.457
NGP	ALQ	11.51	2	0.003
NGP	IP	0.02116	2	0.989
NGP	CROP	5.0816	2	0.079
NGP	COP	4.3007	2	0.116
NGP	WA	5.7239	2	0.057
NGP	ALL	34.972	12	0
COP	CO2	0.34566	2	0.842
COP	ALQ	8.2722	2	0.016
COP	IP	0.42158	2	0.81
COP	CROP	7.9779	2	0.019
COP	NGP	3.5023	2	0.174
COP	WA	1.5962	2	0.45
COP	ALL	34.948	12	0
WA	CO2	0.97502	2	0.614
WA	ALQ	1.3746	2	0.503
WA	IP	9.304	2	0.01
WA	CROP	6.7544	2	0.034
WA	NGP	5.2722	2	0.072
WA	COP	3.4531	2	0.178
WA	ALL	24.305	12	0.018

4.5 Panel Data

We perform Panel data analysis in order to understand the differences observed between each states. Based on the correlation matrix given in Table 2.1, we see RPS requirements are strongly correlated across states. Therefore, the RPS requirement for one state should serve as a pretty good instrument for the RPS requirements for the rest of the states.

There are two common ways to conduct panel data regression; random-effects model and fixed-effect model. In any case, having associations with the observed variables are permitted to the unobserved variables in a fixed-effects model. The effects of time-invariant variables with time-invariant effects are controlled by fixed-effects models [42]. We conduct a Hausman test to determine whether a fixed effect model is appropriate more than a random-effects model. The null hypothesis is that the fixed effects model is more appropriate. According to the result of the Hausman test result given in the Table 4.14, our p-value is 0. That's why we reject null hypothesis which is "random effect model appropriate" instead we accept the alternative. That is the fixed effect model is more appropriate.

Table 4.14: Hausman test results.

Variables	FE(b)	RE(b)	difference(b-B)	sqrt(diag(V_b-V_B)) S.E.
ALQ	-0.0942292	-0.09613	0.0018969	.
CROP	-0.258701	-0.02443	-0.0014365	.
NGP	-0.1117885	-0.13919	0.0274063	.
COP	0.0356132	0.05044	0.0148263	0.0013089
IP	0.0765008	0.023073	0.0534283	0.0063023
WA	-12.73541	-2.62114	-10.11428	1.269304

Table 4.15 shows panel data estimation results. The variables used include the quantity of allowances (ALQ,) crude oil price (CROP), natural gas price (NGP), coal price (COP), industrial production (IP) and Renewable Portfolio Standards (WA) across states. All variables have been considered in linear values. The coefficient signs of the variable's quantity allowances, crude oil price, natural gas price, and RPS are, as expected, negative. Also, the coal price and industrial production index are as expected positively related to the CO_2 price. Also, all the variables are significant at the

Table 4.15: Panel data analysis with fixed effect and robust standard errors

Variables	Coef.	P>t
ALQ	-0,09	0,00
CROP	-0,03	0,00
NGP	-0,11	0,00
COP	0,04	0,00
IP	0,08	0,00
WA	-12,74	0,00
constant	-0,09	0,93
sigma_u	0,48	
sigma_e	0,72	
rho	0,31	
Number of observation	805	
Number of groups	7	
Time periods	115	
R squared	0,6606	
F(6,792)	388,53	
Prob > F	0	

5 percent significance level.

The R square value also indicates the goodness of fit equals 66 percent which is significantly large. The rho value is 0.31 which indicates the individual effects of cross-sections are 0.3 percent. In the fixed effect regression model, Modified Wald test for group-based heteroscedasticity, chi2 is 0.8873. Since the P values are higher than the 0.05, we cannot reject the null hypothesis Thus, the above-fixed effects model is homoscedastic.

When we control autocorrelation with Wooldridge test in panel data, the existence of the first-order autocorrelation is significant.

To solve the problem of autocorrelation, we use Rogers or clustered standard errors so that the standard errors in our new model are wholly robust to serial correlation.

Table 4.16: Panel data analysis with fixed effect and robust standard.

Variables	Coef.	Robust Std.Err.	P>t
ln_CO2P			
ln_ALQ	-0,71	0,014	0*
ln_CROP	-0,36	0,005	0*
ln_COP	0,38	0,026	0*
ln_IP	1,69	0,218	0*
ln_RPS	-0,26	0,042	0*
constant	-4,98	0,970	0*
sigma_u	-0,09		
sigma_e	0,19		
rho	0,18		
Number of observation	805		
Number of groups	7		
Time periods	115		
R squared	0,7560		
F(6,792)	3125,19		
Prob > F	0		

In Table 4.16, we see the coefficients with robust standard errors that means the variables do not carry autocorrelation problems. We already test heteroscedasticity and autocorrelation so we can interpret estimation results. In the panel data analysis, we see ALQ has negative (-0.71) and significant relation with CO2 price, also CROP is negatively (-0.36) related to CO2 price and significant at 5 percent level of significance. However, COP is positively (0.38) and significantly related to CO2. We expect COP to be negatively related to CO2. Moreover, IP is positively (1.69) and significantly related to CO2. Lastly, WA is significantly and negatively (-0.26) related to CO2 price. With panel data analysis, we can analyze the impact of the different targets of the states on CO2. Also, when we look at the Skewness/Kurtosis test for Normality, the residuals of the model are normally distributed, Prob> chi2 is 0.11 which is higher than the 5 percent significance level.

CHAPTER 5

CONCLUSION AND POLICY IMPLICATION

The end of the first decade of the 21st century provides a rare window of time to determine how different policy, technology, and market issues affect US greenhouse gas emissions. During this period, strategies at different government levels began to reduce greenhouse gases directly or indirectly through complementary actions such as renewable portfolio standards. Furthermore, technological advances in the field of hydraulic fracture and horizontal drilling cause an increase in new accessible natural gas reserves, lower prices and long-term use. The transition from high-emission coal to low-emission gas has reduced the emission intensity of electricity generation.

In this thesis, one of our goals is to understand the effect of the RPS policy on the outcome of the RGGI policy. We use the CO2 allowance price to measure the outcome of the RGGI policy. We aim to establish a meaningful and quantitative relationship between CO2 incentives and increased incentives for renewable energy sources in the USA. For this reason, the energy prices (coal, crude oil and natural gas) that is used in the literature, the industrial production index which reflects the economic situation of the country, and the renewable portfolio standards showing the RGGI renewable energy source incentive and also allowance quantity that is showing the supply of permits in the cap and trade system are used as explanatory variables. In that sense, we constructed, 3 different regression models. The first one, the linear regression model captures the information between price and other variables. While we observe a positive and significant relationship between CO2 price and industrial production index, we find a negative and significant relationship between the price of CO2 and crude oil price. We observe a negative and significant relationship with renewable energy targets. As a result, we explain 77 percent in CO2 price variation with industrial production, several allowances, crude oil prices, and the weighted average of RPS.

The second model is the vector error correction model to capture time effect. Results from this model are that the CO2 price has not long-term causality with other independent variables. Also, the CO2 price has short term causality with the lag of coal price and the weighted average of RPS. This is consistent with the linear regression model results.

We know that coal price has a higher magnitude in electricity production in producing electricity, that's why we can expect a significant impact in explaining CO2 price. Moreover, when we look at the weighted average of RPS, we see that it has not a long-term relationship with other independent variables, also RPS targets have short term relationships with a lag of industrial production and natural gas price and with itself. Although RPS programs help reduce carbon emission, the increase in renewable energy displaces mostly natural gas which is less polluting than coal. While the price of electricity and the renewable credits are expected to increase under an RPS, the generation from both coal and natural gas sources should decrease. In general, RPS programs are superior to alternative policies. In the case of industrial production, we expect a positive interaction between RPS targets. When the economic activity increases monthly or yearly within states, we expect to increase in renewable energy production and/or Renewable Portfolio Standards targets.

And finally, panel data analysis results support our linear regression results in the sense that they both show the same energy price signs. However, contrary to the theory and literature, the sign of the coal price is positive. When we consider all these three models, we can see that the rising incentives to renewable energy sources (wind, solar, hydropower, etc.), which are the complementary policy RPS's, actually have a significant effect on CO2 prices. One of the reasons for the low CO2 price in the US is that, due to the increased incentives, the CO2 price has fallen due to the complementary policy. This study shows that renewable energy investments in countries have a significant effect that reduces the amount of carbon market in the USA. Complementary environmental policies should continue to be used as an auxiliary factor in reducing carbon emissions in countries.

As seen in previous years, the price of carbon has remained low for many years due to total allowances being determined as ineffective. However, there has been a significant increase in CO2 prices after the cut in the total cap. One reason for the decline in the sales of allowance quantity is the improvements in the natural gas reserves.

Thanks to the development of the hydraulic fracturing process natural gas reserves increased. In this case, the natural gas price decreases and coal consumption to natural gas consumption has been in transition.This also causes a reduction in the amount of CO2 emissions, which led to companies demanding less allowance. Perhaps the strongest result of this study is that there is both a need and a potential for future research on the questions that this thesis has addressed. This thesis also suggests a possible direction for research to progress in the future.
Regrettably, this study has some limitations. Due to the limited and irregular financial data generated by RGGI and the energy markets, a strong impulse analysis is difficult. Since RGGI is a new and young market, this is considered a problem that is why should not be avoided in interpreting the results. Further research is needed to determine the actual allowance price drivers and to understand how greenhouse gas emissions change with the prices of natural resources and incentives for renewable energy production.

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APPENDIX A

In this part, we present the detailed outputs of vector error correction models for each variable. The interpretations of each case are presented in the related section.

Table A.1: Vector Error Correction Model Results for CO2 price and ALQ

Variable	Coef.	Std.Err.	z	P>z
D_CO2				
_ce1 L1.	-0.2777	0.128959	-2.15	0.031
_ce2 L1.	-0.00733	0.24374	-0.3	0.764
_ce3 L1.	0.131572	0.068834	1.91	0.056
_ce4 L1.	-0.01865	0.011488	-1.62	0.104
_ce5 L1.	0.33635	0.233365	1.44	0.149
_ce6 L1.	0.005692	0.024171	0.24	0.814
CO2				
LD.	0.043271	0.162215	0.27	0.79
L2D.	-0.21792	0.152989	-1.42	0.154
L3D.	0.054976	0.142468	0.39	0.07
L4D.	-0.03748	0.136409	-0.27	0.784
L5D.	-0.14062	0.144512	-0.97	0.331
L6D.	-0.0702	0.133746	-0.52	0.6
L7D.	0.010781	0.12099	0.09	0.929
ALQ				
LD.	0.032447	0.027885	1.16	0.245
L2D.	-0.02962	0.029856	-0.99	0.321
L3D.	0.034561	0.028566	1.21	0.226
L4D.	-0.00624	0.028988	-0.22	0.83
L5D.	-0.03394	0.030458	-1.11	0.265
L6D.	0.028773	0.028336	1.02	0.31
L7D.	0.008024	0.029003	0.28	0.782
IP				
LD.	-0.31621	0.147072	-2.15	0.032
L2D.	-0.1022	0.153768	-0.66	0.506
L3D.	-0.05045	-0.152549	-0.33	0.741
L4D.	0.071864	0.157633	0.46	0.648
L5D.	-0.06775	0.151149	0.45	0.654
L6D.	-0.004795	0.139913	-0.34	0.732
L7D.	0.079687	0.142794	0.56	0.577
CROP				
LD.	0.005331	0.015779	0.34	0.735
L2D.	0.024273	0.014494	1.67	0.094
L3D.	0.010442	0.014702	0.71	0.48
L4D.	0.017365	0.014105	1.23	0.218
L5D.	-0.00134	0.014199	-0.09	0.925
L6D.	-0.00992	0.014045	-0.71	0.48
L7D.	0.023146	0.014236	1.63	0.104
NGP				
LD.	-0.37625	0.23109	-1.63	0.103
L2D.	0.036356	0.198846	0.18	0.855
L3D.	-0.13787	0.183823	-0.75	0.453
L4D.	0.008366	0.192659	0.04	0.965
L5D.	-0.007103	0.181696	-0.39	0.696
L6D.	0.154128	0.172905	0.89	0.373
L7D.	0.030131	0.158252	0.19	0.849
COP				
LD.	0.066385	0.041826	1.59	0.112
L2D.	-0.11898	0.042572	-2.79	0.005
L3D.	-0.00021	0.041414	-0.001	0.996
L4D.	-0.01667	0.0042557	-0.39	0.695
L5D.	-0.05619	0.034287	-1.64	0.101
L6D.	-0.01828	0.035975	-0.51	0.611
L7D.	-0.05017	0.035099	-1.43	0.153
. WA				
LD.	41.02013	17.11927	2.4	0.017
L2D.	-38.0755	17.72382	-2.15	0.032
L3D.	34.22028	18.3731	1.86	0.063
L4D.	1.444153	18.58057	0.08	0.938
L5D.	-16.7701	17.65457	-0.95	0.342
L6D.	7.488168	16.67151	0.45	0.653
L7D.	-12.7922	17.03162	-0.75	0.453
_cons	8.99e-06	0.138798	0	1

Variable	Coef.	Std.Err.	z	P>z
D_ALQ				
_ce1 L1.	-1,004299	0,7250377	-1,39	0,166
_ce2 L1.	-0,3435709	0,1370355	-2,51	0,012
_ce3 L1.	-0,3670438	0,3869992	-0,95	0,343
_ce4 L1.	0,0184082	0,0645866	0,29	0,776
_ce5 L1.	-2,03551	1,31203	-1,55	0,121
_ce6 L1.	0,0957072	0,1358925	0,7	0,481
CO2				
LD.	0,951312	0,9120087	1,04	0,297
LD2.	0,7720238	0,8601385	0,9	0,369
LD3.	1,007318	0,80099	1,26	0,209
LD4.	1,264375	0,7669234	1,65	0,099
LD5.	1,616386	0,8124816	1,99	0,047
LD6.	0,8482	0,7519509	1,13	0,259
LD7.	0,5981749	0,6802349	0,88	0,379
ALQ				
LD.	0,1612518	0,156778	1,03	0,304
LD2.	-0,0612854	0,1678562	-0,37	0,715
LD3.	0,0506652	0,1606037	0,32	0,752
LD4.	0,1476786	0,1629755	0,91	0,365
LD5.	0,0702317	0,1712427	0,41	0,682
LD6.	0,1582616	0,1593094	0,99	0,321
LD7.	0,0918875	0,1630596	0,56	0,573
IP				
LD.	-0,6522963	0,8268713	-0,79	0,43
LD2.	-0,249179	0,8645177	-0,29	0,773
LD3.	-0,2781711	0,8576631	-0,32	0,746
LD4.	0,8783312	0,8862508	0,99	0,322
LD5.	-0,1500452	0,849796	-0,18	0,86
LD6.	1,226325	0,7866212	1,56	0,119
LD7.	-0,1819173	0,8028184	-0,23	0,821
CROP				
LD.	-0,076332	0,0887109	-0,86	0,39
LD2.	-0,0193512	0,0814888	-0,24	0,812
LD3.	0,0245808	0,082655	0,3	0,766
LD4.	0,0281106	0,079303	0,35	0,723
LD5.	0,1138865	0,0798298	1,43	0,154
LD6.	-0,09205	0,0789632	-1,17	0,244
LD7.	0,0058542	0,0800354	0,07	0,942
NGP				
LD.	0,6973881	1,299243	0,54	0,591
LD2.	0,9965764	1,117959	0,89	0,373
LD3.	1,171109	1,033497	1,13	0,257
LD4.	1,58571	1,083175	1,46	0,143
LD5.	1,250711	1,021535	1,22	0,221
LD6.	1,015392	0,9721125	1,04	0,296
LD7.	0,687122	0,8897273	0,77	0,44
COP				
LD.	0,3883546	0,2351566	1,65	0,099
LD2.	0,0838958	0,2393484	0,35	0,726
LD3.	-0,0552702	0,2328402	-0,24	0,812
LD4.	0,0332115	0,2392647	0,14	0,89
LD5.	-0,2184197	0,1927673	-1,13	0,257
LD6.	0,317732	0,2022598	1,57	0,116
LD7.	0,0380245	0,1973358	0,19	0,847
WA				
LD.	11,48613	96,24851	0,12	0,905
LD2.	-55,73055	99,64741	-0,56	0,576
LD3.	-42,51368	103,2978	-0,41	0,681
LD4.	42,51858	104,4642	0,41	0,684
LD5.	-39,70093	99,25808	-0,4	0,689
LD6.	72,52546	93,73105	0,77	0,439
LD7.	65,69958	95,75569	0,69	0,493
_cons	-2,48E-06	0,7803517	0	1

Table A.2: Vector Error Correction Model Results for IP and CROP

Variable	Coef.	Std.Err.	z	P>z
D_IP				
_ce1 L1.	0,003133	0,111857	0,03	0,978
_ce2 L1.	0,0090929	0,0211415	0,43	0,667
_ce3 L1.	-0,2344123	0,0597053	-3,93	0
_ce4 L1.	0,0348127	0,0099643	3,49	0
_ce5 L1.	0,4878356	0,2024167	2,41	0,016
_ce6 L1.	-0,0428057	0,0209652	-2,04	0,041
CO2				
LD.	-0,0864022	0,1407024	-0,61	0,539
L2D.	-0,0152393	0,1327	-0,11	0,909
L3D.	-0,0016659	0,1235747	-0,01	0,989
L4D.	0,2276638	0,118319	1,92	0,054
L5D.	0,0314336	0,1253476	0,25	0,802
L6D.	0,1318036	0,1160091	1,14	0,256
L7D.	-0,1008755	0,1049449	-0,96	0,336
ALQ				
LD.	-0,0266146	0,0241873	-1,1	0,271
L2D.	-0,0036175	0,0258964	-0,14	0,889
L3D.	-0,009263	0,0247775	-0,37	0,709
L4D.	0,0282345	0,0251434	1,12	0,261
L5D.	-0,0107514	0,0264189	-0,41	0,684
L6D.	-0,0018814	0,0245779	-0,08	0,939
L7D.	0,0233342	0,0251564	0,93	0,354
IP				
LD.	-0,2700245	0,1275676	-2,12	0,034
L2D.	-0,3364768	0,1333756	-2,52	0,012
L3D.	-0,1472228	0,1323181	-1,11	0,266
L4D.	-0,1976087	0,1367285	-1,45	0,148
L5D.	-0,0738066	0,1311044	-0,56	0,573
L6D.	,0397781	0,1213579	0,33	0,743
L7D.	0,0607547	0,1238568	0,49	0,624
CROP				
LD.	-0,0415995	0,0136861	-3,04	0,002
L2D.	-0,0177099	0,0125719	-1,41	0,159
L3D.	-0,0065906	0,0127518	-0,52	0,605
L4D.	-0,0194584	0,0122347	-1,59	0,112
L5D.	-0,0081498	0,0123159	-0,66	0,508
L6D.	-0,016703	0,0121822	-1,37	0,17
L7D.	-0,0143625	0,0123477	-1,16	0,245
NGP				
LD.	-0,2542261	0,200444	-1,27	0,205
L2D.	-0,26087	0,1724758	-1,51	0,13
L3D.	0,0527943	0,1594453	0,33	0,741
L4D.	-0,1779556	0,1671095	-1,06	0,287
L5D.	0,0138033	0,1575999	0,09	0,93
L6D.	-0,0085678	0,149975	-0,06	0,954
L7D.	0,0783388	0,1372649	0,57	0,568
COP				
LD.	-0,009158	0,0362794	-0,25	0,801
L2D.	-0,048437	0,0369261	-1,31	0,19
L3D.	-0,0595334	0,035922	-1,66	0,097
L4D.	-0,0016329	0,0369132	-0,04	0,965
L5D.	-0,0121925	0,0297396	-0,41	0,682
L6D.	-0,0538514	0,0312041	-1,73	0,084
L7D.	0,0167068	0,0304445	0,55	0,583
WA				
LD.	-34,2792	14,84898	-2,31	0,021
L2D.	-16,64189	15,37335	-1,08	0,279
L3D.	-6,351088	15,93652	-0,4	0,69
L4D.	-20,42981	16,11648	-1,27	0,205
L5D.	-18,92849	15,31328	-1,24	0,216
L6D.	-18,67013	14,46059	-1,29	0,197
L7D.	-18,44138	14,77294	-1,25	0,212
_cons	2,95E-05	0,1203907	0	1

Variable	Coef.	Std. Err.	z	P>z
D_CROP				
_ce1 L1.	0,0242521	1,337556	0,02	0,986
_ce2 L1.	0,6390475	0,2528042	2,53	0,011
_ce3 L1.	-0,1459466	0,7139396	-0,2	0,838
_ce4 L1.	-0,1722928	0,1191499	-1,45	0,148
_ce5 L1.	1,115585	2,420445	0,46	0,645
_ce6 L1.	-0,3453482	0,2506957	-1,38	0,168
CO2				
LD.	-2,727415	1,682482	-1,62	0,105
L2D.	0,5010391	1,586791	0,32	0,752
L3D.	0,4885243	1,477674	0,33	0,741
L4D.	1,893847	1,414827	1,34	0,181
L5D.	0,8496105	1,498873	0,57	0,571
L6D.	0,8552132	1,387206	0,62	0,538
L7D.	-0,7578142	1,254903	-0,6	0,546
ALQ				
LD.	-1,095294	0,2892254	-3,79	0
L2D.	-0,5370049	0,3096625	-1,73	0,083
L3D.	-0,678637	0,2962831	-2,29	0,022
L4D.	-0,6417611	0,3006587	-2,13	0,033
L5D.	-0,5153514	0,3159101	-1,63	0,103
L6D.	-0,5560173	0,2938955	-1,89	0,059
L7D.	-0,5404086	0,3008138	-1,8	0,072
IP				
LD.	0,029879	1,525419	0,02	0,984
L2D.	-0,6130337	1,59487	-0,38	0,701
L3D.	2,141808	1,582225	1,35	0,176
L4D.	0,3457377	1,634963	0,21	0,833
L5D.	-0,426784	1,567711	-0,27	0,785
L6D.	0,3544477	1,451166	0,24	0,807
L7D.	1,533783	1,481046	1,04	0,3
CROP				
LD.	0,1922822	0,1636546	1,17	0,24
L2D.	-0,0537575	0,1503312	-0,36	0,721
L3D.	-0,1407686	0,1524827	-0,92	0,356
L4D.	-0,0029976	0,1462989	-0,02	0,984
L5D.	0,034691	0,1472708	0,24	0,814
L6D.	-0,2455283	0,145672	-1,69	0,092
L7D.	-0,0361299	0,14765	-0,24	0,807
NGP				
LD.	-1,169867	2,396856	-0,49	0,625
L2D.	-0,0673412	2,06242	-0,03	0,974
L3D.	0,786176	1,906604	0,41	0,68
L4D.	0,4206201	1,998251	0,21	0,833
L5D.	0,420348	1,884538	0,22	0,823
L6D.	-0,0840088	1,793362	-0,05	0,963
L7D.	-1,421068	1,641377	-0,87	0,387
COP				
LD.	-0,1274191	0,433819	-0,29	0,769
L2D.	0,4003067	0,441552	0,91	0,365
L3D.	-0,3092496	0,4295458	-0,72	0,472
L4D.	0,200504	0,4413977	0,45	0,65
L5D.	-0,0498258	0,3556188	-0,14	0,889
L6D.	0,2373435	0,3731307	0,64	0,525
L7D.	0,400798	0,3640469	1,1	0,271
WA				
LD.	-206,508	177,5601	-1,16	0,245
L2D.	-25,0457	183,8304	-0,14	0,892
L3D.	-110,0743	190,5647	-0,58	0,564
L4D.	-149,9152	192,7165	-0,78	0,437
L5D.	-123,7073	183,1122	-0,68	0,499
L6D.	-12,0111	172,9159	-0,07	0,945
L7D.	-273,0244	176,6509	-1,55	0,122
_cons	3,11E-07	1,4396	0	1

Table A.3: Vector Error Correction Model Results for NGP and COP

Variable	Coef.	Std. Err.	z	P>z
D_NGP				
_ce1 L1.	0,0041118	0,1011121	0,04	0,968
_ce2 L1.	-0,002111	0,0191107	-0,11	0,912
_ce3 L1.	0,0089017	0,05397	0,16	0,869
_ce4 L1.	0,0164014	0,0090071	1,82	0,069
_ce5 L1.	-0,297742	0,1829728	-1,63	0,104
_ce6 L1.	-0,0487979	0,0189513	-2,57	0,01
CO2				
LD.	0,0825737	0,1271867	0,65	0,516
L2D.	0,0737151	0,119953	0,61	0,539
L3D.	0,0218666	0,1117043	0,2	0,845
L4D.	-0,0614325	0,1069534	-0,57	0,566
L5D.	0,0041583	0,1133069	0,04	0,971
L6D.	-0,0396917	0,1048654	-0,38	0,705
L7D.	-0,0168784	0,094864	-0,18	0,859
ALQ				
LD.	-0,0649731	0,0218639	-2,97	0,003
L2D.	-0,0079562	0,0234088	-0,34	0,734
L3D.	-0,0063974	0,0223974	-0,29	0,775
L4D.	-0,0373948	0,0227282	-1,65	0,1
L5D.	0,0000256	0,0238811	0	0,999
L6D.	-0,0161395	0,0222169	-0,73	0,468
L7D.	-0,0075197	0,0227399	-0,33	0,741
IP				
LD.	-0,0016069	0,1153136	-0,01	0,989
L2D.	-0,1800678	0,1205637	-1,49	0,135
L3D.	0,0241291	0,1196078	0,2	0,84
L4D.	-0,1794129	0,1235945	-1,45	0,147
L5D.	-0,1122051	0,1185106	-0,95	0,344
L6D.	-0,0043695	0,1097004	-0,04	0,968
L7D.	-0,1238664	0,1119592	-1,11	0,269
CROP				
LD.	-0,0175593	0,0123714	-1,42	0,156
L2D.	-0,0035061	0,0113642	-0,31	0,758
L3D.	-0,011294	0,0115269	-0,98	0,327
L4D.	0,0046872	0,0110594	0,42	0,672
L5D.	-0,0148843	0,0111329	-1,34	0,181
L6D.	0,0065282	0,011012	0,59	0,553
L7D.	0,0044118	0,0111616	0,4	0,693
NGP				
LD.	-0,0143326	0,1811896	-0,08	0,937
L2D.	0,108647	0,155908	0,7	0,486
L3D.	-0,1368937	0,1441291	-0,95	0,342
L4D.	-0,0548402	0,1510572	-0,36	0,717
L5D.	-0,0132361	0,142461	-0,09	0,926
L6D.	-0,1189936	0,1355686	-0,88	0,38
L7D.	-0,1348001	0,1240794	-1,09	0,277
COP				
LD.	0,0415968	0,0327944	1,27	0,205
L2D.	0,0112227	0,033379	0,34	0,737
L3D.	0,0519336	0,0324714	1,6	0,11
L4D.	0,0455166	0,0333673	1,36	0,173
L5D.	0,0731057	0,0268829	2,72	0,007
L6D.	0,0430784	0,0282067	1,53	0,127
L7D.	0,0825502	0,02752	3	0,003
WA				
LD.	-19,53756	13,4226	-1,46	0,146
L2D.	-13,81709	13,8966	-0,99	0,32
L3D.	13,41103	14,40568	0,93	0,352
L4D.	-2,890256	14,56835	-0,2	0,843
L5D.	12,61543	13,84231	0,91	0,362
L6D.	-2,202813	13,07152	-0,17	0,866
L7D.	-0,1365028	13,35387	-0,01	0,992
_cons	1,12E-05	0,1088261	0	1

Variable	Coef.	Std. Err.	z	P>z
D_COP				
_ce1 L1.	-0,3260875	0,43064	-0,76	0,449
_ce2 L1.	0,1360826	0,0813929	1,67	0,095
_ce3 L1.	0,1145057	0,2298603	0,5	0,618
_ce4 L1.	0,0241406	0,0383615	0,63	0,529
_ce5 L1.	1,805531	0,7792875	2,32	0,021
_ce6 L1.	-0,3174172	0,0807141	-3,93	0
CO2				
LD.	1,020435	0,5416924	1,88	0,06
L2D.	0,3791365	0,5108838	0,74	0,458
L3D.	0,7670426	0,4757523	1,61	0,107
L4D.	-0,2924295	0,4555182	-0,64	0,521
L5D.	0,7391827	0,4825778	1,53	0,126
L6D.	0,2909553	0,4466252	0,65	0,515
L7D.	0,1921486	0,4040291	0,48	0,634
ALQ				
LD.	0,0265688	0,0931191	0,29	0,775
L2D.	-0,0879212	0,0996991	-0,88	0,378
L3D.	-0,0900439	0,0953914	-0,94	0,345
L4D.	-0,1324679	0,0968002	-1,37	0,171
L5D.	-0,0110759	0,1017105	-0,11	0,913
L6D.	-0,064913	0,0946227	-0,69	0,493
L7D.	0,0766421	0,0968501	0,79	0,429
IP				
LD.	-0,791327	0,4911246	-1,61	0,107
L2D.	-1,265477	0,5134849	-2,46	0,014
L3D.	-0,9546569	0,5094136	-1,87	0,061
L4D.	-0,6315105	0,5263934	-1,2	0,23
L5D.	-0,4006897	0,5047409	-0,79	0,427
L6D.	0,0591763	0,4672178	0,13	0,899
L7D.	0,4318306	0,4768382	0,91	0,365
CROP				
LD.	-0,0604324	0,0526903	-1,15	0,251
L2D.	0,0265752	0,0484007	0,55	0,583
L3D.	-0,0941013	0,0490934	-1,92	0,055
L4D.	0,0679254	0,0471025	1,44	0,149
L5D.	-0,0300318	0,0474154	-0,63	0,526
L6D.	0,0907747	0,0469006	1,94	0,053
L7D.	0,0779047	0,0475375	1,64	0,101
NGP				
LD.	-0,8912087	0,7716925	-1,15	0,248
L2D.	-0,5569134	0,6640175	-0,84	0,402
L3D.	-1,214439	0,613851	-1,98	0,048
L4D.	-1,05793	0,6433577	-1,64	0,1
L5D.	-1,378285	0,6067464	-2,27	0,023
L6D.	-0,2009451	0,5773914	-0,35	0,728
L7D.	-1,313857	0,5284583	-2,49	0,013
COP				
LD.	0,1134561	0,1396725	0,81	0,417
L2D.	-0,1528804	0,1421622	-1,08	0,282
L3D.	0,1317107	0,1382967	0,95	0,341
L4D.	0,002802	0,1421126	0,02	0,984
L5D.	0,1669148	0,1144951	1,46	0,145
L6D.	0,0992186	0,1201333	0,83	0,409
L7D.	0,0626534	0,1172087	0,53	0,593
WA				
LD.	38,38595	57,16731	0,67	0,502
L2D.	-30,15847	59,18611	-0,51	0,61
L3D.	45,21256	61,35428	0,74	0,461
L4D.	5,222385	62,04708	0,08	0,933
L5D.	46,70293	58,95486	0,79	0,428
L6D.	5,879413	55,67206	0,11	0,916
L7D.	34,62229	56,8746	0,61	0,543
_cons	-1,30E-06	0,463494	0	1

Table A.4: Vector Error Correction Model Results for WA

Variable	Coef.	Std. Err.	z	P>z
D_WA				
_ce1 L1.	-0,0001339	0,0011733	-0,11	0,909
_ce2 L1.	-0,000252	0,0002218	-1,14	0,256
_ce3 L1.	0,0011796	0,0006263	1,88	0,06
_ce4 L1.	-0,0002186	0,0001045	-2,09	0,036
_ce5 L1.	-0,0041088	0,0021232	-1,94	0,053
_ce6 L1.	0,0004046	0,0002199	1,84	0,066
CO2				
LD.	-0,0002664	0,0014759	-0,18	0,857
L2D.	0,0007306	0,0013919	0,52	0,6
L3D.	-0,0000299	0,0012962	-0,02	0,982
L4D.	0,0007782	0,0012411	0,63	0,531
L5D.	-0,0006414	0,0013148	-0,49	0,626
L6D.	0,0006024	0,0012169	0,5	0,621
L7D.	-0,0006409	0,0011008	-0,58	0,56
ALQ				
LD.	-0,0000351	0,0002537	-0,14	0,89
L2D.	0,0001087	0,0002716	0,4	0,689
L3D.	-0,0001961	0,0002599	-0,75	0,45
L4D.	0,0003427	0,0002637	1,3	0,194
L5D.	0,00000225	0,0002771	0,01	0,994
L6D.	0,00000859	0,0002578	0,03	0,973
L7D.	0,0000972	0,0002639	0,37	0,713
IP				
LD.	0,0032774	0,0013381	2,45	0,014
L2D.	0,0021106	0,001399	1,51	0,131
L3D.	0,0021466	0,0013879	1,55	0,122
L4D.	0,0009346	0,0014342	0,65	0,515
L5D.	0,0030666	0,0013752	2,23	0,026
L6D.	0,0008326	0,001273	0,65	0,513
L7D.	-0,0014167	0,0012992	-1,09	0,276
CROP				
LD.	0,000273	0,0001436	1,9	0,057
L2D.	0,0001967	0,0001319	1,49	0,136
L3D.	0,0001599	0,0001338	1,2	0,232
L4D.	0,0000777	0,0001283	0,61	0,545
L5D.	0,000213	0,0001292	1,65	0,099
L6D.	0,0000252	0,0001278	0,2	0,843
L7D.	0,00000506	0,0001295	0,04	0,969
NGP				
LD.	0,0056305	0,0021025	2,68	0,007
L2D.	0,0012249	0,0018092	0,68	0,498
L3D.	0,0019949	0,0016725	1,19	0,233
L4D.	0,0023226	0,0017529	1,33	0,185
L5D.	0,0003856	0,0016531	0,23	0,816
L6D.	0,0000961	0,0015731	0,06	0,951
L7D.	0,0028895	0,0014398	2,01	0,045
COP				
LD.	0,0003586	0,0003805	0,94	0,346
L2D.	0,0003822	0,0003873	0,99	0,324
L3D.	0,0003181	0,0003768	0,84	0,399
L4D.	0,000305	0,0003872	0,79	0,431
L5D.	-0,0001475	0,000312	-0,47	0,636
L6D.	0,0002155	0,0003273	0,66	0,51
L7D.	0,0002437	0,0003193	0,76	0,445
WA				
LD.	-0,0421655	0,155757	-0,27	0,787
L2D.	0,0298617	0,1612574	0,19	0,853
L3D.	-0,3443379	0,1671647	-2,06	0,039
L4D.	-0,0505694	0,1690523	-0,3	0,765
L5D.	-0,0377322	0,1606273	-0,23	0,814
L6D.	-0,2154363	0,151683	-1,42	0,156
L7D.	-0,0993199	0,1549595	-0,64	0,522
_cons	4,17E-03	0,0012628	3,3	0,001