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Modeling Returns on Carbon Emission Allowances: An Application to RGGI

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Claremont McKenna College

Modeling Returns on Carbon Emission Allowances:
An Application to RGGI

Submitted to

Professor Mary Evans

and

Professor Mark Huber

by

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for

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Abstract:

This thesis attempts to model the returns on Regional Greenhouse Gas Initiative (RGGI) allowances using logged monthly returns from 2011-2018. This asset, shown to be a useful diversifier in portfolios, has been identified by previous literature to behave similarly to commodities. I used auto-regressive, GARCH, and Markov regime switching models to analyze the returns because the returns displayed changing volatility. These models were comparatively analyzed both in and out-of-sample. In this limited data analysis, the Markov model outperformed both alternatives in-sample. The Markov and Garch models displayed similar predictive power out-of-sample, however neither were particularly effective.

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Section 1: Introduction

In 2005, the European Union opened what was immediately the largest emissions trading system (ETS) in the world. In 2015, the EU estimated the annual value of emission allowances traded in their market to be \$56 billion¹ (EU ETS Factsheet 2015). In 2018, China eclipsed the EU and opened what is now the world's largest ETS. While the market has yet to finish a full year of trading, there is no doubt that China's program will be substantially larger than the EU ETS. China is responsible for just over 28% of total global carbon emissions, while the EU produces less than 9% of global carbon emissions² (World Bank 2014). Emission allowances are an asset class that burst onto the financial scene in the 1990's and has continued to grow since then.

The financial viability of these assets has been broadly studied with a focus on the European market. Research has found that not only are these allowances a profitable investment opportunity, but that they are distinctly different from stocks and should be held in an investor's well-diversified portfolio (Kosobud 2005; Graham et al. 2016; Narayan and Sharma 2015). While these markets have lower liquidity than traditional commodities, literature suggests that allowance prices are driven by similar market forces (Creti et al. 2011; Zhou et al. 2015; Wei 2010; Alberola et al. 2008; Kocha 2014; Hammoudeh et al. 2014). These similarities have spurred researchers to model ETS allowances as a commodity (Benz, Trueck, 2006; Benz, Trueck, 2009; Hammoudeh et al.

¹ Published as €49 Billion, and converted using the exchange rate of 1.1318 USD to Euro, a market rate on November 30th 2018.

² Percentages based on The World Banks estimates of 2014 pollution levels.

2014). Investor institutions have shown to share this outlook, trading allowance futures under a commodity classification³.

While general carbon finance research is abundant, there is a little literature on RGGI, the literature focuses on the main ETS markets. Those markets being the American sulfur ETS, active from 1990 to 2010, the EU ETS, opened in 2005, and the nine Chinese pilot markets which operated from 2013 to 2017. Smaller markets have been largely ignored in the literature but present a similar diversification opportunity for investors.

One of these markets is the Regional Greenhouse Gas Initiative, RGGI. Established in 2009, RGGI currently regulates the carbon emissions of 9 states⁴ in the North East of America. Literature has shunned RGGI because the market exhibits much lower trading volume than the EU ETS however, the two governing bodies established similar market parameters with which to manage the market. This similarity of parameters indicates that price fluctuations should behave similarly (Bohringer and Lange 2005; Betz et al. 2006). Practitioners seem to acknowledge these conclusions, as it is estimated that approximately 50% of RGGI allowances are held with the main motivation being financial investment⁵. This is to say that half of the allowances are

³ The new California market allowances are traded primarily on “CBL Markets,” who self classifies as an environmental commodities futures exchange.

⁴ Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont. Additionally, RGGI is currently considering plans to expand their membership to include 11 states (Larson 2018).

⁵ This estimate comes from quarterly reports made by Potomac Economics, an independent market monitor contracted by RGGI to protect and foster fair competition.

owned by polluters with the intention of retiring the allowances in exchange for the right to pollute.

This paper aims to model RGGI allowance returns, to be utilized in financial investment decisions. Primarily, these models would aid financial investors in their diversification decisions, but may also be useful in a corporate financial sense. By nature of the market polluters must decide how many allowance they want to hold as a firm, and therefore how much they can pollute. The aim of an ETS is to incentivize companies to adopt pollutant reducing technology at a cost equal to or lower than the market value of their pollution reduction. A model of allowance prices would aid polluters in that decision, but the paper will focus primarily on the use by financial investors. The modeling techniques used are adopted from the 2009 paper by Benz and Trueck, where they use commodity modeling techniques to model EU ETS returns. While Benz and Trueck (2009) modeled daily returns, due to lower frequency trading the RGGI, I have instead modeling monthly returns. My models were built on 5 years, or 60 months, of in-sample log return data and analyzed both in and out-of-sample for effectiveness. In sample, AIC and BIC statistics were used to measure relative predictions of the three models I have created. Out-of-sample, mean absolute error (MAE) was used as the main measure of a model's ability to predict returns. The out-of-sample data is 32 months of monthly log returns. In-sample data ran from January 2011 to December 2015, while the 32 out of sample observations were January 2016- September 2018.

Similarly to previous literature attempting to model EU ETS returns, I found RGGI returns to have heteroscedasticity. In keeping with Benz and Trueck (2009) I

corrected for this heteroscedasticity by using auto-regressive framework. I used a simple AR(1) model as a benchmark to compare my GARCH and Markov regime switching models. Where Benz and Trueck (2009) found the GARCH and regime switching models to be similar in-sample,⁶ my Markov 2-regime switching model was indicated as the better model by both AIC and BIC. My Markov model likely outperformed the GARCH model due to the extreme difference in volatility of the two regimes created by the model. The second regime had ten times the volatility of regime one. Out-of-sample Benz and Trueck (2009) found all of their models to be similar in predictive power. While all of my models performed substantially worse than theirs, in terms of MAE, there was a distinct difference between my AR(1) model in comparison to my GARCH and Markov models. The GARCH and Markov models outperformed the AR(1) model in terms of MAE, but were similar when compared to each other. Given the lack of out-of-sample success, it is clear that more data is required to build robust models in the RGGI marketplace. The needed data could be collected in two different ways. Should the program continue as it currently is, monthly observations will continue to amass, increasing the size of the dataset. Alternatively, should RGGI expand to other states, or increase trade volume in another way, it may become possible to model daily returns instead of monthly.

The next section will give an overview of RGGI and ETS markets in general. Section 3 will give an overview of previous literature on this topic. Section 4 will introduce the data used, and explain the cleaning process. Section 5 is a methodology

⁶ The GARCH was slightly better in terms of BIC, while the regime switching model out-performed in terms of AIC.

section that will describe the models and model measurement techniques. Results of the study are presented in section 6 and conclusions are examined in section 7.

Section 2: Regional Greenhouse Gas Initiative

The Regional Greenhouse Gas Initiative, commonly known as RGGI, is the first mandatory, market-based carbon emissions reduction program in the United State. The program, which began in 2009, initially had 10 member states, but has since fallen to 9 with the withdrawal of New Jersey in 2012⁷. As with many other ETS markets, RGGI has a compliance period system. Rather than have polluters retire allowances at the end of each calendar year, the polluter need only retire at the end of each compliance period. Compliance periods typically span multiple years, in the case of RGGI each compliance period is three years in length. There are four planned compliance periods in the lifespan of RGGI, ending on December 31st of each third year, 2011, 2014, 2017, and 2020.

As with all cap and trade systems, the goal of RGGI is to reduce total emissions in the regulated region over the span of the program. To do this, programs step down the number of allowances issued over time so that come the end of the program, participants have less access to the right to pollute. Target allowance issuance per year is show in Figure 2.1 of the appendix. In the case of RGGI, there were 188 million allowances⁸ issued in 2009. In 2018 RGGI approved just 82 million allowances, with a goal of 55 million in 2030. This forthcoming shortage of allowances should push companies to reduce pollution. Polluters will anticipate the scarcity and prices will begin to rise. As a result of rising prices, emission reducing technology that was previously cost negative for a company, will become cost efficient. Over time, companies will not only adopt these

⁷ In January 2018, New Jersey Governor Phil Murphy signed an executive order to re-enroll the state in the program. This has yet to occur.

⁸ Each allowance permits the polluter one short ton of CO₂ from a regulated source.

technologies, but total R&D spending on pollution reduction should increase. The shortening of supply over-time is the basis for all cap and trade markets, but there exists varying market parameters that can significantly influence the value of an allowance in the market (Burtraw 2002).

Studies have found one of the most important market parameters to be the ability to “bank” allowances. Banking an allowance allows a polluter to hold assets across compliance periods. In a market without banking, any unused allowances would expire at the end of the compliance period. Both RGGI and the EU ETS allow banking of allowances, but you may not borrow allowances from future periods in either market. Other parameters include offsetting⁹, distribution method¹⁰, and price regulations¹¹. RGGI employs some form of each of these parameters. Importantly RGGI auctions allowances quarterly. While initially not all allowances were purchased in auctions, the market has leveled and has reached a market clearing price in every auction over the past five years.

⁹ Offsetting refers to a firms’ ability to save allowances on certain pollution due to their actions in reducing pollution somewhere else.

¹⁰ Different markets distribute allowances to firms using different methods. Some may simply distribute at no cost, while other markets auction the allowances. In the case of an auction there are many types of auctions that could be employed.

¹¹ To counteract attempted market manipulation most markets implement some form of price regulations. Options include price floors/ceilings, or the release of more allowances should certain market conditions be met.

Section 3: Literature Review

The literature surrounding carbon finance has found emission allowance returns to be statistically different from that of traditional equity (Graham et al. 2016). It has been suggested that these assets should also be held in a well-diversified portfolio (Kosobud 2005; Graham et al. 2016). Research found that despite the lower liquidity in carbon allowances, the asset class can be an important portfolio diversifier. Additional research by Narayan and Sharma (2015) supported the profitability available in carbon markets.

The price drivers also differ from traditional equity markets. Price drivers tend to align more with the drivers of commodity prices. Some drivers found to be statistically significant include consumer oil, gas, electricity and coal prices along with weather patterns (Creti et al. 2011; Zhou et al. 2015; Wei 2010; Alberola et al. 2008; Koch 2014; Hammoudeh et al. 2014). The similarities of these price drivers have spurred researchers and investors to model the asset as a commodity (Benz, Trueck 2006, Benz, Trueck, 2009; Hammoudeh et al. 2014). For a more in-depth literature review of the price drivers in the carbon market refer to Ji et al. (2018).

While the allowances have been found to be a valuable financial asset, which can be modeled as a commodity, the bulk of carbon investment activity occurs in the EU market. This is likely due to the higher trade volume and liquidity in the EU market compared to other smaller carbon markets. Traditionally the EU marketplace has been found to account for almost 90% of global carbon emission transactions (Daskalakis et al. 2009; Linacre et al. 2011). This focus on the high-volume EU market has left the low volume RGGI market a relatively unexamined in carbon finance literature. Despite this,

investors are still holding these assets. In quarterly market analysis self-released by RGGI, it is estimated that half of all available allowances are held as a financial investment. This paper attempts to clarify the RGGI investment opportunity by adapting the techniques used to model EU allowances. The modeling techniques focused on in this paper were developed by Benz and Trueck (2009) where they conducted in-sample, out-of-sample forecasting of spot prices.

While adapting the techniques used by Benz and Trueck (2009) I recognize the literature indicating differences between carbon markets. Literature has found that the various independent carbon markets around the world react differently to the same shock (see for example, Burtraw et al. 2002; Mizrach 2011; Conrad et al. 2011). These differences in shock response has largely been attributed to the market parameters set by each market governing body (Bohringer and Lange 2005; Betz et al. 2006). The EU and RGGI markets share similar market parameters, most importantly the presence of “banking,” which is found to have the largest effect.

Section 4: Data

The data I used was collected from the RGGI COATS tracking system, which records and tracks transactions of RGGI allowances. This dataset is ideal for this paper as it contains all transactions of RGGI allowances since the program's inception. I have made a variety of alterations to the original dataset to make the data more applicable to the coming analyses. I eliminated any observations where the price was either not listed, or appears to be incorrectly entered.¹² Transactions associated with futures contracts were also omitted. Due to low trading volume there are not daily price entries over any extended period of time. As an alternative to daily returns I have taken monthly returns. The price for any given month is the price of the last allowance sold in that month.¹³ While alternatives were considered, I felt this method was the best way to incorporate all data up-to the month's end, without including future pricing information. For any months missing transactions all together, the data point was an equally weighted average of the closest two months.¹⁴

Additionally, I trimmed the time frame of the data. Ulreich (2005) found that the first wave of trading in the EU ETS was not indicative of market price determination.

While I did not test for that conclusion in my data, low volume trading early in the first

¹² One observation was removed due to likely entry error. While the average price over the life of RGGI is slightly above \$3, this particular entry had a price of \$5,050. All other entry deletion referenced here is due to the data not having a price value, implying that it does not relate to the sale of an allowance.

¹³ For example if there was a transaction on the final day of a month that price was used. However, if in November there was no transaction made on the 30th, the transaction on the 29th would be used as a proxy for month end price. Similarly if the 29th had no transaction the price from the 28th would have been used.

¹⁴ There were no transactions in May of 2011, for this month the monthly price was calculated as an average of April and June of the same year. This was the only instance of this within the complete sample.

control period would indicate that this might be the case. For this reason, I only used price data from January 2011 up until September 2018, this time period will be referred to as the complete sample. I have separated the complete sample into two separate periods. January 2011 - December 2015 was used as in-sample data to create the models, this time frame will be referred to as the modeling period. The modeling period contains 60 monthly observations which have a mean monthly price of \$3.55. The models predictive power will be tested using fit on out-of-sample data. This data is from January 2016- September 2018, and will be referred to as the testing period, a 32 month range with a higher mean monthly price of \$4.38. The trimming done to the complete sample highlight some of the issues with analyzing RGGI and other smaller emission markets. The low frequency nature of the market results in low number of observations which can limit the predictive ability of models created from statistical analysis. This may be one of the reasons why academia has largely stayed away from modeling smaller emission markets.

For the models I analyze log returns on the prices, which I will refer to simply as returns. Over the course of the complete sample these returns had a standard deviation of 0.187, but in looking at a graph of returns¹⁵ it can be seen that volatility varies over time. Volatility appears to increase surrounding the ends of years, restricting the data to two months on either side of January 1st of each year results in a higher standard deviation of 0.259.¹⁶ Volatility seems to also increase in the lead up to the end of compliance periods, which occurs twice in the complete sample, December of 2012 and 2016. Restricting the

¹⁵ Available as Figure 4.1 in the appendix.

¹⁶ This restriction to November, December, January, February results in 30 data points.

data to the six months leading up to these two events causes the standard deviation to rise to 0.437.¹⁷ This heteroskedastic behavior is not unique to RGGI and is seen in literature examining other emission markets (see for example Benz 2009).

¹⁷ Restricting to the six months leading up to compliance period endings result in 12 observations.

Section 5: Methodology

In this section I introduce the three models that I adapted from Benz and Trueck (2009) and applied to the RGGI market. In addition to introducing the models I discuss the methods I use to determine relative model quality. The primary issue addressed by these models is the heteroscedasticity displayed by the returns. I have used three models, all of which allow volatility to shift. While a traditional linear regression fixes volatility at a singular point these three models allow volatility to change, a common problem with financial assets. Each model adjust for this changing volatility in different ways

The first model, a simple first order auto-regressive model is presented as a benchmark, from which the following two models can be judged. These two following models, a GARCH and a Markov model, deal with heteroscedasticity in different ways. While Benz and Trueck (2009) developed more models than this, the GARCH and Markov were the two sophisticated models that outperformed their similar counterparts.

5.1 Auto-Regressive Model:

I have conducted an auto-regressive, AR, model to benchmark both the GARCH and Markov models against. The AR model postulates that a variable in time t is linearly dependent on the value of the variable in a prior time period. A first order AR model, AR(1), is given by the following equation:

$$R_t = \beta_0 + \beta_1 R_{t-1} + \varepsilon_t$$

Where R_t is the log return of the allowance in time t .

5.2 GARCH Model:

The generalized auto-regressive conditional heteroscedasticity, GARCH, model was introduced by Robert Engle in 1982 to estimate volatility in markets. The GARCH model is a more advanced version of a standard AR model, and allows volatility to shift within the model, a common issue in financial markets. The model postulates that the variable value in time t is dependent upon volatility in period t . Volatility in period t is estimated using a weighted average of prior period's variance and returns. In keeping with both Benz and Trueck (2009) and in line with an AR(1) model, I performed a GARCH(1,1) which is defined as such:

$$R_t = \varepsilon_t \sigma_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 R_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

$$\alpha_0 + \alpha_1 + \beta_1 < 1$$

$$\alpha_1, \beta_1 \geq 0 \text{ and } \alpha_0 > 0$$

Where R_t is the log return of the allowance in time t . The constantly updating volatility allows model features to adjust for the heteroskedastic returns in a more sophisticated way than the AR model. I will refer to my GARCH(1,1) model simply as the Garch model.

5.3 Markov Regime Switching Model:

A Markov Regime Switching Model, approaches heteroscedasticity differently than any iteration of an auto-regressive model. A Markov model postulates that instead of constantly changing overall volatility there are a set number of states with different

volatilities. Volatility is still updated within the individual states. Consistent with Benz and Trueck (2009) and my own hypothesis of distinctly different volatility in the lead up to the end of a compliance period, I performed a two state Markov model defined:

$$R_t = \beta_0 + \beta_{S,t} R_{t-1} + \varepsilon_t$$

Where R_t is the log return of the allowance in time t . $\beta_{S,t}$ refers to the beta that is dependent upon which state the observation falls into. Each state would have a different β_1 such that $\beta_{1,1}$ is not equal to $\beta_{2,1}$. The model will separate each observation into either state one or state two based on the volatility surrounding the observation, and assign a volatility to those states. Based on the separation of data, there will be a probability associated with each state, which will vary with the prior period's state. This is to say that if observation $t-1$ is in state 1, there will be an assigned probability p , that observation t is also in state 1. However, if $t-1$ resides in state 2, the probability observation in time t will not have the same probability of residing in state 1. Due to the changing volatility displayed in the data, I hypothesis that the two states will have vastly different volatility levels. I will refer to this model simply as the Markov model.

5.4 Model Validation Techniques:

I have utilized three methods to determine relative model quality and fit. The first method to examine model fit is out of sample validation. Using each model I will predict returns for the next 32 months and compare model predictions to true data points. Looking at mean absolute error (MAE) and the mean squared error (MSE) for each model will demonstrate the model's relative ability out-of-sample.

I have also used two in-sample techniques to comparatively measure model quality. The Akaike information criterion, AIC, and Bayesian information criterion, BIC, are both statistics that illustrate a tradeoff between model fit and complexity. In the case of both measures, the model with an algebraically lower value is considered to be the better model.

$$\text{AIC} = -2 \ln(L) + 2k$$

$$\text{BIC} = -2 \ln(L) + k \ln(n)$$

Where L is a likelihood measure, k is the number of model inputs, and n is the number of observations in the sample period. In the case of these three models the number of inputs increases in the order I have presented. The k then for each of them is 2, 4, and 6 for the AR(1), Garch and Markov models respectively. BIC more heavily punishes models with a higher number of inputs, emphasizing simple models.

Section 6: Results

In this section, I will present the results of the models against both in and out of sample data, progressing through the models in the same order as they are presented in the methodology section. The in-sample estimation of models over 60 months, January 2011- December 2015, will be measured relative to each other using AIC and BIC statistics. I have also tested each model out of sample by predicting log returns over the subsequent 32 months, January 2016- September 2018. These out-of-sample results were compared by calculating mean absolute error and mean squared error against the true data of the same period. The relative validity of these models in the RGGI marketplace are compared to their relative validity in the EU marketplace as studied by Benz and Trueck (2009).

First I considered the AR(1) model as a simple model to be used as a benchmark for the GARCH and Markov models. While the GARCH model improved over the AR(1) model in terms of both AIC and BIC, the Markov model was the indicated as the best of the three models by both measures. The relative AIC, BIC, and inputs of these values are displayed in Figure 6.1 in the appendix.

Benz and Trueck (2009) found the Markov model to be the better model in terms of AIC, while the GARCH was the better when using BIC. The models appeared to be much closer in validity in the EU as they were only separated by 2.5 and 4.6 in AIC and BIC respectively.¹⁸ The two state Markov model outperformed the GARCH in BIC

¹⁸ The values in Benz (2009) were as follows, GARCH (-1141.44 , -1123.73) and Markov (-1143.92 , -1119.13) [AIC, BIC].

despite having more inputs, which could be attributed to the strong difference in the volatility of the two states. State 2 exhibited significantly higher volatility, approximately ten times higher than that of state 1. As anticipated, the expected duration of state 1 was longer, almost two months longer, 6.69 compared to 5.12 months in state 2. Along with a visible inspection of the returns volatility,¹⁹ this would indicate that observations around year end are likely to be in state two, especially those at the end of a compliance period. In addition to the longer expected duration, an observation had a lower probability of changing states when initially placed in state 1.²⁰ A table summarizing differences between states 1 and 2 is available in the appendix as Figure 6.2.

While the Markov model outperformed the GARCH model in-sample, the two were similar in out-of-sample predictive power. Even though they both beat the AR(1) benchmark in terms of MAE, all three models are unreliable predictors of future returns. Figure 6.3 in the appendix shows descriptive stats for each model's projections against the true data. The AR(1) MAE is the highest at 0.14, but both of the other two models are not far behind at approximately 0.13. Each models absolute error standard deviation exceeds the corresponding MAE, the combination of high MAE and high standard deviation illustrates a highly unreliable model. The MSEs of all three models are all about 0.035. The error statistics were substantially lower in Benz and Trueck (2009) EU models, likely due to a larger dataset both in and out of sample.²¹

¹⁹ The graph of this volatility is Figure 2.1 in the appendix.

²⁰ Labeled in the chart as "Prob of State Change," this value says that given return_{t-1} was in state 1, there was only a 15% chance that return_t changed to state 2.

²¹ Benz (2009) used one year of daily data, approximately 252 observations, for both in and out of sample estimation.

Varying of the length of the sample period does little to change these results. Along with the estimation of models with the 60 month, 5 year, sample period, I also estimated these same models with sample periods of 72 months²² and 92 months.²³ In terms of AIC and BIC the models held the same relationship. That is Markov being estimated as the best model followed by the Garch, both of which outperformed the auto-regressive model. While the 92 month sample period could not be tested out-of-sample, I used the sample technique to analyze out-of-sample performance in the 72 month models. Once again the Garch and Markov performed similarly in terms of MAE, both outperforming the auto-regressive model in this measure. However, in the case of the 60 month sample period, all three models performed equally when measured using MSE, which was not the result for the 72 month models. In the 72 month sample period, both the AR(1) and Markov models had MSEs of 0.0197, while the Garch model displayed an MSE of 0.0186.²⁴

²² Due to limited data availability this shortened the out-of-sample period to 20 months.

²³ This sample period encompasses the complete sample, resulting in no out-of-sample testing of the models.

²⁴ Charts containing measurements of model ability are available in the appendix for the 72 month and 92 month sample periods.

Section 7: Conclusion

Carbon finance has largely ignored RGGI and other smaller markets, focusing on the larger EU ETS for academic research. Literature has found ETS allowances should be held in a diverse portfolio (Kosobud 2005; Graham et al.2016). Correspondingly RGGI finds that nearly half of their allowances are held purely for investment reasons. It would seem that practitioners are taking advantage of allowances value as portfolio diversification tools, even in the RGGI market, but the literature up to this point has not acknowledged this. Now that China has implemented their national ETS, the diversity of allowance options is going to increase. It is important to understand each market and different allowance value to make the proper investment decision.

I have attempted to fill this void in the literature by adapting EU ETS modeling techniques into the American RGGI market. I found RGGI returns displaying similar heteroscedasticity displayed in the EU market. Given this changing volatility auto-regressive models made sense to model the returns, just as Benz and Trueck (2009) had done to EU returns. With limited trade volume in the market, I modeled the monthly log returns of RGGI allowances from January 2011 - December 2016, using three different models. A first order auto-regressive model proved to be the least effective in terms of AIC and BIC values in sample. While the GARCH model of log returns was an improvement over the same measures, the Markov 2-regime switching model presented both the lowest AIC and BIC values. The Markov model was successful in-sample largely due to the tight volatility clustering visible when graphing returns. In the lead up to the end of a compliance period, when firms must hold at least the number of

allowances equivalent to their past three years of pollution, volatility spiked. The Markov model showed that this high volatility state, displayed approximately 10 times the volatility as was displayed in the alternative state.

Benz and Trueck (2009) had fairly accurate models out-of-sample however, of their five models none proved substantially better than the others in terms of MAE or MSE. Out-of-sample my models displayed poor predictability of RGGI returns, but the two more complex models, when compared to the AR(1) model, GARCH and Markov, had notably better results. The GARCH and Markov had near identical mean average errors to each other, but lower than that of the simpler 1st order auto-regressive model. With only 60 in-sample observations, it is not surprising that the models displayed poor performance out-of-sample. Until RGGI trading volume improves it will be difficult to create a reliable model, but it does appear that the modeling techniques used in the EU ETS market can be transferred to the RGGI market. With the creation of larger carbon emission marketplaces, it is important to now forget about the assets held in smaller markets such as RGGI, and their potential value.

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Appendix:

Figure 2.1

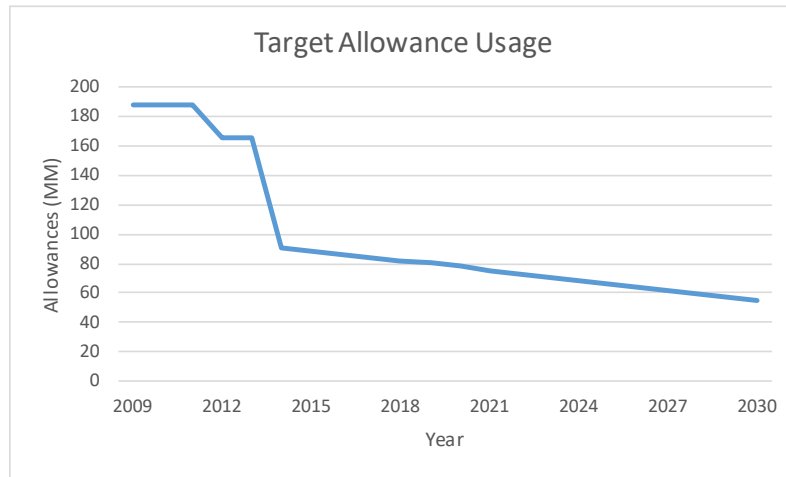


Figure 4.1

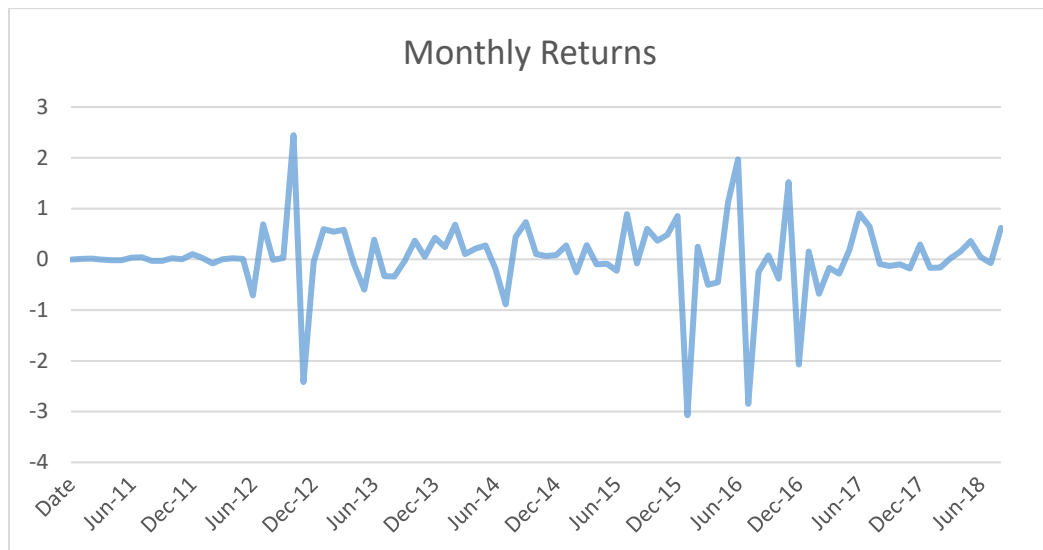


Figure 6.1

Model	k	ln(L)	AIC	BIC
AR(1)	2	19.79	-35.59	-31.40
GARCH	4	31.04	-54.08	-45.70
Markov	6	50.47	-88.93	-76.37

Figure 6.2

Markov Model	State 1	State 2
Volatility	2.8%	27.6%
Expected Duration	6.69	5.12
Prob of State Change	15%	20%

Figure 6.3

Model	Absolute Error		Squared Error	
	Mean	Standard Deviation	Mean	Standard Deviation
AR(1)	0.1438	0.1214	0.0349	0.0509
GARCH	0.1285	0.1372	0.0347	0.0665
Markov	0.1297	0.1389	0.0355	0.0696

Figure 6.4

72 Month Sample Period				
Model	AIC	BIC	MAE	MSE
AR(1)	-35.59	-31.40	0.104	0.020
GARCH	-45.48	-36.37	0.090	0.019
Markov	-88.93	-76.37	0.094	0.020

Figure 6.5

92 Month Sample Period		
Model	AIC	BIC
AR(1)	-53.24	-48.19
GARCH	-74.15	-64.02
Markov	-109.73	-94.54