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Using Difference-in-Differences Analysis and the Kocyk Geometric Lag Model to Estimate Aspects of Carbon Tax Effectiveness in Nordic Countries

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ABSTRACT

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This paper generally looks at the connections between carbon taxes and carbon emission levels in Nordic countries over a period from the 1960s to the early 2010s. Most of the existing literature on this topic looks at and finds that carbon taxes do have a significant impact upon carbon emissions levels in some countries while not in others. In many countries which have this policy there is not a significant impact that can be seen and there is a discussion as to why this might be the case and what needs to be done to fix these potential issues to effectively combat climate change. There are many other ideas about what policies may or may not lower emissions levels, and one such idea is looking at how carbon taxes might become less effective reducing carbon emissions. This paper attempts to take a more in depth look at the way carbon taxes impact emissions levels and how the effectiveness might change and deviate over time.

Using different econometric approaches, this paper asks a slightly different question than what most of the existing literature looks at. Instead of looking at the short-term impacts of carbon taxes on carbon emissions this paper looks at this question from a longer-term perspective where the effect of these taxes can change and deviate, especially if the rate of carbon taxes is not updated to a degree where it keeps up with increasing price levels within a country. This is where the Koyck geometric lag model is used. Another approach which is used throughout is to use difference-in-differences

analysis where a control country with no carbon taxes is used to compare treatment countries which have active carbon tax policies to look at the differences in emission levels between countries which do and do not have tax policies. This style of econometrics is utilized to somewhat simulate how a traditional scientific experiment would be constructed, by looking at the causal impacts of a policy implementation which in this case is the carbon tax.

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TABLE OF CONTENTS

TABLE OF FIGURES

CHAPTER ONE

INTRODUCTION

Much of the research that has been done on carbon taxes focuses on the short-term impact on overall carbon emissions rate. It is important to look at the impact of how carbon taxes work on emissions levels in countries, and part studies have indicated a significant negative relationship between the two variables in only some of the countries which they looked at, but the main topic of this paper is more nuanced. This paper is looking at the impact of countries not consistently updating their carbon tax policies to see if when a carbon tax is implemented it loses effectiveness over the years because things like inflation might make the taxes less impactful on those making business decisions regarding energy consumption.

One of the main hypotheses of this paper is that carbon taxes do have a declining effectiveness on emission levels when they are not constantly updated. The three countries which this paper will look at and try to compare will be the countries with similar economic standings and long periods of carbon tax history which are Finland, Sweden, and Denmark. Iceland will be used as a control in a difference in differences model. In the framework of the econometrics this would mean that the value of lambda in the geometric lag model would be between zero and one to a statistically significant degree. The null hypothesis is that there is no decaying effectiveness of carbon taxes on long term emission rates. If this ends up being the conclusion, then many of the countries with a long-standing history of carbon tax policy will have done a sufficient job of implementation. The conclusions that can be drawn from this paper do appear to be somewhat limited as it is only looking at a specific selection of countries and so the results might not be as transferable as we would hope, but in general more time is needed to collect data as many nations do not have a long-standing history of carbon taxes.

The other main hypothesis of this paper is that countries who have carbon tax policies would have lower levels of carbon emissions than countries who do not have these carbon taxes because these taxes lower emissions. The reason for this would be because the taxes would have a negative impact on the emissions levels and so when we compare the treatment countries of Finland, Sweden, and Denmark to the control country of Iceland land we would expect that emissions after the carbon tax implementation would be lower in the three countries when compared to Iceland. Iceland is used as a control because it is a Nordic country and so it has a somewhat comparable economic status, technology level, population, and somewhat similar energy consumption patterns to the other three countries in the dataset. It is also a useful country to utilize since carbon taxes were not implemented until 2011 whereas all the other countries in the treatment groups implemented their carbon taxes in the early 1990s so there is a period where these countries all have taxes except for Iceland.

At this point in the paper, it would be a good place to discuss some of the underlying economic theory of how carbon emissions levels can change due to the progression of a society. There are two important concepts to look at and those are the idea of the Kuznets Curve and the idea of convergence theory. The idea behind Kuznets curve is an idea which has to do with the impact of economic growth on emissions levels which explains the relationship between economic growth but also technological growth which creates a greater energy efficiency. The general thought behind the Kuznets curve is the idea that when nations are low on the economic development scale and they experience growth they have a period in their development where emissions are high because production has gone up so much. This production is not often done with a great deal of concern for emissions, but after a certain point of growth that nation will eventually develop the technology or will be able to pay for greener sources of energy creating a decline in emissions levels even though from a production standpoint, they produce a lot as a developed nation.

Likewise, the idea of convergence theory is tangentially related to the Kuznets curve as it describes the phenomenon at the macroeconomic level where nations with a low level of economic development will grow on average faster than nations with a higher level of current development. These ideas are important for understanding carbon emissions levels on a macroeconomic level and should be used carefully as controls in this experiment, but in a way, they are not as important in this paper as this paper is comparing Nordic nations which have a similar level of economic standing, but if this paper were looking at comparing many countries with vastly different economic conditions these two ideas would likely be a big part of what needs to be controlled for.

CHAPTER TWO

LITERATURE REVIEW

This section of the paper provides a review of existing literature on how the implementation of carbon taxes in various countries has affected the carbon emissions levels. Some of these sources focus on the main area of concern for this paper which is the processes created after the introduction of carbon taxes in Nordic countries. This section also looks at Koyck's distributed lag model and how it can be best used as an econometric tool in this paper.

A. Learning from 19 Carbon Taxes: What Does the Evidence Show?

Nadel (2016) finds that rather unsurprisingly that carbon taxes do have a statistically significant positive impact on carbon emissions for most of the countries and provinces in this study. He found that this was done in both parts by decreasing the demand for energy and by also causing a switch to lower polluting energy sources in some of the nations which he looked at such as Austria. Part of my inspiration for this paper comes from a comment in this paper since the authors of the paper cover such a broad selection of countries and carbon taxes, they do not go into detail about all of the findings. Nadel posits the idea that carbon taxes in Finland have been having decreasing impact on carbon emissions and eventually had a statistically insignificant effect on carbon emissions beyond the years when the carbon tax policies were set up. The author does not explain and/or know why and they state that more complex analysis is needed to determine the reasons why this declining impact has happened. The author points out that there is some ambiguity as to why the effects have declined over time and that could be because the impacts of the policy trail off over time or because there are other external factors which contribute to the declining effect. This is the main inspiration for this paper as the main regression in this paper uses a geometric lag model to try and see if the effects trail off while controlling for external factors which have changed over the years such as economic growth.

B. The effect of carbon tax on per capita CO2 emissions

Looking at carbon taxes general effect on emissions is important, but also looking at why some countries have different outcomes than others in terms of their rates of carbon emission reductions is important. This is what Lin and Li (2011) find as they state that the rates of taxes do have an impact on the rates of reducing emissions, but they also find that exemptions play a large role in the reduction of emissions and that in Northern European countries which have less exemptions are far more successful in their reduction of emissions than those with more exemptions. They also find that GDP per capita which is one of the controls is significantly correlated with carbon emissions per capita and so it should be accounted for as a control in a regression, but they also found that urbanization does not have a significant impact and so it can be dropped as a control. Unfortunately, this study does not focus a great deal on the long-term impact of carbon taxes on carbon emissions in part because that was not the main goal of this paper. Since it does a good job at analyzing the impacts per year and it does a good job of setting up controls this paper can be used as a good basis to set up a model to use for looking at long-term changing effects.

C. Should a carbon tax be differentiated across sectors?

The paper by Hoel (1996) asks whether carbon taxes should be implemented as a blanket tax or as a different tax across sectors of the economy and he looks in detail on international trade side of the economy. He found that tariffs on carbon are something significantly important and that if they exist and are sufficient carbon taxes can be implemented as a blanket tax. This paper gives another variable that should possibly looked at as a control in the long term; if tariffs changed overtime in a country this could be part of the reason for a declining impact, so it is necessarily needed as a possible control. This paper was also created relatively early in the implementation of carbon taxes so it would be interesting to see if this holds up in the long term which is one of the goals of this paper.

D. On the econometrics of the geometric lag model

Frances and Oest (2006) find that much of the problems with using Koyck's geometric lag model is trying to solve the Davies problem which is when beta is equal to zero in the null hypothesis lambda drops out of the equation which is a problem as lambda is the decaying rate which is the most important part of a geometric lag regression. The paper concludes that while doing a regression using a t-statistic is not a reliable method given the previous problem and so test statistics must be constructed so that they fit the new values of lambda in the regression. Much of the existing uses of the geometric lag are on advertising and marketing and that is one of the deficiencies for this paper and many others which cover the geometric lag regressions. This is one way this thesis paper adds to use of geometric lag because it is not used in econometrics all that much outside of marketing and advertising, but it can be a useful tool in quantifying the long-term decaying impacts and in this case, it can be used to look at the long-term impact of carbon taxes on emissions in Finland.

E. Gasoline Tax Policy, Carbon Emissions and the Global Environment

Sterner, Dahl and Franzen (1992) find from the regression that if gasoline taxes were at a relatively high-level for Italy, emissions could drop by thirty percent in the eight years after this paper was published. The authors' regression uses the geometric lag model using the elasticities of gasoline instead of using the direct taxes. The major problem with this paper is that it covers a different tax than what this main paper is about since this specific paper is on gasoline taxes instead of carbon taxes. This paper is useful however for one specific reason as it is the closest use of Koyck's geometric lag model to the use of the model in this paper as both try and quantify the decaying impact of an energy tax on the overall emissions rate for following years after the taxes were implemented. This paper is useful because it provides ideas and tests that can be applied to carbon taxes rather than gasoline taxes which can be a useful tool in helping to set up the main paper.

F. The process of peak CO2 emissions in developed economies: A perspective of industrialization and urbanization

Economic development and growth are two factors which can lead to a higher rate of carbon emissions, but countries who are more developed tend to have lower emissions per capita because of cleaner sources of energy but more developed nations tend to have higher emissions in general because they have a higher productivity, this idea is commonly referred to as Kuznet's curve hypothesis. Dong, Wang, Su, Hua, and Zhang (2019) state that in developed nations such as Finland carbon intensity peaked first, followed by per capita carbon emissions and total carbon emissions in terms of emissions development, and in each country, there is a point where emissions per capita is the highest until it crosses over to a society which produces more carbon in total. The main issue with this paper in terms of in relation to mine is that it has a lot of theory that is just too hard to quantify and fully to fully account for these ideas. Interpreting where Finland, Sweden, and Denmark are at this type of curve would be important to know as it could be a large part of the error term as these kinds of relationships appear to be too hard and intangible to measure because in large part it is theoretical and would require its own paper and separate regression to figure it out, but this would appear to be a good thing to note as a potential error term in this paper. GDP per capita is one term which captures economic development to a potentially sufficient level, but this theory is a potential justification for adding this control to the regression.

G. Determinants of carbon dioxide emissions: Empirical evidence from 69 countries

There are many variables which would seem to impact carbon emissions other than carbon taxes and so developing a list of them is important to either strengthen or weaken the relationship you are looking for. In this paper Sharma (2011) looks at variables which would cause the levels of emissions and so she looks at GDP per capita, urbanization, Per capita electric power consumption, Per capita total primary energy consumption, and trade openness. Sharma splits nations into high, middle, and low-income nations to see if there is anything that is statistically significant in one income group but maybe not the others. Sharma finds that GDP per capita is significant in the groups except for the high-income group because of the Kuznet curve hypothesis. The author also finds that the other variables are not significant in the groups except the fact that the type of energy used does appear to have a significant impact on emissions in the high-income nations, and that urbanization has a positive impact on emissions in developing nations. One problem that this paper has is that it could have more variables for different types of energy used such as geothermal or some sort of renewable energy source to make a better regression for higher income nations. This paper helps expand my topic because it allows the use of past controls to best account for outside variables in an attempt to limit omitted variable bias. This can hopefully lead to a cleaner regression which has all the relevant controls while not having irrelevant variables to remain efficient in a least squares regression to find the relationship of decaying impact of carbon taxes on carbon emissions. Since the paper splits the nations into high and low income countries, looking at the high income section would be important for this paper and maybe points to the fact that the type of energy used in Finland might be more important than the growth rate, but for poorer countries this might be the opposite.

H. Bioenergy Policy and Market Development in Finland and Sweden

This paper states the rise of bioenergy markets in the two countries largely because of an increase in carbon taxes and more pressure to lower carbon emissions. Ericsson, Huttunen, Nilsson, and Svenningsson (2004) find that biomass energy in the early nineties was cheaper in Finland because of the carbon taxes which would back up the reasonable claim that these taxes forced many to switch to a renewable energy source. The main deficiency of this paper is there is no large main econometric equation, but it does have a great deal of data and information on the changes which have taken place in the renewable energy sectors in Finland and Sweden. This is different from other papers in the section because it does not just state energy consumption by either gas based or electric consumption and it goes into other types of energy which cause changes. Putting renewable energy sources as a right-hand side variable probably would be something to consider and it might be beneficial to add this sort of data into a regression.

I. Carbon emission and mitigation cost comparisons between fossil fuel, nuclear and renewable energy resources for electricity generation

Accounting for the types of energy used in a high-income country would appear to cause a decline in carbon emissions, but it is also likely that carbon taxes themselves would push many people and businesses towards renewable energy. In this paper Sims, Rogner, and Gregory (2003) compare the carbon emissions reduction effect in nuclear and other renewable energy sources such as solar, hydro, wind, and bioenergy. The authors found that the slight adoption of these policies could result in a global reduction of carbon emissions from anywhere from one and a half percent to eighteen percent given the feasible rates of adoption. The authors ran a regression and they have results from it but the main problem with this article is that they never clearly state or show their one regression equation or multiple equations they use in this paper. From previous articles Finland and Sweden have grown in terms of their usage of bioenergy but looking for data on the other energy sources would be helpful to the equation since they all limit carbon emissions it would be important to see how much of a decline in emissions is responsible from taxes and how much is from changing in energy sources. The expectation would be that these two ideas would not be able to be separated since it is assumed that taxes would cause a societal shift towards cheaper renewable sources of energy in other sectors.

J. The influence of real output, renewable and non-renewable energy, trade and financial development on carbon emissions in the top renewable energy countries

This paper looks at essentially the developed nations and so Dogan and Sekar (2016) use real income, renewable energy consumption, non-renewable energy consumption, trade openness and financial development on CO_2 emissions in the EKC model as controls. The authors find that Kuznet's hypothesis can be detected within their results and they also find that increases in trade create a technology spillover where new countries adopt new environmentally friendly technology from trading, this is interesting and a different conclusion from other papers, but this seems unlikely to play much of a role in developed countries such as Finland. The main deficiency of this paper is that renewable and non-renewable energy consumption could be expanded upon and could be more specific at least when looking at one country with a specific amount of each energy source. The reason why this paper is significant is because it looks at the long-term impact of these policies as it takes the time before the carbon taxes were implemented and it compares that to the time after they have been implemented which involves a time period similar to my main regression.

K. On the relationships between CO2 emissions, energy consumption and income: The importance of time variation

When looking what how much waste is omitted from energy use it is important to look at what kind of energy used and how open to or reluctant to switching to renewable resources would surely impact each nation differently because of differences in demand elasticities for different sources of energy. This paper by Ajmi, Hammoudeh, Nguyen, and Sato (2015) looks at the G7 countries. The authors found that the optimal solution to reducing carbon emissions would be by increasing energy infrastructure to encourage renewable sources of energy and one way this can be achieved is by making it comparatively less expensive by taxing carbon emissions on nonrenewable energy sources. The findings of this paper are also varied for the different countries as they have different energy dependencies and elasticities. This is how my paper can add to this by looking at the demand for certain energy sources in Finland how that could affect emissions rates, this effect would be specific to Finland since it is looking at how much and what proportion of energy comes from renewable or nonrenewable sources.

L. Analysis of carbon tax efficiency in energy industries of selected EU countries

In this paper Hajek, Zimmermannova, Helman, and Rozensky (2019) attempt to find out whether a long-term carbon tax in energy industries is efficient. The authors conclude that this is that case, but critically in this paper they state that these taxes need to be updated to stay efficient. This is one of the most interesting parts of this paper regarding my own as it is fundamentally concerned with the same idea. The one issue with this paper is that it does not go into detail about why these taxes need to be updated as much of the paper is dedicated to finding out whether these rates are efficient rather than the paper being on why do rates occasionally stop being efficient. The regression does not quantify by how much these policies become inefficient and how much these policies need to be updated which leads nicely into the main topic of my paper which hopes to solve these two questions which the paper briefly introduces at the end of the conclusion.

M. Dynamic simulation and environmental policy analysis: beyond comparative statics and the environmental Kuznets curve

One of the more important ideas in environmental economics is the Kuznets curve which has been stated in previous papers in this section, but like many other ideas on economic theory the relationship is not as perfect as it sounds as some countries simply put more emphasis on developing ways to become more energy efficient than others even if they are at a similar level of income such as the United States versus many Nordic countries including Finland and Sweden. In this paper Anderson and Cavendish (2001) create their own model using many variables to compare to the standard popular theory of Kuznets curve hypothesis. The authors find a few conclusions which have been stated in the previous papers, but one of them is a new idea to that section and that is that the authors find that there is a policy lag in which when a carbon tax is implemented there is some time for the markets and different sectors of the economy to react in a fully rational way. The one slight issue is that the time duration of reaction is never stated or really looked at in this paper: for example, is the policy lag a quarter? A year? Or is it somewhere in between? In a sense this creates a problem in the regression since my main lag geometric equation is essentially going in the opposite direction to these policy lags and so this is something that should be noted in the final regression and this might end up being part of the error term unless it makes sense and it reasonably easy to include in the main regression.

N. Mitigation costs, distributional effects, and ancillary benefits of carbon policies in the Nordic countries, the U.K., and Ireland

In this paper Bye, Kverndokk, and Rosendahl (2002) discuss the idea of carbon taxes potential impact on welfare of a society and the main goal of their research was to find if the carbon tax rate could be set at an efficient rate. One of the problems that the authors state is that the models lack short term rigidities which could affect the total costs of the policy. The authors found that welfare losses are relatively small compared to the reduction of carbon taxes as the effect was around one and a half cents for twenty to thirty cent reductions in carbon emissions. This is an important question for the fact that if these policies proved to be inefficient and caused a great loss of societal welfare it could be a reason for slowing down the tax rates, but this does not seem to be the case from the results of this regression.

O. How does carbon tax affect social welfare and emission reduction in Finland?

When looking at a policy decision it is important to look at more than just what is intended to happen and so in this case it makes sense to look at the societal impact of taxes specifically, in Finland. Khastar, Aslani, Nejati (2020) found that in this study there was loss in welfare resulting from the carbon taxes that were implemented in Finland. This is an interesting finding as previous literature on this idea stated that this was not likely to be the case, but when looking at Finland specifically there does seem to be a decrease in welfare. This decrease in welfare according to the author is because in Finland taxes are applied upstream to corporations and large-scale production, but after a while the impacts of the taxes flow downstream towards the consumers and this is where a large portion of the welfare loss occurs. A possible reason for this was stated by the authors who gave the idea that since there were no large-scale studies on the early introduction of carbon taxes in Finland that policy makers might not have set an efficient level of carbon taxes and this could possibly play a role in why there has been a decreasing effect of taxes on carbon emissions.

P. Technology Diffusion and the Rate of Technical Change

This paper looks at the general rate of technological diffusion and the authors of this paper found that this diffusion can create a decline in research and development and overall productivity. In a way this paper is useful in explaining the mechanics of technological diffusion, but it does not have much of a basis in terms of environmental economics. The background has a good explanation but a further paper specifically focusing on the environment and carbon taxes would help for this paper.

Q. Exploring China's carbon emissions peak for different carbon tax scenarios

This paper looks at the ways in which carbon taxes impact variables such as technology diffusion and that things such as investor confidence can create an increase in technological diffusion. This paper is great in explaining how carbon tax can impact technological diffusion and how the relationship can exist in the other way. This does create a possible problem of reverse causality as it could be possible that carbon emissions and taxes rising creates an incentive for more technological diffusion to occur.

CHAPTER THREE

DATA ANALYSIS

The main dependent variable for this paper is carbon emissions and the main independent variable is carbon taxes. Carbon emissions are measured in metric tons of CO_2 per capita from 1960 to 2016 for the four countries in the dataset. This data is particularly useful since it is in per capita we do not need a separate control for the population size of each country. Carbon tax is a slightly more complicated variable as the start dates for the data are different for each country. Finland has data from 1990 onwards as it was the first country to implement a carbon tax and Sweden and Denmark followed suit shortly after by creating a tax in 1991. Iceland was much later in creating a carbon tax as they only implemented one in 2010 and so it is a good choice to use as a control for the difference in difference model as it has a long period without any carbon taxes affecting emission levels. All these countries changed their carbon policies in the mid-2010s to have less exemptions and therefore we could not add these tax figures into the data because they are different from the earlier taxes. Both data for these variables came from the World Bank's country database.

There are also many controls which we need to account for in the models and these variables include energy type and technological diffusion. From existing literature, the type of energy used in advanced countries had a significant impact on emission levels. This is a good control for these countries because many of them have been implementing policies to try and encourage a greater amount of renewable energy usage to cut down emissions and so this is something that could cause bias in the results and so it should be accounted for. The data for this was again found on the World Bank's country database and the data itself is split into specific types of energy from all the way back in 1965 and so the new variables are coal, gas, geo biomass, hydro, solar, wind, oil, and biofuels. All these controls are in EJ which is an exajoule the only exception is biofuels which is in twh which is terawatt hours.

According to existing literature on the safest and cleanest sources of energy from most to the least polluting energy sources are coal, oil, gas, biomass, hydro, nuclear, wind, and solar. This generally reflects the correlation coefficients as coal is .608, oil is .193, gas is .299, biomass is -.197, hydro is -.454, nuclear is -.467, wind is -.334, and solar is -.238. Now none of these correlations have perverse results as each control has the signs we would expect, but some of them do fall outside of the order which is stated in existing literature. For example, the coefficient for oil is lower than gas but it is not likely a problem since one would suspect the differences could be in the transportation of each energy source since the source it is from was looking at only goes over usage rather than including how an energy source gets to people who use it. Also, wind and solar are slightly out of order in terms of the most to least polluting energy sources but one would assume that is because some of these countries do not have certain renewable energy sources for example not every country used in the data set has substantial usage of nuclear energy. This means that any perverse control coefficients in the models would likely not be from the data but instead it would point towards there being an issue with the models, not enough observations, or some unobserved phenomenon that this paper is not aware of in an individual country.

Technological diffusion is a somewhat more interesting control in terms of how it impacts emission levels. In the existing literature this is not being used as a control variable and instead urbanization or growth of real GDP per capita are used. However, in this literature urbanization and GDP growth were not found to have a significant impact on emission levels in developed nations like the one which I am looking at. An explanation for that can be down to the previously mentioned idea of the Convergence theory which would point towards the idea that these countries do not see enough growth to really impact the results. Expanding upon this idea the Kuznets curve also adds to this point because whatever small amounts of economic growth these Nordic countries receive it is likely to not have much of an impact on emissions because the economic growth is becoming increasingly based on renewable sources of energy and other efficient means of production which simply do not pollute as much. Technological diffusion is not an important control as it is less applicable to the countries which are being used for this data set and that is why they were not included in the final dataset. Another reason is that there are not enough observations when we look at the individual countries so getting rid of the most controls possible is the best way to set up the model.

Looking at the data which is used it is from a large-scale macroeconomic country level while a lot of the existing literature is trending towards using firm level microeconomic data to understand how climate change policies impact the economy from a different perspective. Others have noted that industry level data in the countries might also be an interesting section to look at in this paper, but the main problem with doing this analysis is the issue of trying to collect carbon emissions data for each sector of the economy in three different countries. Also, this complicates the data involving carbon taxes because in two of three countries carbon emission taxes are differentiated across different sectors and there are different exemptions for different sectors in Sweden and

Denmark. Finland is the only country which has a blanket carbon tax where there are no exemptions and so if there is a difference in the results of the paper between Denmark and Sweden compared to Finland.

Table 1. Correlation between Taxed and Carbon Tax rate:

Pairwise correlations

Variables	(1)	(2)
(1) CarbonTaxRate	1.000	
(2) Taxed	0.423	1.000

One question that could be raised when looking at the quality of the regression for this difference in differences analysis is whether there is a correlation between the carbon tax rate and the value for taxed and if this might be causing bias in the equation. The taxed variable is just the dummy binary variable and it is applied at the country level and so when a country in the dataset has a carbon tax, they have a value of one regardless of whether the observation is before the tax was implemented. The table above is the Pearson coefficient of correlation and the value of the coefficient is .423 which would indicate a moderate level of correlation, but it is not terribly highly correlated. The reason I would assume that they are not extremely highly correlated is the fact that taxed is applied at the country level rather than the time when a tax is in place meaning that for both countries there are large periods where the tax rate is zero dollars regardless of whether the country has a value of one or zero for the dummy variable.

CHAPTER FOUR

METHODOLOGY

Part A: The Koyck Geometric Lag Model

To start this section, it is important to give background on the type of econometric model which the paper utilizes. The type of econometric equation comes from the idea of the infinite geometric sequence which sums up all the impacts of an independent variable on a theoretically infinite number of time periods. The value of lambda to illustrate my hypothesis would need to be between zero and one to show a decaying affect. If the value of lambda is above one it either shows that the relationship, I am looking for is not there and that instead the impact of carbon taxes would become more powerful over time on carbon emissions, although another explanation might be that when the value is above one it can often point towards an omitted variable bias. If the value of lambda is negative, then the effects of carbon taxes simply go in the opposite direction of what they would normally do if the value is positive, but the magnitude of change is more important. For this paper it might not make a ton of sense conceptually for the values to be negative as when that happens its often an overshot in response to a policy shock and so if the value is negative it would more likely point towards some sort of econometric error. A potential error that could arise is stationarity bias, but the time period used in the analysis is not terribly long so the bias will not likely be there.

The specific equation that will be used in this paper is $\text{Carbon Emissions}_{it} = \lambda * \text{Carbon Emissions}_{i(t-1)} + \beta_0 + \beta_1 * \text{Carbon Taxes}_{it} + \beta_2 * \text{Coal}_{it} + \beta_3 * \text{Gas}_{it} + \beta_4 * \text{Geobiomass}_{it} + \beta_5 * \text{Hydro}_{it} + \beta_6 * \text{Nuclear}_{it} + \beta_7 * \text{Solar}_{it} + \beta_8 * \text{Wind}_{it} + \beta_9 * \text{Oil}_{it} +$

β_{10}*$Biofuels_{it}$+ ε_{it}. This equation loosely comes mathematically from Carbon $Emissions_t$ = β_0 + β_1*Carbon $Taxes_{it}$ + β_2*Carbon $Taxes_{t-1}$ + β_3* Carbon $Taxes_{t-2}$ +…+ β_k *EnergyType which is just an infinite geometric sequence subtracted by = λ*Carbon $Emissions_{i(t-1)}$ = $\lambda\beta_0$ + $\lambda\beta_1$*Carbon $Taxes_{t-1}$ + $\lambda\beta_2$*Carbon $Taxes_{t-2}$ +… +$\lambda\beta_k$ * $EnergyType_{t-1}$ and so this is the mathematical proof for why the equation is formatted in the way that it is. This equation is set up to show potential decaying impacts of carbon taxes on carbon emissions.

Part B: Difference-in-Differences Analysis

The entire idea and theory of the difference-in-difference model is based on the differences in a treated and untreated group, and it is largely dependent on the idea of fixed effects. The main idea of this regression technique is to find the change in ΔY_t - ΔY_c where Y_t is the change in the dependent variable in the treated groups or in the case of this paper countries, and Y_c is the change in the dependent variable in the untreated countries. In terms of a regression equation in OLS a difference-in-difference model should follow the form of $Y_{it} = \beta_0 + \beta_1 Treated_i + \beta_2 After_t + \beta_3(Treated_i \text{ x } After_t) + \varepsilon_{it}$. The model uses binary variables to capture the differences between the two groups. Treated value equals one for the treated group and zero for the control group where the After value equals one after the policy change and zero before. The variable (Treated x After) is the interaction term which equals one for the treated groups in the post-treatment stage and zero for the other observations. This model is also easy to add other variables to the model as controls in OLS because you can include other variables as covariates.

Event Study graphs are another important feature which can be used in analysis using the difference-in-difference model. It is a method to easily showcase the impact of a policy event in graphical form.

In this section of the paper, I will attempt to compare the rate of carbon emissions in a country with a long history of carbon taxes and one without one which is economically and culturally similar. The treatment group for this section would be using the countries of Finland, Sweden, and Denmark which have the longest periods of carbon taxes and the control group would be Iceland which has only recently implemented a tax. I would also use the time period before the tax was implemented in Finland and I would stop the analysis in 2011 when Iceland first implemented their carbon tax. I could go back twenty years into carbon emissions data before Finland implemented taxes and stopping at 2010 would unfortunately cut of some of that data I could use with taxes in Finland, but it would still be the best way the measure the differences in a country with and without carbon taxes. The model and controls are the same as in Part A of this methodology. The equation for this analysis is Carbon $\text{Emissions}_{it} = \beta_0 + \beta_1{*}\text{CarbonTaxes}_{it} + \beta_2{*}\text{y90}_{it} + \beta_3{*}\text{Taxed}_{it} + \beta_4{*}\text{y90Taxed}_{it} + \beta_5{*}\text{Coal}_{it} + \beta_6{*}\text{Gas}_{it} + \beta_7{*}\text{Geobiomass}_{it} + \beta_8{*}\text{Hydro}_{it} + \beta_9{*}\text{Nuclear}_{it} + \beta_{10}{*}\text{Solar}_{it} + \beta_{11}{*}\text{Wind}_{it} + \beta_{12}{*}\text{Oil}_{it} + \beta_{13}{*}\text{Biofuels}_{it} + \varepsilon_{it}$. The first binary variable is the variable y90 and if a time observation is before 1990 the value of the variable will be zero and if the observation is after 1990 it will have a value of one. In the equation there will be a dummy, binary variable called Taxed and it is if a country has a tax and for every year all the countries who have a carbon tax they will have a value of one and Iceland the country without carbon taxes will have a value of zero. The interaction term is the variable y90Taxed and if the observation is after 1990 and is in a country with carbon taxes it will have the value of one and all other observations will have a value of zero and the interaction term allows us to see the Pre-Policy and Post-Policy implementation periods.

CHAPTER FIVE

RESULTS

The Koyck Geometric Lag Regression Results:

Table 2. Finland Geometric Lag Regression:

Fitting full model:
Iteration 0: log likelihood = -11.791209
Iteration 1: log likelihood = -11.693021
Iteration 2: log likelihood = -11.691985
Iteration 3: log likelihood = -11.691985
Heteroskedastic linear regression Number of obs = 46
ML estimation
Wald chi2(7) = 2052.09
Log likelihood = -11.69198 Prob > chi2 = 0.0000

C02Emissions	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
C02Emissions						
C02Emissions						
L1.	0.163	0.063	2.580	0.010	0.039	0.286
CarbonTaxRate	0.080	0.027	2.950	0.003	0.027	0.134
Coal	20.605	1.655	12.450	0.000	17.362	23.848
GeoBiomass	-13.064	4.133	-3.160	0.002	-21.164	-4.965
Nuclear	-6.688	1.092	-6.130	0.000	-8.828	-4.549
Wind	-412.936	217.121	-1.900	0.057	-838.485	12.613
Oil	10.743	1.276	8.420	0.000	8.242	13.243
_cons	0.681	0.232	2.940	0.003	0.226	1.136
lnsigma2						
C02Emissions	0.293	0.158	1.860	0.063	-0.016	0.602
_cons	-5.331	1.629	-3.270	0.001	-8.523	-2.139

LR test of lnsigma2=0: chi2(1) = 2.81 Prob > chi2 = 0.0936

The main point of doing a geometric lag regression is to look at the lagged CO_2 emissions to see if there is a decaying impact of a policy which in this case would be the carbon taxes. Any coefficient that was positive for this variable would indicate a decaying effect unless the confidence interval includes the value of zero or any negative values. If the ninety-five percent confidence interval contains zero or negative values, then we cannot prove a declining impact since we cannot disprove either no relationship or an increasing relationship between taxes and emissions.

The equation that is used is Carbon $Emissions_{it}$ = λ*Carbon $Emissions_{i(t-1)}$ + β_0 + β_1*Carbon $Taxes_{it}$ + β_2*$Coal_{it}$ + β_3*$GeoBiomass_{it}$ + β_4*$Nuclear_{it}$ + β_5*$Wind_{it}$ + β_6*Oil_{it} + $\varepsilon_{it.}$ The variables hydro, gas, and solar were dropped from the original equation due to them not being significant and again because of the high number of variables compared to observations it is a good idea to drop as many unimportant variables as possible. It should be noted that even before any controls were dropped the lagged variable was still slightly positive and significantly different from zero. Coal and oil both had positive coefficients which would make sense since we would expect an increase in the use of these non-renewable sources to cause an increase in emissions. Wind, biomass, and nuclear all had negative coefficients which would be expected since they are all low-pollution energy sources.

The main variable we are looking at in this regression is the lagged value of CO_2 Emissions which happens to be .163 which would indicate that there is a decaying effectiveness of carbon taxes overtime at the rate of 16.3% per year. This would indicate that there is a decaying effect which would point to the overall price levels in the country increasing at a rate higher than how quickly carbon taxes are rising. The Carbon tax rate coefficient is .08 which would indicate that a one percent increase in the carbon taxes would cause an increase in .08 tons per capita of carbon emissions and this does not seem to make sense as we would expect the opposite to be true where an increase in taxes would cause a decrease in emissions.

The value of the lagged term is like the results done before this regression and is what we would expect, but the good thing which came from this regression is that the controls have the signs we would expect as we would expect a nonrenewable energy source to have a negative sign and running the regression this way seems to have fixed that issue. The tax rate is now significantly positive which does not make much logical sense.

Table 3. Sweden Geometric Lag Regression:

Fitting full model:
Iteration 0: log likelihood = -28.992871
Iteration 1: log likelihood = -28.168082
Iteration 2: log likelihood = -28.143949
Iteration 3: log likelihood = -28.143935
Iteration 4: log likelihood = -28.143935
Heteroskedastic linear regression Number of obs = 50
ML estimation
Wald chi2(7) = 502.98
Log likelihood = -28.14394 Prob > chi2 = 0.0000

CO2emissions	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
CO2emissions						
CO2emissions						
L1.	0.950	0.100	9.510	0.000	0.754	1.146
CarbonTaxRate	-0.011	0.009	-1.230	0.219	-0.028	0.007
Coal	9.094	4.457	2.040	0.041	0.360	17.829
Gas	10.910	9.142	1.190	0.233	-7.008	28.829
Geo	-3.484	2.923	-1.190	0.233	-9.213	2.246
Solar	-1216.182	893.407	-1.360	0.173	-2967.229	534.864
Wind	10.802	6.044	1.790	0.074	-1.043	22.648
_cons	-0.827	1.027	-0.810	0.421	-2.839	1.186
lnsigma2						
CO2emissions	0.603	0.134	4.510	0.000	0.341	0.865
_cons	-6.075	0.988	-6.150	0.000	-8.011	-4.138

LR test of lnsigma2=0: chi2(1) = 24.28 Prob > chi2 = 0.0000

The equation that is used is Carbon $\text{Emissions}_{it} = \lambda*\text{Carbon Emissions}_{i(t-1)} + \beta_0 + \beta_1*\text{Carbon Taxes}_{it} + \beta_2*\text{Coal}_{it} + \beta_3*\text{Gas}_{it} + \beta_4*\text{Geobiomass}_{it} + \beta_5*\text{Solar}_{it} + \beta_6*\text{Wind}_{it} + \varepsilon_{it}$. Due to insignificance at all levels oil, biofuels, hydro, and nuclear energy could be dropped in the equation. Coal and gas both had positive coefficients of 9.094 and 10.91

meaning that for every increase of 9.094 EJ of coal or 10.91 EJ of gas would cause an increase by one ton of CO_2. Geo and solar were both statistically significantly negative which is what we would expect. The only real unexpected result in the controls would be the fact that wind has a positive coefficient of 10.802 meaning that when wind use goes up by 10.802 EJ carbon emissions go up one ton and this does not seem to make logical sense and we would expect the opposite result to be true.

After dropping all these insignificant controls in the regression, the lag value moved into significance at the five percent level. The coefficient of .95 would also point out a strong decaying effect of taxes on emissions meaning that 95 percent of the carbon taxes effective would vanish each year due to general price level increases. Looking at price level changes in Sweden might be the answer as inflation was generally high in the country in the nineteen eighties at rates above fifteen percent but in recent times inflation has declined a great deal to a rate consistently lower than five percent. This might be one reason why in existing literature the carbon tax rate does not have much of an effect in Sweden and this might be because the taxes effectiveness declines so quickly after the prices of the taxes change. Another reason why this rate might seem weird is because carbon tax rate has a small impact on emissions with a coefficient of -0.011 which is not significant so maybe the decaying rate is so high because there is just no relationship between the taxes and emissions.

This test produces several results which do not look entirely right for example the coefficient on the lagged term of .95 would indicate that there is a large declining effect, and I would not at all expect it to be this high. The carbon tax rate is not statistically significantly different from zero which should be expected, but the control for wind is in the wrong direction in terms of sign and that is possibly concerning.

Table 4. Denmark Geometric Lag Regression:

Fitting full model:
Iteration 0: log likelihood = -3.8408746
Iteration 1: log likelihood = -3.5051207
Iteration 2: log likelihood = -3.5007985
Iteration 3: log likelihood = -3.5007971
Iteration 4: log likelihood = -3.5007971
Heteroskedastic linear regression Number of obs = 51
ML estimation
Wald chi2(6) = 2065.43
Log likelihood = -3.500797 Prob > chi2 = 0.0000

CO2emissions	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
CO2emissions						
CO2emissions						
L1.	-0.103	0.057	-1.800	0.072	-0.215	0.009
CarbonTaxRate	-0.018	0.009	-1.990	0.047	-0.036	-0.000
Coal	16.048	0.905	17.720	0.000	14.273	17.823
Gas	8.858	1.079	8.210	0.000	6.744	10.972
GeoBiomass	-23.480	10.130	-2.320	0.020	-43.335	-3.626
Oil	14.426	0.705	20.460	0.000	13.043	15.808
_cons	0.843	0.650	1.300	0.195	-0.431	2.116
lnsigma2						
CO2emissions	-0.065	0.147	-0.440	0.659	-0.353	0.224
_cons	-2.037	1.515	-1.340	0.179	-5.008	0.933

LR test of lnsigma2=0: chi2(1) = 0.19 Prob > chi2 = 0.6604

The equation that is used is $\text{Carbon Emissions}_{it} = \lambda*\text{Carbon Emissions}_{i(t-1)} + \beta_0 + \beta_1*\text{Carbon Taxes}_{it} + \beta_2*\text{Coal}_{it} + \beta_3*\text{Gas}_{it} + \beta_4*\text{Geobiomass}_{it} + \beta_5*\text{Oil}_{it} + \varepsilon_{it}$ The variables for biofuels and nuclear were automatically omitted for collinearity since both were zero throughout the years, and so it is reasonable to drop these variables since there was no significant use of biofuels or nuclear energy within the country so it would not affect the emissions levels. Wind, solar, and nuclear were clearly insignificant controls that were dropped. Coal, gas, and oil expectedly all had positive coefficients meaning when their usage rose, so did carbon emissions. Geobiomass was a control with a negative coefficient of 23.48 meaning that for every increase in one EJ of geobiomass energy carbon emissions dropped by 23.48 tons of CO_2 per capita. The coefficient of the lagged variable is only -.103 and so it is not significant at the five percent level, but it is at the ten percent level which likely indicates that there is some slight decreasing effectiveness of carbon taxes overtime, but we cannot say for sure. One of possible reason for this is the fact that the coefficient for carbon taxes is negative .018 which means that it is barely insignificant at the five percent level but it is significant at the ten percent level. We would likely assume that if carbon taxes did not have any real impact on emissions there would not be a declining effectiveness since they were not effective in the first place according to the regression results. The zero impact of taxes on emissions is quite like other papers which exist on the topic and it is likely do to the fact that there are many tax exemptions in the carbon tax laws in Denmark.

General Koyck's Geometric Model Conclusions from Individual Countries:

The most important conclusion that I got from the regressions so far is that for there to be a decaying effectiveness overtime of carbon taxes on emissions there must be an overall effectiveness of carbon taxes on emissions. So, what was found in the regressions above largely went along with existing research on this topic since other papers noted that there was not much effectiveness of taxes on emissions in the countries of Sweden and Denmark. Going off that it is likely that since there was no initial effectiveness it is unlikely that there would be any decreasing effectiveness. A reason for the difference between the results of Finland compared to Sweden and Denmark is that Finland has a much broader tax policy with less exemptions which makes its tax more effective. Since Finland appears to be the only country with a truly effective tax it would make sense that they should be the ones most concerned with a decreasing effectiveness due to inflation, and this is likely why Finland is the only country where we can accept the hypothesis that there is a decaying rate of effectiveness.

Analyzing the lag variable coefficient and the tax rate are the same as before as they likely are not causing any change. The controls do all go in a way in which we would expect and make more sense than the ones in OLS.

Table 5. Combined Geometric Lag Regression:

Fitting full model:
Iteration 0: log likelihood = -126.95594
Iteration 1: log likelihood = -124.3712
Iteration 2: log likelihood = -124.22816
Iteration 3: log likelihood = -124.22764
Iteration 4: log likelihood = -124.22764
Heteroskedastic linear regression Number of obs = 147
ML estimation
Wald chi2(7) = 2774.30
Log likelihood = -124.2276 Prob > chi2 = 0.0000

C02Emissions	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
C02Emissions						
C02Emissions						
L1.	0.541	0.050	10.810	0.000	0.443	0.639
CarbonTaxRate	0.008	0.006	1.390	0.164	-0.003	0.019
Coal	8.026	1.208	6.650	0.000	5.660	10.393
Hydro	-1.577	0.633	-2.490	0.013	-2.818	-0.336
Nuclear	-1.752	0.403	-4.350	0.000	-2.541	-0.963
Wind	-10.911	2.573	-4.240	0.000	-15.953	-5.868
Oil	2.319	0.488	4.760	0.000	1.363	3.274
_cons	2.203	0.328	6.710	0.000	1.560	2.846
lnsigma2						
C02Emissions	0.291	0.062	4.720	0.000	0.170	0.412
_cons	-3.828	0.580	-6.600	0.000	-4.966	-2.691

LR test of lnsigma2=0: chi2(1) = 18.30 Prob > chi2 = 0.0000

In this regression the data for Denmark, Finland, and Sweden are combined to do the same style of regression on a data set with a lot more observations. The controls for Geobiomass, solar, and gas were dropped due to insignificance. Coal and oil were both positive and hydro, nuclear, and wind were all negative which is what would be expected, and it is good sign that the controls are what we would expect.

The lagged variable seems too high and it appears to be impacted by the oddly high rate that was found in the Sweden regression. The carbon tax rate is not significant and that is not particularly surprising since it was only significant in Finland's model. The coefficient moved towards significance when the insignificant controls were dropped, but it never ended up being significant. More controls are significant than I would have expected since the different countries had different controls that were significant, and all these controls have signs which are in the direction we would expect.

Table 6. Combined Geometric Lag Regression with Year Dummies:

Fitting full model:
Iteration 0: log likelihood = -26.688504
Iteration 1: log likelihood = -10.33696 (not concave)
Iteration 2: log likelihood = 3.491867
Iteration 3: log likelihood = 7.0011455
Iteration 4: log likelihood = 8.5721697
Iteration 5: log likelihood = 8.73885
Iteration 6: log likelihood = 8.9276453
Iteration 7: log likelihood = 8.9556693
Iteration 8: log likelihood = 8.956648
Iteration 9: log likelihood = 8.9566486
Heteroskedastic linear regression Number of obs = 147
ML estimation
Wald chi2(59) = 327558.19
Log likelihood = 8.956649 Prob > chi2 = 0.0000

C02Emissions	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
C02Emissions						
C02Emissions						
L1.	0.338	0.027	12.630	0.000	0.285	0.390
CarbonTaxRate	0.010	0.008	1.280	0.199	-0.006	0.026
Coal	16.156	1.332	12.130	0.000	13.546	18.766
Gas	17.738	2.143	8.280	0.000	13.537	21.939
Hydro	-0.777	0.363	-2.140	0.032	-1.488	-0.065

Solar	-81.895	5.151	-15.900	0.000	-91.991	-71.799
Wind	-32.665	5.995	-5.450	0.000	-44.414	-20.916
Oil	2.044	0.299	6.840	0.000	1.458	2.630
Year						
1966	0.709	0.031	22.990	0.000	0.649	0.770
1967	0.197	0.044	4.530	0.000	0.112	0.283
1968	0.960	0.053	18.110	0.000	0.856	1.064
1969	1.250	0.111	11.250	0.000	1.033	1.468
1970	1.353	0.173	7.840	0.000	1.015	1.692
1971	1.335	0.180	7.430	0.000	0.983	1.687
1972	1.815	0.283	6.410	0.000	1.260	2.370
1973	2.160	0.537	4.020	0.000	1.107	3.213
1974	1.111	0.299	3.710	0.000	0.524	1.697
1975	1.283	0.286	4.490	0.000	0.722	1.843
1976	1.811	0.597	3.040	0.002	0.642	2.981
1977	1.358	0.484	2.810	0.005	0.410	2.307
1978	0.449	0.350	1.280	0.200	-0.238	1.136
1979	0.957	0.533	1.800	0.073	-0.088	2.002
1980	-0.485	0.223	-2.170	0.030	-0.923	-0.048
1981	0.179	0.173	1.030	0.302	-0.161	0.519
1982	-0.525	0.134	-3.930	0.000	-0.787	-0.263
1983	-0.620	0.113	-5.480	0.000	-0.842	-0.398
1984	-0.753	0.128	-5.880	0.000	-1.004	-0.502
1985	-0.579	0.153	-3.770	0.000	-0.879	-0.278
1986	-1.263	0.150	-8.410	0.000	-1.557	-0.969
1987	-1.182	0.158	-7.490	0.000	-1.491	-0.873
1988	-1.288	0.149	-8.660	0.000	-1.579	-0.996
1989	-1.330	0.144	-9.260	0.000	-1.612	-1.049
1990	-1.888	0.139	-13.550	0.000	-2.161	-1.615
1991	-1.744	0.086	-20.190	0.000	-1.913	-1.575
1992	-1.712	0.099	-17.360	0.000	-1.906	-1.519
1993	-1.670	0.101	-16.610	0.000	-1.867	-1.473
1994	-1.601	0.101	-15.860	0.000	-1.798	-1.403
1995	-1.562	0.095	-16.510	0.000	-1.747	-1.376
1996	-1.965	0.123	-15.930	0.000	-2.207	-1.723
1997	-1.966	0.148	-13.300	0.000	-2.256	-1.677
1998	-1.841	0.143	-12.900	0.000	-2.120	-1.561
1999	-1.944	0.139	-13.990	0.000	-2.216	-1.672
2000	-1.766	0.112	-15.770	0.000	-1.986	-1.547
2001	-1.703	0.107	-15.950	0.000	-1.912	-1.494
2002	-1.316	0.104	-12.640	0.000	-1.520	-1.112
2003	-2.052	0.148	-13.830	0.000	-2.342	-1.761
2004	-1.911	0.138	-13.840	0.000	-2.181	-1.640
2005	-1.943	0.130	-14.970	0.000	-2.198	-1.689
2006	-2.361	0.132	-17.930	0.000	-2.619	-2.103
2007	-2.190	0.130	-16.890	0.000	-2.444	-1.936
2008	-1.796	0.136	-13.250	0.000	-2.061	-1.530
2009	-1.875	0.109	-17.130	0.000	-2.089	-1.660
2010	-1.214	0.108	-11.200	0.000	-1.426	-1.001
2011	-0.520	0.086	-6.050	0.000	-0.689	-0.352
2012	-0.250	0.114	-2.180	0.029	-0.474	-0.026
2013	0.336	0.171	1.970	0.049	0.002	0.671
2014	0.892	0.250	3.570	0.000	0.402	1.382
2015	1.636	0.323	5.070	0.000	1.004	2.268
2016	1.311	0.246	5.340	0.000	0.829	1.793

_cons	2.251	0.136	16.570	0.000	1.985	2.517
lnsigma2						
C02Emissions	1.674	0.221	7.580	0.000	1.242	2.107
_cons	-18.377	2.036	-9.020	0.000	-22.368	-14.386

LR test of lnsigma2=0: chi2(1) = 129.59 Prob > chi2 = 0.0000

In this regression we created dummy variables for each year in the data and we can now do this with the combined data set since there are more observations, so the power of the model is higher than if we just used one country.

The control variables for geobiomass and nuclear were dropped from the original equation as they were not statistically significant. The control variables all had coefficients with signs that we would expect since coal, gas, and oil are positive meaning an increase in use causes an increase in emissions and hydro, solar, and wind all have negative coefficients meaning they decrease emissions. The general lagged variable for emissions is .338 which still seems a little high that 33.8% decaying effectiveness but there is a significant value between one and zero so that at least indicates that there is possibly some decaying effectiveness.

The whole point of creating year dummies is to control for time effects on carbon emissions because there may be factors unique to each year which impact carbon emissions. The problem is that even though the general lagged coefficient makes sense many of the year dummy coefficients do not. Some are negative and some are positive, and it is not an error that some are negative that would in fact likely point towards some sort of increasing effectiveness of the taxes relative to the price range. The problem is that many of the variables are outside of the range of zero to one and this causes the logic of the equation to breakdown. It does not make sense to interpret a coefficient greater than one in the geometric lag model and it usually points at some sort of error and in this case, it is likely due to the power of the model since there are so many dummy variables for a relatively limited number of observations.

Difference-in-Differences Regression Results:

Table 7. Finland Difference-in-Differences Regression:

Linear regression

C02Emissions	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CarbonTaxRate	.122	.031	3.93	0	.06	.183	***
y90	-.042	.167	-0.25	.802	-.374	.29	
Taxed	-6.604	.504	-13.11	0	-7.606	-5.601	***
y90taxed	.183	.396	0.46	.646	-.606	.972	
Coal	20.502	2.14	9.58	0	16.246	24.759	***
GeoBiomass	-20.681	6.804	-3.04	.003	-34.218	-7.145	***
Nuclear	-4.677	1.437	-3.25	.002	-7.536	-1.818	***
Wind	-613.173	265.57	-2.31	.023	-1141.476	-84.871	**
Oil	14.015	1.206	11.62	0	11.616	16.415	***
Constant	7.186	.097	74.04	0	6.993	7.379	***

Mean dependent var	8.848	SD dependent var	1.870
R-squared	0.945	Number of obs	92.000
F-test	155.575	Prob > F	0.000
Akaike crit. (AIC)	128.928	Bayesian crit. (BIC)	154.146

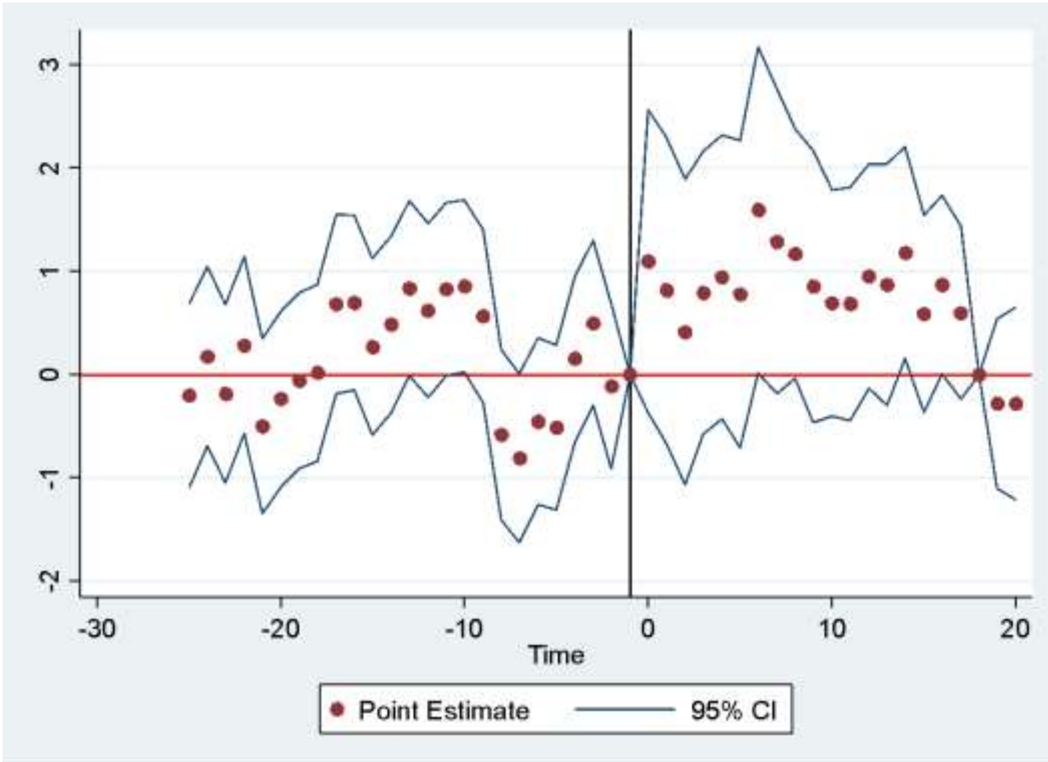
*** *p*<.01, ** *p*<.05, * *p*<.1

The equation for this analysis is Carbon $\text{Emissions}_{it} = \beta_0 + \beta_1$CarbonTaxrate+ β_2y90 + β_3*taxed+ β_4*(y90*taxed) + β_5Coal + β_6GeoBiomass + β_7Nuclear + + β_8Wind + β_9Oil + $\varepsilon_{it.}$ The method used throughout all these regressions to drop controlled variables was the same and that was to drop the least significant control variable one at a time to increase significance while making sure that variables which turned out to be significant were not accidentally dropped. Some discretion was used for example some controls technically are not significant, but are very close and so they were left in because likely they probably are significant but because of the quality of the data we can leave it in.

In this regression Biofuels, hydro, gas, and solar were dropped because they were all not statistically significantly different from zero. Geobiomass, nuclear, and wind are all controls that had negative coefficients which meant they had negative impacts on emissions which makes sense since they are an alternative to much higher CO_2 polluting energy sources. Coal and oil both had positive coefficients which is to be expected since they are high polluting energy sources.

The variables which are much more central to the question are carbon tax rate, y90, taxed, and y90taxed. The coefficient of the carbon tax rate is .122 which would mean that for every one-unit dollar increase in carbon taxes emissions would increase by .122 tons of CO_2 per capita and that logically does not make sense as we would expect the coefficient to be negative and sense the confidence interval does not include zero or negative it likely is positive which does not logically make sense. Y90 has a coefficient of negative .014 and is not significant where taxed has a negative coefficient of 6.604 and is significant and both are not the most important since y90 is only looking at years after 1990 so there likely would be no change overall where the taxed is just comparing countries and it so the negative coefficient would indicate that Finland has a lower level of carbon emissions. The fact that the variable for taxed is negative means that generally Finland had a lower level of emissions due to the taxes, but since the interaction term is not significant, we cannot conclude that this difference is before and after the tax introduction. The coefficient of the interaction term of y90taxed is .183 but it is not at all significant which would mean that we can really be sure that there is any decrease in carbon emissions caused by carbon taxes when comparing these two countries with different carbon tax policies, a likely cause for this problem is the lack of observations relative to the amount of variables.

Figure 1. Finland Event Study Graph:



The main point of an event study graph is to look at the changes between the treatment and the control to see if a policy or change had any real impact on a central independent variable. The problem with drawing any type of conclusion from this graph is the fact that the ninety-five percent confidence interval includes the value of zero for almost every single year of the data. This means that it is feasible for there to be no change after the policy change and the fact that the confidence interval is almost centered on zero throughout points to there being no change or relationship between the treatment and the main independent variable which in this paper are the carbon tax and the CO_2 emissions.

Table 8. Effect of Tax rate Every Year by plotting Coefficients Finland DID:

Linear regression

C02Emissions	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
y90taxed	-.725	.325	-2.23	.031	-1.381	-.068	**
Taxed	-5.144	.593	-8.68	0	-6.341	-3.947	***
1b.timevar	0	.	.	.	.	.	
5.timevar	.793	.431	1.84	.073	-.077	1.663	*

6.timevar	1.166	.421	2.77	.008	.317	2.015	***
7.timevar	.803	.419	1.92	.062	-.042	1.649	*
8.timevar	1.273	.412	3.09	.004	.441	2.105	***
9.timevar	.492	.406	1.21	.233	-.329	1.313	
10.timevar	.758	.406	1.87	.069	-.061	1.577	*
11.timevar	.93	.408	2.28	.028	.106	1.754	**
12.timevar	1.008	.408	2.47	.018	.183	1.833	**
13.timevar	1.672	.414	4.04	0	.836	2.509	***
14.timevar	1.688	.406	4.16	0	.868	2.507	***
15.timevar	1.257	.408	3.08	.004	.432	2.082	***
16.timevar	1.482	.407	3.64	.001	.659	2.304	***
17.timevar	1.828	.406	4.50	0	1.008	2.648	***
18.timevar	1.622	.404	4.01	0	.806	2.438	***
19.timevar	1.825	.407	4.48	0	1.003	2.647	***
20.timevar	1.859	.405	4.59	0	1.041	2.676	***
21.timevar	1.547	.406	3.81	0	.727	2.368	***
22.timevar	.402	.403	1.00	.324	-.411	1.215	
23.timevar	.178	.402	0.44	.661	-.634	.989	
24.timevar	.534	.402	1.33	.191	-.278	1.346	
25.timevar	.487	.406	1.20	.236	-.332	1.307	
26.timevar	1.151	.403	2.86	.007	.337	1.965	***
27.timevar	1.498	.405	3.69	.001	.679	2.316	***
28.timevar	.888	.406	2.19	.034	.069	1.707	**
29.timevar	1	.405	2.47	.018	.183	1.818	**
30.timevar	1.196	.423	2.83	.007	.342	2.049	***
31.timevar	.915	.422	2.17	.036	.062	1.768	**
32.timevar	.512	.425	1.21	.235	-.346	1.371	
33.timevar	.899	.419	2.14	.038	.052	1.746	**
34.timevar	1.046	.415	2.52	.016	.209	1.884	**
35.timevar	.806	.404	1.99	.053	-.01	1.623	*
36.timevar	1.634	.406	4.02	0	.814	2.455	***
37.timevar	1.26	.395	3.19	.003	.462	2.058	***
38.timevar	1.155	.397	2.91	.006	.353	1.957	***
39.timevar	.812	.394	2.06	.046	.016	1.608	**
40.timevar	.736	.398	1.85	.072	-.067	1.539	*
41.timevar	.741	.394	1.88	.067	-.055	1.536	*
42.timevar	1.01	.394	2.56	.014	.214	1.806	**
43.timevar	.918	.393	2.33	.025	.124	1.713	**
44.timevar	1.24	.388	3.20	.003	.457	2.022	***
45.timevar	.676	.397	1.70	.096	-.125	1.477	*
46.timevar	1.002	.388	2.58	.013	.218	1.785	**
47.timevar	.746	.386	1.93	.06	-.034	1.526	*
48.timevar	.152	.392	0.39	.7	-.639	.943	
49.timevar	-.054	.389	-0.14	.891	-.839	.732	
50o.timevar	0	.	.	.	.	.	
CarbonTaxRate	.052	.013	3.88	0	.025	.079	***
Coal	15.39	1.968	7.82	0	11.417	19.364	***
Oil	11.512	1.443	7.98	0	8.598	14.425	***
Constant	6.109	.293	20.88	0	5.518	6.7	***

Mean dependent var	8.848	SD dependent var	1.870
R-squared	0.981	Number of obs	92.000
F-test	42.080	Prob > F	0.000
Akaike crit. (AIC)	113.153	Bayesian crit. (BIC)	241.765

**** p<.01, ** p<.05, * p<.1*

In this regression we created dummy variables for each year by looking at the tax rates effect every year by plotting the coefficients. This model really does not work well using only the data for Finland, to improve it you would likely need more data points to properly accommodate the number of year dummies. The fact that the control variables nuclear, hydro, gas, wind, geobiomass, solar, and biofuels all were dropped because they were insignificant really showcases that there are too many variables for the number of observations within this data set. Coal and Oil were the only controls which remained significant and when coal increased by 15.39 EJ and oil by 11.512 EJ the carbon emissions rose by one ton of carbon dioxide which would be a reasonable thing to assume.

The variable y90 was dropped because of the style of regression you do not want extra variables which are there to account for time. The variable for taxed has a coefficient of -5.144 which indicates that Finland has a consistently lower level of emissions when accounting for controls. The interaction term y90taxed was insignificant at the start, but after removing all the insignificant variables the term became significant even though it looked like there was a slight general relationship before dropping the other variables. The coefficient for y90 taxed was -.725 which is a good sign as it indicates that after adding the policy to the treatment group there was a decline in emissions relative to the control group of Iceland.

Table 9. Sweden Difference-in-Differences Regression:

Linear regression

C02Emissions	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CarbonTaxRate	.034	.018	1.91	.059	-.001	.069	*
y90	-.019	.171	-0.11	.913	-.358	.321	
Taxed	-3.555	1.195	-2.97	.004	-5.931	-1.18	***
y90taxed	-.143	.436	-0.33	.744	-1.01	.724	
Coal	17.181	7.273	2.36	.02	2.724	31.637	**

GeoBiomass	-15.906	4.479	-3.55	.001	-24.809	-7.003	***
Nuclear	-4.413	.573	-7.70	0	-5.552	-3.274	***
Solar	-2528.152	1176.262	-2.15	.034	-4866.101	-190.203	**
Oil	4.449	.748	5.94	0	2.961	5.937	***
Constant	7.416	.109	68.16	0	7.199	7.632	***

Mean dependent var	7.348	SD dependent var	1.542
R-squared	0.892	Number of obs	97.000
F-test	80.159	Prob > F	0.000
Akaike crit. (AIC)	162.048	Bayesian crit. (BIC)	187.795

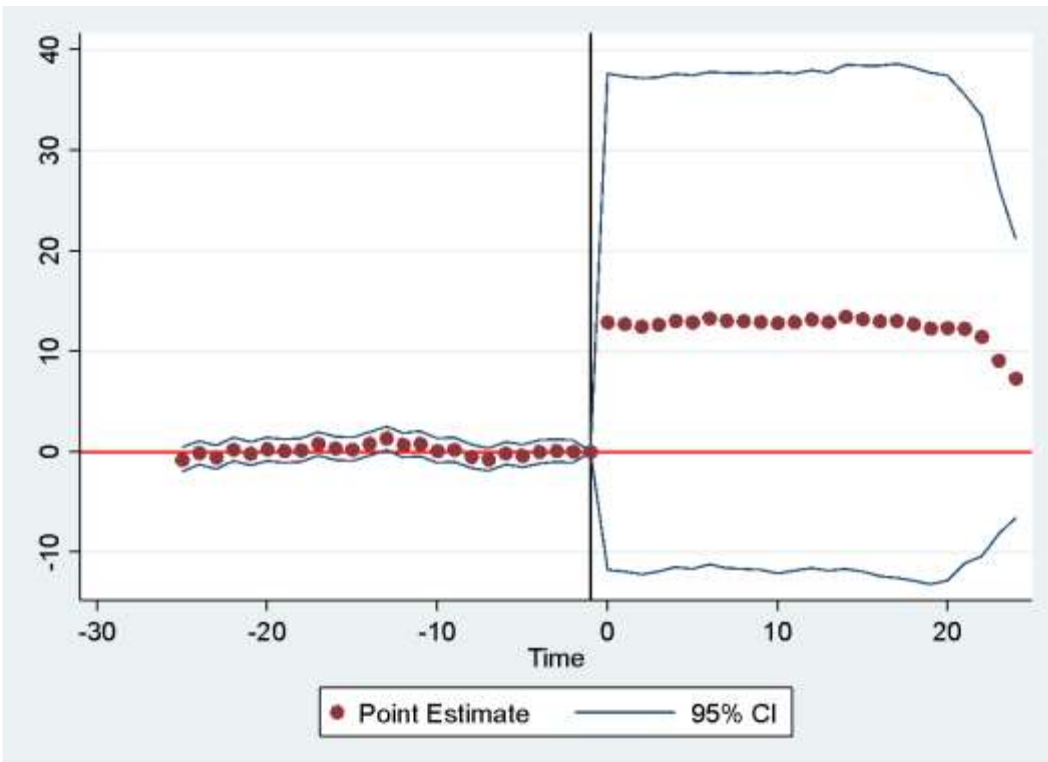
**** p<.01, ** p<.05, * p<.1*

This Difference-in differences regression compares the policy implementation in Sweden to the data from Iceland in the same way the last DID was ran. The equation for this regression is Carbon $Emissions_{it} = \beta_0 + \beta_1 CarbonTaxrate + \beta 2*y90 + \beta_3*taxed + \beta_4*(y90*taxed) + \beta_5 Coal + \beta_6 GeoBiomass + \beta_7 Nuclear + \beta_8 Solar + \beta_9 Oil + \varepsilon_{it.}$

The controls for biofuels, hydo, gas, and wind were dropped from the original regression as they were not statistically different from zero. Looking at the coefficients for the controls coal and oil were both positive meaning that as their usage increased by one EJ of coal and one EJ of oil emissions would increase by 17.18 tons of carbons emissions for coal and 4.449 tons of CO_2 for oil. Geobiomass, nuclear and solar were all negative which means as their usage went up carbon emissions decreased and that is a reasonable conclusion to make. All the controls had the coefficients in the directions which we expected and that is a good sign for the model validity.

The controls looked good, but the main variables which we are looking at do not have as clear results. The variables for carbon tax rate, the binary variables, and the interaction term were all insignificant in the original regression and after removing all insignificant controls only the binary variable for taxed became significantly different from zero. The carbon tax rate coefficient is .034 which does not make much sense since it is positive, but it is so close to zero that it is likely insignificant. Since the interaction term is not significant at any confidence interval and the carbon tax rate is only significant at the ten percent level and so it is hard to draw any conclusions upon the results of this equation. This result is probably what we should expect since many of the economic data from Sweden indicates that the taxes are not having a strong impact on the emission levels.

Figure 2. Sweden Event Study Graph:



Much like the results of the regression it is hard to make much of anything from this graph since almost all the confidence intervals deviate around zero which indicates that there is no significant change from the interaction term which looks at the differences from the treatment group of Sweden and the control of Iceland. The range of the confidence intervals is very interesting to look at as at the point of the year 1990 when the carbon tax policy was implemented there is a greater deal of variability in the confidence interval. When looking at the emissions data in Sweden it is strange since the emissions levels do not appear to fluctuate a lot more after 1990 then they did before the policy implementation. In this way the graph looks like a regression discontinuity graph because there seems to be a sharp change in the point estimation and the confidence interval before and after the main policy change.

Table 10. Effect of Tax rate Every Year by Plotting Coefficients Sweden DID:

Linear regression

C02Emissions	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
y90taxed	-.251	.556	-0.45	.654	-1.375	.872	
Taxed	2.051	1.335	1.54	.132	-.648	4.749	
1b.timevar	0	.	.	.	.	.	
5.timevar	-.313	1.443	-0.22	.829	-3.23	2.603	
6.timevar	.366	1.442	0.25	.801	-2.548	3.281	
7.timevar	-.026	1.429	-0.02	.986	-2.914	2.863	
8.timevar	.703	1.428	0.49	.625	-2.183	3.589	
9.timevar	.204	1.451	0.14	.889	-2.728	3.137	
10.timevar	.724	1.45	0.50	.621	-2.207	3.655	
11.timevar	.607	1.414	0.43	.67	-2.25	3.465	
12.timevar	.601	1.409	0.43	.672	-2.246	3.449	
13.timevar	1.413	1.39	1.02	.315	-1.396	4.222	
14.timevar	.931	1.397	0.67	.509	-1.893	3.755	
15.timevar	.809	1.402	0.58	.567	-2.024	3.642	
16.timevar	1.337	1.413	0.95	.35	-1.518	4.192	
17.timevar	1.672	1.419	1.18	.245	-1.195	4.54	
18.timevar	1.201	1.414	0.85	.4	-1.656	4.058	
19.timevar	1.524	1.406	1.08	.285	-1.318	4.366	
20.timevar	.633	1.408	0.45	.656	-2.213	3.479	
21.timevar	.519	1.411	0.37	.715	-2.332	3.371	
22.timevar	-.258	1.425	-0.18	.858	-3.138	2.623	
23.timevar	-.356	1.401	-0.25	.801	-3.187	2.474	
24.timevar	.382	1.396	0.27	.786	-2.438	3.203	
25.timevar	.378	1.392	0.27	.787	-2.436	3.192	
26.timevar	.63	1.433	0.44	.663	-2.267	3.526	
27.timevar	.825	1.397	0.59	.558	-1.999	3.649	
28.timevar	.668	1.405	0.48	.637	-2.172	3.508	
29.timevar	.589	1.397	0.42	.676	-2.235	3.413	
30.timevar	.694	1.547	0.45	.656	-2.433	3.821	
31.timevar	.397	1.485	0.27	.791	-2.606	3.399	
32.timevar	.319	1.445	0.22	.826	-2.601	3.238	
33.timevar	.589	1.442	0.41	.685	-2.325	3.503	
34.timevar	.706	1.49	0.47	.638	-2.305	3.716	
35.timevar	.695	1.454	0.48	.635	-2.243	3.632	
36.timevar	1.011	1.488	0.68	.501	-1.996	4.018	
37.timevar	.943	1.335	0.71	.484	-1.755	3.641	
38.timevar	.993	1.334	0.74	.461	-1.702	3.688	
39.timevar	.755	1.344	0.56	.578	-1.962	3.472	
40.timevar	.694	1.329	0.52	.604	-1.992	3.381	
41.timevar	.818	1.366	0.60	.553	-1.942	3.579	
42.timevar	.974	1.393	0.70	.488	-1.84	3.789	

43.timevar	.575	1.395	0.41	.683	-2.244	3.394	
44.timevar	.975	1.355	0.72	.476	-1.764	3.713	
45.timevar	.815	1.304	0.62	.536	-1.82	3.45	
46.timevar	.414	1.351	0.31	.761	-2.317	3.145	
47.timevar	.361	1.308	0.28	.784	-2.283	3.004	
48.timevar	.202	1.225	0.16	.87	-2.273	2.677	
49.timevar	-.608	1.307	-0.47	.644	-3.249	2.033	
50.timevar	-.139	1.272	-0.11	.913	-2.71	2.432	
51.timevar	.771	.971	0.79	.432	-1.191	2.733	
52.timevar	.658	.944	0.70	.49	-1.249	2.565	
53.timevar	-.019	1.013	-0.02	.985	-2.066	2.028	
54.timevar	-.183	.995	-0.18	.855	-2.194	1.828	
55o.timevar	0	.	.	.	.	.	
CarbonTaxRate	-.026	.021	-1.26	.216	-.068	.016	
Hydro	-3.048	1.754	-1.74	.09	-6.592	.497	*
Nuclear	-3.395	.727	-4.67	0	-4.865	-1.925	***
Oil	1.792	.896	2.00	.052	-.018	3.603	*
Constant	6.928	1.375	5.04	0	4.15	9.707	***

Mean dependent var	7.348	SD dependent var	1.542
R-squared	0.951	Number of obs	97.000
F-test	13.867	Prob > F	0.000
Akaike crit. (AIC)	179.706	Bayesian crit. (BIC)	326.464

**** p<.01, ** p<.05, * p<.1*

For Sweden, the controls for biofuels, solar, wind, gas, geobiomass, and coal were all dropped because they were not significant from zero. Hydro and Nuclear both had negative coefficients meaning that as their usage rose by 3.048 EJ and 3.395 EJ respectively emissions levels decreased by one ton of CO_2. The coefficient for oil was positive which means that the results for the remaining controls make logical sense.

Unfortunately, this regression tells us a lot less than the one for Finland since both y90taxed and taxed are insignificant. Also, only five of the fifty-year dummies had any significance and this is half of the number for Finland and so we can’t really say much about what happened before or after policy implementation and what happened for each year when we look at comparing Sweden to Iceland.

Table 11. Denmark Difference-in-Differences Regression:

Linear regression

C02Emissions	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CarbonTaxRate	-.01	.013	-0.76	.447	-.036	.016	
y90	.025	.152	0.17	.869	-.277	.328	
Taxed	-6.513	.558	-11.67	0	-7.622	-5.404	***
y90taxed	-.303	.38	-0.80	.428	-1.058	.452	
Coal	14.864	1.064	13.97	0	12.749	16.978	***
Gas	9.108	1.99	4.58	0	5.154	13.062	***
GeoBiomass	-23.979	6.046	-3.97	0	-35.991	-11.966	***
Oil	13.133	.742	17.69	0	11.658	14.608	***
Constant	7.215	.087	83.29	0	7.043	7.387	***

Mean dependent var	8.905	SD dependent var	1.968
R-squared	0.958	Number of obs	98.000
F-test	254.121	Prob > F	0.000
Akaike crit. (AIC)	117.023	Bayesian crit. (BIC)	140.287

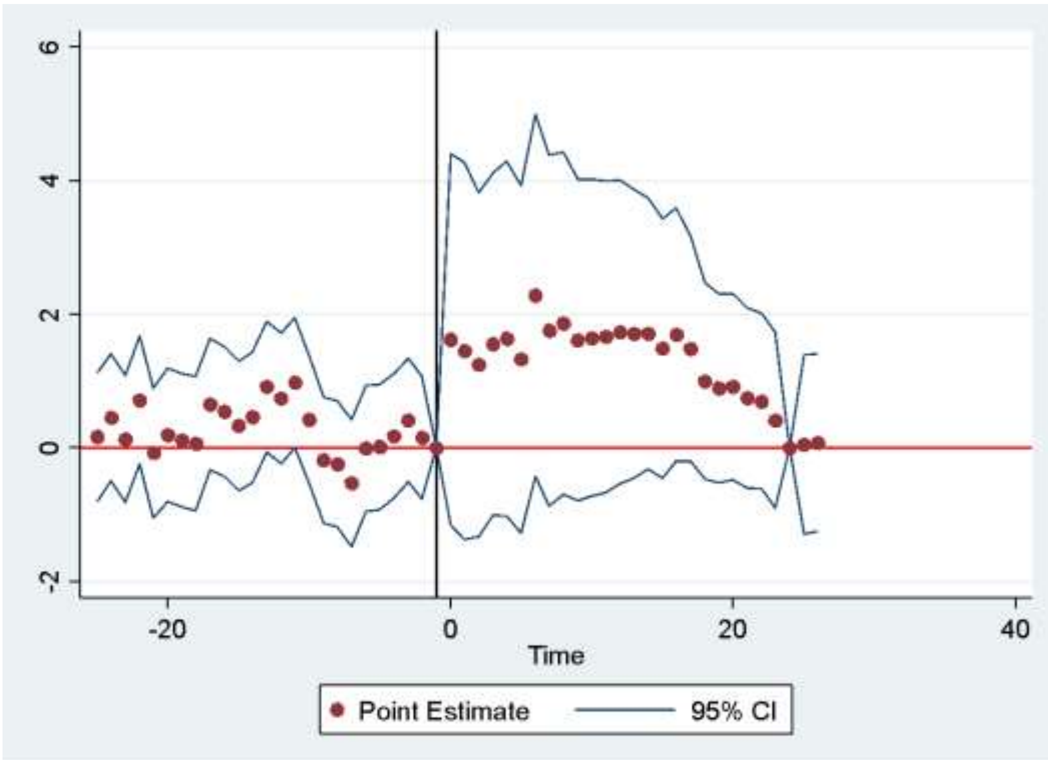
**** p<.01, ** p<.05, * p<.1*

This Difference-in differences regression uses Denmark as the treatment country and Iceland as the control. The equation for this regression is Carbon $\text{Emissions}_{it} = \beta_0 + \beta_1\text{CarbonTaxrate} + \beta 2{*}y90 + \beta_3{*}\text{taxed} + \beta_4{*}(y90{*}\text{taxed}) + \beta_5\text{Coal} + \beta_6\text{Gas} + \beta_7\text{GeoBiomass} + \beta_8\text{Oil} + \varepsilon_{it.}$ The controls for nuclear and biofuels were immediately. omitted for collinearity since both variables had a value of zero throughout. The variables wind, hyrdo, and solar were all dropped because they were not statistically significant.

All the main variables were insignificant at the start at the ninety-five percent confidence interval other than the variable for taxed. After all the insignificant controls were dropped the main variables moved closer to significance but ultimately still not significant at any level. The coefficient for tax rate was -.01 and although it is good that this value is negative it is almost perfectly zero, so we have to say that in this regression the tax rate likely has no impact upon emission levels. This result is not terribly surprising and it does back existing literature which generally points to an insignificant effect of carbon taxes in Denmark due to the taxes implementation. The coefficient for

Taxed however is significant with a coefficient of -6.513 which would indicate that the country with the tax policy has the lower emission levels.

Figure 3. Denmark Event Study Graph:



Much like for the other event study graphs not much of a conclusion can be obtained by the graph above as the confidence interval includes the value of zero throughout. Like the Sweden DID there is an interesting pattern where at nineteen-ninety the confidence interval begins to be consistently wider making this graph look like a regression discontinuity graph and again the reasons for why this is the case are confusing as the emission levels do not fluctuate more after 1990 than they did before 1990 and so there must be some sort of explanation for this occurrence.

Table 12. Effect of Tax rate Every Year by plotting Coefficients Denmark DID:

Linear regression

C02Emissions	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
y90taxed	.145	.388	0.37	.71	-.638	.929	
Taxed	-4.364	.874	-4.99	0	-6.13	-2.599	***
1b.timevar	0	.	.	.	.	.	
5.timevar	2.108	.618	3.41	.001	.86	3.355	***
6.timevar	2.414	.63	3.83	0	1.141	3.686	***
7.timevar	2.093	.628	3.34	.002	.826	3.361	***
8.timevar	2.683	.631	4.25	0	1.409	3.956	***
9.timevar	1.917	.649	2.96	.005	.607	3.227	***
10.timevar	2.195	.659	3.33	.002	.864	3.526	***
11.timevar	2.109	.646	3.26	.002	.803	3.414	***
12.timevar	2.068	.657	3.15	.003	.74	3.395	***
13.timevar	2.649	.653	4.05	0	1.329	3.968	***
14.timevar	2.527	.637	3.97	0	1.241	3.813	***
15.timevar	2.312	.634	3.65	.001	1.031	3.592	***
16.timevar	2.456	.652	3.77	.001	1.14	3.773	***
17.timevar	2.915	.658	4.43	0	1.587	4.243	***
18.timevar	2.743	.662	4.14	0	1.406	4.08	***
19.timevar	2.976	.665	4.48	0	1.633	4.318	***
20.timevar	2.412	.671	3.60	.001	1.057	3.767	***
21.timevar	1.787	.647	2.76	.009	.481	3.093	***
22.timevar	1.717	.648	2.65	.011	.409	3.025	**
23.timevar	1.423	.641	2.22	.032	.129	2.717	**
24.timevar	1.95	.644	3.03	.004	.649	3.251	***
25.timevar	2.009	.665	3.02	.004	.665	3.353	***
26.timevar	2.19	.666	3.29	.002	.845	3.535	***
27.timevar	2.433	.658	3.70	.001	1.103	3.762	***
28.timevar	2.181	.651	3.35	.002	.866	3.497	***
29.timevar	2.019	.634	3.18	.003	.738	3.299	***
30.timevar	2.129	.678	3.14	.003	.761	3.498	***
31.timevar	1.989	.705	2.82	.007	.565	3.413	***
32.timevar	1.72	.648	2.66	.011	.412	3.028	**
33.timevar	2.036	.656	3.10	.003	.711	3.361	***
34.timevar	2.152	.672	3.20	.003	.794	3.509	***
35.timevar	1.846	.652	2.83	.007	.529	3.164	***
36.timevar	2.849	.707	4.03	0	1.421	4.277	***
37.timevar	2.309	.663	3.48	.001	.97	3.647	***
38.timevar	2.407	.647	3.72	.001	1.101	3.713	***
39.timevar	2.126	.634	3.36	.002	.846	3.405	***
40.timevar	2.142	.626	3.42	.001	.878	3.407	***
41.timevar	2.159	.628	3.44	.001	.892	3.426	***
42.timevar	2.213	.626	3.54	.001	.949	3.477	***
43.timevar	2.164	.636	3.40	.001	.88	3.448	***
44.timevar	2.125	.615	3.46	.001	.883	3.367	***
45.timevar	1.873	.61	3.07	.004	.641	3.104	***
46.timevar	2.065	.636	3.25	.002	.781	3.349	***
47.timevar	1.772	.621	2.85	.007	.518	3.026	***
48.timevar	1.208	.604	2.00	.052	-.013	2.429	*
49.timevar	1.07	.594	1.80	.079	-.13	2.27	*
50.timevar	1.068	.592	1.80	.079	-.128	2.264	*
51.timevar	.793	.647	1.23	.227	-.513	2.1	
52.timevar	.696	.633	1.10	.278	-.582	1.974	
53.timevar	.423	.637	0.66	.511	-.865	1.71	
54.timevar	-.062	.64	-0.10	.923	-1.354	1.23	
55.timevar	.032	.629	0.05	.96	-1.238	1.302	

56o.timevar	0	.	.	.	.	.	
CarbonTaxRate	.015	.02	0.73	.468	-.026	.056	
Coal	12.947	1.678	7.72	0	9.559	16.335	***
Oil	10.108	1.159	8.72	0	7.766	12.449	***
Constant	5.019	.549	9.14	0	3.91	6.128	***

Mean dependent var	8.905	SD dependent var	1.968
R-squared	0.978	Number of obs	98.000
F-test	33.316	Prob > F	0.000
Akaike crit. (AIC)	147.549	Bayesian crit. (BIC)	294.892

*** *p<.01, *** *p<.05, * *p<.1*

Like in other models using Denmark the controls for Nuclear and biofuels were automatically removed for multicollinearity. Also, wind, geobiomass, gas, and solar were dropped due to their insignificance. Coal and oil were the only controls left with coefficients of 12.947 EJ and 10.108 EJ meaning their usage causes emissions to rise.

The taxed variable has a coefficient of -4.364 which is significant, and this indicates that Denmark has lower emissions levels than Iceland but since the interaction term of y90taxed is insignificant we cannot draw any conclusions from before and after policy implementation. Again, only eleven out of fifty of the year dummies have any significance but again most of them are between zero and one meaning they are in percent change.

Table 13. Combined Difference-in-Differences Regression:

Linear regression

C02Emissions	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
y90taxed	-.495	.247	-2.01	.046	-.982	-.008	**
Taxed	-1.932	.332	-5.81	0	-2.587	-1.276	***
Coal	10.132	1.238	8.18	0	7.689	12.575	***
Gas	10.575	2.086	5.07	0	6.459	14.691	***
Hydro	-6.689	.64	-10.46	0	-7.951	-5.428	***
Nuclear	-1.388	.527	-2.63	.009	-2.429	-.348	***
Wind	-32.696	3.243	-10.08	0	-39.094	-26.297	***
Oil	6.265	.421	14.87	0	5.434	7.096	***
Biofuelstwh	.251	.04	6.28	0	.172	.33	***
Constant	7.548	.101	74.87	0	7.349	7.747	***

Mean dependent var	8.766	SD dependent var	2.207
R-squared	0.913	Number of obs	196.000
F-test	216.811	Prob > F	0.000
Akaike crit. (AIC)	406.993	Bayesian crit. (BIC)	439.774

*** p<.01, ** p<.05, * p<.1*

The controls for Geobiomass and solar were dropped as they were not statistically significant, but everything else is significant and that is important as this regression has a lot more controls which are statistically significant while the individual countries models with less observations have less significant control variables. Coal, gas, and oil all had expectedly positive coefficients of 10.132, 10.575, and 6.265. Biofuels were unexpectedly positive with a coefficient of .251 which would mean that for an increase in one twh of biofuels usage would cause an increase in .251 metric tons of carbon emissions per capita. This does not make a ton of sense since we would expect more biofuel usage to decrease carbon emissions and so we could consider this result a perverse one. Although the coefficient is only .251 which is very close to zero but the result itself is significant even at the one percent level so we cannot say that the effect of zero or negative is a possibility which again does not make a ton of sense.

Looking at the taxed value which is -1.932 which is also statistically significant and so we can conclude that in this regression countries with carbon taxes have a lower level of emissions and so these three countries have lower emissions compared to Iceland. The interaction term is finally significant and the value of that is -.495 which would state that there is a negative change in emissions due to the existence of a carbon tax rate when looking at the treatment group which includes Finland, Sweden, and Denmark compared to the control group of Iceland.

Table 14. Combined Difference-in-Differences Regression with Time Dummies:

Linear regression

C02Emissions	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
y90taxed	-1.11	.365	-3.04	.003	-1.832	-.389	***
Taxed	-1.461	.376	-3.88	0	-2.205	-.716	***

1b.timevar	0	.	.	.	.	.	
5.timevar	-1.953	.776	-2.52	.013	-3.488	-.419	**
6.timevar	-1.355	.773	-1.75	.082	-2.884	.175	*
7.timevar	-1.616	.776	-2.08	.039	-3.15	-.082	**
8.timevar	-.987	.775	-1.27	.205	-2.52	.546	
9.timevar	-1.028	.774	-1.33	.187	-2.559	.504	
10.timevar	-.686	.777	-0.88	.379	-2.221	.85	
11.timevar	-.73	.781	-0.94	.351	-2.274	.813	
12.timevar	-.56	.781	-0.72	.475	-2.104	.984	
13.timevar	-.048	.777	-0.06	.95	-1.585	1.489	
14.timevar	-.448	.779	-0.58	.566	-1.988	1.092	
15.timevar	-.604	.779	-0.78	.44	-2.144	.937	
16.timevar	-.317	.775	-0.41	.683	-1.849	1.216	
17.timevar	-.087	.774	-0.11	.91	-1.618	1.444	
18.timevar	-.683	.772	-0.88	.378	-2.211	.845	
19.timevar	-.438	.772	-0.57	.571	-1.965	1.088	
20.timevar	-.84	.767	-1.10	.275	-2.357	.676	
21.timevar	-1.082	.769	-1.41	.162	-2.602	.438	
22.timevar	-1.818	.766	-2.37	.019	-3.332	-.303	**
23.timevar	-1.94	.766	-2.53	.012	-3.456	-.425	**
24.timevar	-1.68	.767	-2.19	.03	-3.197	-.164	**
25.timevar	-1.403	.771	-1.82	.071	-2.929	.122	*
26.timevar	-1.43	.776	-1.84	.068	-2.963	.104	*
27.timevar	-1.032	.781	-1.32	.189	-2.577	.513	
28.timevar	-1.52	.784	-1.94	.055	-3.071	.031	*
29.timevar	-1.697	.789	-2.15	.033	-3.257	-.137	**
30.timevar	-1.084	.766	-1.41	.159	-2.6	.432	
31.timevar	-1.004	.763	-1.32	.19	-2.512	.504	
32.timevar	-1.306	.768	-1.70	.091	-2.826	.213	*
33.timevar	-1.083	.768	-1.41	.16	-2.601	.435	
34.timevar	-1.057	.763	-1.39	.168	-2.567	.452	
35.timevar	-1.191	.77	-1.55	.124	-2.713	.331	
36.timevar	-.73	.767	-0.95	.343	-2.247	.786	
37.timevar	-.804	.766	-1.05	.296	-2.32	.711	
38.timevar	-.802	.767	-1.05	.298	-2.319	.715	
39.timevar	-1.094	.768	-1.42	.157	-2.613	.425	
40.timevar	-.969	.764	-1.27	.207	-2.479	.541	
41.timevar	-.937	.762	-1.23	.221	-2.444	.57	
42.timevar	-.806	.754	-1.07	.287	-2.297	.685	
43.timevar	-.995	.746	-1.33	.185	-2.47	.48	
44.timevar	-.633	.739	-0.86	.393	-2.096	.829	
45.timevar	-1.033	.74	-1.40	.165	-2.496	.43	
46.timevar	-1.095	.736	-1.49	.139	-2.551	.361	
47.timevar	-.981	.723	-1.36	.177	-2.411	.45	
48.timevar	-1.291	.724	-1.78	.077	-2.722	.14	*
49.timevar	-1.721	.723	-2.38	.019	-3.15	-.292	**
50.timevar	-1.458	.709	-2.06	.042	-2.86	-.056	**
51.timevar	-.407	.664	-0.61	.54	-1.72	.905	
52.timevar	-.151	.654	-0.23	.818	-1.444	1.142	
53.timevar	-.091	.627	-0.15	.885	-1.331	1.149	
54.timevar	.183	.61	0.30	.765	-1.024	1.39	
55.timevar	.962	.61	1.58	.117	-.245	2.169	
56o.timevar	0	.	.	.	.	.	
Coal	11.168	1.541	7.25	0	8.122	14.215	***
Gas	14.256	2.442	5.84	0	9.426	19.085	***
Hydro	-5.286	.649	-8.14	0	-6.569	-4.002	***

Nuclear	-1.351	.604	-2.24	.027	-2.545	-.157	**
Wind	-40.826	5.454	-7.49	0	-51.611	-30.04	***
Oil	4.925	.453	10.86	0	4.028	5.821	***
Biofuelstwh	.225	.04	5.66	0	.147	.304	***
Constant	8.567	.701	12.22	0	7.181	9.954	***

Mean dependent var	8.766	SD dependent var	2.207
R-squared	0.949	Number of obs	196.000
F-test	41.808	Prob > F	0.000
Akaike crit. (AIC)	404.520	Bayesian crit. (BIC)	604.485

*** *p<.01*, ** *p<.05*, * *p<.1*

I think the fact that most of the controls and the main interaction terms are significant would point towards the idea that the power of the model is significantly more powerful. Therefore, the combined difference-in-differences model is more important than the individual difference-in-differences models as we can now include the year fixed effects as there are a lot more observations with one hundred and ninety-six compared to around fifty for each country and that means we can more reliably include more variables which in this case is the variables for year fixed effects.

The controls for Geobiomass and solar were dropped as they were not statistically significant, but everything else is significant and that is important as this regression has a lot more controls which are statistically significant. Coal, gas, and oil all had expectedly positive coefficients of 11.168, 14.256, and 4.925. Biofuels were unexpectedly positive with a coefficient of .225 which would mean that for an increase in one twh of biofuels usage would cause an increase by .225 metric tons of carbon emissions per capita. This does not make a ton of sense since we would expect more biofuel usage to decrease carbon emissions and so we could consider this result a perverse one. Although the coefficient is only .225 which is very close to zero but the result itself is significant even at the one percent level so we cannot say that the effect of zero or negative is a possibility which again does not make a ton of sense.

Looking at the taxed value which is -1.461 which is also statistically significant and so we can conclude that in this regression countries with carbon taxes have a lower level of emissions and so these three countries have lower emissions compared to Iceland. The interaction term is finally significant and the value of that is -1.11 which would state that there is a negative change in emissions when looking at the treatment group which includes Finland, Sweden, and Denmark compared to the control group of Iceland. So far, most results in this regression have made a great deal of sense and we are able to make conclusions about the main variables, but the problem is that most of the time variables are still insignificant. Since there are more observations it would seem more likely that most of the time dummies just might not be significant and important, because looking at the individual country models you could say that most of the time dummies are insignificant because of a lack of observations, but even after you pool all of the observations together, we still cannot make too much of a definite conclusion about most of the year dummy variables.

CHAPTER SIX

CONCLUSION

Geometric Lag Overall Conclusions:

The most important conclusion that I got from the regressions so far is that for there to be a decaying effectiveness overtime of carbon taxes on emissions there must be an overall effectiveness of carbon taxes on emissions. So, what was found in the regressions above largely went along with existing research on this topic since other papers noted that there was not much effectiveness of taxes on emissions in the countries of Sweden and Denmark. Going off that it is likely that since there was no initial effectiveness it is unlikely that there would be any decreasing effectiveness. A reason for the difference between the results of Finland compared to Sweden and Denmark is that Finland has a much broader tax policy with less exemptions which makes its tax more effective. Since Finland appears to be the only country with a truly effective tax it would make sense that they should be the ones most concerned with a decreasing effectiveness due to inflation, and this is likely why Finland is the only country where we can accept the hypothesis that there is a decaying rate of effectiveness.

Analyzing the lag variable coefficient and the tax rate are the same as before as they likely are not causing any change. The controls do all go in a way in which we would expect and make more sense than the ones in OLS.

Difference-in-Differences Overall Conclusions:

Unfortunately, a lot of the results from the individual country DID analysis do not really tell us anything significant about the interaction terms. However, when we pool all the country data a lot more of the controls become significant also more importantly the taxed coefficient and the interaction term becomes significant and so the combined data somewhat covers the biggest problems within the individual country models since there are just simply more observations so we can include year fixed effects. After including year fixed effects, a lot of the time variables do not become significant and so I am not sure whether the number of observations is still an issue or is there nothing the year dummies can really tell us. I am leaning towards the first theory and I think it would be good to revisit this method of analysis later when there are more observations and possibly more countries to do analysis on and including the new updated taxes in these countries might also help when more data about these new taxes is available.

Comparison of Results to Emissions Tables:

Figure 4. Finland CO_2 Emissions Graph:

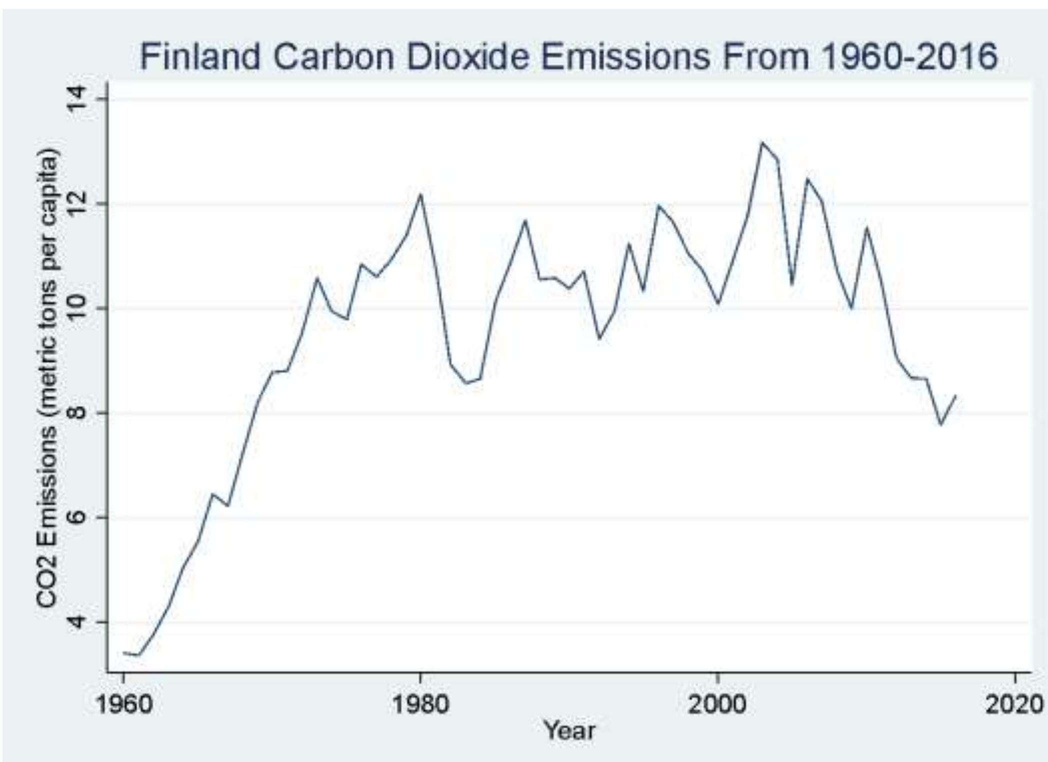


Figure 5. Sweden CO_2 Emissions Graph:

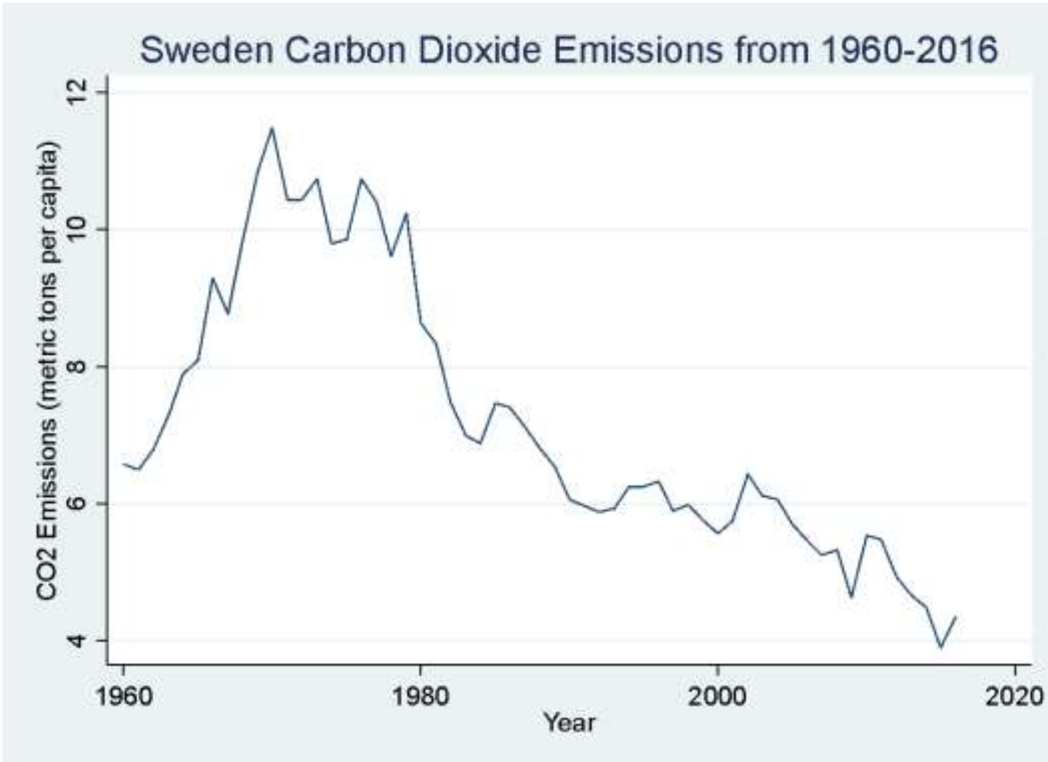
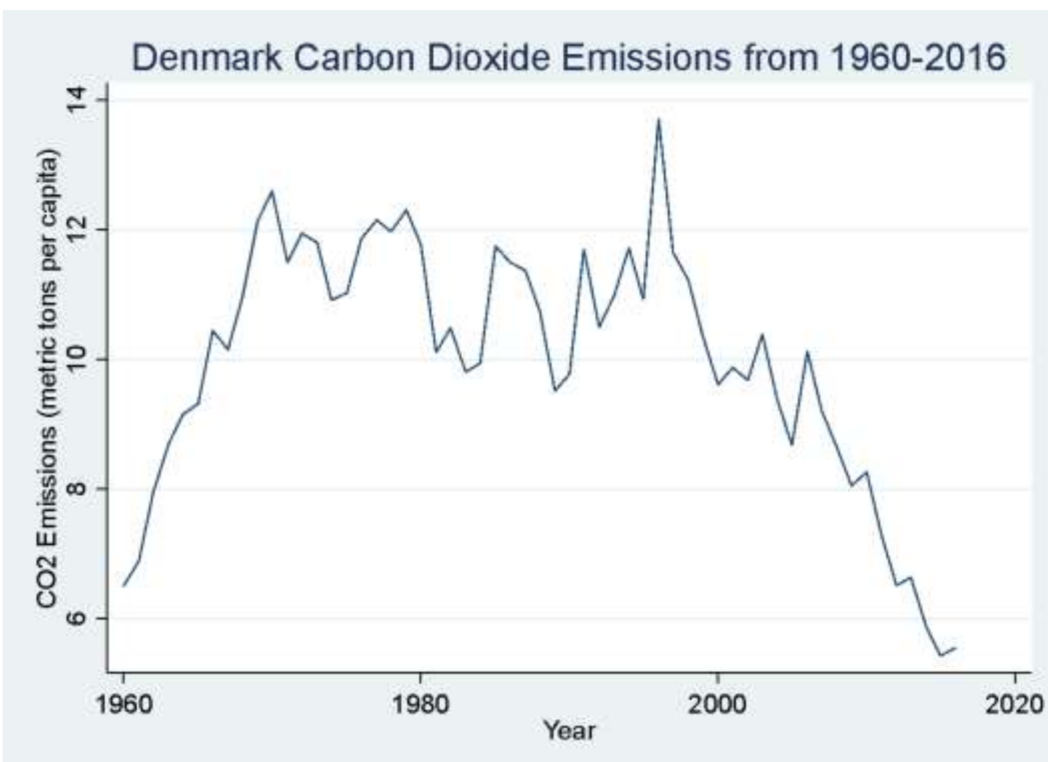


Figure 6. Denmark CO_2 Emissions Graph:



Comparing the emissions tables to the general results of the regressions is a very interesting thing because it would appear as if my results in general run against the emission trends in these countries. For example, Finland had the most significant impact of tax rate lowering emissions levels, but Finland is the country with the least amount of decline in emissions levels since the early 1990s. The fact that emission levels in Sweden steadily decline before the period of tax implementation points towards some other variable which is lowering emissions levels. This would make sense since emissions levels do not appear to be impacted much by the taxes in Sweden. For Denmark there is another interesting pattern, but in my opinion, I think that carbon taxes might have eventually impacted the emissions levels, but they are not the carbon taxes I looked at in my regressions. This is because Denmark changed their carbon tax policy in the mid-2010s to make less exceptions to the tax laws, and so I could not compare the initial tax figures in the nineties and the 2000s because they have different applications and do not work in the same exact way. I am not concerned with the validity of my regressions and methods used since existing literature which looks at the relationship between the tax rate and emissions levels generally mirrors the results that I found. In general it is likely that other factors are the ones driving the decline in Sweden, while other factors appear to be increasing emissions levels in Finland at a rate that makes the effects of the tax policies somewhat obsolete even though the taxes are relatively effective, and as for Denmark I think that the fact that I could not include later tax policies made it appear as if they had no effect because they did not for a while, but as more data comes out for the newer tax policies it would be interesting to see if the tax rate does eventually impact emissions. It would have been nice to run a regression on the new types of carbon taxes in each country which have less tax exemptions, but it would have been impossible to create a model with any statistical power since there would be a maximum of four observations and that is not even close enough to create any meaningful results.

Overall Conclusion:

There are several things that would be nice if I could do them differently and they mostly revolve around the access to data. Having monthly emission data would be great because you could add the time dummies to the individual country difference-in-differences models to avoid bias. It would also be great to look at the new types of taxes with less exemptions but there simply is not enough data because of the recency of their implementation and so if someone would like to replicate this model with those taxes, they would have to wait a few years. It would also be interesting to the same analysis just with microeconomic industry level data, but unfortunately that was not available.

One would have to be very careful to extrapolate these models to other countries especially lower income nations because it would be likely that they would need different controls. Also, if you were to combine the data for different countries you would likely have to be careful that you would be combining countries with similar economic conditions, and energy consumption patterns to avoid bias. Expanding this model to other countries in the current day likely would not be an issue as almost all the countries with carbon taxes are highly economically developed nations in Europe.

As far as summing up the results of the regressions combining the data was the biggest success since it was the model with by far the most amount of statistical power. When we did that, we proved our hypothesis results to be true in the sense that overall the durability of carbon taxes decreased, and that after implementing taxes emissions declined, but the problem comes when we try to draw conclusions about the individual regressions. It is hard to say much about the individual countries, especially since Finland seems to be the main driver of the combined results it is hard to see any real results of carbon taxes on emissions when we look at Sweden, and Denmark, but again that is not terribly surprising since that is what others have found.

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APPENDIX

Figure 1. Finland Event Study Graph:

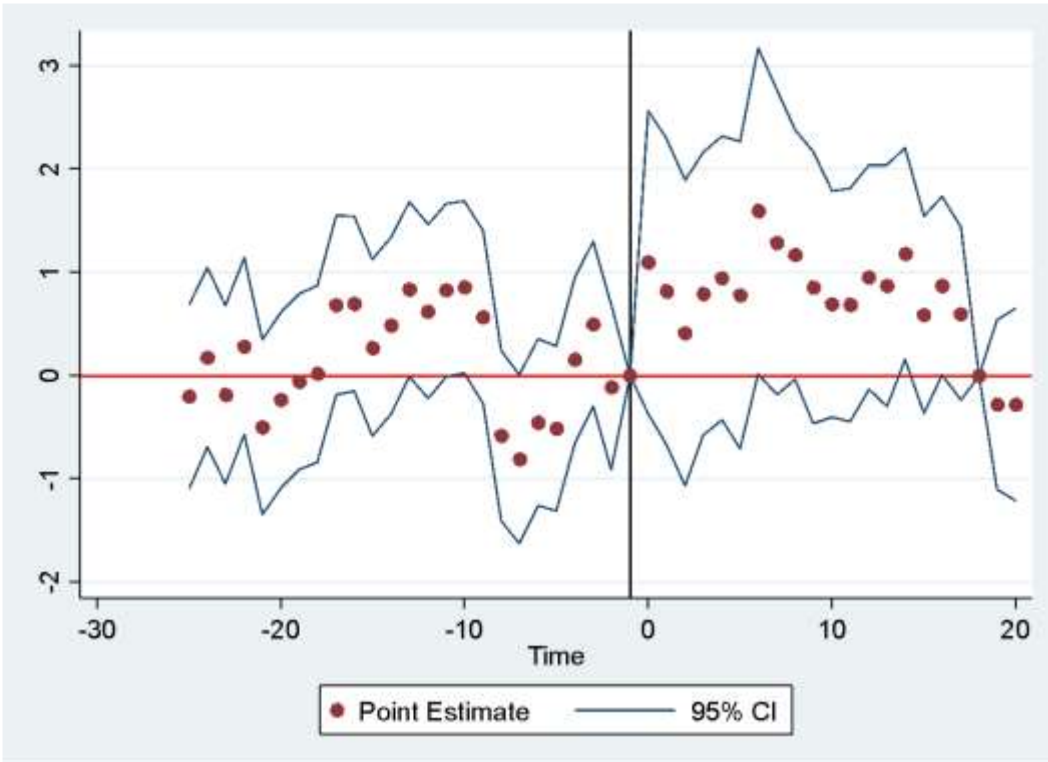

Figure 2. Sweden Event Study Graph:

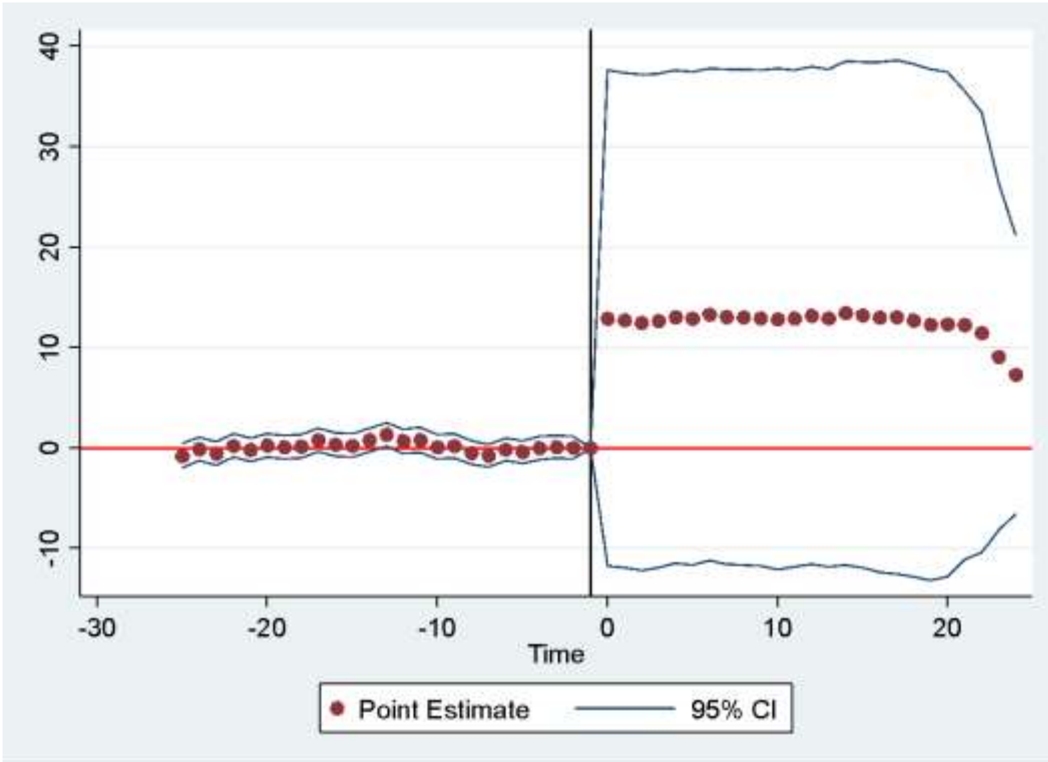

Figure 3. Denmark Event Study Graph:

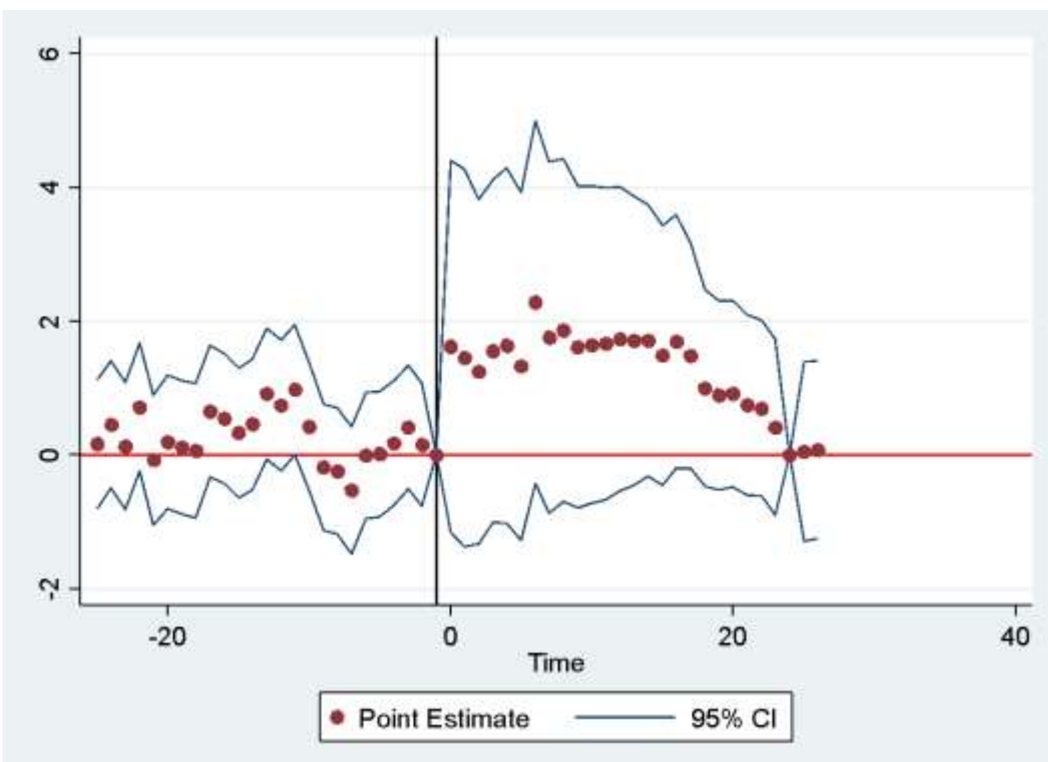

Figure 4. Finland CO_2 Emissions Graph:

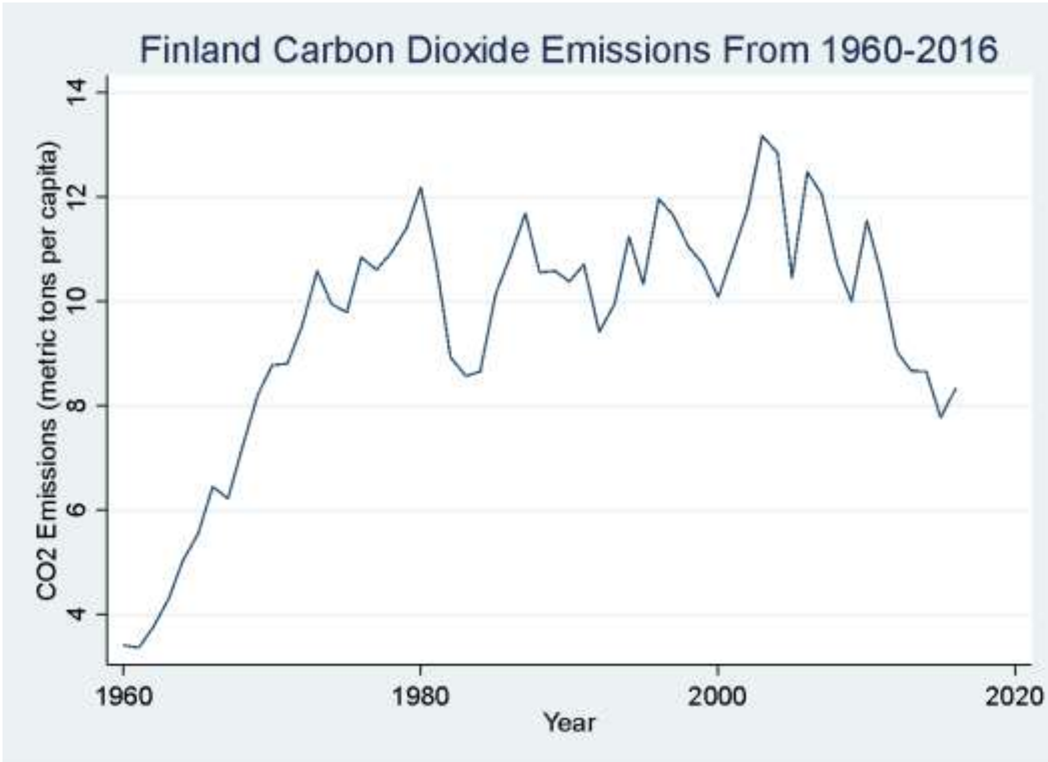

Figure 5. Sweden CO_2 Emissions Graph:

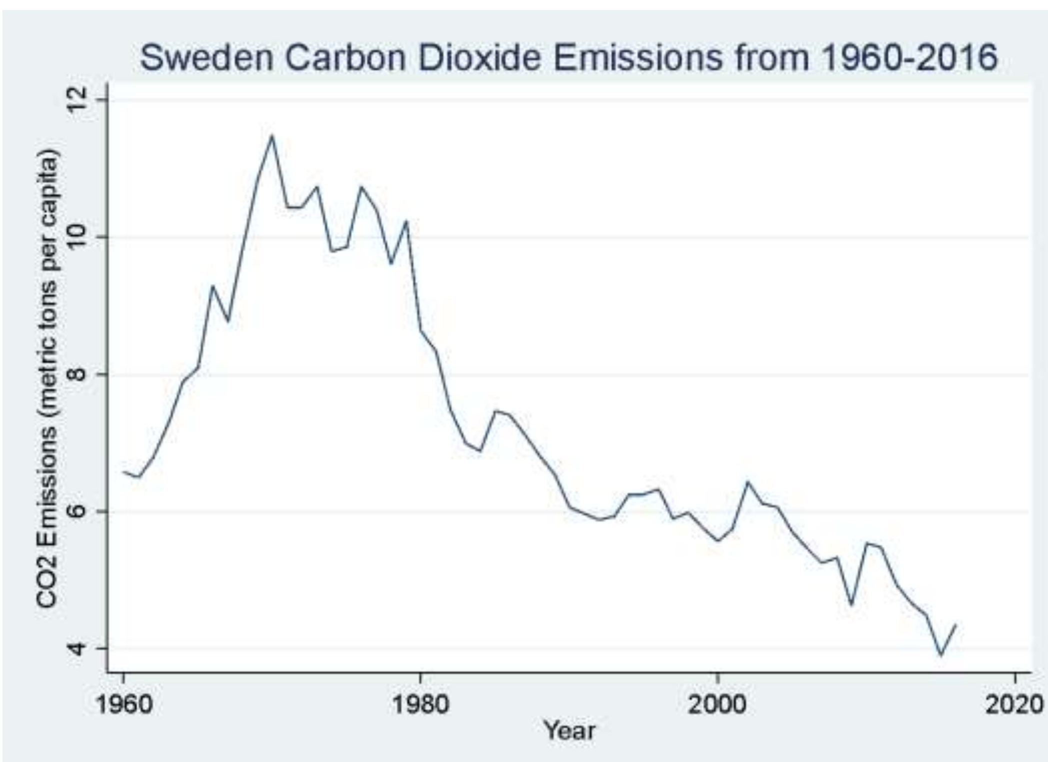

Figure 6. Denmark CO_2 Emissions Graph:

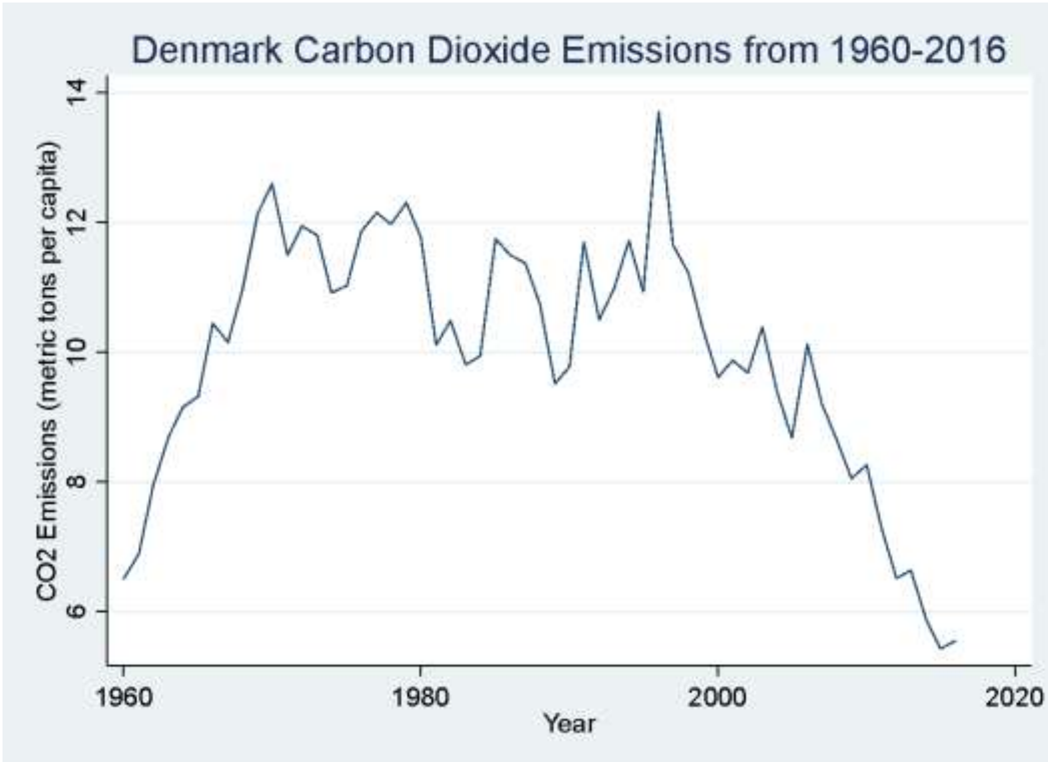

Table 1. Correlation between Taxed and Carbon Tax rate:

Pairwise correlations

Variables	(1)	(2)
(1) CarbonTaxRate	1.000	
(2) Taxed	0.423	1.000

Table 2. Finland Geometric Lag Regression:

Fitting full model:
Iteration 0: log likelihood = -11.791209
Iteration 1: log likelihood = -11.693021
Iteration 2: log likelihood = -11.691985
Iteration 3: log likelihood = -11.691985
Heteroskedastic linear regression Number of obs = 46
ML estimation
Wald chi2(7) = 2052.09
Log likelihood = -11.69198 Prob > chi2 = 0.0000

C02Emissions	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
C02Emissions						
C02Emissions						
L1.	0.163	0.063	2.580	0.010	0.039	0.286
CarbonTaxRate	0.080	0.027	2.950	0.003	0.027	0.134
Coal	20.605	1.655	12.450	0.000	17.362	23.848
GeoBiomass	-13.064	4.133	-3.160	0.002	-21.164	-4.965
Nuclear	-6.688	1.092	-6.130	0.000	-8.828	-4.549
Wind	-412.936	217.121	-1.900	0.057	-838.485	12.613

Oil	10.743	1.276	8.420	0.000	8.242	13.243
_cons	0.681	0.232	2.940	0.003	0.226	1.136
lnsigma2						
C02Emissions	0.293	0.158	1.860	0.063	-0.016	0.602
_cons	-5.331	1.629	-3.270	0.001	-8.523	-2.139

LR test of lnsigma2=0: chi2(1) = 2.81 Prob > chi2 = 0.0936

Table 3. Sweden Geometric Lag Regression:

Fitting full model:
Iteration 0: log likelihood = -28.992871
Iteration 1: log likelihood = -28.168082
Iteration 2: log likelihood = -28.143949
Iteration 3: log likelihood = -28.143935
Iteration 4: log likelihood = -28.143935
Heteroskedastic linear regression Number of obs = 50
ML estimation
Wald chi2(7) = 502.98
Log likelihood = -28.14394 Prob > chi2 = 0.0000

CO2emissions	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
CO2emissions						
CO2emissions						
L1.	0.950	0.100	9.510	0.000	0.754	1.146
CarbonTaxRate	-0.011	0.009	-1.230	0.219	-0.028	0.007
Coal	9.094	4.457	2.040	0.041	0.360	17.829
Gas	10.910	9.142	1.190	0.233	-7.008	28.829
Geo	-3.484	2.923	-1.190	0.233	-9.213	2.246
Solar	-1216.182	893.407	-1.360	0.173	-2967.229	534.864
Wind	10.802	6.044	1.790	0.074	-1.043	22.648
_cons	-0.827	1.027	-0.810	0.421	-2.839	1.186
lnsigma2						
CO2emissions	0.603	0.134	4.510	0.000	0.341	0.865
_cons	-6.075	0.988	-6.150	0.000	-8.011	-4.138

LR test of lnsigma2=0: chi2(1) = 24.28 Prob > chi2 = 0.0000

Table 4. Denmark Geometric Lag Regression:

Fitting full model:
Iteration 0: log likelihood = -3.8408746
Iteration 1: log likelihood = -3.5051207
Iteration 2: log likelihood = -3.5007985
Iteration 3: log likelihood = -3.5007971
Iteration 4: log likelihood = -3.5007971
Heteroskedastic linear regression Number of obs = 51
ML estimation
Wald chi2(6) = 2065.43
Log likelihood = -3.500797 Prob > chi2 = 0.0000

CO2emissions	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
CO2emissions						
CO2emissions						

L1.	-0.103	0.057	-1.800	0.072	-0.215	0.009
CarbonTaxRate	-0.018	0.009	-1.990	0.047	-0.036	-0.000
Coal	16.048	0.905	17.720	0.000	14.273	17.823
Gas	8.858	1.079	8.210	0.000	6.744	10.972
GeoBiomass	-23.480	10.130	-2.320	0.020	-43.335	-3.626
Oil	14.426	0.705	20.460	0.000	13.043	15.808
_cons	0.843	0.650	1.300	0.195	-0.431	2.116
lnsigma2						
CO2emissions	-0.065	0.147	-0.440	0.659	-0.353	0.224
_cons	-2.037	1.515	-1.340	0.179	-5.008	0.933

LR test of lnsigma2=0: chi2(1) = 0.19 Prob > chi2 = 0.6604

Table 5. Combined Geometric Lag Regression:

Fitting full model:
Iteration 0: log likelihood = -126.95594
Iteration 1: log likelihood = -124.3712
Iteration 2: log likelihood = -124.22816
Iteration 3: log likelihood = -124.22764
Iteration 4: log likelihood = -124.22764
Heteroskedastic linear regression Number of obs = 147
ML estimation
Wald chi2(7) = 2774.30
Log likelihood = -124.2276 Prob > chi2 = 0.0000

C02Emissions	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
C02Emissions						
C02Emissions						
L1.	0.541	0.050	10.810	0.000	0.443	0.639
CarbonTaxRate	0.008	0.006	1.390	0.164	-0.003	0.019
Coal	8.026	1.208	6.650	0.000	5.660	10.393
Hydro	-1.577	0.633	-2.490	0.013	-2.818	-0.336
Nuclear	-1.752	0.403	-4.350	0.000	-2.541	-0.963
Wind	-10.911	2.573	-4.240	0.000	-15.953	-5.868
Oil	2.319	0.488	4.760	0.000	1.363	3.274
_cons	2.203	0.328	6.710	0.000	1.560	2.846
lnsigma2						
C02Emissions	0.291	0.062	4.720	0.000	0.170	0.412
_cons	-3.828	0.580	-6.600	0.000	-4.966	-2.691

LR test of lnsigma2=0: chi2(1) = 18.30 Prob > chi2 = 0.0000

Table 6. Combined Geometric Lag Regression with Year Dummies:

Fitting full model:
Iteration 0: log likelihood = -26.688504
Iteration 1: log likelihood = -10.33696 (not concave)
Iteration 2: log likelihood = 3.491867
Iteration 3: log likelihood = 7.0011455

Iteration 4: log likelihood = 8.5721697
Iteration 5: log likelihood = 8.73885
Iteration 6: log likelihood = 8.9276453
Iteration 7: log likelihood = 8.9556693
Iteration 8: log likelihood = 8.956648
Iteration 9: log likelihood = 8.9566486
Heteroskedastic linear regression Number of obs = 147
ML estimation
Wald chi2(59) = 327558.19
Log likelihood = 8.956649 Prob > chi2 = 0.0000

C02Emissions	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
C02Emissions						
C02Emissions						
L1.	0.338	0.027	12.630	0.000	0.285	0.390
CarbonTaxRate	0.010	0.008	1.280	0.199	-0.006	0.026
Coal	16.156	1.332	12.130	0.000	13.546	18.766
Gas	17.738	2.143	8.280	0.000	13.537	21.939
Hydro	-0.777	0.363	-2.140	0.032	-1.488	-0.065
Solar	-81.895	5.151	-15.900	0.000	-91.991	-71.799
Wind	-32.665	5.995	-5.450	0.000	-44.414	-20.916
Oil	2.044	0.299	6.840	0.000	1.458	2.630
Year						
1966	0.709	0.031	22.990	0.000	0.649	0.770
1967	0.197	0.044	4.530	0.000	0.112	0.283
1968	0.960	0.053	18.110	0.000	0.856	1.064
1969	1.250	0.111	11.250	0.000	1.033	1.468
1970	1.353	0.173	7.840	0.000	1.015	1.692
1971	1.335	0.180	7.430	0.000	0.983	1.687
1972	1.815	0.283	6.410	0.000	1.260	2.370
1973	2.160	0.537	4.020	0.000	1.107	3.213
1974	1.111	0.299	3.710	0.000	0.524	1.697
1975	1.283	0.286	4.490	0.000	0.722	1.843
1976	1.811	0.597	3.040	0.002	0.642	2.981
1977	1.358	0.484	2.810	0.005	0.410	2.307
1978	0.449	0.350	1.280	0.200	-0.238	1.136
1979	0.957	0.533	1.800	0.073	-0.088	2.002
1980	-0.485	0.223	-2.170	0.030	-0.923	-0.048
1981	0.179	0.173	1.030	0.302	-0.161	0.519
1982	-0.525	0.134	-3.930	0.000	-0.787	-0.263
1983	-0.620	0.113	-5.480	0.000	-0.842	-0.398
1984	-0.753	0.128	-5.880	0.000	-1.004	-0.502
1985	-0.579	0.153	-3.770	0.000	-0.879	-0.278
1986	-1.263	0.150	-8.410	0.000	-1.557	-0.969
1987	-1.182	0.158	-7.490	0.000	-1.491	-0.873
1988	-1.288	0.149	-8.660	0.000	-1.579	-0.996
1989	-1.330	0.144	-9.260	0.000	-1.612	-1.049
1990	-1.888	0.139	-13.550	0.000	-2.161	-1.615
1991	-1.744	0.086	-20.190	0.000	-1.913	-1.575
1992	-1.712	0.099	-17.360	0.000	-1.906	-1.519
1993	-1.670	0.101	-16.610	0.000	-1.867	-1.473
1994	-1.601	0.101	-15.860	0.000	-1.798	-1.403
1995	-1.562	0.095	-16.510	0.000	-1.747	-1.376
1996	-1.965	0.123	-15.930	0.000	-2.207	-1.723
1997	-1.966	0.148	-13.300	0.000	-2.256	-1.677

1998	-1.841	0.143	-12.900	0.000	-2.120	-1.561
1999	-1.944	0.139	-13.990	0.000	-2.216	-1.672
2000	-1.766	0.112	-15.770	0.000	-1.986	-1.547
2001	-1.703	0.107	-15.950	0.000	-1.912	-1.494
2002	-1.316	0.104	-12.640	0.000	-1.520	-1.112
2003	-2.052	0.148	-13.830	0.000	-2.342	-1.761
2004	-1.911	0.138	-13.840	0.000	-2.181	-1.640
2005	-1.943	0.130	-14.970	0.000	-2.198	-1.689
2006	-2.361	0.132	-17.930	0.000	-2.619	-2.103
2007	-2.190	0.130	-16.890	0.000	-2.444	-1.936
2008	-1.796	0.136	-13.250	0.000	-2.061	-1.530
2009	-1.875	0.109	-17.130	0.000	-2.089	-1.660
2010	-1.214	0.108	-11.200	0.000	-1.426	-1.001
2011	-0.520	0.086	-6.050	0.000	-0.689	-0.352
2012	-0.250	0.114	-2.180	0.029	-0.474	-0.026
2013	0.336	0.171	1.970	0.049	0.002	0.671
2014	0.892	0.250	3.570	0.000	0.402	1.382
2015	1.636	0.323	5.070	0.000	1.004	2.268
2016	1.311	0.246	5.340	0.000	0.829	1.793
_cons	2.251	0.136	16.570	0.000	1.985	2.517
lnsigma2						
C02Emissions	1.674	0.221	7.580	0.000	1.242	2.107
_cons	-18.377	2.036	-9.020	0.000	-22.368	-14.386

LR test of lnsigma2=0: chi2(1) = 129.59 Prob > chi2 = 0.0000

Table 7. Finland Difference-in-Differences Regression:

Linear regression

C02Emissions	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CarbonTaxRate	.122	.031	3.93	0	.06	.183	***
y90	-.042	.167	-0.25	.802	-.374	.29	
Taxed	-6.604	.504	-13.11	0	-7.606	-5.601	***
y90taxed	.183	.396	0.46	.646	-.606	.972	
Coal	20.502	2.14	9.58	0	16.246	24.759	***
GeoBiomass	-20.681	6.804	-3.04	.003	-34.218	-7.145	***
Nuclear	-4.677	1.437	-3.25	.002	-7.536	-1.818	***
Wind	-613.173	265.57	-2.31	.023	-1141.476	-84.871	**
Oil	14.015	1.206	11.62	0	11.616	16.415	***
Constant	7.186	.097	74.04	0	6.993	7.379	***

Mean dependent var	8.848	SD dependent var	1.870
R-squared	0.945	Number of obs	92.000
F-test	155.575	Prob > F	0.000
Akaike crit. (AIC)	128.928	Bayesian crit. (BIC)	154.146

**** p<.01, ** p<.05, * p<.1*

Table 8. Effect of Tax rate Every Year by plotting Coefficients Finland DID:

Linear regression

C02Emissions	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Taxed	-5.144	.593	-8.68	0	-6.341	-3.947	***
y90taxed	-.725	.325	-2.23	.031	-1.381	-.068	**
5.timevar	-.122	.435	-0.28	.78	-1.001	.757	
6.timevar	.251	.423	0.59	.556	-.603	1.104	
7.timevar	-.112	.42	-0.27	.791	-.96	.736	
8.timevar	.358	.413	0.87	.392	-.476	1.192	
9.timevar	-.423	.407	-1.04	.304	-1.245	.398	
10.timevar	-.158	.404	-0.39	.699	-.973	.658	
11.timevar	.014	.404	0.04	.972	-.802	.831	
12.timevar	.093	.404	0.23	.82	-.724	.91	
13.timevar	.757	.409	1.85	.071	-.069	1.582	*
14.timevar	.772	.403	1.91	.063	-.043	1.587	*
15.timevar	.341	.405	0.84	.403	-.475	1.158	
16.timevar	.566	.405	1.40	.17	-.252	1.385	
17.timevar	.913	.405	2.26	.029	.096	1.73	**
18.timevar	.706	.407	1.74	.09	-.116	1.528	*
19.timevar	.91	.408	2.23	.031	.085	1.734	**
20.timevar	.943	.409	2.31	.026	.117	1.77	**
21.timevar	.632	.404	1.56	.126	-.184	1.448	
22.timevar	-.513	.403	-1.27	.21	-1.328	.301	
23.timevar	-.738	.406	-1.82	.076	-1.557	.081	*
24.timevar	-.381	.408	-0.94	.355	-1.205	.442	
25.timevar	-.428	.415	-1.03	.309	-1.267	.411	
26.timevar	.235	.41	0.57	.569	-.593	1.064	
27.timevar	.582	.415	1.40	.168	-.255	1.42	
28.timevar	-.028	.415	-0.07	.947	-.866	.811	
29.timevar	.085	.414	0.21	.838	-.751	.921	
30.timevar	.28	.385	0.73	.471	-.497	1.058	
31b.timevar	0	.	.	.	.	.	
32.timevar	-.403	.386	-1.05	.302	-1.182	.376	
33.timevar	-.016	.386	-0.04	.967	-.795	.763	
34.timevar	.131	.389	0.34	.738	-.655	.918	
35.timevar	-.109	.39	-0.28	.781	-.897	.679	
36.timevar	.719	.394	1.82	.076	-.077	1.515	*
37.timevar	.345	.397	0.87	.39	-.457	1.147	
38.timevar	.24	.394	0.61	.546	-.556	1.036	
39.timevar	-.104	.401	-0.26	.797	-.913	.706	
40.timevar	-.18	.398	-0.45	.654	-.983	.624	
41.timevar	-.175	.396	-0.44	.661	-.974	.624	
42.timevar	.095	.397	0.24	.813	-.707	.896	
43.timevar	.003	.414	0.01	.994	-.834	.84	
44.timevar	.324	.413	0.78	.437	-.51	1.159	
45.timevar	-.239	.413	-0.58	.566	-1.074	.595	
46.timevar	.087	.413	0.21	.835	-.747	.92	
47.timevar	-.17	.415	-0.41	.685	-1.007	.668	
48.timevar	-.763	.431	-1.77	.084	-1.633	.107	*
49.timevar	-.969	.42	-2.31	.026	-1.816	-.121	**
50.timevar	-.915	.422	-2.17	.036	-1.768	-.062	**
CarbonTaxRate	.052	.013	3.88	0	.025	.079	***
Coal	15.39	1.968	7.82	0	11.417	19.364	***
Oil	11.512	1.443	7.98	0	8.598	14.425	***
Constant	7.024	.298	23.61	0	6.423	7.625	***

Mean dependent var	8.848	SD dependent var	1.870
R-squared	0.981	Number of obs	92.000
F-test	42.080	Prob > F	0.000

Akaike crit. (AIC)	113.153	Bayesian crit. (BIC)	241.765

*** p<.01, ** p<.05, * p<.1

Table 9. Sweden Difference-in-Differences Regression:

Linear regression

C02Emissions	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CarbonTaxRate	.034	.018	1.91	.059	-.001	.069	*
y90	-.019	.171	-0.11	.913	-.358	.321	
Taxed	-3.555	1.195	-2.97	.004	-5.931	-1.18	***
y90taxed	-.143	.436	-0.33	.744	-1.01	.724	
Coal	17.181	7.273	2.36	.02	2.724	31.637	**
GeoBiomass	-15.906	4.479	-3.55	.001	-24.809	-7.003	***
Nuclear	-4.413	.573	-7.70	0	-5.552	-3.274	***
Solar	-2528.152	1176.262	-2.15	.034	-4866.101	-190.203	**
Oil	4.449	.748	5.94	0	2.961	5.937	***
Constant	7.416	.109	68.16	0	7.199	7.632	***

Mean dependent var	7.348	SD dependent var	1.542
R-squared	0.892	Number of obs	97.000
F-test	80.159	Prob > F	0.000
Akaike crit. (AIC)	162.048	Bayesian crit. (BIC)	187.795

*** p<.01, ** p<.05, * p<.1

Table 10. Effect of Tax rate Every Year by Plotting Coefficients Sweden DID:

Linear regression

C02Emissions	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
y90taxed	-.251	.556	-0.45	.654	-1.375	.872	
Taxed	2.051	1.335	1.54	.132	-.648	4.749	
5.timevar	-.71	.571	-1.24	.221	-1.864	.444	
6.timevar	-.03	.563	-0.05	.958	-1.167	1.107	
7.timevar	-.422	.561	-0.75	.456	-1.557	.712	
8.timevar	.306	.556	0.55	.585	-.818	1.431	
9.timevar	-.192	.56	-0.34	.733	-1.325	.94	
10.timevar	.327	.563	0.58	.564	-.81	1.464	
11.timevar	.211	.556	0.38	.707	-.914	1.335	
12.timevar	.205	.557	0.37	.715	-.921	1.331	
13.timevar	1.017	.564	1.80	.079	-.124	2.157	*
14.timevar	.535	.559	0.96	.345	-.595	1.664	
15.timevar	.412	.553	0.75	.461	-.706	1.531	
16.timevar	.94	.553	1.70	.097	-.177	2.058	*
17.timevar	1.276	.551	2.32	.026	.163	2.389	**
18.timevar	.805	.571	1.41	.166	-.348	1.958	
19.timevar	1.128	.588	1.92	.062	-.061	2.316	*
20.timevar	.236	.563	0.42	.677	-.903	1.375	
21.timevar	.123	.554	0.22	.826	-.996	1.242	
22.timevar	-.654	.55	-1.19	.241	-1.765	.457	
23.timevar	-.753	.552	-1.36	.181	-1.869	.363	
24.timevar	-.014	.557	-0.03	.979	-1.14	1.111	
25.timevar	-.018	.56	-0.03	.974	-1.15	1.113	
26.timevar	.233	.561	0.42	.679	-.9	1.366	

27.timevar	.429	.563	0.76	.451	-.71	1.567	
28.timevar	.272	.564	0.48	.632	-.868	1.411	
29.timevar	.193	.567	0.34	.736	-.953	1.338	
30.timevar	.297	.544	0.55	.588	-.803	1.397	
31b.timevar	0	.	.	.	.	.	
32.timevar	-.078	.545	-0.14	.887	-1.179	1.024	
33.timevar	.193	.547	0.35	.727	-.914	1.299	
34.timevar	.309	.53	0.58	.563	-.762	1.381	
35.timevar	.298	.533	0.56	.579	-.779	1.376	
36.timevar	.614	.538	1.14	.26	-.472	1.701	
37.timevar	.546	.559	0.98	.334	-.583	1.676	
38.timevar	.597	.571	1.05	.302	-.556	1.75	
39.timevar	.358	.561	0.64	.527	-.776	1.493	
40.timevar	.298	.587	0.51	.615	-.888	1.483	
41.timevar	.422	.566	0.74	.461	-.722	1.566	
42.timevar	.578	.542	1.07	.292	-.517	1.673	
43.timevar	.178	.544	0.33	.745	-.921	1.277	
44.timevar	.578	.551	1.05	.3	-.535	1.692	
45.timevar	.418	.574	0.73	.47	-.741	1.578	
46.timevar	.017	.551	0.03	.975	-1.097	1.131	
47.timevar	-.036	.568	-0.06	.95	-1.183	1.112	
48.timevar	-.195	.614	-0.32	.753	-1.436	1.047	
49.timevar	-1.004	.577	-1.74	.09	-2.171	.163	*
50.timevar	-.536	.589	-0.91	.369	-1.727	.655	
51.timevar	.374	.972	0.38	.702	-1.591	2.339	
52.timevar	.261	1.018	0.26	.799	-1.796	2.319	
53.timevar	-.416	.951	-0.44	.664	-2.338	1.506	
54.timevar	-.58	.961	-0.60	.55	-2.521	1.362	
55.timevar	-.397	1.485	-0.27	.791	-3.399	2.606	
CarbonTaxRate	-.026	.021	-1.26	.216	-.068	.016	
Hydro	-3.048	1.754	-1.74	.09	-6.592	.497	*
Nuclear	-3.395	.727	-4.67	0	-4.865	-1.925	***
Oil	1.792	.896	2.00	.052	-.018	3.603	*
Constant	7.325	.395	18.56	0	6.527	8.122	***

Mean dependent var	7.348	SD dependent var	1.542
R-squared	0.951	Number of obs	97.000
F-test	13.867	Prob > F	0.000
Akaike crit. (AIC)	179.706	Bayesian crit. (BIC)	326.464

**** p<.01, ** p<.05, * p<.1*

Table 11. Denmark Difference-in-Differences Regression:

Linear regression

C02Emissions	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CarbonTaxRate	-.01	.013	-0.76	.447	-.036	.016	
y90	.025	.152	0.17	.869	-.277	.328	
Taxed	-6.513	.558	-11.67	0	-7.622	-5.404	***
y90taxed	-.303	.38	-0.80	.428	-1.058	.452	
Coal	14.864	1.064	13.97	0	12.749	16.978	***
Gas	9.108	1.99	4.58	0	5.154	13.062	***
GeoBiomass	-23.979	6.046	-3.97	0	-35.991	-11.966	***
Oil	13.133	.742	17.69	0	11.658	14.608	***
Constant	7.215	.087	83.29	0	7.043	7.387	***

Mean dependent var	8.905	SD dependent var	1.968

Table 12. Effect of Tax rate Every Year by plotting Coefficients Denmark DID:

Linear regression

C02Emissions	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Taxed	-4.364	.874	-4.99	0	-6.13	-2.599	***
y90taxed	.145	.388	0.37	.71	-.638	.929	
5.timevar	.119	.494	0.24	.811	-.879	1.117	
6.timevar	.425	.484	0.88	.386	-.553	1.402	
7.timevar	.104	.485	0.21	.831	-.876	1.085	
8.timevar	.694	.485	1.43	.16	-.285	1.672	
9.timevar	-.072	.484	-0.15	.883	-1.049	.906	
10.timevar	.206	.489	0.42	.676	-.782	1.194	
11.timevar	.12	.493	0.24	.809	-.875	1.115	
12.timevar	.079	.495	0.16	.874	-.921	1.078	
13.timevar	.66	.489	1.35	.184	-.327	1.646	
14.timevar	.538	.488	1.10	.277	-.447	1.524	
15.timevar	.323	.489	0.66	.513	-.664	1.309	
16.timevar	.467	.485	0.96	.341	-.512	1.447	
17.timevar	.926	.484	1.91	.063	-.051	1.903	*
18.timevar	.754	.483	1.56	.126	-.222	1.73	
19.timevar	.987	.481	2.05	.047	.016	1.958	**
20.timevar	.423	.478	0.88	.382	-.543	1.388	
21.timevar	-.202	.479	-0.42	.675	-1.169	.765	
22.timevar	-.272	.48	-0.57	.574	-1.241	.697	
23.timevar	-.566	.482	-1.17	.247	-1.54	.408	
24.timevar	-.039	.482	-0.08	.936	-1.012	.934	
25.timevar	.02	.48	0.04	.967	-.95	.99	
26.timevar	.201	.481	0.42	.678	-.77	1.172	
27.timevar	.444	.482	0.92	.363	-.53	1.418	
28.timevar	.192	.482	0.40	.692	-.782	1.167	
29.timevar	.03	.487	0.06	.952	-.954	1.013	
30.timevar	.14	.451	0.31	.757	-.77	1.051	
31b.timevar	0	.	.	.	.	.	
32.timevar	-.269	.468	-0.57	.569	-1.215	.676	
33.timevar	.047	.471	0.10	.921	-.904	.998	
34.timevar	.163	.47	0.35	.731	-.787	1.113	
35.timevar	-.143	.479	-0.30	.767	-1.111	.825	
36.timevar	.86	.492	1.75	.088	-.133	1.853	*
37.timevar	.32	.472	0.68	.502	-.633	1.272	
38.timevar	.418	.466	0.90	.375	-.523	1.36	
39.timevar	.137	.47	0.29	.773	-.812	1.085	
40.timevar	.153	.47	0.33	.746	-.795	1.102	
41.timevar	.17	.467	0.36	.718	-.774	1.114	
42.timevar	.224	.468	0.48	.635	-.721	1.168	
43.timevar	.175	.467	0.37	.71	-.768	1.118	
44.timevar	.136	.478	0.28	.777	-.829	1.101	
45.timevar	-.116	.48	-0.24	.81	-1.086	.853	
46.timevar	.076	.467	0.16	.872	-.867	1.019	
47.timevar	-.217	.475	-0.46	.65	-1.177	.742	
48.timevar	-.781	.538	-1.45	.154	-1.867	.305	
49.timevar	-.919	.519	-1.77	.084	-1.967	.129	*

50.timevar	-.921	.523	-1.76	.086	-1.978	.136	*
51.timevar	-1.196	.709	-1.69	.099	-2.629	.237	*
52.timevar	-1.293	.719	-1.80	.079	-2.746	.159	*
53.timevar	-1.566	.699	-2.24	.03	-2.978	-.155	**
54.timevar	-2.051	.734	-2.80	.008	-3.533	-.569	***
55.timevar	-1.957	.707	-2.77	.008	-3.384	-.53	***
56.timevar	-1.989	.705	-2.82	.007	-3.413	-.565	***
CarbonTaxRate	.015	.02	0.73	.468	-.026	.056	
Coal	12.947	1.678	7.72	0	9.559	16.335	***
Oil	10.108	1.159	8.72	0	7.766	12.449	***
Constant	7.008	.36	19.48	0	6.282	7.735	***

Mean dependent var	8.905	SD dependent var	1.968
R-squared	0.978	Number of obs	98.000
F-test	33.316	Prob > F	0.000
Akaike crit. (AIC)	147.549	Bayesian crit. (BIC)	294.892

*** *p<.01, ** p<.05, * p<.1*

Table 13. Combined Difference-in-Differences Regression:

Linear regression

C02Emissions	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
y90taxed	-.495	.247	-2.01	.046	-.982	-.008	**
Taxed	-1.932	.332	-5.81	0	-2.587	-1.276	***
Coal	10.132	1.238	8.18	0	7.689	12.575	***
Gas	10.575	2.086	5.07	0	6.459	14.691	***
Hydro	-6.689	.64	-10.46	0	-7.951	-5.428	***
Nuclear	-1.388	.527	-2.63	.009	-2.429	-.348	***
Wind	-32.696	3.243	-10.08	0	-39.094	-26.297	***
Oil	6.265	.421	14.87	0	5.434	7.096	***
Biofuelstwh	.251	.04	6.28	0	.172	.33	***
Constant	7.548	.101	74.87	0	7.349	7.747	***

Mean dependent var	8.766	SD dependent var	2.207
R-squared	0.913	Number of obs	196.000
F-test	216.811	Prob > F	0.000
Akaike crit. (AIC)	406.993	Bayesian crit. (BIC)	439.774

*** *p<.01, ** p<.05, * p<.1*