Economics 35: Econometrics
Final Project

Estimating the Effect of Carbon Taxes on CO_2 Emissions

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Code files: finalproject.do, finalprojectlog.smcl
Data files: finaldata-FE.dta, finaldata-synth.dta

ABSTRACT

Due to the rising threat of climate change, carbon pricing schemes are rapidly being introduced to reduce emissions. This paper hopes to contribute to the burgeoning body of literature focused on the efficacy of carbon pricing schemes. We take a two fold quasi-experimental approach of fixed effect models and synthetic controls on European countries. The fixed-effect model revealed that every dollar of tax reduced emission levels by over 0.1% and growth rates by over 0.02%. A follow up case study of Ireland using a synthetic control also revealed that implementation of carbon taxes led to lower emissions. While it is impossible to control for all relevant influencers of emissions, we consistently find that the emissions trajectories of European with and without carbon prices tend to diverge over time.

Introduction

Climate change is a major threat to the health and prosperity of every sentient being on Planet Earth. As such, it is urgent for policy makers to rapidly craft solutions that will mitigate the worst effects of climate change. Carbon dioxide (CO_2) is the primary compound driving global warming through the greenhouse effect, with methane (CH_4) as a secondary contributor. Both compounds are waste products of the chemical reactions necessary to sustain industrial civilization. Although they cannot simply be banned or eliminated, they can be significantly reduced. This paper will focus on developing the empirical estimates for carbon dioxide; the issue of methane, while quite important, will be left for future work.

Looking at neoclassical economics, the theory of externalities offers a pragmatic framework for the construction of policy focused on the reduction of carbon dioxide and methane emissions. Theoretically, constructing the carbon price for carbon dioxide only requires the policy maker to know the marginal social cost of carbon. However, reality is not as simple, and given the magnitude of the estimated social cost, policy makers will have to create plans that allow for gradual adjustment to carbon pricing. As such, the estimation of the elasticity of emissions to carbon pricing will help policy designers create policy that will ramp up carbon pricing at a reasonable rate.

The intention of this paper is to contribute to the burgeoning body of literature focused on the efficacy of carbon taxes and estimations of the elasticity of emissions to carbon pricing. Section I will review the relevant literature on this topic and Section II will discuss the underlying economic theory on relevant forms of carbon pricing. Section III will describe the data we used and data limitations we experienced. Sections IV and V will explore two different methods for modeling the effects of carbon pricing. Section IV takes a broad view European countries and discusses the fixed-effects method and its results. Section V conducts a case study of Ireland and discusses the synthetic control method and its results. Finally, Section VI will discuss the implications of the results presented in sections IV and V and potential avenues for future research.

I. Literature Review

While not the subject of research of this paper, current research on the Social Cost of Carbon (SCC) requires discussion. Once estimates are presented to the reader, the reader will have a deeper appreciation of the need for intelligent policy design – given the high cost, it is essential to design a policy scheme with an incremental ramp up of the pricing. There are numerous estimates of the SCC, and given the limited scope of this paper, we narrowed two different estimates that are the most recent work from two different novel approaches to estimating the SCC.

Ricke et al. in their 2018 paper[1] utilized a more traditional approach of modeling the rise in temperature and then using damage functions to calculate the economic damages of the rise in temperature. Temperature change and damages were calculated at the country level and then summed to reach the global SCC. Their approach estimated that the global SCC was $417 per $tCO_{2.}$

Pindyck (2019)[2] calculated an average cost of carbon by analyzing data gathered through expert elicitation. Reaching out to cited scholars in the fields of economics or climate science, he sent them a questionnaire with the pivotal data being their estimates of the economic damages of climate change in certain time intervals. After collecting and analyzing the data, Pindyck

[1] Ricke et al
[2] Pindyck (2019)

concluded that the estimate that he had most confidence in was $80 to $100 per tCO_2. It is the opinion of these authors that Pindyck made assumptions that systematically underestimated the SCC. Instead, it is the view of the authors that the average cost as found by the data before any value based adjustments of the data set is the most accurate estimate found in the paper. That estimate is $291 per tCO_2.

Although carbon pricing has been a policy idea for several decades, effective implementation of carbon pricing has only occurred in the last two decades. Since the implementation of carbon pricing, there has been voluminous work on the efficacy of carbon pricing schemes. Best et al. (2020)[3] conducted a line of inquiry focusing on 142 countries over a two decade period. Their paper took three different approaches: fixed effects for emissions growth, fixed effects for emissions per capita, and cross sectional regressions for emissions growth. Their results found that carbon pricing reduced emissions growth by 2% compared to countries without carbon pricing. Additionally, they found that a 1 euro increase in carbon pricing was associated with a 0.3 percentage point decrease in emissions growth.

Anderrson (2019)[4] examined the impacts of a Swedish carbon tax through a quasi-experimental design that used a synthetic control. His results found that the carbon tax reduced transportation emissions by 11%. Furthermore, he highlights that the carbon tax elasticity of gasoline demand is three times larger than the price elasticity of gasoline. This discrepancy leads him to argue that price elasticities cannot be used to simulate carbon pricing.

Aydin and Esen (2017)[5] argued that the relationship between environmental taxes and abatement would be nonlinear and asymmetrical. In their creation of nonlinear estimators, Aydin and Esen focused on establishing a threshold point at which environmental taxes started to have

[3] Best et al.
[4] Anderrson
[5] Aydin and Esen

negative associations with emissions. Their estimate for EU countries found that the revenue for carbon pricing would have to be over 2.20% of the GDP for the tax to cause reductions in CO_2 emissions.

While some research has found a robust impact from carbon pricing, other work has found either limited or no impact. Lin and Li (2011)[6] examined the implementation of carbon taxes in Denmark, Finland, Sweden, Netherlands and Norway. Using a difference in differences approach, they only found a statistically robust reduction of per capita emissions in Finland.

Haites et al. (2018)[7] published work that shed light on the underlying conditions that have stymied empirical analysis of carbon pricing. First, they highlight that carbon pricing is idiosyncratic to each implementation. There is the obvious divide between Emission Trading Systems (ETS) and taxation systems. Furthermore, the exact form of emissions regulated (transit vs powerplant vs etc.) causes the effect of the pricing to be highly variant to the elasticity of the sectors being regulated. Despite all these complications, they were able to conclude that ETSs achieved higher emissions reductions with lower prices than taxation systems.

II. Theory

Carbon pricing is theoretically grounded in negative externalities and Pigouvian taxes. Negative externalities are instances where the production or consumption of a good produces adverse effects on individuals not involved in the production or consumption of said good. However, the market in said good will not consider the social harm of the good, and instead, the market will lead to the production and consumption of said good to the quantity where marginal cost equals marginal private benefit. Pigouvian taxes intend to “internalize the externality” by

[6] Lin and Li
[7] Haites et al

placing a tax on the good equal to social harm that it creates. After the introduction of a Pigouvian tax, the market will produce to the point where marginal private benefit equals (marginal cost + marginal social cost). Theoretically, it does not matter if the tax is placed on the consumption or production of goods.

An alternative policy to a Pigouvian tax is a cap and trade system. Cap and trade systems create a market where firms purchase permits to produce certain quantities of the social externality. In such a system, the total number of permits should be a quantity that leads to the market producing to the point where marginal private benefit equals (marginal cost + marginal social cost). Additionally, the expected market price of a permit will then be equal to the marginal social cost of the pollutant. As a result, cap and trades and Pigouvian Taxes should result in the same market efficient outcomes.

Within carbon pricing, both Pigouvian taxes and cap and trade systems are used. The Pigouvian tax is referred to as a carbon tax, and the cap and trade is referred to as an Emission Trading System (ETS). As mentioned in the literature review, some researchers have found evidence that the two systems do not have identical outcomes. This discrepancy likely emerges from the uncertainty around both the SCC and the marginal private benefit of carbon. The intention of this paper is to try to understand the elasticity of carbon emissions to carbon pricing. Since the elasticity of emissions to carbon pricing is the derivative of the private marginal benefit curve, the elasticity will offer insight into how the market will respond to changes in carbon pricing. One key departure from theory is that, due to the nature of carbon emissions, policy makers are targeting zero carbon emissions. As such, the intent is not to correct the market, rather eliminate the market by gradual reductions in emissions. As such, establishing the efficacy of carbon pricing and an empirical estimate of the elasticity is a vital step for policy makers trying to decide the correct path of increasing carbon pricing to reach zero emissions.

III. Data

The underlying dataset of this analysis is from the World Bank Carbon Pricing Dashboard. Since the dashboard data only focused on data points directly related to the carbon pricing schemes, we got additional control variables from the World Bank's open access data sets. Then, we processed the raw data into a panel format. The panel we subsequently used contains data from 28 countries covered by the baseline E.U. Emissions Trading System (ETS) initiated in 2005, 15 of which implement carbon taxes at some point during the period 1990-2016. The panel is strongly balanced but there is some missing data for covariates during this period, but there does not appear to be any systematic loss; total $N = 756$. The following table provides the summary statistics of the relevant variables chosen for this study.

Table III.1: Summary statistics of World Bank Data.

Descriptive Statistics of 28 countries, 15 of which have carbon taxes, in period 1990-2016.

	N	Mean	Std. Dev.	Min.	Max.
CO_2 emissions (tons/capita)	722	7.99	3.77	1.28	27.4
Carbon price (USD/ton)	753	8.77	23.7	0	168.8
GDP/capita, PPP (constant 2017 international $)	710	37510.8	18106.8	9492.2	115415.4
Fossil fuel energy consumption (% of total)	697	71.0	20.3	10.3	98.5
Electricity production from renewable sources (% of total)	702	5.58	8.06	0	65.4
Alternative and nuclear energy (% of total energy use)	697	15.8	14.3	0	50.6
Energy use (kg of oil equivalent per capita)	697	4007.6	2336.4	1591.7	18178.1
Agriculture, value added (% of GDP)	656	3.28	3.01	0.12	21.8
Trade (% of GDP)	705	96.6	51.4	33.9	408.4
Population density (people per sq. km of land area)	736	118.7	100.7	2.54	505.5
GDP growth (annual %)	721	2.34	3.62	-14.8	25.2

IV. View of Europe - Fixed Effects

Our ultimate intention is to isolate the causal impact of carbon pricing on emissions in Europe. In order to do this, we use three fixed-effect (FE) models. Country-fixed effects controls for differences between countries that are constant over time, such as land size. Time-fixed effects controls for differences across years that are constant over the countries. Arguably, this could Europe- or world-wide policies or recessions. What country-time fixed effects cannot control for are the changes within countries over time that are different between countries. These can include global policies if they differentially impact countries as well as major changes in governance and laws of each individual country. Although it is not possible to control all such differences, we included a suite of covariates that control for the major changes factors within each country that may affect carbon emissions independent of carbon pricing.

The covariates included in our three models are GDP per capita (adjusted for purchasing power parity as of the 2017 international dollar), the proportions of total energy produced by fossil fields, renewables, and alternative sources, energy use per capita, proportions of GDP involved in agriculture and trade, annual GDP growth, and population density; a summary of them is presented in Table III.1. We chose these variables because they all change differently between countries over time. Firstly, the variables that pertain to energy and production, arguably, affect both the explanatory variable carbon price and response variable carbon emissions, hence causing omitted variable bias. Secondly, their changes are, albeit imperfect, indicators of other changes within the country, such as laws and attitudes which we cannot possibly control, that impact emissions independent of carbon pricing; if carbon taxes were changed at the same time as countries changed other policies, we might instead be measuring the impact of the other policies. Lastly, the other variables are then included to check for robustness.

By doing so, we hope to accurately approximate the effect of carbon pricing on emissions relative to what would have been the case without carbon pricing.

Method

The three FE models (M1, M2, and M3) are inspired by Best et al. (2020)[8].

1. Fixed-effects panel estimations for levels of emissions per capita
2. Fixed-effects panel estimations for levels of emissions per capita using lagged prices
3. Fixed-effects growth rate panel regressions

Model 1 measures the association between within-country carbon taxes and within-country levels of emissions, controlling for yearly changes in global factors and the country specific covariates. By regressing log-emissions on price, we estimate the percentage change in emissions for each dollar/ton change in carbon tax. M1:

$$\log CO2_{ct} = \beta_0 + \beta_1 Price_{ct} + I_c + I_t + \theta \mathbf{Covariates}_c + \epsilon_{ct}$$

Model 2 is similar to M1 but addresses two possible critiques of M1. First, there may be a risk of reverse causation in the relationship between price and emissions. Second, carbon prices may have a delayed or lagged effect on emissions. So, M2 includes a lagged price variable for lags D = 1,2,3 years instead of a contemporaneous price to see the effects in the near future. Hence, M2 measures the association between within-country carbon taxes and within-country levels of emissions D-years later, controlling for yearly changes in global factors and the country specific covariates. By regressing log-emissions on D-year prior price, we estimate the percentage change in emissions for each dollar/ton change in carbon tax D-years ago. M2:

[8] Best et al.

$$\log CO2_{ct} = \beta_0 + \beta_1 Price_{c(t-D)} + I_c + I_t + \theta \mathbf{Covariates}_c + \epsilon_{ct}$$

While M1 and M2 focus on the levels of emissions, Model 3 focuses on the growth rate. M3 measures the association between within-country carbon taxes and within-country average annual rate of change of emissions over the next D-years for D = 1,3,5, while controlling for yearly changes in global factors and the country specific covariates. We note that 5-year growth rate analyses are common in macroeconomic growth literature. We calculate the average annual rate of change of carbon emissions over D-years by taking log emissions for a year and subtracting the D-year lagged log emissions and then dividing by D. We regress this variable on D-year lagged price and D-year lagged log emissions as well as the contemporaneous covariates. Prior emissions is used as an explanatory due to the fact that emissions as a response variable is not independent of prior emissions. By regressing the average period-differenced logs over D-years on D-year prior price, we estimate the percentage change in average annual rate of change in emissions for each dollar/ton change in carbon tax D-years ago. In calculus terms, the coefficient of price is the second-order partial-derivative of emissions function. M3:

$$(\log CO2_{ct} - \log CO2_{c(t-D)})/D = \beta_0 + \beta_1 Price_{c(t-D)} + \beta_3 \log CO2_{c(t-D)} + I_c + I_t + \theta \mathbf{Covariates}_c + \epsilon_{ct}$$

Results

Tables IV.1, IV.2, and IV.3 in the following pages summarize the results of M1, M2, and M3 respectively. Let us briefly interpret the main results of these models.

M1 was implemented in three ways (Table IV.1). With M1.1, we see that a 1 dollar/ton increase in within-country carbon taxes is significantly associated with a 0.097% reduction in within-country carbon emissions, controlling for yearly changes in global factors (p-value<0.01).

We can explain 36.9% of the variation in emissions with price alone. In addition, when we control for log GDP/capita, fossil fuel usage, renewable energy sources, and agriculture in M1.2, the estimate is 0.112% (p-value<0.001). Moreover, these covariates are all significant predictors of emissions, which makes intuitive sense considering we included them because they are energy and production related factors that change over time. M1.2 is able to explain 72.5% of the variation in emissions. As an extension, M1.3 tests for robustness by adding alternative energy, energy/capita, population density, and GDP growth, estimating at 0.122% (p-value<0.001). None of these additional variables are significant predictors and the explained variation being 76.4%, only 3.9 points higher than M1.2. So, additional attempts of robustness checks showed similar results: the estimated change in levels in emissions with price floated around 0.1% with extremely high statistical significance with the major energy and production related covariates explaining almost all of the variation in emissions.

M2 was implemented three times to address the drawbacks of M1 discussed earlier (Table IV.2). With M2.1, we see that a 1 dollar/ton increase in within-country carbon taxes is significantly associated with a 0.146% reduction in within-country carbon emissions 1 year later, controlling for yearly changes in global factors and the relevant covariates from M1.2 and GDP growth. The estimate is 0.140% for a 2-year lag and 0.124% for a 3-year lag. For all three specifications of M2, p-value<0.001 and we are able to explain at least 73% of the variation in emissions. Since these estimates are consistent with our findings through M1, we rule out some fear of reverse causation. One could speculate that these slightly higher estimates pertain to the fact that carbon taxes have a stronger effect in the following years than in the contemporary year. M3 may shed light on this further.

M3 was implemented for 3 different time periods (Table IV.3). With M2.1, we see that a 1 dollar/ton increase in within-country carbon taxes is significantly associated with a 0.084% reduction in within-country average annual rate of change in emissions, controlling for yearly changes in global factors and the relevant covariates similar to those used in M1.3. The estimates are 0.037% for 3-year periods and 0.022% for 5-year periods. For all three specifications of M3, p-value <0.001 and we are able to explain 53.7%, 75%, and 84% of the variation in emissions respectively. Moreover, while energy and production related variables appeared significant with M1 and M2, GDP growth in particular is now significant even though it was not earlier. These estimates suggest a couple of things. Firstly, we notice that the average annual rate of change in emissions decreases as the time period increases. This seems to suggest that the effect of taxes are greater in the short term than in the medium on reducing growth rate, rather than a constant effect. This could point to a curving or levelling-off effect of carbon emissions as it is subject to taxes over time, assuming that we are controlling for major unobserved variables. In any case, this interpretation should be made with caution without a further detailed study with time periods greater than 5 years. Secondly, and perhaps intuitively, economic growth, and not merely economic prosperity, has a major impact on carbon emissions.

In conclusion, not only have we seen through M1 and M2 that carbon prices decrease levels of emissions in Europe, they also decrease the emissions growth rate as seen through M3. Note that this conclusion includes causal language since we have attempted to control for most major influencers of carbon emission levels and rates. However, there are limitations to note.

Limitations

A limitation is that we are not directly able to control for other within-country policy measures. Such country specific data is difficult to procure and unavailable through major sources such as the World Bank. Moreover, it is unclear how reliable or complete such data would have been given different standards of reporting between countries on niche variables. In any case, since we cannot control for all unobserved variables, we interpret causality cautiously.

Furthermore, we experience some attrition which is not completely random as we add covariates. However, we did not experience severe attrition considering there were no systematic gaps. So, we do not suspect that our results are skewed due to this fact.

As a brief comment on the interpretation of the estimates, M1 and M2 may at first glance suggest that there is approximately a 10% decrease in emission levels and with a $100/ton carbon tax. This may be true but we caution against this interpretation for two reasons. Firstly, although the relationship between prices and emissions has been estimated with a linear model, it is not obvious from our tables alone that the underlying relationship is necessarily perfectly linear. This is concurred by M3 which seems to show a non-constant decrease in growth rate of emissions over time. Secondly, the degree of non-linearity of the relationship may also significantly vary by country.

Another objection may be that it is not necessarily carbon price rates themselves that have a tangible impact but the act of implementing a carbon tax. A further study may be conducted to see the effect of carbon tax law as a binary variable. Moreover, we noted earlier the possibility of differential impacts and degrees of non-linearity within each country. The only way to verify this is by performing case studies on the countries. In section V, we do this with Ireland to see the binary effect of a carbon tax law.

Table IV.1: Fixed-effects panel estimations for levels of emissions per capita

M1

	(M1.1)	(M1.2)	(M1.3)
	log CO_2 emissions (log ton/capita)		
Carbon Price (USD/ton)	-0.000965** (0.000345)	-0.00112*** (0.000271)	-0.00122*** (0.000320)
log GDP per capita (log USD)		0.329*** (0.0645)	0.281*** (0.0435)
Fossil fuel energy (% of total energy)		0.0137*** (0.00329)	0.0150* (0.00613)
Renewable electricity (% of total energy)		-0.00458** (0.00129)	-0.00447* (0.00187)
Agriculture value (% of total GDP)		0.0166** (0.00509)	0.0141** (0.00435)
Alternative energy (% of total energy)			-0.000249 (0.00549)
Energy use (kg of oil/capita)			0.0000260 (0.0000164)
Trade value (% of total GDP)			-0.000293 (0.000421)
Population density (people/sq. km)			-0.000822 (0.000781)
GDP growth (annual %)			0.000819 (0.000998)
N	719	620	606
R^2	0.369	0.725	0.764
Fixed-Effects	Country-Year	Country-Year	Country-Year

Note: Country-time fixed effects include data on 28 countries from 1990-2016. Initial $N = 756$. Robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Fixed-effects panel estimations for levels of emissions per capita using lagged prices

M2

	(M2.1)	(M2.2)	(M2.3)
Lag:	1-year	2-year	3-year
	log CO_2 emissions (log ton/capita)		
Lagged Carbon Price (USD/ton)	-0.00146***	-0.00140***	-0.00124***
	(0.000312)	(0.000313)	(0.000312)
log GDP per capita (log USD)	0.290***	0.294***	0.297***
	(0.0498)	(0.0498)	(0.0498)
Fossil fuel energy (% of total energy)	0.00986	0.00994	0.0102
	(0.00566)	(0.00571)	(0.00575)
Renewable electricity (% of total energy)	-0.00593**	-0.00583**	-0.00567**
	(0.00186)	(0.00188)	(0.00189)
Alternative energy (% of total energy)	-0.00365	-0.00360	-0.00337
	(0.00534)	(0.00540)	(0.00538)
Agriculture value (% of total GDP)	0.0125*	0.0125*	0.0122*
	(0.00468)	(0.00470)	(0.00474)
GDP growth (annual %)	0.000577	0.000563	0.000324
	(0.000994)	(0.000998)	(0.000980)
N	583	583	582
R^2	0.742	0.738	0.734
Fixed-Effects	Country-Year	Country-Year	Country-Year

Note: Country-time fixed effects include data on 28 countries from 1993-2016 to accommodate 3-year lag. Initial $N = 672$. Robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Fixed-effects growth rate panel regressions

M3

	(M3.1)	(M3.2)	(M3.3)
Period:	1-year	3-year	5-year
	average annual CO2 growth rate for periods (log ton/capita per year)		
Lagged Carbon Price (USD/ton)	-0.000842*** (0.000146)	-0.000365*** (0.0000568)	-0.000218*** (0.0000513)
Lagged log CO_2 emissions (ton/capita)	-0.434*** (0.0750)	-0.216*** (0.0253)	-0.155*** (0.0105)
log GDP per capita (USD)	0.141*** (0.0203)	0.0996*** (0.0148)	0.0792*** (0.0152)
Fossil fuel energy (% of total energy)	0.00681 (0.00368)	0.00302 (0.00166)	0.00181 (0.00114)
Renewable electricity (% of total energy)	-0.00240** (0.000746)	-0.00125** (0.000436)	-0.000981* (0.000354)
Alternative energy (% of total energy)	-0.000868 (0.00283)	-0.000387 (0.00134)	-0.000485 (0.000940)
Agriculture value (% of total GDP)	0.00768*** (0.00204)	0.00443** (0.00122)	0.00284** (0.000947)
Trade value (% of total GDP)	-0.000178 (0.000188)	-0.0000918 (0.0000926)	-0.0000534 (0.0000679)
Population density (people/sq. km)	-0.00126* (0.000464)	-0.000537* (0.000243)	-0.000275 (0.000166)
GDP growth (annual %)	0.00379*** (0.000738)	0.00121*** (0.000258)	0.000490** (0.000176)
N	547	547	536
R^2	0.537	0.750	0.840
Fixed-Effects	Country-Year	Country-Year	Country-Year

Note: Country-time fixed effects include data on 28 countries from 1995-2016 to accommodate 5-year lag. Initial $N = 616$. Robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

V. Case Study of Ireland - Synthetic Control

Abadie and Gardeazabal (2003)[9] pioneered empirical application of the synthetic control method in their paper relating terrorism in the Basque region of Spain. In that paper, they used the synthetic control method to create an artificial Basque region that was not affected by terrorism, and they compared it to the real Basque region. The synthetic state is comprised of a selection of parts of other states dependent on similarities within a group of variables. Like using the nearest neighbor matching method, synthetic controls allow for a comparison to a similar state that was unaffected by a specific change. We selected to use synthetic controls instead of the matching method, because it allows for the creation of improved control variables that are as similar to the state experiencing the "treatment" as possible, without being impacted by the variable of study. Due to the major differences between countries in the European Union, this method allowed us to create the most accurate possible control. For this project, we created two different synthetic control models using different groupings of countries to generate the synthetic controls. We selected Ireland as the country of study for the project because the country implemented a large carbon tax that covered a majority of emissions in 2010, and this tax has remained in effect and increased over the past decade. Other comparable European countries implemented carbon taxes in a gradual piecemeal approach that made it difficult to define a clear treatment effect. Additionally, our dataset became less robust in the 90s and in the past few years, so having the treatment effect in 2010 allowed us to most effectively use the data we have available to us.

Our first synthetic control model used twenty five European countries that are all affected by the European Union's Emissions Trading System (EU ETS). These countries also may or may

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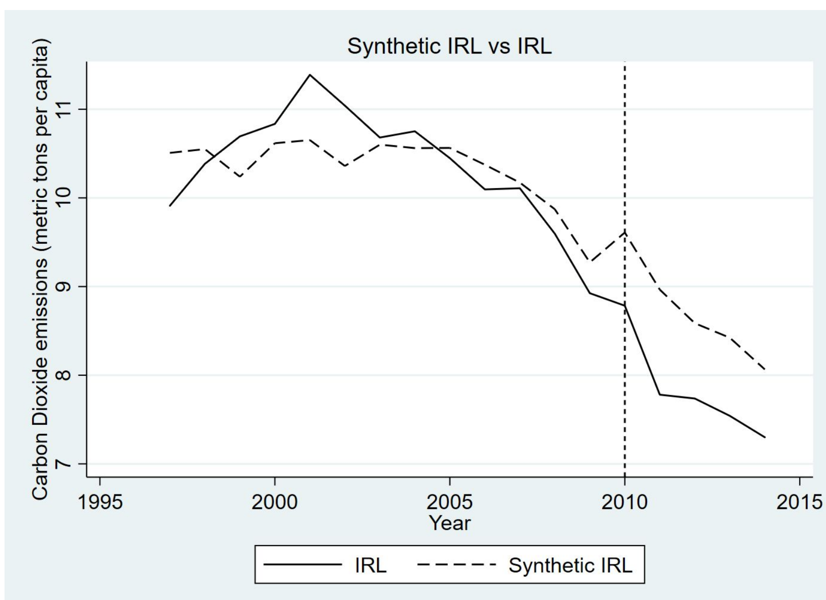
[9] Abadie and Gardeazabal

not have implemented their own carbon taxes in addition to the trading system. We assert that, as countries in the EU under the common EU regulatory framework, these states have many inherent similarities, especially related to efforts of environmental sustainability and decreasing greenhouse gas emissions. In Figure V.1 below, the results of this initial control model are reported. Before its implementation in 2010, this figure shows similar trends for synthetic control and real Ireland. In 2010 after the implementation of the Irish carbon tax, both synthetic and real Ireland continued to trend towards decreasing emissions per capita; however, real Ireland decreases at a more rapid rate. Through the whole treatment period, real Irish emissions per capita remain below synthetic control emissions per capita. Therefore, despite the natural decrease in emissions that would have occurred, the tax caused a much more significant decline in per capita carbon dioxide emissions.

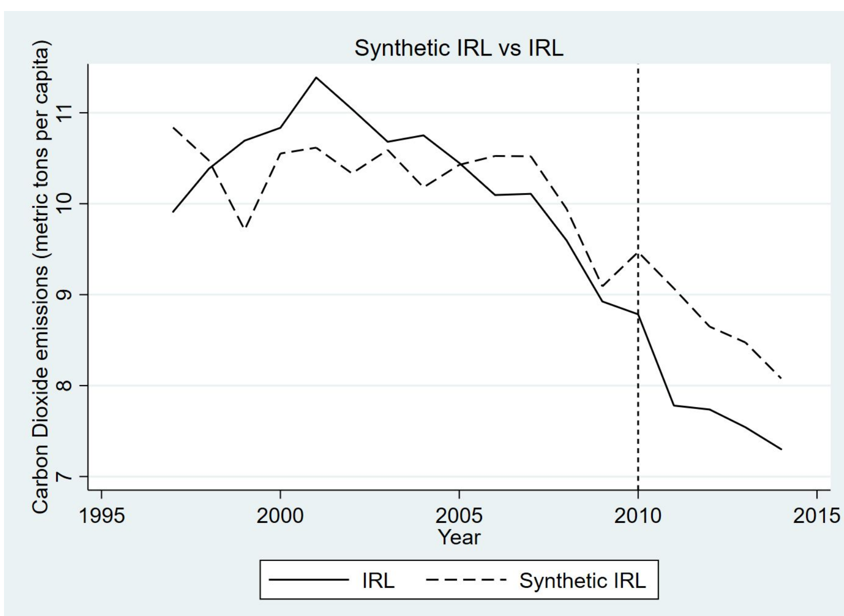
Figure V.1:



The countries used to build the synthetic control are seen in Table V.1 and the values of the predictor variables are shown in Table V.2. A concern with this model is that other countries implemented carbon taxes before and after the treatment effect, which may be impacting the emissions estimates for the synthetic control, leading to an underestimate of the effectiveness of taxation.

In our second synthetic control model, we use thirteen nations from within the previous subset of European countries that have not implemented any carbon taxes in addition to the EU ETS. Although decreasing the sample size of countries used to build the control is not ideal, this method should provide a secondary view of the effectiveness of taxation and serve as a robustness check for the primary model. The results of this secondary synthetic control are shown in Figure V.2. below. Before implementation in 2010, the synthetic control is similar to the actual emissions data. But in 2010, despite a general decline in emissions for both the control and the actual data, the actual data shows a more rapid decrease in emissions.

Figure V.2:



The countries used to build the synthetic control are seen in Table V.3 and the values of the predictor variables are shown in Table V.4. One concern within this model is the potential for fundamental differences between the countries that have chosen to implement additional taxes and those that have not that we may not be controlling for. However, as seen in our previous model, the synthetic control remains similar within these two selections of countries being used.

Despite the numerous advantages to the synthetic control method, it is limited by the variables used to develop the artificial state. For this project, we used nine different variables obtained from the World Bank's World Development Indicators (WDI) to create a synthetic control to predict carbon dioxide emissions per capita as accurately as possible. These predictor variables are similar to those used by Anderrson (2019)[10] where he uses a synthetic control to measure the effectiveness of Sweden's tax program. Rather than replicating Andersson's focus on vehicle emissions, our predictor variables encompass a number of more general potential indicators for levels of emissions, including those related to trade. In Table V.3, the metrics for all these variables are shown with definitions provided by the World Bank. We use several indicators that are not directly relevant to carbon dioxide emissions as predictor variables. These variables include trade as a percentage of GDP, GDP (constant PPP), agricultural land as a percentage of land area, land area in square kilometers, and population density in people per square kilometers. These indicators are intended to ensure the similarities between the synthetic control and Ireland for factors that may indirectly affect emissions or the ease in which sustainable practices can be adopted. We also use several indicators that are related to emissions and sustainability practices directly. First we use the average tons of CO_2 per capita emitted in years before the tax was implemented. We also used indicators for the amount of energy used in kg of oil equivalent, the use of alternative and nuclear energy as a percentage of total energy use,

[10] Anderrson

and electricity production from renewable sources as a percentage of total energy use.[11]

Tables for both Synthetic controls:

Table V.1:

Unit Weights for Synthetic Control 1

World Bank Country Code	Unit Weight
BEL	.44
CZE	.207
GRC	.16
LUX	.049
PRT	.143
Total	1.00

Table V.2:

Predictor Balance for Synthetic Control 1

Predictor	Treated	Synthetic
Land Area (sq km)	68890	63145.02
Population Density (people per sq km)	52.63025	217.2183
Agricultural Land (% total)	73.20965	51.19062
GDP (constant PPP)	1.72e+11	3.41e+11
Renewable Energy Production (% total)	1.362725	1.314882
Alternative and Nuclear Energy (% total)	.8421538	9.614128
Trade (% of GDP)	120.4446	97.24435
Energy Use (kg oil equiv.)	2821.39	4097.382
Per Capita tons of CO_2 (1997)	9.911617	10.47883
Per Capita tons of CO_2 (1998)	10.38459	10.54005
Per Capita tons of CO_2 (1999)	10.69399	10.23413
Per Capita tons of CO_2 (2000)	10.83474	10.59373
Per Capita tons of CO_2 (2001)	11.38823	10.6293
Per Capita tons of CO_2 (2002)	11.04125	10.32499
Per Capita tons of CO_2 (2003)	10.68118	10.57956
Per Capita tons of CO_2 (2004)	10.75164	10.54666
Per Capita tons of CO_2 (2005)	10.44852	10.5344
Per Capita tons of CO_2 (2006)	10.09594	10.3423
Per Capita tons of CO_2 (2007)	10.10918	10.13394
Per Capita tons of CO_2 (2008)	9.596427	9.853906
Per Capita tons of CO_2 (2009)	8.925395	9.262462

Root Mean Squared Prediction Error

RMSPE	**.5797218**

[11] World Bank (2020a)

Table V.3:

Unit Weights for Synthetic Control 2	
World Bank Country Code	Unit Weight
AUT	.034
CZE	.742
GRC	.014
HUN	.184
ITA	.026
Total	1.00

Table V.4:

Predictor Balance for Synthetic Control 2

Predictor	Treated	Synthetic
Land Area (sq km)	68890	86123.49
Population Density (people per sq km)	52.63025	129.0264
Agricultural Land (% total)	73.20965	57.62231
GDP (constant PPP)	1.72e+11	3.17e+11
Renewable Energy Production (% total)	1.362725	.6331409
Alternative and Nuclear Energy (% total)	.8421538	6.836682
Trade (% of GDP)	120.4446	94.8424
Energy Use (kg oil equiv.)	2821.39	3952.48
Per Capita tons of CO_2 (1997)	9.911617	10.83811
Per Capita tons of CO_2 (1998)	10.38459	10.47704
Per Capita tons of CO_2 (1999)	10.69399	9.712655
Per Capita tons of CO_2 (2000)	10.83474	10.55226
Per Capita tons of CO_2 (2001)	11.38823	10.61682
Per Capita tons of CO_2 (2002)	11.04125	10.33375
Per Capita tons of CO_2 (2003)	10.68118	10.59149
Per Capita tons of CO_2 (2004)	10.75164	10.17989
Per Capita tons of CO_2 (2005)	10.44852	10.4281
Per Capita tons of CO_2 (2006)	10.09594	10.52508
Per Capita tons of CO_2 (2007)	10.10918	10.52174
Per Capita tons of CO_2 (2008)	9.596427	9.944002
Per Capita tons of CO_2 (2009)	8.925395	9.091472

Root Mean Squared Prediction Error

RMSPE	**.6799734**

VI. Discussion

Climate change is one of the foremost problems facing our society today. The worsening effects of greenhouse gas emissions will exacerbate economic and social inequality, extreme weather events, create agricultural problems, and continue to impact society in many other ways. A primary driver of climate change is carbon dioxide emissions, and it is therefore increasingly necessary for countries to develop effective methods for controlling emissions. Through the fixed effects and synthetic control methods, we explore the effectiveness of carbon taxes both across the EU, and focused on one country, Ireland, within that group.

Using the country-year fixed effects method, we found that each dollar/ton carbon tax decreases carbon emissions by approximately 0.1% with a lagged effect that is slightly higher. Also, we found that the growth rate of emissions also decreases due to carbon prices: the average growth rate of emissions decreases by 0.02% over 5 years. We noted the potential threats to our causal claims and stated that a follow-up case study on each country may help to confirm these results. Through the synthetic controls method, we conclude the implementation of the 2010 carbon taxation program in Ireland contributed to a decrease in emissions within the country, as compared to the two synthetic controls we created. This finding supplements our hunch from the fixed-effects result.

The primary limitation to this work was the quality of the data we worked with. For example, our synthetic control approach was attempted with countless approaches but we could not achieve as tight of a fit as desired. We believe that further research should be conducted to refine this synthetic control approach to carbon pricing. In summation, we consistently reported a relationship between a change in price to a change in percentage of emissions. Given the vitalness of this relationship to policy design, further work should be done to check the accuracy of our findings. Finally, this work focused exclusively on the European Union, as such the estimates we found based on EU data will likely not hold for other regions, limiting the external validity. Therefore, it is imperative that research is done on all regions of the world and compare the findings with SCC research in order to implement better policies.

References

Abadie, Alberto, and Javier Gardeazabal. 2003. "The Economic Costs of Conflict: A Case Study of the Basque Country." American Economic Review, 93 (1): 113-132.

Andersson, Julius (2019). Carbon Taxes and CO2 Emissions: Sweden as a Case Study. American Economic Journal: Economic Policy, 11(4): 1–30 https://doi.org/10.1257/pol.20170144

Aydin, C. & Esen, Ö. (2018) Reducing CO_2 emissions in the EU member states: Do environmental taxes work?, Journal of Environmental Planning and Management, 61:13, 2396-2420, DOI: 10.1080/09640568.2017.1395731

Best, R. & Burke, P.J. & Jotzo, F. (2020). Carbon Pricing Efficacy: Cross-Country Evidence. Environmental Resource Econ 77, 69–94. https://doi.org/10.1007/s10640-020-00436-x

Haites, E. & et al. (2018). Experiences with Carbon Taxes and Greenhouse Gas Emissions Trading Systems. Duke Environmental Law & Policy Forum, 29(109): 109-182.

Lin, B. & Li, X. (2011). The Effect of Carbon Tax on CO2 Emissions. Energy Policy 39(9):5137-5146

Pindyck, Robert (2019). The Social Cost of Carbon Revisited. National Bureau of Economic Research Working Paper. http://www.nber.org/papers/w22807

Ricke, K. & Drouet, L. & Caldeira, K. et al. Country-Level Social Cost of Carbon. Nature Climate Change 8, 895–900 (2018). https://doi.org/10.1038/s41558-018-0282-y

World Bank (2020a). "Carbon Pricing Dashboard."

World Bank (2020b). "World Development Indicators."