A Cross-Country Empirical Analysis of the Porter Hypothesis in the Chemical Industry

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Senior Project

Spring 2020

Acknowledgments

I would like to thank Dr. Renna for helping me navigate the process of the senior research project, without his assistance the analysis would not have been possible. I would like to thank Dr. Erickson for her support as the Honors College advisor within the Economics Department. Further thank you to Dr. Nelson, for his continuous assistance in econometrics, which formed my fundamental understanding of economic and data analysis. I would like to thank Dr. Weinstein for sparking my passion for environmental economics during my undergraduate career, which inspired my project. I would like to thank Dr. Ghosh. Her unwavering support as a professor and mentor matches her extensive experience in international economic theory. Finally, I would like to thank Elvira Ochatiouk and my fellow classmates who have pushed me to succeed and made my time at the University of Akron all the more memorable. Thank you.

Abstract

This paper examines whether there is evidence to support or refute the Porter Hypothesis on a high polluting industry through analyzing the effect of environmental stringency on innovation in the chemical industry. Taking data from the Organization for Economic Cooperation and Development (OECD), we use country-level data from 2003-2015, to analyze how a country's number of Class C chemical patents is affected by their Environmental Policy Stringency (EPS) Index. Using a fixed effect model, we controlled for differences in GDP, exports, investment in research and development, market competitiveness and participation in the industry. The initial results of this regression found that as a country's EPS Index changes by one unit, we would expect a decrease in about 45 patents in a year at the 99 percent significance level. These findings support our hypothesis that there is evidence against the strong form of the Porter Hypothesis.

This suggests policies aimed at reaching environmental goals may need to create flexibility to stimulate innovation. This could be through creating more opportunities for innovation through government funded grants or creating incentives for private investment in research and development. However, this research could be enhanced by more country observations and industry level data.

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I. Introduction

Since 2019, the International Panel on Climate Change has stressed the necessity of closer adherence to international environmental agreements in order to avoid catastrophe caused by increased average global temperatures. However, there may be evidence that stricter adherence to these regulations could hurt important high-polluting industries. One example of such an industry is the chemical industry, which produced 537.83 million tons of sulfur-oxide and 517.32 million tons of nitrogen-oxide from 2000-2008. While European countries continue to call for stronger policies against these types of pollutants, it could mean falling behind globally in their most competitive industry. Now, for the first time in years, China has ousted the European Union as the leader in the chemical industry by 545 billion Euros in 2018.

Traditional economic theory would state that when a policy increases the cost of production, we would see less productivity and greater deadweight losses than without said policy. Yet, Michael Porter (1995) hypothesized that the opposite may be true. His hypothesis argued that not only could good environmental policy decrease the cost of production over time by forcing firms to be more efficient, but regulation could also promote innovation over time too. This paper will apply this theory to analyze the impact of environmental stringency on the innovation of one of the most polluting industries in the world, the chemical industry.

The objective of this paper is to analyze whether we can find support of the Porter Hypothesis for patent applications within the Organization Economic Cooperation and Development (OECD) countries' chemical industries. Using a two-way fixed effects model, we can analyze a panel data set of these countries' patent applications against their environmental stringency level. While previous research traditionally uses pollution abatement and costs expenditure (PACE) within a country or industry to measure environmental regulation, this paper will instead use the OECD's Environmental Policy Stringency (EPS) Index. In this way, we aim to improve on past literature by limiting endogeneity and by focusing on how OECD countries' measured environmental goals have been realized in their chemical industry's innovation.

Global cooperation is fundamental to successful climate change policies. However, firms and states are less likely to support strict regulation if it hinders their economic opportunities. Understanding how these policies effect innovation can help policy makers create incentive structures or support that target most affected industries like the chemical industry that could make their policy more economically and politically feasible. Through this analysis we seek to learn more about the Porter Hypothesis in high polluting industries and how policy makers can create well-rounded policies to adhere to environmental goals.

II. Literature Review

Studies testing the Porter Hypothesis have been popular since its inception in 1995. Most have compared cross-country economic effects with aggregate economic data, while others have chosen to examine specific industries, or subsections of industries, with firm-level data. Despite this difference, almost every paper finds similar results. Many find support for the "weak" form of the Porter Hypothesis at the country, industry, and firm levels—Rubashkina et al (2014.), De Santis (2012), and Hill et al. (2019).

The approaches for choosing the explanatory variable of environmental stringency have varied over the past decade. Rubashkina, Y., Galeotti, M., & Verdolini, E. (2014), used Pollution Abatement Control Expenditure (PACE), while De Santis, R. (2012) used the membership of multilateral environmental agreements. Papers that used firm level data proxied this variable by creating surveys for firms and calculating stringency based on their responses and expenses towards pollution abatement. The environmental stringency variable can be difficult to proxy because it comes with a few endogeneity issues. Most notably, Rubashkina (2014) notes that an "important feature" of any paper which looks at the impact of environmental stringency on firms' productivity, is how to account for the endogeneity of the environmental stringency variable.

An endogeneity problem arises in this instance because the most common, appropriate proxy variables for environmental stringency may be measuring other types of regulation as well. Moreover, there are concerns that these proxy variables could show possible reverse causality between the environmental stringency variables and a firm or industry's productivity. For example, a firm may lobby to relax environmental regulation after incurring negative shock in productivity. In this case, the positive results may not be observed from the Porter hypothesis but observed as a positive relationship between productivity and environmental regulation in an ordinary least squares (OLS) regression as a result of this behavior.

One method to overcome this issue might be by using shadow prices to estimate models that do not account for the simultaneity of policy variables and performance variables. A paper by Hill and Mobius (2019), found positive and significant coefficients that showed a 2.1 percent increase in multi-factor productivity (MFP) growth for each dollar increase in the energy shadow price using this method. However, when controlled for simultaneity, they found a 6.3 percent increase in MFP growth as a country's EPS Index per value added increased by one.

Beyond their concerns for the explanatory variable, each paper discussed the importance of creating the proper empirical model structure for analysis to observe the effects of policy on productivity. Rubashkina Y., Galeotti M, & Verdolini E. (2014) used a one-year lag variable model. They found no harm in productivity stemming from more stringent policies when using national, industry or firm level data. However, Albrizio, Kozluk and Zipper (2014), found that on an aggregate economy level, there was a notable negative effect on productivity a year before the policy implementation, not after. They attribute these results to the "announcement effect", which is described as the effects caused by a policy being announced before it is implemented. Eventually, the firms would adjust to the new environment, and in fact, the negative effect of the announcement is offset three years after the policy is implemented. This could suggest that using multiple years to test out different lag models could reveal long-term effects more accurately.

Yet the most clear takeaway, is all papers in the literature review provide a great amount of suggestions for improving modeling the effects of environmental policy stringency on innovation and productivity. Our research will move away from the PACE variable, and instead follow a similar route as the De Santis R. (2012), and Hill and Mobius (2019), papers by using the EPS Index created by the OECD to measure stringency. This index is more focused specifically on environmental regulation. However, there could be still be endogeneity issues with this variable as seen in the Rubashkina, Y., Galeotti, M., & Verdolini, E. (2014) paper that are noted with the PACE variable. Based on the Albrizio, Kozluk and Zipper (2014) paper, firms time to adjust to new regulations alters the observed effects of environmental stringency on productivity. Therefore, it is important to keep in mind that these effects could be overstated as was found in the Hill and Mobius (2019) paper. Finally, this paper seeks to set itself apart by analyzing a high-polluting industry that is rarely recognized in literature, the chemical industry.

III. Theoretical Model and Hypothesis

The Porter Hypothesis (PH) was developed in 1995, by Michael Porter. He argues that "properly designed" environmental policies can offset the costs of compliance. The logic is as firms face new costs, they will begin to adapt to the new regulations. Then, they will not only become more efficient to reduce their environmental impact but will also increase the quality of their products over time. The hypothesis was split up into three different forms labelled "weak", "narrow", and "strong" by Jaffe and Palmer (1997). The "weak" PH states environmental policy stimulates certain environmental innovations. The "narrow" PH states that flexible policies (for example cap and trade policies) may stimulate incentives to innovate standards. Finally, the "strong" PH states that regulation will stimulate innovation to a point that, over time, it will negate the cost it took for a firm to comply with the given regulation. While these hypotheses are based on the same argument, they measure different levels of effectiveness caused by the environmental policy.

Innovation offsets are ascribed to two different scenarios: product offsets and process offsets. Product offsets refer to regulations that lead to higher product quality. This could mean a few different things. A product could have safer standards, or it could mean that these products could have a higher resale value that makes it more attractive to customers. This would justify the increased costs of production. Process offsets, on the contrary, comes about through forcing a "leaner" production process to meet efficiency goals or standards.

"Lean and Green" is the best description of Porter's hypothesis on how firms will adjust to adhere to stricter environmental regulation. Companies would have to reduce material to prevent pollution from waste, decrease down-time to save energy costs, and change pollution causing processes if necessary, to meet standards. In turn, these firms would likely see reduced storage costs as overproduction decreases, and increased safety to workers from reduction in polluting products and processes. This behavior is supported through basic economic principles like the substitution effect. If the production of certain products (for example, a bucket of paint) had traditionally used a polluting or hazardous material like lead, then a regulation which makes the item more expensive for the company to produce that product may cause a firm to find greener alternatives to offset this cost. This makes the production of paint safer and Porter finds that consumers would be willing to purchase the premium product because the safety consideration justifies the increase in price.

However, traditional economic theory would suggest that government intervention and regulation would create a decrease of GDP and production within a country. Some regulations will tax pollution or require firms invest in procedures that will reduce the negative impact of production on the environment. The result is an increase of costs of production for the polluting firm which decreases the supply of chemical production at every price level. This shifts the supply curve of chemicals leftwards at every price level which increases the equilibrium price from P_1 to $P_{2.}$ (shown in Figure 1 below). The higher price decreases the amount the country may consume (from Q_1 to Q_3) of that good and increases the amount they must import. Therefore, the regulating country will see a deadweight loss from both the reduction in producer surplus and consumer surplus. While their trading partner will also consume less at this higher price, but their firms will benefit from the increased revenue to meet the demand of exports.

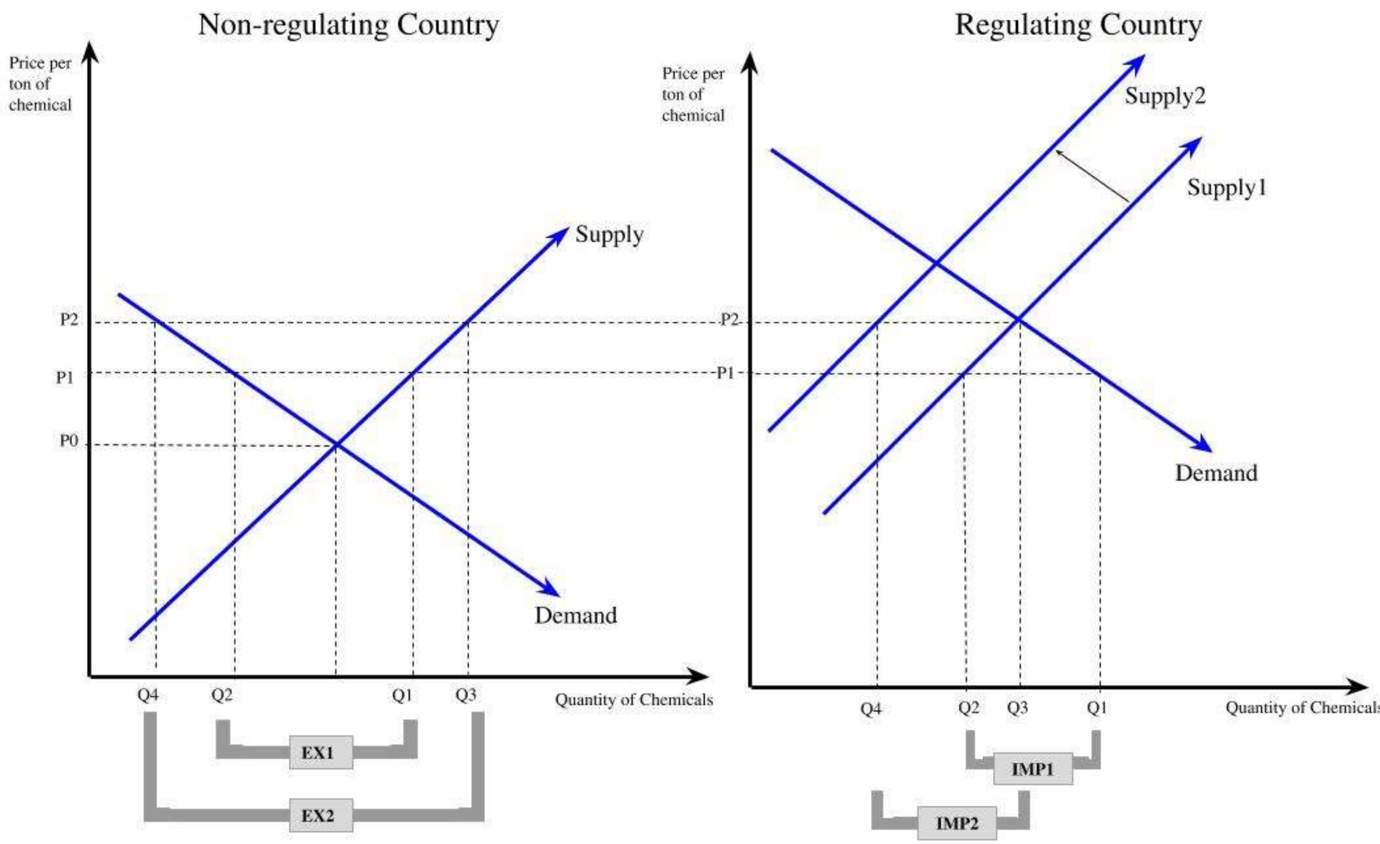

Figure 1.

Beyond the concern the effects may have on firms' profits, this can bleed through to more macro-economic based issues like a decrease in exports, gross domestic product, and a loss in jobs. If country level regulations begin effecting the cost of research and production of a service or product (GDP), a country that does not have those regulations will beat their price in the international market. The loss in exports could not only affect a country's GDP negatively, but incentivize firms to move to countries with less stringent regulations. This behavior is explained by the Ricardian competitive advantage theory. The international trade theory states that countries will export what they can most efficiently produce. Therefore, if a country's regulations create an environment where producing chemical products will be inefficient (which may be the case in Europe today) they will begin importing more (IMP_1 to IMP_2 in Figure 1.). At the same time, countries with more relaxed regulations will find they can more efficiently produce chemicals (which may be the case in China today), leading to increased exports (EX_1 to EX_2 in Figure 1.). However, Michael Porter argues this shift in supply can be offset by the cost-saving innovation that results from firms working around environmental regulation in their production and processes.

IV. Empirical Examination

Empirical Methodology

To examine the effect of environmental stringency on the innovation within the chemical industry, this paper uses a two-way fixed effects model using data from 29 countries within a period of seven years (2006-2013). Using the Porter Hypothesis as our economic theory, we create a model that analyzes the impact environmental regulation has on patent production within a country's chemical industry. :

(1) $Log(Patents_{i,t}) = \beta_0 + \beta_1 Log(EPS_{i,t-1}) + \beta_2 Log(RD_{i,t-1}) + \beta_3 Log(TradeOpenness_{i,t-1}) + \beta_4 Log(VA_{i,t-1}) + \beta_5 Log(Patents_{i,t-1})\ \beta_6 Log(GE_{i,t-1}) + \beta_7 Log(Deathrate_{i,t-1}) + \varepsilon$

Our dependent variable is $Patents_{i,t}$. which measures the number of Class C (Chemical and Metallurgy) Patents and is used as a proxy for innovation in the Chemical Industry for a country *i* at time *t-1* (a time lag by one year). This is similar to previous studies that have proxied innovation using patent applications in log-log models (see Rubashkina, Y., Galeotti, M., & Verdolini, E. (2014)). The patents are collected from the Triadic Patent family to avoid double counting patents that are sent to multiple patent offices and to encompass international patents (as opposed to patents that may be applied for locally but not internationally). This variable uses fractions to account for patents with multiple applicants from a country. For example, an application of one American and one French resident would show up as ½ for each country.

The explanatory variable for this paper is labelled $EPS_{i,t-1}$, which is the Environmental Policy Stringency Index for a country *i* at time *t-1*. Created by the OECD, this index is used to compare countries' environmental stringency on a scale from 0-6, where 0 is not stringent and 6 is the highest degree granted for stringency. The index uses 14 policy instruments that are relevant to targeting climate and air pollution goals. These instruments are primarily focused on climate and air pollution and may use the cost of abatement to examine how stringent one country is relative to another country. To respect the lag variable model recommendations in our literature review, data collection explanatory and control variables began in 2005 and ended in 2012, while our dependent variable was collected from the years 2006 to 2013.

In order to account for the differences in competitiveness across countries we used multiple control variables in our model. The purpose for these controls is to isolate the difference in patent applications caused by environmental stringency, from the differences that are caused by a country who has more matured economies and industries. Since this paper is focused on the weak form of the Porter Hypothesis, the model's results will be focused on how environmental stringency affects the innovation within the chemical industry.

In order to control for the differences between countries, we first began by controlling for the difference between countries' knowledge stock by using the variables $RD_{i,t-1}$ and $Patents_{i,t-1}$. The data for R&D is collected from the OECD Analytical Business Enterprise R&D database. The data is measured in Purchasing Power Parity Current U.S. Dollars (PPP USD). We expect countries with heavy R&D expenditure to be more productive in applying for patents than countries without the same level of investment. Next, since we are measuring percent change in patents for a year as our dependent variable, we lag this same variable by a year. This is because we expect countries with high patent productivity would be more likely to have higher percent changes in patent applications (Rubashkina 2014). Therefore, the patent applications for a country with a matured industry may have more applications because they are, as Sir Isaac Newton stated, "standing on the shoulder of giants".

$VA_{i,t-1}$ and $TradeOpenness_{i,t-1}$ control for the macroeconomic make-up of these countries. Wealthier countries may have more patent applications simply because there is more money to invest in capital and infrastructure that can drive forward innovation and productivity. Countries with high trade openness may be more likely to apply for patents because they need to increase efficiency to compete against other international markets. Measures for GDP, exports and imports were collected from the International Monetary Fund's Balance of Payments Statistics (2018). We use value added in our model because measures used in the EPS Index may be impacted by the amount of industry that is found in a country. The logic behind this is if that country targets most of their environmental policies to counteract the negative externalities caused from total industry, this could incorrectly state the impact regulation has on innovation of specific industries. Value added data is total value added of all goods by a country that is consumed by final demand in the rest of the world by source country i at a time $t-1$. The data is taken from the Trade in Value Added (TiVa) dataset by the OECD (2016).

Finally, we controlled for Government Effectiveness $(GE_{i,t-1})$ using the World Bank's World Governance Indicators (2019). The index is calculated through a variety of indicators, from quality of bureaucracy to coverage area and resource efficiency. Data for this index is sourced from institutional assessments, the Gallup World Poll, the Global Integrity Index, and other international governance assessors and surveyors. This is then used to produce a ranking from -2.5 (less effective) to 2.5 (most effective). The rationale for this variable is to explain how differences in a government's policies are perceived and how effective their policies are. There may be environmentally stringent countries that lack the quality and credibility to create the "good" policies that are required to meet the conditions of Porter's Hypothesis.

OLS Analysis

After running an initial Ordinary Least Squares Regression (OLS), we were left with a small amount of observations with only 20 of 36 OECD countries being represented. This was due to the amount of countries who had missing observations in the variable $Deathrate_{i,t}$. Therefore, we removed this variable to create a restricted model that allows us to include a wider range of OECD countries in our sample as shown in equation (2).

(2) $$Log(Patents_{i,t}) = \beta_0 + \beta_1 Log(EPS_{i,t-1}) + \beta_2 Log(RD_{i,t-1}) + \beta_3 Log(TradeOpenness_{i,t-1}) + \beta_4 Log(VA_{i,t-1}) + \beta_5 Log(Patents_{i,t-1}) + \beta_6 GE_{i,t-1} + \varepsilon$$

The results of this OLS model follow closely with the findings within previous literature. First, we see insignificant results of environmental effects on productivity when we use patents as a proxy for productivity. Previous literature suggests that for high polluting industries we could not see an impact for almost three years after the policy. Therefore, it could be the case that a lag of one year is not reflective of the time it takes an industry to adjust to regulation. Next, we find that EPS has very little, if any impact, on percent change in patents. The parameter estimates that as a country's EPS Index increases by 1percent, the given country should see an increase of about 1.18 percent in patent applications. However, the root means squared error of this regression states the variation of percent change in patents is 50.26 percent. This fact as well as the fact that the p-value for the coefficient is nearly one, means that not only is this result outweighed by the variation of percent change, but that it also is insignificant at every confidence level.

This OLS model has a R-squared value of 0.96, meaning it can explain 96 percent of the variation within the percent change in patents. With a high F-value of 827.63, this model was found to be significant at the 99 percent confidence level. While all the control variables (except our value-added variable) had a positive relationship significant at the 99percent confidence level, it is important to note this model may not be appropriate. Multicollinearity was found between our explanatory and independent variables, which can be seen in Table 3 of the Appendix. Based on past research, we found that to combat the problem for controlling heterogeneity between countries and years would be by using a two-way fixed effects model.

Fixed-Effect Analysis

The Fixed Effect model delivered 25 country cross sections within an 8-year period of time. The empirical model shows a high R^2 value that implies our model explains 98.5 percent of the percent change in patents and a high f-value that shows our model is significant at the 98.1 percent confidence level. Here we found very different results than we saw in our OLS model. The model finds that $EPS_{i,t}$ was significant at the 99 percent confidence level. It estimates that as a country's EPS increases by 1 percent, Type C patent applications for a country *i* in year *t* will increase by 47.8 percent.

Surprisingly, many of our control variables no longer showed significance at any confidence level and some even took on more negative relationships with our dependent variable. The reason for this may be two-fold. First, the chemical industry at times can make up too little of a country's total GDP to be accurately measured using national level data, and instead industry level data would be most accurate. Second, there is not enough industry level data to make up observations that would be appropriate for describing an international trend instead of describing the specifics of the small amount of European countries that report this data.

V. Conclusions and Limitations

The Fixed Effects models reported that at the 99 percent confidence level, Type C patent applications by country would increase by about 48 percent more patents the year after their EPS Index increased by one unit, satisfying the hypothesis of my research. This analysis would benefit from deeper dives into specific policies at an industry level to be more convincing in support or refute of the Porter Hypothesis. While more robust modelling would help provide more confidence in our results that would support this finding, there are many takeaways from this analysis on the research level and policy level.

Environmental stringency will see the same increase of patent productivity in high polluting industries as past research has seen in manufacturing and in total industry. While firms work to meet standards through expenses in production changes or in cost of abatement, they may see increased efficiency that saves them time and resources to focus on innovation. While knowledge stock may impact the number of patents, competition is what drives that percent change in patents from one year to another. Therefore, countries should not fear the impact of their regulation will have on their industry's ability to compete. Instead, countries should focus on ways they can support firms transitioning to regulations in the short-term to ensure they do not lose competitive advantage and to minimize the deadweight loss caused by any shifts in their supply curves.

Yet, there are many limitations when researching the Porter Hypothesis, as the Porter Hypothesis was built on very specific conditions that must be met. First, policies must be deemed as “good, flexible” policies as described in Porter’s theory. Second, the effects must be long-term. These two conditions are a challenge to meet as they are very broad conditions. Good, flexible policies would need to be analyzed individually first. The best way to do this would be through firm-level data which is difficult to obtain. Finally, the long-term condition at this time makes analysis very difficult as environmental regulation and innovation has changed dramatically since the 1990s. Most multilateral climate agreements have only been signed in the past six years. This means the necessary data would come from 2014-2019. Yet, most international data is self-reported and comes in a few years behind. Data collected could only reach up to 2015 and EPS index data stops at 2012. This is a concern because many strides in environmental policy have been made as a result of multilateral agreements signed around the time of 2014 and 2015. Considering past research, this means that firms may not have had time to adjust to the long-term implications of what have been the most sweeping environmental regulations made in the past two decades.

This research also faces similar trials as past research has faced. While the EPS Index data may control for some endogeneity issues that PACE faced, it is not perfect. There are still ways other policies, not aimed at environmental regulation, can find itself being accounted for in the EPS Index. This index also relies on self-reported data from countries like the PACE variable, which causes a bias in the data since countries may choose not to report all their data.

For this reason, we recommend future research should use a two-stage least squares (TSLS) regression as it may be the case the error term and independent variables are correlated.

Finally, the EPS Index is not calculated on an annual basis, making recent observations non-existent. Therefore, we would suggest further research uses other means to proxy for this variable like shadow pricing to avoid these concerns. Another recommendation is that further research is focused on the implications of similar environmental policy regulations on innovation as opposed to all environmental regulation. Since the Porter Hypothesis stresses the importance of “good” policy, it would be very interesting to see what variables show strong relationships with changes in innovation either positively or negatively.

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Appendix:

Table 1:

Data Description		
Variable Name	**Definition**	**Source**
Log(Patents $_{i,t}$)	*Number of Class C (chemical and metallurgy) patents filed together at the European Patent Office, Japanese Patent Office and the U.S. Patent and Trade Office protecting the same invention.*	OECD Science and Technology Industry Outlook (2020)
Log(EPS $_{i,t-1}$)	*OECD's Environmental Policy Index. Units from 0 (not stringent) to 6 (most stringent).*	OECD Environmental Policy Stringency Index. (2012)
Log(RD $_{i,t-1}$)	*Gross expenditure of Purchasing Price Parity current U.S. Dollars invested in total research and development.*	OECD Analytical Businesse Enterprise R&D Database (2020)
Log(TradeOpenness $_{i,t-1}$)	*Sum of imports and exports to Gross Domestic Product. All data taken from the World Bank in current Purchasing Price Parity current U.S. Dollars.*	International Monetary Fund Balance of Payments Statistics (2018)
Log(VA $_{i,t-1}$)	*Amount of current U.S. Dollars added to each stage of production from a country that is consumed in final demand by the rest of the world.*	OECD Trade in Value-Added: Origin of Value-Added in Final Demand (2018)
Log(GE $_{i,t-1}$)	*Government Effectiveness Rate from the World Governance Indicators. From -2.5 (least effective) to 2.5 (most effective).*	World Bank Bank World Governance Indicators (2018).
Log(Deathrate $_{i,t-1}$)	*Percent of employee enterprise deaths to total employee enterprises within a country.*	OECD Structural and Demographic Business Statistics. (2017)

Table 2:

Descriptive Statistics					
Variable Name	**Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Log(Patents $_{i,t}$)	200	314.24	655.89	0.07	2654.1
Log(EPS $_{i,t-1}$)	186	2.87	0.91	0.63	5.38
Log(RD $_{i,t-1}$)	191	40257.75	84451.01	482.38	457612
Log(TradeOpenness $_{i,t-1}$)	200	0.83	0.38	0.25	1.82
Log(VA $_{i,t-1}$)	200	1669557.57	2938199.41	37006.2	16262347
Log(GE $_{i,t-1}$)	200	1.35	0.57	0.09	2.35
Log(Deathrate $_{i,t-1}$)	91	9.45E+00	4.27E+00	1.00E+00	3.37E+01

Table 3:

Pearson Correlation Coefficients: Prob > |r| under H0: Rho=0 Number of Observations						
Variable	$Log(EPS_{i,t-1})$	$Log(RD_{i,t-1})$	$Log(TradeOpenness_{i,t-1})$	$Log(VA_{i,t-1})$	$Log(GE_{i,t-1})$	$Log(Deathrate_{i,t-1})$
$Log(EPS_{i,t-1})$	1.00 200	0.2 .005 190	0.14 0.05 200	0.05 0.47 200	0.57 <.0001 200	0.24 0.02 91
$Log(RD_{i,t-1})$	0.2 .005 190	1 190	-0.57 <.0001 190	0.95 <.0001 190	0.25 .0004 190	-0.31 0.003 91
$Log(TradeOpenness_{i,t-1})$	0.14 0.05 200	-0.57 <.0001 190	1.0 200	-0.66 <.0001 200	0.14 0.05 200	0.21 0.05 91
$Log(VA_{i,t-1})$	0.05 0.47 200	0.95 <.0001 190	-0.66 <.0001 200	1.0 200	0.08 0.23 200	-0.28 0.006 91
$Log(GE_{i,t-1})$	0.57 <.0001 200	0.25 .0004 190	0.14 0.05 200	0.08 0.23 200	1.0 200	-0.2 0.06 91
$Log(Deathrate_{i,t-1})$	0.24 0.02 91	-0.31 0.003 91	0.21 0.05 91	-0.28 0.006 91	-0.2 0.06 91	1.0 91

Table 4:

Environmental Stringency's Effect on Innovation Dependent Variable: $Log(Patents_{i,t})$			
	Model:		
Variable	(1) FE	(2) OLS	(1) OLS
Intercept	-1.49 (-0.24)	-4.46 (-4.14)***	-2.1 (-1.54)
Log(EPS $_{i,t-1}$)	0.48 (2.61)***	0.01 (0.10)	0.14 (0.66)
Log(RD $_{i,t-1}$)	0.32 (1.02)	0.41 (3.6)***	0.34 (2.14)**
Log(TradeOpenness $_{i,t-1}$)	1.27 (1.93)*	0.37 (2.56)**	0.07 (0.38)
Log(VA $_{i,t-1}$)	0.32 (0.81)	0.08 (0.67)	-0.05 (-0.30)
Log(Patents $_{i,t-1}$)	-0.17 (-2.26)**	0.67 (13.78)***	0.8 (11.22)***
Log(GE $_{i,t-1}$)	-0.04 (-0.15)	0.32 (3.14)**	0.12 (1.00)
Log(Deathrate $_{i,t-1}$)			-0.02 (-1.23)
N	190	190	91
Adjusted R-squared	0.98	0.95	0.96
F-Value	6.52	656.19	303.63
T-Values in Paranthesis *, **, and *** represent signigicance at 90 percent, 95, percent, and 99 percent level respectively			

SAS Code:

```
Libname Project "C:\Users\mmvwo\OneDrive\Desktop\Project2";
Proc import out= Project.EPS
	datafile ="C:\Users\mmvwo\OneDrive\Desktop\Project2\EPS.csv";
	run;
Data work.EPS;
set Project.EPS;
run;
proc sort data=Project.EPS;
by country year;
run;



Proc import out= Project.GE
	datafile ="C:\Users\mmvwo\OneDrive\Desktop\Project2\GovEffectiveness.csv";
	run;
Data work.GE;
set Project.GE;
run;
proc sort data=Project.GE;
by country year;
run;

Proc import out= Project.Deathrate
	datafile ="C:\Users\mmvwo\OneDrive\Desktop\Project2\Deathrate.csv";
	run;
Data work.Deathrate;
set Project.Deathrate;
run;
proc sort data=Project.Deathrate;
by country year;
run;


Proc import out= Project.VAs
	datafile ="C:\Users\mmvwo\OneDrive\Desktop\Project2\VAs.csv";
	run;
Data work.VAs;
set Project.VAs;
run;
proc sort data=Project.VAs;
by country year;
run;
```

```
Proc import out= Project.VAp
        datafile ="C:\Users\mmvwo\OneDrive\Desktop\Project2\QVA.csv";
        run;
Data work.VAp;
set Project.VAp;
run;
proc sort data=Project.VAp;
by country year;
run;


Proc import out= Project.Patents
        datafile ="C:\Users\mmvwo\OneDrive\Desktop\Project2\Patents.csv";
        run;
Data work.Patents;
set Project.Patents;
run;
proc sort data=Project.Patents;
by country year;
run;


Proc import out= Project.WorldBank
        datafile ="C:\Users\mmvwo\OneDrive\Desktop\Project2\WorldBank.csv";
        run;
Data work.WorldBank;
set Project.WorldBank;
run;
proc sort data=Project.WorldBank;
by country year;
run;

Proc import out= Project.chemRD
        datafile ="C:\Users\mmvwo\OneDrive\Desktop\Project2\chemRD.csv";
        run;
Data work.chemRD;
set Project.chemRD;
run;
proc sort data=Project.chemRD;
by country year;
run;

Proc import out= Project.RD
        datafile ="C:\Users\mmvwo\OneDrive\Desktop\Project2\RD.csv";
        run;
```

```
Data work.RD;
set Project.RD;
run;
proc sort data=Project.RD;
by country year;
run;




Data Project.Merged;
merge Project.Patents Project.WorldBank Project.VAs Project.EPS  Project.GE  Project.chemrd
Project.RD Project.Deathrate;
by country year;

tradeopenness= (imports+exports)/gdp;
lagtradeopenness= lag(tradeopenness);

logPatents= log(patents);
laglogPatents = lag(logPatents);

logEPS = log(EPS);
lagEPS= lag2(logEPS);

logRD= log(RD);
lagRD= lag(logrd);

logva = log(totalVA2);
lagva= lag(logva);

logGE = log(GE);
lagGE = lag(GE);

lagdeathrate= lag(deathrate);

if year gt 2013 then delete;
if year lt 2006 then delete;

if country = "CHL" then delete;
if country = "EST" then delete;
if country = "HUN" then delete;
if country = "ISL" then delete;
if country = "ISR" then delete;
if country = "LUX" then delete;
if country = "NZL" then delete;
if country = "POL" then delete;
```

```
if patents = "." then delete;

run;

/* without deathrates*/
proc means
data=project.merged;
var  patents  EPS GE  deathrate  RD  GDP  tradeopenness totalVA2 ;
run;


proc sgscatter data=project.merged;
plot logpatents*EPS;
run;

proc sgscatter data=project.merged;
plot logpatents*lagtradeopenness;
run;
run;
proc corr
data=project.merged;
var  lagEPS lagRD  lagtradeopenness lagva  laglogPatents lagGE deathrate;
run;
quit;
proc reg
data=project.merged;
model  logpatents = lagEPS lagRD  lagtradeopenness lagva  laglogPatents lagGE deathrate;
run;
quit;
proc reg
data=project.merged;
model  logpatents = lagEPS lagRD  lagtradeopenness lagva  laglogPatents lagGE;
run;
quit;

proc panel
data=project.merged;
model  logpatents = lagEPS lagRD  lagtradeopenness lagva  laglogPatents lagGE/fixtwo;
id country year;
run;
quit;
```