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Abstract

We empirically investigate the impacts of the implementation of Transatlantic Trade and Investment Partnership (TTIP) on per capita emissions of eight air pollutants and municipal waste. We employ the same explanatory variables and apply the same empirical strategy and methodologies as in (Qirjo and Pascalau, 2019). We provide robust evidence suggesting that the implementation of TTIP could be beneficial to the environment because it may help reduce per capita emissions of NO_2 and $HFCs/PFCs/SF_6$ in a typical TTIP member. This result is based on the statistically significant evidence showing that, on average, the pollution haven motive based on national per capita income variations is dominated by the Factor Endowment Argument based on the classical Heckscher-Ohlin trade theory and the pollution haven motive originating from an inverse measurement of national population density differences. However, we also report generally statistically significant evidence implying that the implementation of TTIP could denigrate the environment because it may help increase per capita emissions of SO_2, SO_x, NO_x, SF_6, and NH_3.

JEL Classification: F11, Q15

Keywords: Free Trade, Environmental Economics, TTIP.

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1 Introduction

In this paper we employ the same empirical methodology used in (Qirjo and Pascalau, 2019), but now we focus on eight other air pollutants and municipal waste. Therefore, using data over the 1989-2013 time period, for 28 EU members and the U.S., we empirically investigate the role of the implementation of Transatlantic Trade and Investment Partnership (TTIP) on per capita emissions of eight air pollutants; SO_2, SO_x, CH_4, $HFCs/PFCs/SF_6$, NO_2, NO_x, SF_6, and NH_3, and a general pollutant such as municipal waste.

We find statistically significant evidence suggesting that the implementation of TTIP, may help reduce per capita emissions of $HFCs/PFCs/SF_6$ and NO_2. More specifically, holding all the other factors constant, we show that, on average, a one percent increase in bilateral trade between the U.S. and a typical EU member may help reduce per capita emission of $HFCs/PFCs/SF_6$ and NO_2 by about 3 Teragrams (Tg) in CO_2 in-equivalent and 10 Gigagrams (Gg) in a year, respectively. On the other hand, we also report potential environmental degradation due to the implementation of TTIP. In particular, holding everything else constant, we report generally statistically significant evidence suggesting that one percent increase in bilateral trade between the U.S. and a typical EU member may help increase per capita emissions of SO_2, SO_x, NO_x, SF_6, and NH_3 by about 360 Kilograms (Kg), 446 Gg, 528 Gg, 750 Gg in CO_2 in-equivalent, and 45 Gg, respectively. In the case of CH_4 we find the existence of unit root. Thus, for CH_4, we re-estimate the results using the first difference and find no statistically significant evidence for the trade variable. Furthermore, we do not find any statistically significant evidence that indicates changes on municipal waste per capita as a consequence of the implementation of TTIP.

Note that a typical TTIP member is poorer and more densely populated as compared to the U.S. Thus, a poor country may act as a pollution haven because it adopts lax environmental laws following PHH1 (Pollution Haven Hypothesis based on national per capita income differences). On the other hand, the U.S. may act as a pollution haven because it is sparsely populated as compared to a typical TTIP member according to PHH2 (Pollution Haven Hypothesis generated from national density of population variations). Consequently, it may produce the pollution-intensive goods at cheaper prices, and therefore, export them in the EU (see for example (Frankel and Rose, 2005), which was the first empirical study to introduce PHH2) due to the implementation of TTIP. In conclusion, in the case of the above two air pollutants, the U.S. may act as a pollution haven due to the implementation of TTIP if PHH1 is dominated by PHH2. Moreover, if this is the case, then FEH (Factor Endowment Hypothesis) may further denigrate the environment in the U.S. since the latter is a capital-abundant country as compared to an average TTIP member. Thus, the

U.S. would export capital-intensive goods (that are considered pollution-intensive goods) in a typical labor-abundant EU member and import labor intensive-goods (that are considered environmental friendly goods) from an average EU member due to the implementation of TTIP. Analogously, a typical TTIP member may act as a pollution haven if PHH1 dominates PHH2. However, under this scenario, the implementation of TTIP could still be beneficial to the environment in a typical TTIP member if FEH dominates PHH1.

Our empirical exercise shows that the implementation of TTIP, on average, is more likely to help in the fight against global warming because it may help reduce per capita emissions of NO_2 and $HFCs/PFCs/SF_6$. This is because for the latter two air pollutants, we observe a stronger FEH and PHH2 as compared to PHH1. In other words, more openness to trade between the U.S. and the EU could help reduce per capita emissions of NO_2 and $HFCs/PFCs/SF_6$ because being labor-abundant and densely populated typical EU member appears to be more environmentally efficient despite the fact of being poorer than the U.S. This result is consistent with Qirjo and Pascalau (2019) who using the same empirical methodology and explanatory variables with the current study, provide robust evidence suggesting that the implementation of TTIP may help reduce per capita emissions of CO_2 and *GHGs*, respectively. It is also consistent with Qirjo et al. (2019b) who empirically analyze the impacts of CETA on four main *GHGs* during 1990-2016 time period. They show that the implementation of CETA could contribute in the fight against global warming because it may help reduce per capita emissions of CO_2, CH_4, $HFCs/PFCs/SF_6$, and N_2O, respectively.

However, our empirical findings suggest that the implementation of TTIP could assist in increasing global warming because it may help increase per capita emissions of SO_2, SO_x, NO_x, SF_6, and NH_3. It appears that for SO_2, this result stands because being a poor EU member pollute the environment more despite the fact of being labor-abundant and densely populated EU member as compared to the U.S. For SO_x and NO_x, we show that more trade intensity between the U.S. and the EU may help increase per capita emissions of SO_x and NO_x because being a capital-abundant EU member pollute the air more despite of being a rich EU member relative to the U.S. For SF_6 and NH_3, it appears that there is a positive and statistically significant evidence between the trade intensity variable and per capita emissions of SF_6 and NH_3 because the U.S. may act as pollution haven due to being sparsely populated even though it is richer than a typical EU member.

In an average TTIP member, we find robust empirical evidence in support of PHH1 and PHH2. In particular, on average, we find generally statistically significant evidence suggesting that per capita emissions of SO_x, $HFCs/PFCs/SF_6$, NO_2, SF_6, and NH_3 go up, respectively, as EU members get poorer relative to the U.S. due to the implementation of TTIP. Furthermore, we report generally robust empirical evidence pointing out that the less densely populated countries may act as pollution havens due to the implementation of TTIP in the case of *HFCs/PFCs/*SF_6, NO_2, CH_4, SF_6, and NH_3, respectively. Moreover, we find statistically significant evidence in support of the FEH suggesting that, on average and under the assumption that capital-intensive goods are considered pollution-intensive goods (for a theoretical basis on FEH see (Antweiler et al., 2001)), an EU member with a lower capital to labor ratio relative to the U.S. will find per capita emissions of *HFCs/PFCs/*SF_6 and NO_2 to decrease in response to the implementation of TTIP. See also (Qirjo and Christopherson, 2016) for an empirical analysis of the implementation of TTIP accounting for FEH and PHH1, but in the absence of PHH2.

We find statistically significant evidence, implying that the implementation of TTIP in countries that use English as an official language may help increase per capita emissions of NO_2, *HFCs/PFCs/*SF_6, CH_4, SF_6, SO_2, and NH_3 relative to countries where English is not an official language. In the case of NO_2 and *HFCs/PFCs/*SF_6, this result could be because on average per capita emissions of the latter two air pollutants maybe reduced more in the former Ex-Communist members of the EU, which produce more labor-intensive goods due to higher trade intensity with the U.S. In the case of SF_6, SO_2, and NH_3, this result stands because there is more trade due to language similarities between the U.S. and each of the English speaking EU members respectively.

Our results show that the implementation of TTIP in countries that have sea or ocean access may help reduce per capita emissions of CH_4, SO_2, SF_6, *HFCs/PFCs/*SF_6, and NO_2 relative to countries that are landlocked. We claim that this result stands for the latter two air pollutants because the EU members with sea access trade more with the U.S. as compared to landlocked EU members. However, the implementation of TTIP in countries that have sea access may help reduce per capita emissions of CH_4, SO_2, and SF_6 relative to countries that are landlocked, despite the fact that we report a positive relationship between the trade intensity variable and per capita emissions of each of the latter 3 air pollutants. We also show that the implementation of TTIP in countries that have sea access may help increase per capita emissions of SO_x and NO_x as compared to landlocked countries. This result stands because EU members with sea access trade more with the U.S. as compared to landlocked EU members as a result of the implementation of TTIP.

We report robust evidence indicating that the implementation of TTIP in countries that have adopted Euro as their official currency may help increase more per capita emissions of SO_x as compared to TTIP members where Euro is not an official currency. This is because for SO_x, on average, EU members that have adopted Euro trade more with the U.S. We find robust evidence suggesting that more trade openness between the EU members that have adopted Euro as their official currency and the U.S. would increase per capita emissions of SF_6 and NH_3 less. We claim that the latter result stands because they may benefit from stronger technique effects due to trading more with the U.S., which is in a similar stage of economic development. We show statistically significant evidence implying that the implementation of TTIP in EU members that have adopted Euro as their official currency may help reduce more per capita emissions of $HFCs/PFCs/SF_6$ and NO_2. This result may stand because EU members that have adopted Euro could be trading more with the U.S. due to lower exchange transaction's costs. And more trade between the former EU members and the U.S. is associated with lower per capita emissions of $HFCs/PFCs/SF_6$ and NO_2, respectively.

The rest of this paper is organized as follows. Section 2 describes our dataset and its sources. Section 3 presents our empirical results. Finally, section 4 concludes.

2 Data Description of Pollutants and their Sources

We denote methane by CH_4. We obtain the data for CH_4 from (CAIT, 2014).[1] They are expressed in CO_2 in equivalent Gg per capita emissions. Methane is the second most prevalent *GHG* originating from human activities emitted in the U.S. In particular, in 2013, CH_4 accounted for about 10% of all U.S. *GHGs* emissions coming from human activities. The main sources of CH_4 from human activities originate from the raising of livestock and leakage from natural gas systems. Despite the fact that CH_4's lifetime in the atmosphere is much shorter than CO_2, the comparative impact of CH_4 on climate change is 25 times greater than CO_2 over a 100 years period.

Our models denote Sulfur Oxides, Sulfur Dioxide, Nitrogen Oxides and Nitrogen Dioxide with SO_x, SO_2, NO_x, and NO_2 respectively. We obtain the data of the above pollutants from the following sources: SO_2 data are based on (Stern, 2006). SO_x data are from (EEA, 2015). NO_x data are from (NECNFR, 2015). NO_2 are from (UNFCCC, 2015). SO_x is measured in *Gg* per capita. SO_2 is measured in Kg sulfur emission per capita. NO_x are measured in *Gg* per capita using the entire territory. NO_2 are measured in *Gg* emissions per capita. All these pollutants are released into the atmosphere as byproducts of the energy transformation process when converting fossil fuels to energy. In the air these substances are turned into acidifying agents, often called acid rain, and on the ground these pollutants cause both soil and water acidification. (Factbook, 2014) reports that over the past

[1] Please note that CAIT data are derived from several sources. Full citations are available at http://cait2.wri.org/faq.html#q07. FAOSTAT Emissions database, http://faostat3.fao.org/faostat-gateway/go/to/browse/G2/*/E.

Table 1: *Data Sources of Pollutants and their unit of measurement*

Variable	*Source*	*Unit of Measurement*
CH_4 (Methane)	CAIT (2015)	Gg in CO_2 equiv. per capita
HFCs/PFCs/SF_6	UNFCCC (2015)	Tg in CO_2 equiv. per capita
NH_3 (Ammonia)	NEC/NFR (2015)	Gg per capita
NO_2 (Nitrogen Dioxide)	UNFCCC (2015)	Gg per capita
NO_x (Nitric Oxide)	NEC/NFR (2015)	Gg per capita
SF_6 (Sulfur Hexafluoride)	UNFCCC (2015)	Gg in CO_2 equiv. per capita
SO_2 (Sulfur Dioxide)	Stern (2006)	Kg per capita
SO_x (Sulfur Oxide)	EEA (2015)	Gg per capita
Municipal Waste	Eurostat (2015)	Kg per capita

25 years, we have seen a decline in all the above air pollutant emissions, due to several reasons, such as: a switch to more non-fossil fuel energy sources, energy conservation technological improvements, and stronger environmental regulations. However, this improvement in OECD countries has been offset in other parts of the world, where growth has resulted in increased fossil fuel use.

Municipal solid waste, or simply municipal waste is denoted by *MW* throughout our paper. (USEPA, 2016) defines municipal waste as the waste collected and treated by or for municipalities. It covers waste mainly from appliances, batteries, bottles, cans, clothing, food scraps, furniture, grass clippings, product packaging, newspapers paint and plastic materials. All these trashes are mainly generated from households, houses, hospitals, schools, government enterprises and private businesses. (USEPA, 2016) claims that *"In 2012, Americans generated about 251 million tons of trash and recycled and composted almost 87 million tons of this material, equivalent to a 34.5 percent recycling rate. On average, Americans recycled and composted 1.51 pounds of their individual waste generation of 4.38 pounds per person per day... In 2012, newspaper/mechanical papers recovery was about 70 percent (5.9 million tons), and about 58 percent of yard trimmings were recovered. Organic materials continue to be the largest component of MW. Paper and paperboard account for 28 percent and yard trimmings and food waste account for another 28 percent. Plastics comprise about 13 percent; metals make up 9 percent; and rubber, leather, and textiles account for 8 percent. Wood follows at around 6 percent and glass at 5 percent. Other miscellaneous wastes make up approximately 3 percent of the MW generated in 2011... Recycling and composting prevented 86.6 million tons of material away from being disposed in 2012, up from 15 million tons in 1980. This prevented the release of approximately 168 million metric tons of carbon dioxide equivalent into the air in 2012—equivalent to taking over 33 million cars off the road for a year."* We obtain the data of municipal waste from (EUROSTAT, 2015). We use Kg of municipal waste generated per capita as a unit of measurement for this pollutant.

We denote sulfur hexafluoride with SF_6. We obtain per capita emissions of SF_6 from (UNFCCC, 2015). They are in *Gg* in CO_2 equivalent per capita emissions. According to (IPPC, 2007), SF_6 is evaluated as the most potent gas out of all *GHGs*. It is used mainly by electronics manufacturers and electrical utilities and in the industry of magnesium production. Pound per pound, the comparative impact of SF_6 on climate change is approximately 2300 times greater than CO_2 over a 100 years period. SF_6 is extremely long-lived in the atmosphere. However, according to (IPPC, 2007) despite being the most potent *GHGs* its contribution to global warming is estimated to be less than .02 percent. This is due to the fact of its very low releases in the atmosphere as compared to those of CO_2. According to (USEPA, 2016), emissions of SF_6 in the U.S. have declined during the 1990 to 2013 time period, due to reduction efforts in the electricity transmission and distribution industry. In the U.S., emissions of SF_6 are expected to decline by 25% between 2005 to 2020.

We denote ammonia, or azane, or as known in chemistry, nitrogen trifluoride with NH_3. We obtain per capita emissions of NH_3 from (NECNFR, 2015). They are in *Gg* per capita emissions. NH_3 is a gas that is mainly released into the atmosphere from the decay process of nitrogenous animal and vegetable matter.

We denote hydrofluorocarbons with *HFCs* and perfluorocarbons with *PFCs*. Both these *GHGs* together with SF_6 and nitrogen trifluoride (NH_3) are called fluorinated gases, or simply F-Gases. (USEPA, 2016) states that *"unlike many other greenhouse gases, fluorinated gases have no natural sources and only come from human-related activities. They are emitted through a variety of industrial processes such as aluminum and semiconductor manufacturing. Many fluorinated gases have very high global warming potentials relative to other greenhouse gases, so small atmospheric concentrations can have large effects on global temperatures. They can also have long atmospheric lifetimes, in some cases, lasting thousands of years. Like other long-lived greenhouse gases, fluorinated gases are well-mixed in the atmosphere, spreading around the world after they are emitted. Fluorinated gases are removed from the atmosphere only when they are destroyed by sunlight in the far upper atmosphere. In general, fluorinated gases are the most potent and longest lasting type of greenhouse gases emitted by human activities."* According to (USEPA, 2016), *HFCs* are used as refrigerants aerosol propellants, solvents, and fire retardants. The major emissions source of these compounds is their use as refrigerants, or in air conditioning systems in both vehicles and buildings. *PFCs* are compounds produced as a byproduct of various industrial processes associated with aluminum production and the manufacturing of semiconductors. In the U.S., between 1990 and 2015, emissions of *HFCs* have increased by 250% because they have been widely used as a substitute for ozone-depleting substances. However, during the same time period, emissions of *PFCs* have declined due to emission reduction efforts in the aluminum production industry. We have aggregate data for per capita emissions of *HFCs, PFCs* and SF_6 but not for NH_3. We obtain them from (UNFCCC, 2015) and they are in Tg in CO_2 equivalent per capita emissions. In Table 2 we provide a statistical description of these variables along with their results of a unit root (Im-Pesharan-Shin) test. Note that the data for all our variables are over the 1989-2013 time period, for 28 EU members and the U.S. All the other variables are explained in (Qirjo and Pascalau, 2019). See also (Pascalau and Qirjo, 2017a) for details on filling out the missing observations using the Amelia 2 program in *R*. Moreover, see the former paper for the presentation and economic interpretation of three econometric models (*M1, M2, & M3*) that we use in this paper.

3 Empirical Results

We apply exactly the same empirical methodology as in (Qirjo and Pascalau, 2019). The effects of TTIP on *HFCs/PFCs/*SF_6, CH_4, SO_2, *MW*, SO_x, NO_2, NO_x, SF_6, NH_3 per capita emissions and municipal waste per capita are reported in Tables 3 through 11, respectively. Analogously to (Qirjo and Pascalau, 2019), each Table, in this section, reports the estimation results using fixed effects for *M1*, *M2* & *M3* in the first, second and third columns respectively and the estimation results of the same models, using random effects are reported in the fourth, fifth, and sixth columns, respectively. Further, the estimation results of the three models, using cross-sectional fixed effects are reported in the seventh, eighth and ninth columns, respectively, while the estimation results of the same models, using serial-correlation fixed effects are reported in the tenth, eleventh and twelfth columns, respectively.

Scale-Technique Effects and EKC: In all columns of Tables 3 through 11, we report the scale-technique effects. The 6^{th}row indicates the proxy of the scale-technique effect as measured by one period lagged three-year moving average of income per capita. In the 7^{th} row, we report its squared value in order to investigate the empirical validity of the Environmental Kuznets Curve (EKC). In the case of NO_x, we provide statistically significant evidence for most of our models and estimation methods, consistent with the EKC argument, which indicates that for low income per capita values, there is exist a positive relationship between per capita income and per capita emissions of NO_x, but for high income per capita values, there is a negative relationship between the latter two variables. In other words, initially for low levels of income per capita the scale effect dominates the technique effect, but then eventually for high levels of income per capita their role is inverted.[2] However, in the case of NO_2 and NH_3, we find moderately statistically significant evidence of a positive and monotonic relationship between growth and per capita emissions of each of the latter two air pollutants, respectively. This implies that for both these air pollutants, the scale effect dominates the technique effect. On the other hand, for SO_2 and SO_x, we find statistically significant evidence of a negative and monotonic relationship between income per capita and emissions per capita of each of the latter two air pollutants, respectively. Thus, for both these air pollutants, the technique effect dominates the scale effect. Note that the empirical validity of the EKC is analyzed further in (Pascalau and Qirjo, 2017b), who employ the same dataset with the current study, but they also control for the cube of income per capita variable, and political economic variables such the GINI coefficient, corruption measures, rule of law, contract enforcement, etc... They report empirical evidence in support of EKC for *HFCs/PFCs/*SF_6, CH_4, and CO_2, but they find a positive and monotonic relationship between per capita income and per capita emissions of *GHGs,* SF_6, and NO_2, respectively. The also find an U-shaped relationship between per capita income and per capita emissions of SO_2, and SO_x, respectively. [3]

Composition Effects: We report the direct composition effect of growth, as measured by the capital-labor ratio, and the composition effect of growth, as measured by the cross product of income per capita and capital-labor ratio, in the 8^{th} and 10^{th} rows respectively in each of the Tables 3 through 11 for all our models. We also include the square of the capital-labor ratio, in the 9^{th} row of our tables, in order to capture the diminishing effect of capital accumulation at the margin. We find that the accumulation of capital increases per capita emissions of CH_4, NO_x, and SF_6, respectively. We also find a positive and statistically significant relationship between the composition of growth and per capita emissions of SO_2. However, we show a negative and statistically significant evidence between the composition of growth and per capita emissions of NO_2 and NH_3, respectively.

Population Density Effects: We report the relationship between an inverse measurement of population density, as proxied by land per capita, and pollution in the 14^{th} row, only for M2 & M3 under each estimation method in Tables 3-11. We also include its squared value in the 15^{th} row in order to capture its diminishing returns. We provide positive (negative)

[2]Moreover, we also find moderately statistically significant evidence of the EKC for *HFCs/PFCs/*SF_6(per capita income is positive and statistically significant and the square of income per capita is negative but not statistically significant for almost every empirical specification or model we use in the study) and SF_6 (per capita income is almost always positive and statistically significant, but the squared income per capita is negative and statistically significant only when using *M3* under serial correlation fixed effects with Driscoll-Kraay robust standard errors).

[3]In addition, using the same empirical specifications and models, but a dataset that contains the 28 EU members and Canada during the 1990-2016 time period, Qirjo et al. (2019a) and Qirjo et al. (2019b), among other things, investigate the existence of the EKC and find no evidence in its support for per capita emissions of *GHGs* and CO_2.

and statistically significant evidence of population density (land per capita) and per capita emissions o*f MW,* SO_x, CH_4, and NO_x. However, inconsistent with the environmental economics literature, we find statistically significant evidence that population density (land per capita) reduces (increases) per capita pollution of $HFCs/PFCs/SF_6$, SF_6 , and NO_2. For the latter air pollutant, this relationship is statistically significant only when employing fixed effects method with cross-sectional dependence robust standard errors.

FDI Effects: We show the effects of FDI (over the stock of capital) on pollution in the 13^{th} row when using *M2* & *M3* for each estimation method in Tables 3 through 11. We report a statistically significant and positive relationship between the FDI measurement and the per capita emissions of $HFCs/PFCs/SF_6$ (even thought is moderately statistically significant). This follows the classical pollution haven argument which claims that multinational corporations locate their production in countries that have lax environmental regulations and policies. However, we also report a statistically significant and negative relationship between the FDI variable and the per capita emissions of SO_2, SF_6, and SO_x, respectively. This negative relationship is consistent with the technique effect of FDI which argues that multinational corporations spread out their environmentally cleaner production methods for quality control, or engineering from their countries of origin. Consequently, in this case multinationals may help reduce per capita emissions of the latter three air pollutants.

*F*EH: We use the cross-product of trade intensity and relative capital to labor ratio to capture the FEH. This is denoted by *T(RKL)* and it is reported in the 2^{nd} row of Tables 3 through 11. We present the squared term of the cross-product of trade and relative capital to labor ratio (in order to measure its diminishing returns) in the 3^{rd} row of Tables 3 through 11. Keep in mind that, since we are investigating the possible role of the implementation of TTIP on environment, the relative capital-labor ratios are expressed relative to the U.S., and trade intensity is expressed as the ratio of the volume of bilateral trade of each EU member and the U.S. divided by national GDP (in the case of the U.S., it is its total of exports and imports with all the EU members divided by the GDP of the U.S.). FEH suggests that the implementation of TTIP would increase pollution in capital-abundant countries, but decrease it in labor-abundant countries. Following the literature on trade and environment, capital-intensive goods are considered pollution-intensive goods, while labor-intensive goods are considered environmental friendly goods. Hence, following the classical Heckscher-Ohlin theory, a further trade openness between the capital-abundant U.S. and a typical labor-abundant EU member would increase the production of capital-intensive goods in the U.S. and the labor-intensive ones in an average EU member. Note that there are only 3 EU members that have higher capital to labor ratio as compared to the U.S. (these are Austria, Italy, and Luxembourg), while all the other EU members have lower capital to labor ratio relative to the U.S. Thus, higher trade intensity between the U.S. and a typical EU could lead to higher pollution in the U.S., but lower pollution in an average EU member. In our sample, on average, focusing on the signs of *T(RKL)* and $T(RKL)^2$, we find statistically significant evidence consistent with the FEH for $HFCs/PFCs/SF_6$ and NO_2, respectively. Moreover, we find statistically significant evidence implying a convex relationship between relative to the U.S. capital to labor ration and per capita emissions of SO_x, $NH_3$and NO_x, respectively.

PHH1 & *PHH2*: We employ the cross-product of trade intensity and relative income per capita to capture PHH1. This is denoted by *T(RI)* and it is reported in the 4th row of Tables 3 through 11. We report its squared value in the 5th row in order to capture its diminishing returns. Keep in mind that income per capita is measured as the three-year lagged moving average of real GDP ($I_{it} = .6 * I_{it-1} + .3 * I_{it-2} + .1 * I_{it-3}$). Also, since we are investigating the possible role of the implementation of TTIP on environment, the relative income per capita of each country is expressed relative to the U.S. PHH1 claims that the environmental friendly goods are luxury goods. In this sense poor countries are encouraged to adopt lax environmental regulation and policies, and therefore, produce mainly pollution-intensive goods. Analogously, rich countries adopt stringent environmental regulation and policies that force them to produce environmentally cleaner goods. In our sample, there are only 3 EU members that are richer than the U.S. (these are Denmark, Luxembourg, and Sweden), while all the other EU members are poorer than the U.S. Therefore, following PHH1, more trade openness between the U.S. and the EU should decrease pollution in the U.S., but increase it in a typical EU member. On average, we find generally statistically significant evidence in support of the PHH1 for SO_x, $HFCs/PFCs/SF_6$, NO_2, SF_6, and NH_3. In other words, on average, per capita emissions of the latter 5 air pollutants go down as countries get richer due to the implementation of TTIP.

We also use an alternative method to test the existence of the PHH2 due to the implementation of TTIP. More specifically, we use the cross-product of trade intensity and relative land per capita to detect PHH2. This is denoted by *T(RLPC)* and it is reported in the 11th row of Tables 3 through 11. We report its squared value in the 12th row in order to measure its diminishing returns. Again, the relative land per capita of each country is expressed relative to the U.S. Consistent with PHH2 argument, the implementation of TTIP may move the production of pollution-intensive goods from densely populated countries towards sparsely populated ones. In our sample, there are only 2 EU members that are more sparsely populated than the U.S. (these are Finland and Sweden). All the other EU members are more densely populated than the U.S. Thus, the less densely populated U.S. may act as pollution haven due to the implementation of TTIP. We find generally statistically significant evidence in accordance to PHH2 for *HFCs/PFCs/*SF_6*,* NO_2*,* CH_4*,* SF_6*,* and NH_3. In other words, there is a positive concave relationship between relative land per capita and emissions per capita of each of the latter 5 air pollutants, respectively. Furthermore, for SO_2*,* we find statistically significant evidence suggesting a convex relationship between relative to the U.S. land per capita and emissions per capita of each of SO_2.

Race to the bottom or race to the top hypothesis: What could be the overall effects of TTIP on the environment? In order to capture the possible impact of TTIP on pollution, we employ the trade intensity term, *T (the sum of bilateral exports and imports between each EU member and the U.S. over GDP)* and report it in the 1st row of Tables 3 through 11. We find strongly statistically significant evidence suggesting the existence of the race to the top argument due to the implementation of TTIP for *HFCs/PFCs/*SF_6 and NO_2 (although for *HFCs/PFCs/*SF_6 it is statistically significant only when using *M2* & *M3* under fixed and random effects or using *M2* & *M3* under fixed effects with cross-sectional dependent robust standard errors. For NO_2 it is significant, at 10% level of significance, only when employing *M1* under fixed effects and when using *M3* under random effects or fixed specification with cross-sectional dependent robust standard errors). This an important positive result of this study, since it shows that the implementation of TTIP may be beneficial to the environment because it may help reduce per capita pollution emissions of *HFCs/PFCs/*SF_6 and NO_2. Taking a closer look at Tables 3 and 4, we observe that in a typical TTIP member the implementation of TTIP could help reduce per capita emissions of NO_2*,* and *HFCs/PFCs/*SF_6 because PHH1 is dominated by FEH and PHH2. In simple words, more openness to trade between the U.S. and the EU could help reduce per capita emissions of the latter 2 air pollutants because being labor-abundant and densely populated typical EU member appears to be more environmentally efficient despite the fact of being poorer than the U.S.

However, there are also some potentially bad news in regards to the effects of the implementation of TTIP on the environment. We find some statistically significant evidence consistent with the race to the bottom hypothesis. In particular, we find that the implementation of TTIP may help increase per capita emissions of SO_2 (generally statistically significant under each of our models and empirical specifications with the exception of the serial correlation fixed effects with Driscoll-Kraay robust standard errors)*,* SO_x (statistically significant only when using *M1* & *M2* under fixed or random effects and fixed method with cross-sectional dependent robust standard error)*,* NO_x (statistically significant only when using *M1* & *M2* under fixed or random effects and when employing each of our three models under fixed specification with cross-sectional dependent robust standard error)*,* SF_6 (statistically significant only when using *M1* & *M2* under each of the 4 of our estimation methods), and NH_3 (statistically significant only when using *M1* & *M2* under fixed or random effects and fixed method with cross-sectional dependent robust standard error and when employing M2 under the serial correlation fixed effects with Driscoll-Kraay robust standard errors). Focusing on the signs and statistically significance of the coefficients associated to FEH, PHH1, & PHH2, it appears that for SO_2, the implementation of TTIP could help increase per capita emissions of SO_2 because PHH1 dominates FEH & PHH2. Put it differently, the implementation of TTIP could help increase per capita emissions of SO_2 because being a poor EU member is more important (in terms of environmental policies associated to SO_2) than being labor-abundant and densely populated EU member as compared to the U.S. In the case of SO_x and NO_x, it turns out that more trade intensity between the U.S. and the EU may help increase per capita emissions of SO_x and NO_x because FEH dominates PHH1. In other words, the implementation of TTIP may help increase per capita emissions of SO_x and NO_x because being a capital-abundant EU member (or the U.S. being more capital abundant that an average EU member) is more important for emissions per capita of SO_x and NO_x than being a rich EU member relative to the U.S. (or the U.S. being richer than an average EU member). In the case of SF_6 and NH_3, it appears that there is a positive and statistically significant evidence between the trade intensity variable and per capita emissions of SF_6 and NH_3. This result stands because PHH2 dominates PHH1. In simple words, the implementation of TTIP may help increase per capita emissions of SF_6 and NH_3, because the U.S. may act as pollution haven due to being sparsely populated despite the fact that it is richer than a typical EU member.

Further Globalization Effects: Bilateral trade between the U.S. and a subset of EU members in the sample could be influenced by geographical, cultural, or political reasons. In particular, some TTIP members use English as an official language, or they have access to sea or ocean, or they officially adopt the same currency. In order to capture these effects, as described in (Qirjo and Pascalau, 2019), we employ three dummy variables. In the first one, we use the cross-product of the trade intensity variable with a dummy that is 1 if the official language is English (English=1) and o otherwise. This is denoted by *English=1 x Trade* and it is reported in the 16th row. In the second one, we employ the cross-product of trade with the Sea dummy that is 1 if the TTIP member has access to the sea or the ocean (Sea=1) and o otherwise. This is denoted by *Sea=1 x Trad*e and it is reported in the 17th row. Finally, for the third dummy variable, we use the cross-product of the trade intensity variable with the Euro dummy, where an EU member get a value of 1 for the years that have adopted Euro as their official language (Euro=1) and 0 otherwise. This is denoted by *Euro=1 x Trade* and it is reported in the 18th row of Tables 3 through 11.

We find statistically significant evidence, implying that the implementation of TTIP in countries that use English as an official language may help increase per capita emissions of NO_2, $HFCs/PFCs/SF_6$, CH_4, SF_6, SO_2, and NH_3 relative to countries where English is not an official language. Remember that for the first two air pollutants, we find a negative relationship between the trade intensity variable and their per capita emissions, respectively. Thus, the latter result combine with the result of this dummy variable implies that per capita emissions of NO_2 and $HFCs/PFCs/SF_6$ would be reduced less in TTIP members that use English as their official language (the U.S., the UK, Malta and Ireland) as compared to the EU members that do not use English as their official language due to the implementation of TTIP. This could be because, on average, per capita emissions of the latter 2 air pollutants maybe reduced more in the former Ex-Communist members of the EU which could be producing more labor-intensive goods due to higher trade intensity with the U.S. We find that there is a positive relationship between the trade intensity variable and per capita emissions of SF_6, SO_2, and NH_3, respectively. Therefore, the possible implementation of TTIP may help increase per capita emissions of the latter 3 air pollutants, respectively. The interpretation of the latter two results could be related to the fact that there is more trade due to language similarities between the U.S. and each of the English speaking EU members (the U.K., Ireland, and Malta) respectively, as compared to trade between the U.S. and each of the other EU members.

The results show that the implementation of TTIP in countries that have sea or ocean access may help reduce per capita emissions of CH_4, SO_2, SF_6, $HFCs/PFCs/SF_6$, and NO_2 relative to countries that are landlocked. This could suggest that for the latter two air pollutants, their emissions per capita, as a consequence of TTIP, could be reduced more in countries that have sea access because they trade more with the U.S. as compared to landlocked EU members due to shipping costs differences. However, the implementation of TTIP in countries that have sea access may help increase per capita emissions of SO_x and NO_x as compared to landlocked countries. Analogous to $HFCs/PFCs/SF_6$ and NO_2, per capita emissions of SO_x and NO_x could be increased more in countries that have sea access because they trade more with the U.S. as compared to landlocked EU members as a result of the implementation of TTIP. On the other hand, in a counter-intuitive manner, the implementation of TTIP in countries that have sea access may help reduce per capita emissions of CH_4, SO_2, and SF_6 relative to countries that are landlocked, despite the fact that we report a positive relationship between the trade intensity variable and per capita emissions of each of the latter 3 air pollutants.

We report statistically significant evidence indicating that the implementation of TTIP in countries that have adopted Euro as their official currency may help increase more per capita emissions of SO_x as compared to TTIP members, where Euro is not an official currency. This result may imply that due to the implementation of TTIP, per capita emissions of SO_x could be increased more in EU members that have adopted Euro since they trade more as a group with the U.S. due to lower exchange transaction's costs as compared to the other part of the EU members that have not adopted Euro as their official currency. We find statistically significant evidence suggesting that more trade openness between the EU members that have adopted Euro as their official currency and the U.S. would increase per capita emissions of SF_6 and NH_3 less as compared to the EU members that have not adopted Euro as their official currency. Note that for most of the years in our sample, in general, EU members that have adopted Euro as their official currency are at higher development stages as compared to EU members that have not adopted Euro as their official currency (however, a notable exception of this claim is the UK). Therefore, despite the fact that the EU members that have adopted Euro as their official currency may trade more with the U.S. due to lower exchange transaction's costs, they may benefit from stronger technique effects (adaptation of environmental friendly technologies as a result of higher trade intensity) because of trading more with the U.S., which is in a similar stage of economic development. We show robust evidence implying that the implementation of TTIP in EU members that have adopted Euro as their official currency may help reduce more per capita emissions of $HFCs/PFCs/SF_6$ and NO_2 as compared to TTIP members where Euro is not an official currency. This result may stand because EU members that have adopted Euro could be trading more as a group with the U.S. due to lower exchange transaction's costs relative to the EU members that have not adopted Euro as their official currency. And more trade between the former EU members and the U.S. is associated with lower per capita emissions of $HFCs/PFCs/SF_6$ and NO_2, respectively.

In the rest of the Tables, similar to (Qirjo and Pascalau, 2019), we use two different instrumental approaches for robustness purposes. In particular, in Tables 12 through 20, we provide evidence of the robustness of our result for all our pollutants by employing the lag of trade as an instrumental variable for the contemporaneous variable of trade. Furthermore, in Tables 21 through 29 we provide another robustness check for our 8 air pollutants and municipal waste using an instrumental approach based on the gravity model similar to (Frankel and Rose, 2005). For more details on each of these two instrumental variable approaches see Qirjo and Pascalau (2019). The results of Tables 12-20 and 21-29, generally resemble those of Tables 3-11, respectively.

4 Conclusion

This paper evaluates the impact of the possible implementation of a TTIP on 8 air pollutants SO_2, SO_x, CH_4, $HFCs/PFCs/SF_6$, NO_2, NO_x, SF_6, NH_3, and municipal waste, respectively. We employ the same econometric techniques, models, and explanatory variables as in Qirjo and Pascalau (2019). We use a panel dataset for 28 EU members and the U.S., over the 1989-2013 time period. We find that trade liberalization could assist in the fight against global warming because it may help reduce per capita emissions of two air pollutants in a typical TTIP member. More specifically, keeping everything else constant, we find consistently statistically significant evidence implying that one percent increase in bilateral trade between the U.S. and a typical EU member may help reduce per capita emissions of $HFCs/PFCs/SF_6$ and NO_2 by about 3 Tg in CO_2 in-equivalent and 10 Gg, respectively. On the other hand, we also provide generally statistically significant evidence implying that trade liberalization could also denigrate the environment. This is related to our finding that suggest that the possible implementation of TTIP, on average, may help increase per capita emissions of five air pollutants. In particular, holding everything else constant, we report generally statistically significant evidence suggesting that one percent increase in bilateral trade between the U.S. and a typical EU member may help increase per capita emissions of SO_2, SO_x, NO_x, SF_6, and NH_3 by about 360 Kg, 446 Gg, 528 Gg, 750 Gg in CO_2 in-equivalent, and 45 Gg, respectively.

Focusing on the average TTIP member, we provide statistically significant evidence consistent with PHH1 due to the implementation of TTIP, for SO_x, $HFCs/PFCs/SF_6$, NO_2, SF_6, and NH_3. Put it differently, on average, per capita emissions of these five air pollutants decrease as poor EU members get richer relative to the U.S. due to the implementation of TTIP. Furthermore, we find statistically significant evidence consistent with PHH2 due to the implementation of TTIP, for $HFCs/PFCs/SF_6$, NO_2, CH_4, SF_6, and NH_3. In other words, the U.S. may act as pollution haven according to PHH2 for the latter five air pollutants as a consequence of the implementation of TTIP. Moreover, we report statistically significant evidence consistent with FEH due to the implementation of TTIP for $HFCs/PFCs/SF_6$ and NO_2. Thus, for these two air pollutants, the implementation of TTIP may help reduce air pollution in labor-abundant EU members and increase it in capital-abundant ones.

Since a typical EU member is a poorer, more labor-abundant, and more densely populated country as compared to the U.S., we cannot predict theoretically in an unambiguous way the effects of the implementation of TTIP on the environment. We provide statistically significant evidence suggesting that in the cases of NO_2 and $HFCs/PFCs/SF_6$, trade openness between the U.S. and the EU could be beneficial to the environment because FEH and PHH2 dominates PHH1. At the same time, we report statistically significant evidence implying that the implementation of TTIP could denigrate the environment because PHH1 dominates FEH & PHH2 for SO_2 , and/or FEH dominates PHH1 for SO_x and NO_x, and/or PHH2 dominates PHH1 for SF_6 and NH_3.

We find generally statistically significant evidence implying that the implementation of TTIP in countries that have access to sea may help reduce per capita emissions of CH_4, SO_2, SF_6, $HFCs/PFCs/SF_6$, and NO_2 more than in countries that are landlocked. However, the opposite is true for SO_x and NO_x. Moreover, we report statistically significant evidence, indicating that the implementation of TTIP in countries that use Euro as their common currency may help reduce per capita emissions of $HFCs/PFCs/SF_6$ and NO_2 more than in countries where Euro is not their official currency. However, the opposite is true for SO_x. Further, more trade openness between the EU members that have adopted Euro as their official currency and the U.S. would increase per capita emissions of SF_6 and NH_3 less relative to the EU members that have not adopted Euro as their official currency. In addition, we provide statistically significant evidence, indicating that the implementation of TTIP in countries that use English as their official language may help increase per capita emissions of NO_2, $HFCs/PFCs/SF_6$, CH_4, SF_6, SO_2, and NH_3 as compared to countries where English is not one of their official languages.

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Descriptive Statistics

Table 2: Summary Statistics and Unit Root Tests

Variable	Dimension	N	Mean	SD	Min	Max	Unit Root Tests
SO_2	Level	725	20.838	18.599	0.178	121.245	2.018
Municipal Waste	Level	725	473.323	132.485	159.814	800.636	-7.568***
SO_x	Level	725	35.221	33.692	0.886	267.715	-2.410***
CH_4	Level	725	1.128	0.576	0.456	3.972	0.196
$HFC/PFC/SF6$	Level	725	0.134	0.126	0.000	0.900	-1.930**
NO_2	Level	725	2.804	1.412	0.085	8.936	-6.496***
NO_x	Level	725	38.481	39.928	7.247	308.537	-4.330***
SF_6	Level	725	13.304	25.830	0.000	220.686	-2.695***
NH_3	Level	725	9.807	5.223	3.459	32.799	-6.225***

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. For all series, with the exception of the "relative" series, we use the *Z-t-tilde-bar* statistic of the Im-Pesaran-Shin unit-root test where the AR parameter is panel specific. In all cases, we also include a time trend. For the "relative" series, we compute the Harris-Tzavalis unit-root test since the Im-Pesaran-Shin test did not meet the required assumptions. The null states that all panels contain unit roots, while the alternative states that some panels are stationary.

Table 3: Dependent Variable (Y) - HFC/PFC/SF6 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	–.394	–1.917*	–4.580***	–1.220	–1.800*	–4.217***	–.394	–1.917**	–4.580***	–.344	–.230	–.495
Trade × RKL	–.631	3.132	7.632***	.877	2.445	3.211	–.631	3.132*	7.632***	–.925	–.806	1.287
Trade × $(RKL)^2$	–.771	–2.479**	–4.335***	–1.772	–2.343**	–2.449**	–.771	–2.479**	–4.335***	.436	.299	–.599
Trade × RI	–2.886*	–5.076***	–3.618*	–.766	–2.975	.172	–2.886*	–5.076**	–3.618	.676	.140	–.709
Trade × $(RI)^2$	1.767**	2.905***	2.475**	.805	1.827*	.678	1.767**	2.905**	2.475**	–.358	.064	.327
I	.006**	.008***	.008***	.007***	.008***	.006**	.006***	.008***	.008***	.001	.001	.002
I^2	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000*	–.000**	–.000**
KL	.000	.000	–.000	.000	.000	.000	.000	.000	–.000	.000	.000	.000
$(KL)^2$	.000	.000	.000	–.000	.000	.000	.000	.000	.000*	–.000	–.000	–.000
KL × I	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	.000*	.000**	.000**
Trade × RLPC		1.493	6.573***		2.756*	3.437**		1.493	6.573***		–.470	.793
Trade × $(RLPC)^2$		.911	–1.604		–.930	–1.041		.911	–1.604*		.438	.126
FDI/K		.119**	.163***		.025	.036		.119***	.163***		.033	.044
LPC		4.775***	4.656***		–.203	–.221		4.775***	4.656***		–.069	.344
$(LPC)^2$		–.250***	–.243***		.008	.009		–.250***	–.243***		.009	–.012
English=1 × Trade			4.246***			2.784***			4.246***			1.262***
Sea=1 × Trade			–3.820***			–1.286			–3.820***			–1.774**
Euro=1 × Trade			–.236			–.535**			–.236			.249
Y(t-1)										.882***	.886***	.851***
Constant	.054	–22.581***	–22.004***	.015	1.180	1.348	.045	–22.796***	–22.293***	–.012	–.113	–2.230

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient.

Main results

Table 4: Dependent Variable (Y) - NO2 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	9.225*	–2.024	–9.363	7.146	–5.408	–11.450*	9.225	–2.024	–9.363*	3.709	1.134	–.027
Trade × RKL	–5.079	20.195*	36.252***	–4.969	27.043**	36.347***	–5.079	20.195*	36.252***	.421	7.443	10.228**
Trade × $(RKL)^2$	4.038	–13.353**	–20.920***	4.005	–12.268*	–18.135***	4.038	–13.353**	–20.920***	1.423	–3.283	–5.332*
Trade × RI	–16.861*	–37.319***	–25.530**	–7.184	–38.552***	–15.885	–16.861	–37.319***	–25.530**	–16.085***	–23.304***	–15.143***
Trade × $(RI)^2$	–6.540	9.126*	4.928	–11.558**	5.057	–2.620	–6.540	9.126	4.928	4.669**	9.052***	6.021**
I	.009	.016	.012	.018	.041***	.027**	.009	.016	.012	.008	.012*	.008
I^2	.001***	.001**	.001***	.001***	.001**	.001***	.001***	.001**	.001***	.000	.000	.000
KL	.001	–.001	–.002	.001	–.002	–.002	.001	–.001	–.002	.000	–.000	–.000
$(KL)^2$	.000	.000	.000	.000	.000	.000	.000	.000	.000*	–.000	–.000	.000
KL × I	–.000***	–.000**	–.000***	–.000***	–.000***	–.000***	–.000***	–.000***	–.000***	–.000	–.000	–.000
Trade × RLPC		47.146***	63.621***		63.819***	73.918***		47.146***	63.621***		13.582***	17.145***
Trade × $(RLPC)^2$		–22.111***	–30.627***		–32.712***	–38.904***		–22.111***	–30.627***		–5.968	–8.422**
FDI/K		–.316	–.112		–.119	.089		–.316	–.112		–.048	.030
LPC		7.069	6.637		–1.661	–2.277		7.069**	6.637**		.143	–.237
$(LPC)^2$		–.181	–.161		.127	.161		–.181	–.161		.044	.061
English=1 × Trade			14.014***			11.083***			14.014***			2.322*
Sea=1 × Trade			–15.937***			–13.397***			–15.937***			–3.967
Euro=1 × Trade			–2.117			–4.632***			–2.117			–1.753***
Y(t-1)										.874***	.823***	.809***
Constant	3.027***	–46.561*	–44.214*	2.789***	7.049	9.984	3.032***	–46.920***	–44.889***	.167	–4.767	–2.760
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.445	.564	.594				.925	.941	.945	.984	.985	.985
R2 adj.	.387	.514	.545									
BIC	691.157	576.221	552.006	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient.

Table 5: Dependent Variable (Y) - CH4 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	1.022	2.369	–1.209	.169	–3.148*	–8.936***	1.022	2.369	–1.209	140.428	2.137	–1.359
Trade × RKL	–2.847	–3.352	2.145	–2.267	7.504*	13.593***	–2.847	–3.352	2.145	–64.843	–3.136	2.453
Trade × $(RKL)^2$	1.337	.535	–2.145	.947	–3.851*	–6.814***	1.337	.535	–2.145	–560.773	.505	–2.254
Trade × RI	1.442	–3.430	2.796	4.726*	–5.320	4.230	1.442	–3.430	2.796	672.797	–3.455	3.160
Trade × $(RI)^2$	–4.609***	–.952	–3.044*	–6.089***	–.537	–3.670*	–4.609*	–.952	–3.044	–164.974	–.972	–3.234
I	–.005	–.003	–.006	–.004	.004	–.002	–.005	–.003	–.006	–.415	–.003	–.006
I^2	.000*	.000	.000	.000*	–.000	.000	.000	.000	.000	.054***	.000	.000
KL	.002**	.002**	.002**	.002*	.001	.001	.002***	.002***	.002**	.054	.002***	.002**
$(KL)^2$	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	.001	–.000	–.000
KL × I	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.013**	–.000	–.000
Trade × RLPC		1.882	8.701***		15.669***	23.877***		1.882	8.701***		2.124	8.908***
Trade × $(RLPC)^2$		1.192	–2.672		–7.245***	–12.088***		1.192	–2.672		1.169	–2.662
FDI/K		–.044	.044		.160*	.276***		–.044	.044		–.038	.056
LPC		–8.038***	–8.549***		–1.399**	–1.005*		–8.038***	–8.549***		–7.680***	–8.068***
$(LPC)^2$		.468***	.492***		.088**	.063**		.468***	.492***		.449***	.467***
English=1 × Trade			5.450***			6.299***			5.450***			5.380***
Sea=1 × Trade			–5.476***			–5.222***			–5.476***			–5.649***
Euro=1 × Trade			–1.284***			–1.973***			–1.284**			–1.357**
Y(t-1)										.603***	.000	.001**
Constant	1.198***	35.151***	37.848***	1.177***	6.464**	5.039**	.897***	35.214***	37.830***	241.176***	33.465***	35.490***
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.436	.536	.591				.957	.965	.969	.912	.965	.969
R2 adj.	.376	.483	.541									
BIC	–734.007	–821.397	–877.915	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient.

Table 6: Dependent Variable (Y) - SO2 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	190.074*	586.499***	298.228**	201.739*	379.583***	213.149	190.074	586.499***	298.228**	9.620	47.869	–6.668
Trade × RKL	–103.619	–1071.608***	–871.338***	–142.476	–631.664***	–365.190	–103.619	–1071.608***	–871.338***	55.427	–44.157	–68.644
Trade × $(RKL)^2$	–96.864	406.151***	366.983***	–75.629	156.779	92.434	–96.864	406.151***	366.983***	–29.196	18.043	34.459
Trade × RI	–113.391	527.049***	376.065	–77.878	382.599*	182.289	–113.391	527.049***	376.065**	–57.467	19.394	36.452
Trade × $(RI)^2$	227.477**	–170.917	–90.117	180.565*	–55.791	8.532	227.477***	–170.917**	–90.117	35.336	–7.316	–4.981
I	–1.572***	–1.943***	–1.962***	–1.201***	–1.618***	–1.527***	–1.572***	–1.943***	–1.962***	–.039	–.110	–.159
I^2	–.009*	.001	.001	–.012**	–.005	–.006	–.009**	.001	.001	–.004***	–.003**	–.003**
KL	–.076	–.040	–.044	–.037	–.016	–.031	–.076*	–.040	–.044	–.015	–.013	–.010
$(KL)^2$	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000
KL × I	.004***	.002*	.002*	.004***	.004**	.004***	.004***	.002***	.002***	.001***	.001***	.001***
Trade × RLPC		–1079.362***	–703.662***		–889.324***	–631.415***		–1079.362***	–703.662***		–114.548*	–73.451
Trade × $(RLPC)^2$		627.744***	439.963***		615.504***	528.364***		627.744***	439.963***		72.514*	40.842
FDI/K		–24.413***	–23.796***		–8.848	–9.052		–24.413***	–23.796***		–3.099*	–3.102*
LPC		–750.567***	–775.785***		–2.748	–7.256		–750.567***	–775.785***		–50.048	–67.610
$(LPC)^2$		37.326***	38.724***		–.109	.082		37.326***	38.724***		2.478	3.342
English=1 × Trade			283.160***			276.105***			283.160***			20.693
Sea=1 × Trade			–53.174			–185.545*			–53.174			41.529
Euro=1 × Trade			23.664			53.738*			23.664			–8.906
Y(t-1)										.941***	.929***	.925***
Constant	55.519***	3777.708***	3893.578***	45.629***	85.003	113.325	60.297***	3818.431***	3934.792***	3.189	255.932	346.483
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.286	.391	.418				.815	.842	.849	.977	.977	.978
R2 adj.	.211	.321	.347									
BIC	4342.424	4277.772	4269.294	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient.

Table 7: Dependent Variable (Y) - Municipal Waste Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	–420.084	256.928	479.624	–309.759	–528.030	–212.012	–420.084	256.928	479.624	140.428	488.818	364.042
Trade × RKL	295.660	–1141.339	–922.590	65.239	630.752	1362.116	295.660	–1141.339	–922.590	–64.843	–803.883	–811.341
Trade × $(RKL)^2$	–1556.719*	–642.751	–829.811	–1462.282*	–1708.625*	–2046.987**	–1556.719*	–642.751	–829.811	–560.773	–204.612	–207.432
Trade × RI	1456.209	1805.792	2390.800	1759.489	986.062	797.597	1456.209*	1805.792*	2390.800**	672.797	884.848	1100.362
Trade × $(RI)^2$	128.277	–344.918	–597.213	–157.572	237.577	188.579	128.277	–344.918	–597.213	–164.974	–293.519	–354.977
I	.413	.853	.765	2.414	3.234*	3.881**	.413	.853	.765	–.415	–.469	–.632
I^2	.034	.037	.039	.014	–.006	–.011	.034	.037*	.039*	.054***	.052***	.053***
KL	.035	.022	.015	.297	.293	.260	.035	.022	.015	.054	.076	.082
$(KL)^2$	.001	.000	.000	.000	–.000	–.000	.001	.000	.000	.001	.001	.001
KL × I	–.009	–.011	–.011	–.005	–.002	–.001	–.009	–.011	–.011	–.013**	–.012**	–.013**
Trade × RLPC		1022.348	963.260		1792.503	1994.072*		1022.348	963.260		165.005	296.201
Trade × $(RLPC)^2$		–1838.279*	–1811.949*		–1825.048**	–1852.251**		–1838.279*	–1811.949*		–716.305	–820.753
FDI/K		–49.872	–44.413		24.682	23.381		–49.872	–44.413		–17.924	–16.120
LPC		–3897.202***	–3866.236***		–433.879*	–418.266**		–3897.202***	–3866.236***		–1669.256***	–1709.739***
$(LPC)^2$		194.543***	192.754***		22.865*	22.134*		194.543***	192.754***		85.965***	87.877***
English=1 × Trade			12.071			260.996			12.071			71.225
Sea=1 × Trade			–442.212			–851.105			–442.212			14.022
Euro=1 × Trade			–96.893			115.926			–96.893			–57.040
Y(t-1)										.603***	.583***	.583***
Constant	433.231***	19680.168***	19545.996***	372.297***	2403.947**	2318.402**	504.173***	19920.814***	19775.065***	241.176***	8341.354***	8554.679***
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.293	.331	.332				.859	.867	.867	.912	.913	.913
R2 adj.	.218	.254	.251									
BIC	6668.342	6666.510	6685.103	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient.

Table 8: Dependent Variable (Y) - SOx Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	316.860*	618.041***	363.761	357.084**	450.223**	229.465	316.860*	618.041***	363.761	140.428	199.774	161.330
Trade × RKL	165.902	–549.856	–728.103*	138.647	–181.649	–209.455	165.902	–549.856*	–728.103**	–64.843	–160.387	–310.941
Trade × $(RKL)^2$	–278.803	60.160	248.009	–270.285	–144.017	–12.006	–278.803*	60.160	248.009	–560.773	7.260	100.068
Trade × RI	–518.345*	–109.905	–843.894**	–595.431**	–287.434	–1074.688***	–518.345**	–109.905	–843.894***	672.797	–153.362	–350.794
Trade × $(RI)^2$	346.871**	124.814	432.842**	387.374***	257.197	557.433***	346.871***	124.814	432.842***	–164.974	90.250	175.526
I	–1.002**	–1.332***	–1.180**	–1.036***	–1.327***	–.986**	–1.002**	–1.332***	–1.180***	–.415	–.102	–.086
I^2	–.002	.001	–.002	–.002	–.001	–.005	–.002	.001	–.002	.054***	–.005	–.005
KL	.057	.088	.092	.059	.089	.086	.057	.088	.092	.054	.059	.064
$(KL)^2$	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000*	.001	–.000	–.000
KL × I	.002	.002	.002	.002	.003	.003	.002	.002	.002	–.013**	.002	.002
Trade × RLPC		–460.113	–358.873		–239.144	–72.274		–460.113	–358.873		–23.419	–78.625
Trade × $(RLPC)^2$		3.190	–28.864		–67.900	–110.044		3.190	–28.864		–38.412	–15.225
FDI/K		–18.363*	–24.642**		–6.934	–11.256		–18.363***	–24.642***		–6.753	–9.216
LPC		–822.446***	–845.138***		–160.330***	–158.617**		–822.446***	–845.138***		–175.994	–193.241
$(LPC)^2$		42.700***	44.165***		9.090***	8.947***		42.700***	44.165***		9.194	10.126
English=1 × Trade			27.751			66.751			27.751			–67.281
Sea=1 × Trade			445.471**			315.004*			445.471**			211.022**
Euro=1 × Trade			129.570***			149.550***			129.570***			30.661
Y(t-1)										.603***	.738***	.732***
Constant	56.858***	3981.776***	4068.128***	57.355***	759.068***	756.120***	38.791***	3999.751***	4097.072***	241.176***	841.298	926.568
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.546	.564	.576				.845	.851	.855	.912	.940	.940
R2 adj.	.498	.514	.524									
BIC	4873.635	4880.483	4883.533	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient.

Table 9: Dependent Variable (Y) - NOx Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	509.377**	570.143**	460.278	590.502***	487.469**	438.614	509.377**	570.143*	460.278**	11.035	165.947	25.055
Trade × RKL	–1017.080**	–1107.082**	–1377.720***	–1215.591***	–930.287*	–1000.020**	–1017.080*	–1107.082	–1377.720*	–75.062	–379.146	–228.566
Trade × $(RKL)^2$	498.201**	627.530**	790.043***	634.461***	505.274*	588.146**	498.201	627.530	790.043*	32.305	268.975	224.765
Trade × RI	–243.331	–354.288	–607.140	–332.786	–572.134	–997.724**	–243.331	–354.288	–607.140	–90.332	–11.281	–82.150
Trade × $(RI)^2$	54.192	3.348	123.809	117.444	229.871	387.091	54.192	3.348	123.809	60.715	–87.203	–51.253
I	1.832***	2.228***	2.208***	1.536***	1.783***	1.993***	1.832***	2.228***	2.208***	.450*	.657	.635
I^2	–.025***	–.023**	–.024**	–.025***	–.027***	–.029***	–.025*	–.023	–.024*	–.018	–.014	–.015
KL	.213**	.180*	.191*	.191*	.172	.171	.213**	.180*	.191**	–.100	–.107	–.117
$(KL)^2$	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000
KL × I	.002	.001	.001	.002	.002	.003	.002	.001	.001	.004	.003	.003
Trade × RLPC		482.412	427.019		417.187	421.331		482.412	427.019		–140.149	44.579
Trade × $(RLPC)^2$		–354.693	–347.909		–248.087	–230.804		–354.693	–347.909		89.251	5.358
FDI/K		–10.238	–13.695		5.298	2.068		–10.238	–13.695		–7.098	–6.530
LPC		–804.253***	–840.655***		–1.447	–.851		–804.253**	–840.655**		–643.417**	–646.396**
$(LPC)^2$		38.865***	40.740***		–.171	–.219		38.865**	40.740**		30.399**	30.620**
English=1 × Trade			–102.406			–47.490			–102.406			157.009
Sea=1 × Trade			377.750*			207.826			377.750*			–68.295
Euro=1 × Trade			29.701			82.677			29.701			15.401
Y(t-1)										.895***	.895***	.913***
Constant	2.822	4081.424***	4256.860***	9.797	35.646	33.577	–37.765***	4077.414**	4263.600**	9.819	3362.505**	3372.340**
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.283	.311	.315				.867	.872	.873	.904	.908	.909
R2 adj.	.208	.231	.232									
BIC	5124.539	5132.921	5148.009	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient.

Table 10: Dependent Variable (Y) - SF6 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	1001.282***	836.024***	–229.776	701.552***	573.371***	173.313	1001.282***	836.024***	–229.776	11.035	294.092***	41.154
Trade × RKL	–1520.577***	–1282.843***	–549.923	–1051.131**	–896.681*	–868.066*	–1520.577***	–1282.843***	–549.923*	–75.062	–343.399**	–165.214
Trade × $(RKL)^2$	700.348***	520.190**	272.557	411.382*	382.391	303.996	700.348***	520.190***	272.557	32.305	194.742*	182.666
Trade × RI	–1891.103***	–1931.282***	–1447.853***	–1241.870***	–1561.042***	60.431	–1891.103***	–1931.282***	–1447.853***	–90.332	–707.022***	–1116.809***
Trade × $(RI)^2$	705.933***	761.511***	683.929***	477.343***	568.214***	–27.354	705.933***	761.511***	683.929***	60.715	309.061***	480.982***
I	2.791***	2.846***	2.305***	1.983***	2.421***	1.112**	2.791***	2.846***	2.305***	.450*	.357	.527*
I^2	–.009	–.005	–.003	–.004	–.002	.003	–.009	–.005	–.003	–.018	–.008*	–.010**
KL	.239**	.187*	.187*	.206**	.127	.160	.239***	.187***	.187***	–.100	.088**	.083**
$(KL)^2$	–.001*	–.000	–.000	–.001*	–.000	–.000	–.001***	–.000**	–.000**	–.000	–.000***	–.000***
KL × I	–.001	–.001	–.002	–.001	–.002	–.001	–.001	–.001	–.002	.004	.002*	.002*
Trade × RLPC		268.964	1724.217***		891.878***	617.467**		268.964	1724.217***		38.480	392.161**
Trade × $(RLPC)^2$		328.606	–503.338*		–206.712	–96.275		328.606**	–503.338***		75.401	–64.706
FDI/K		–21.169*	–11.022		–25.448**	–21.324**		–21.169	–11.022		10.421	8.396
LPC		407.537*	243.421		34.315	36.570		407.537***	243.421*		–.839	5.987
$(LPC)^2$		–19.405*	–11.233		–2.813	–2.901		–19.405**	–11.233		.235	.170
English=1 × Trade			1060.303***			331.216***			1060.303***			272.804***
Sea=1 × Trade			–410.310**			–253.877			–410.310***			–21.124
Euro=1 × Trade			–140.367***			–244.032***			–140.367**			73.751
Y(t-1)										.895***	.837***	.811***
Constant	–29.973***	–2121.834**	–1299.041	–18.987**	–94.638	–96.106	13.493	–2093.263***	–1267.725*	9.819	–14.788	–69.025
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.282	.319	.457				.679	.695	.757	.904	.924	.927
R2 adj.	.207	.240	.391									
BIC	5112.060	5112.315	4993.387	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient.

Table 11: Dependent Variable (Y) - NH3 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	60.248***	45.875***	10.027	55.300***	31.509**	–13.631	60.248***	45.875**	10.027	13.671	16.018*	8.966
Trade × RKL	–90.383***	–74.379**	–56.851*	–90.646***	–44.463	–26.784	–90.383**	–74.379*	–56.851	2.142	–2.266	–2.768
Trade × $(RKL)^2$	53.307***	31.912*	26.573	53.299***	27.183	19.937	53.307**	31.912	26.573	–2.998	–3.884	–5.353
Trade × RI	–77.146***	–70.523***	–51.867*	–50.959**	–73.266***	–25.283	–77.146**	–70.523*	–51.867	–50.915***	–56.039***	–30.141
Trade × $(RI)^2$	11.058	20.384	17.298	–3.124	10.605	–1.925	11.058	20.384	17.298	21.658**	26.739**	18.190
I	.031	–.002	–.023	.067*	.100***	.068*	.031	–.002	–.023	.029	.028	.012
I^2	.002***	.002**	.002***	.002**	.001	.001*	.002**	.002**	.002**	–.001	–.001	–.000
KL	.001	–.000	–.000	.002	–.000	.001	.001	–.000	–.000	–.002	–.002	–.002
$(KL)^2$	.000***	.000***	.000***	.000**	.000**	.000***	.000***	.000***	.000***	.000	–.000	.000
KL × I	–.001***	–.001***	–.001***	–.001***	–.001***	–.001***	–.001***	–.001***	–.001***	–.000	.000	–.000
Trade × RLPC		43.652*	88.954***		111.787***	160.439***		43.652	88.954***		18.827	28.086
Trade × $(RLPC)^2$		–31.446*	–58.673***		–77.175***	–107.207***		–31.446*	–58.673***		–14.840	–23.055**
FDI/K		–1.517*	–1.202		–.723	.041		–1.517	–1.202		–.616	–.414
LPC		36.599**	30.098**		4.236	3.371		36.599**	30.098*		–22.952**	–25.554***
$(LPC)^2$		–1.494*	–1.173		–.120	–.093		–1.494	–1.173		1.307***	1.426***
English=1 × Trade			31.455***			35.660***			31.455***			4.835
Sea=1 × Trade			–6.990			–8.221			–6.990			–2.706
Euro=1 × Trade			–5.695			–12.688***			–5.695			–6.231***
Y(t-1)										.766***	.757***	.749***
Constant	11.692***	–196.949***	–164.181**	10.793***	–18.331	–12.458	11.074***	–199.380**	–166.298**	2.636***	103.325**	117.419***
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.646	.683	.697				.963	.967	.969	.989	.990	.990
R2 adj.	.609	.646	.660									
BIC	1845.838	1811.117	1802.480	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient.

Table 12: Dependent Variable (Y) - HFC/PFC/SF6 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	.459	–.660	–4.246***	–.652	–1.225	–3.929***	.459	–.660	–4.246***	–.043	.300	.512
Trade × RKL	–3.146	–.394	6.370***	–.849	.599	2.910	–3.146	–.394	6.370***	–1.196	–1.670	–.252
Trade × $(RKL)^2$	.393	–.806	–3.704***	–1.087	–1.577	–2.318*	.393	–.806	–3.704***	.580	.837	.179
Trade × RI	–1.989	–3.706**	–2.889	.169	–2.222	.156	–1.989	–3.706*	–2.889	.886	.637	–.131
Trade × $(RI)^2$	1.179	2.046**	2.060**	.215	1.366	.476	1.179	2.046**	2.060**	–.525	–.336	–.059
I	.005**	.006**	.005**	.006***	.007***	.005**	.005***	.006***	.005**	.001	.001	.001
I^2	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000**
KL	.000	.000	.000	.001	.000	.000	.000	.000	.000	.000	.000	.000
$(KL)^2$	–.000	.000	.000	–.000	–.000	–.000	–.000	.000	.000	–.000	–.000	–.000
KL × I	–.000	–.000	–.000	–.000	–.000	.000	–.000	–.000	–.000	.000	.000	.000*
Trade × RLPC		.878	7.455***		3.203**	4.457***		.878	7.455***		–1.153	–.585
Trade × $(RLPC)^2$		1.532	–1.768		–.847	–1.169		1.532	–1.768*		1.032	1.003
FDI/K		.099*	.124**		.014	.022		.099**	.124**		.026	.033
LPC		4.356***	4.148***		–.231	–.227		4.356***	4.148***		–.522	–.214
$(LPC)^2$		–.228***	–.216***		.009	.008		–.228***	–.216***		.031	.017
English=1 × trade			4.256***			2.732***			4.256***			.724*
Sea=1 × trade			–3.814***			–1.501*			–3.814***			–1.393**
Euro=1 × trade			–.203			–.440			–.203			.219
Y(t-1)										.887***	.894***	.873***
Constant	.054	–20.586***	–19.618***	.013	1.346	1.429	.052	–20.769***	–19.865***	–.011	2.138	.510
N	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000
R2	.300	.327	.404				.740	.750	.779	.893	.894	.896
R2 adj.	.223	.246	.329									
BIC	–1347.274	–1338.369	–1390.221	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use the first lag of Trade as an instrument for its own level and correspondingly, to avoid the endogeneity problem of Trade and Income we instrument Income with its own second lag.

IV regressions

Table 13: Dependent Variable (Y) - NO2 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	13.430**	4.188	−3.327	10.774*	.352	−8.561	13.430**	4.188	−3.327	−31.677***	1.353	.303
Trade × RKL	−8.548	10.570	32.410***	−6.759	21.024*	38.021***	−8.548	10.570	32.410***	72.829***	5.316	10.237*
Trade × $(RKL)^2$	3.269	−9.925	−20.051***	1.995	−11.586*	−20.658***	3.269	−9.925	−20.051***	−48.150***	−1.849	−4.851
Trade × RI	−26.950***	−41.147***	−36.246***	−17.045**	−45.805***	−27.337**	−26.950**	−41.147***	−36.246***	12.296	−19.610***	−13.612***
Trade × $(RI)^2$	−3.285	9.598**	8.335	−8.055*	8.067	1.867	−3.285	9.598*	8.335	−11.161	7.539***	5.235**
I	.021	.020	.017	.031**	.042***	.033***	.021	.020	.017	.014	.005	.004
I^2	.001***	.001***	.000**	.001***	.000*	.000**	.001***	.001***	.000***	.000	.000	.000
KL	.000	−.001	−.002	.001	−.001	−.002	.000	−.001	−.002	−.007*	−.000	−.000
$(KL)^2$	.000	.000	.000	.000	.000	.000	.000	.000	.000*	.000*	−.000	.000
KL × I	−.000***	−.000***	−.000**	−.000***	−.000**	−.000***	−.000***	−.000***	−.000***	−.000	−.000	−.000
Trade × RLPC		33.228***	50.829***		52.823***	66.848***		33.228***	50.829***		5.091	8.634
Trade × $(RLPC)^2$		−13.528**	−21.998***		−26.222***	−34.102***		−13.528**	−21.998***		−1.834	−3.918
FDI/K		−.124	−.015		.153	.282		−.124	−.015		.087	.135
LPC		5.009	4.982		−2.893	−3.364		5.009**	4.982*		.343	.188
$(LPC)^2$		−.047	−.042		.201	.225		−.047	−.042		.024	.031
English=1 × Trade			12.231***			9.535***			12.231***			1.768
Sea=1 × Trade			−15.201***			−11.920**			−15.201***			−4.088
Euro=1 × Trade			−.842			−4.026***			−.842			−1.279*
Y(t-1)										.716***	.833***	.824***
Constant	3.006***	−39.048	−39.098	2.760***	12.015	14.520	2.987***	−39.317***	−39.687***	4.084***	−4.691	−3.884
N	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000
R2	.493	.604	.623				.932	.947	.949	.986	.985	.985
R2 adj.	.438	.557	.576									
BIC	590.813	479.638	470.119	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use the first lag of Trade as an instrument for its own level and correspondingly, to avoid the endogeneity problem of Trade and Income we instrument Income with its own second lag.

Table 14: Dependent Variable (Y) - CH4 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	2.415	3.793**	−.587	1.348	−1.463	−9.856***	2.415	3.793***	−.587	.592	.575	.471
Trade × RKL	−4.302	−5.539	3.273	−3.081	5.239	16.067***	−4.302	−5.539*	3.273	−1.144	−.712	.008
Trade × $(RKL)^2$	1.428	1.548	−2.527	.644	−3.096	−8.008***	1.428	1.548	−2.527	1.429*	1.004*	.638
Trade × RI	−.784	−4.955*	−1.594	2.421	−6.791**	1.086	−.784	−4.955	−1.594	−1.180	−2.483**	−2.291**
Trade × $(RI)^2$	−3.917***	−.578	−1.478	−5.272***	−.051	−2.408	−3.917*	−.578	−1.478	−.165	.731	.649
I	−.003	−.002	−.004	−.001	.003	−.002	−.003	−.002	−.004	.003*	.003*	.003*
I^2	.000	.000	.000	.000	−.000	−.000	.000	.000	.000	−.000	−.000*	−.000**
KL	.002**	.002***	.002**	.002**	.002**	.001	.002***	.002***	.002***	−.000	−.000	−.000
$(KL)^2$	−.000	−.000	−.000	−.000	−.000	−.000	−.000	−.000	−.000	−.000	−.000	−.000
KL × I	−.000	−.000	.000	−.000	.000	.000	−.000	−.000	.000	.000	.000	.000
Trade × RLPC		−.322	7.926***		13.519***	25.123***		−.322	7.926**		.594	1.076
Trade × $(RLPC)^2$		2.669	−1.650		−5.916***	−12.419***		2.669	−1.650		.231	.031
FDI/K		.045	.089		.211**	.287***		.045	.089		.043**	.047**
LPC		−7.975***	−8.330***		−1.623**	−1.148**		−7.975***	−8.330***		−.379	−.410
$(LPC)^2$		.472***	.490***		.102***	.071**		.472***	.490***		.036*	.038
English=1 × Trade			5.108***			6.335***			5.108***			.378*
Sea=1 × Trade			−5.298***			−4.601***			−5.298***			−.617*
Euro=1 × Trade			−.751*			−1.847***			−.751			−.028
Y(t-1)										.983***	.942***	.935***
Constant	1.135***	34.144***	35.940***	1.114***	7.265**	5.600**	.823***	34.194***	35.904***	−.043	.388	.492
N	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000
R2	.452	.570	.609				.962	.970	.973	.997	.998	.998
R2 adj.	.392	.519	.560									
BIC	−775.686	−884.926	−920.947	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use the first lag of Trade as an instrument for its own level and correspondingly, to avoid the endogeneity problem of Trade and Income we instrument Income with its own second lag.

Table 15: Dependent Variable (Y) - SO_2 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	151.651	509.999***	188.542	155.573	336.747***	150.845	151.651	509.999***	188.542	–33.169	–15.019	–81.948
Trade × RKL	–149.388	–944.618***	–628.450**	–171.326	–643.473***	–340.220	–149.388	–944.618***	–628.450***	80.803	20.814	27.713
Trade × $(RKL)^2$	18.875	425.507***	345.218**	20.233	237.753*	167.269	18.875	425.507***	345.218***	–26.489	–5.108	–1.378
Trade × RI	–79.027	404.815**	130.819	–26.311	417.185**	85.456	–79.027	404.815***	130.819	–7.117	63.647	77.341
Trade × $(RI)^2$	151.603	–161.794	–24.088	103.206	–127.375	2.869	151.603**	–161.794**	–24.088	–5.294	–40.233	–38.251
I	–1.595***	–1.692***	–1.760***	–1.283***	–1.553***	–1.509***	–1.595***	–1.692***	–1.760***	–.031	–.076	–.114
I^2	–.006	–.001	–.003	–.009**	–.003	–.006	–.006	–.001	–.003	–.003**	–.002	–.001
KL	–.053	–.049	–.054	–.014	–.012	–.018	–.053	–.049	–.054	–.027	–.029	–.029
$(KL)^2$	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000**	–.000	–.000	–.000
KL × I	.004**	.003*	.003**	.004***	.003**	.004***	.004***	.003***	.003***	.001**	.001*	.001*
Trade × RLPC		–1046.338***	–594.941***		–940.207***	–647.604***		–1046.338***	–594.941***		–93.310	–31.308
Trade × $(RLPC)^2$		630.402***	412.126***		650.653***	547.696***		630.402***	412.126***		74.039	32.995
FDI/K		–19.683***	–20.651***		–8.397	–8.823		–19.683***	–20.651***		–3.560**	–3.793**
LPC		–715.236***	–735.637***		13.683	9.310		–715.236***	–735.637***		–1.280	–16.641
$(LPC)^2$		35.128***	36.382***		–1.019	–.825		35.128***	36.382***		.071	.814
English=1 × Trade			290.826***			273.596***			290.826***			22.525
Sea=1 × Trade			–55.812			–149.132			–55.812			36.779
Euro=1 × Trade			47.849			72.666**			47.849*			–7.754
Y(t-1)										.959***	.952***	.949***
Constant	52.876***	3637.161***	3721.856***	43.767***	9.589	36.305	56.093***	3674.157***	3759.385***	4.191	11.354	91.825
N	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000
R2	.252	.366	.394				.818	.846	.853	.978	.978	.979
R2 adj.	.170	.290	.317									
BIC	4115.230	4050.999	4044.341	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use the first lag of Trade as an instrument for its own level and correspondingly, to avoid the endogeneity problem of Trade and Income we instrument Income with its own second lag.

Table 16: Dependent Variable (Y) - Municipal Waste Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	–159.043	77.318	–75.287	–65.717	–342.436	–161.473	–159.043	77.318	–75.287	–33.169	244.617	8.379
Trade × RKL	–134.351	–275.337	–262.249	–369.507	418.571	694.378	–134.351	–275.337	–262.249	80.803	–62.867	–300.990
Trade × $(RKL)^2$	–1257.584	–1024.013	–1023.215	–1213.517	–1510.677*	–1621.758*	–1257.584	–1024.013	–1023.215	–26.489	–549.769	–416.560
Trade × RI	1369.082	608.804	713.950	1777.245*	551.533	143.372	1369.082*	608.804	713.950	–7.117	–366.285	–265.035
Trade × $(RI)^2$	423.939	633.157	608.733	76.124	658.235	760.275	423.939	633.157	608.733	–5.294	747.936*	735.629
I	–1.176	–.206	–.296	1.072	2.141	2.699*	–1.176	–.206	–.296	–.031	–1.345	–1.498
I^2	.030	.014	.015	.007	–.016	–.024	.030	.014	.015	–.003**	.022	.025
KL	.063	–.018	–.018	.376	.424	.456	.063	–.018	–.018	–.027	.155	.166
$(KL)^2$	.000	–.000	–.000	–.000	–.001	–.001	.000	–.000	–.000	–.000	–.000	–.000
KL × I	–.006	–.005	–.005	–.002	.002	.004	–.006	–.005	–.005	.001**	–.004	–.005
Trade × RLPC		2121.469	2259.357		2258.186**	2382.267**		2121.469	2259.357*		1878.644	1961.845
Trade × $(RLPC)^2$		–2090.724**	–2190.788**		–1797.310**	–1824.545**		–2090.724**	–2190.788**		–1391.008	–1496.660
FDI/K		–24.773	–24.869		34.510	35.069		–24.773	–24.869		11.363	9.575
LPC		–3403.476***	–3438.238***		–382.451*	–362.060*		–3403.476***	–3438.238***		–1425.929***	–1494.023***
$(LPC)^2$		170.290***	171.919***		19.824*	18.826*		170.290***	171.919***		73.247***	76.421***
English=1 × Trade			33.995			135.763			33.995			–66.364
Sea=1 × Trade			85.536			–336.679			85.536			373.133
Euro=1 × Trade			–34.676			106.386			–34.676			–50.128
Y(t-1)										.959***	.548***	.549***
Constant	442.879***	17213.363***	17395.044***	371.707***	2177.816**	2066.016**	538.308***	17458.501***	17644.622***	4.191	7174.902***	7543.883***
N	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000
R2	.302	.333	.333				.883	.888	.888	.978	.926	.926
R2 adj.	.225	.253	.249									
BIC	6248.767	6253.577	6272.596	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use the first lag of Trade as an instrument for its own level and correspondingly, to avoid the endogeneity problem of Trade and Income we instrument Income with its own second lag.

Table 17: Dependent Variable (Y) - SOx Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	438.653***	732.205***	515.662**	476.970***	594.355***	391.638*	438.653**	732.205***	515.662*	274.211**	402.941**	292.922*
Trade × RKL	213.309	–427.169	–743.287*	182.331	–169.818	–362.581	213.309	–427.169	–743.287**	94.773	–170.343	–330.183
Trade × $(RKL)^2$	–250.034	62.357	329.058	–233.854	–86.458	134.289	–250.034	62.357	329.058**	–91.104	39.937	161.990
Trade × RI	–755.998***	–432.476	–1194.091***	–844.929***	–510.255*	–1335.257***	–755.998***	–432.476*	–1194.091***	–496.122**	–370.461**	–652.493***
Trade × $(RI)^2$	433.040***	245.589	565.458***	479.579***	324.593**	652.212***	433.040***	245.589*	565.458***	237.266**	162.536*	285.938**
I	–.796**	–.917**	–.901**	–.870**	–1.084***	–.910**	–.796**	–.917***	–.901***	.147	.089	.060
I^2	–.003	–.002	–.003	–.002	–.001	–.005	–.003	–.002	–.003	–.003	–.002	–.002
KL	.063	.074	.102	.058	.078	.109	.063	.074	.102*	.031	.037	.050
$(KL)^2$	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000**	–.000	–.000	–.000
KL × I	.002	.002	.002	.002	.002	.003	.002	.002	.002	.000	.000	.000
Trade × RLPC		–625.376**	–574.822*		–460.461*	–341.558		–625.376**	–574.822**		–341.605	–316.373
Trade × $(RLPC)^2$		194.357	184.120		137.544	112.231		194.357	184.120		185.821	168.204
FDI/K		–13.578	–19.801**		–5.784	–9.664		–13.578**	–19.801***		–4.357	–7.161
LPC		–777.549***	–797.887***		–122.731**	–122.969**		–777.549***	–797.887***		–266.418*	–291.707*
$(LPC)^2$		40.074***	41.432***		7.007**	6.998**		40.074***	41.432***		13.647*	15.025*
English=1 × Trade			22.015			65.618			22.015			–1.255
Sea=1 × Trade			480.696***			383.839**			480.696***			237.232***
Euro=1 × Trade			140.195***			157.350***			140.195***			47.519
Y(t-1)										.705***	.693***	.683***
Constant	48.582***	3783.632***	3856.843***	50.721***	584.074**	586.594**	30.353***	3799.568***	3884.810***	–2.910	1296.426*	1419.641*
N	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000
R2	.571	.590	.604				.864	.870	.875	.943	.944	.944
R2 adj.	.524	.540	.554									
BIC	4534.381	4539.925	4537.536	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use the first lag of Trade as an instrument for its own level and correspondingly, to avoid the endogeneity problem of Trade and Income we instrument Income with its own second lag.

Table 18: Dependent Variable (Y) - NOx Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	510.439**	623.995**	623.769*	626.089***	573.518**	654.780**	510.439*	623.995	623.769**	31.935	234.392	77.254
Trade × RKL	–1218.091***	–1384.346***	–1659.153***	–1487.391***	–1363.608***	–1449.554***	–1218.091*	–1384.346	–1659.153**	–257.141	–602.063	–298.840
Trade × $(RKL)^2$	650.985**	788.675***	943.342***	842.417***	780.879***	858.950***	650.985	788.675	943.342*	179.763	417.101	302.115
Trade × RI	–73.297	–141.443	–336.848	–210.409	–280.349	–709.921	–73.297	–141.443	–336.848	12.960	57.641	–44.939
Trade × $(RI)^2$	–47.788	–98.678	–20.994	43.078	74.125	222.475	–47.788	–98.678	–20.994	–20.192	–135.666	–81.509
I	1.615***	1.905***	1.917***	1.302***	1.382***	1.570***	1.615***	1.905***	1.917***	.382	.588*	.529
I^2	–.024***	–.025***	–.024**	–.023***	–.024***	–.027***	–.024*	–.025*	–.024*	–.016	–.015	–.016
KL	.225**	.192*	.206*	.196*	.192*	.202*	.225***	.192**	.206**	–.100	–.104	–.121
$(KL)^2$	–.000	–.001*	–.001*	–.001	–.001	–.001*	–.000	–.001*	–.001*	–.000	–.000	–.000
KL × I	.002	.002	.002	.003	.003	.003	.002	.002	.002	.004	.003	.003
Trade × RLPC		331.132	196.738		213.228	139.304		331.132	196.738		–271.509	–14.491
Trade × $(RLPC)^2$		–305.622	–243.342		–159.720	–91.384		–305.622	–243.342		135.638	24.855
FDI/K		–15.171	–17.576		1.016	–1.551		–15.171*	–17.576**		–6.043	–5.402
LPC		–968.443***	–978.249***		–7.063	–7.572		–968.443***	–978.249***		–714.643**	–706.773**
$(LPC)^2$		47.052***	47.565***		.228	.261		47.052***	47.565***		33.880**	33.624**
English=1 × trade			–106.264			–34.293			–106.264			197.601
Sea=1 × trade			263.334			83.454			263.334			–152.014
Euro=1 × trade			32.913			98.543			32.913			23.361
Y(t-1)										.887***	.882***	.908***
Constant	2.401	4895.009***	4940.852***	10.292	55.080	55.539	–37.364***	4899.683***	4951.910***	12.531	3726.927**	3676.561**
N	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000
R2	.264	.297	.300				.860	.867	.867	.896	.901	.902
R2 adj.	.184	.213	.211									
BIC	4892.574	4897.815	4914.428	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use the first lag of Trade as an instrument for its own level and correspondingly, to avoid the endogeneity problem of Trade and Income we instrument Income with its own second lag.

Table 19: Dependent Variable (Y) - SF6 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	1146.531***	1047.570***	–393.683	778.953***	676.414***	171.954	1146.531***	1047.570***	–393.683**	144.405	168.982*	26.361
Trade × RKL	–1966.129***	–1834.921***	–495.902	–1303.859***	–1123.200**	–770.691*	–1966.129***	–1834.921***	–495.902	–286.944	–273.553	–223.820
Trade × $(RKL)^2$	853.353***	719.847**	187.013	467.681*	403.031	184.676	853.353***	719.847***	187.013	158.412	170.728	164.510
Trade × RI	–1688.055***	–1645.066***	–1038.524**	–1051.300***	–1418.671***	108.089	–1688.055***	–1645.066***	–1038.524**	–128.179	–251.393	–286.185
Trade × $(RI)^2$	649.963***	691.788***	600.863***	414.265**	573.311***	–8.043	649.963***	691.788***	600.863***	38.077	100.310	130.838
I	2.223***	2.146***	1.484***	1.689***	2.000***	.961**	2.223***	2.146***	1.484***	–.115	–.054	–.081
I^2	–.005	–.002	–.002	–.004	–.005	–.001	–.005	–.002	–.002	–.003	–.004	–.004
KL	.287***	.257**	.208**	.248**	.190*	.175*	.287***	.257***	.208***	.066*	.075**	.077**
$(KL)^2$	–.001**	–.001	–.000	–.001*	–.001*	–.000	–.001***	–.001**	–.000**	–.000**	–.000**	–.000**
KL × I	–.001	–.001	–.001	–.000	–.001	.000	–.001	–.001	–.001	.001	.001	.001
Trade × RLPC		–53.194	1879.313***		763.552**	621.979**		–53.194	1879.313***		–68.633	108.809
Trade × $(RLPC)^2$ c		436.087	–681.366**		–172.987	–121.137		436.087***	–681.366***		86.005	–11.818
FDI/K		–13.462	–9.613		–16.937	–14.448		–13.462	–9.613		8.535	7.842
LPC		340.559	131.415		21.277	27.963		340.559**	131.415		–37.932	–55.260
$(LPC)^2$		–15.390	–5.193		–1.989	–2.372		–15.390*	–5.193		2.164	3.050
English=1 × Trade			983.307***			269.189***			983.307***			84.328
Sea=1 × Trade			–284.051			–229.031			–284.051*			37.981
Euro=1 × Trade			–195.615***			–248.727***			–195.615***			–6.763
Y(t-1)										.843***	.844***	.830***
Constant	–24.760**	–1842.822	–775.160	–16.978**	–42.922	–59.300	21.663	–1808.789**	–731.190	7.814	171.560	259.473
N	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000
R2	.277	.303	.420				.673	.685	.738	.913	.914	.914
R2 adj.	.198	.220	.347									
BIC	4843.110	4853.598	4765.967	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use the first lag of Trade as an instrument for its own level and correspondingly, to avoid the endogeneity problem of Trade and Income we instrument Income with its own second lag.

Table 20: Dependent Variable (Y) - NH3 Results

Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade	77.497***	71.201***	46.875**	71.295***	52.310***	2.063	77.497***	71.201***	46.875**	6.230	9.181	8.144
Trade × RKL	–125.396***	–126.236***	–99.733***	–120.722***	–84.308***	–36.577	–125.396***	–126.236***	–99.733***	6.901	–1.333	4.515
Trade × $(RKL)^2$	71.069***	61.002***	50.321***	67.323***	45.607**	24.116	71.069***	61.002***	50.321**	–3.606	–1.895	–7.925
Trade × RI	–95.289***	–78.466***	–69.884**	–71.026***	–84.639***	–39.895	–95.289***	–78.466***	–69.884**	–33.084**	–31.124**	–2.152
Trade × $(RI)^2$	18.617*	20.584*	19.658	6.489	17.476	4.459	18.617	20.584	19.658	9.468	10.318	–.801
I	.039	.009	–.001	.070**	.083**	.069**	.039	.009	–.001	.016	.013	.008
I^2	.001*	.001*	.001	.001	.000	.000	.001	.001	.001	–.000	–.000	–.000
KL	.004	.003	.002	.006	.005	.004	.004	.003	.002	–.000	–.001	–.002
$(KL)^2$	.000	.000*	.000*	.000	.000	.000	.000*	.000**	.000***	–.000	–.000	.000
KL × I	–.001***	–.001***	–.001***	–.001***	–.000**	–.000**	–.001***	–.001***	–.001***	–.000	–.000	–.000
Trade × RLPC		17.678	52.330*		85.104***	149.168***		17.678	52.330*		12.058	14.638
Trade × $(RLPC)^2$		–19.408	–38.788**		–62.589***	–100.310***		–19.408	–38.788**		–12.822	–16.535
FDI/K		–1.443*	–1.364*		–.549	.023		–1.443*	–1.364*		–.814*	–.651
LPC		7.463	4.341		–2.026	–.937		7.463	4.341		–25.830***	–27.446***
$(LPC)^2$		.006	.160		.232	.143		.006	.160		1.429***	1.490***
English=1 × Trade			18.786**			28.211***			18.786**			–1.546
Sea=1 × Trade			–8.276			–9.961			–8.276			–6.020
Euro=1 × Trade			–2.786			–11.536***			–2.786			–6.244***
Y(t-1)										.767***	.757***	.760***
Constant	10.878***	–57.779	–41.988	10.082***	8.645	6.330	10.158***	–59.030	–43.175	2.254***	119.278***	128.782***
N	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000	580.000
R2	.673	.703	.707				.971	.973	.974	.991	.992	.992
R2 adj.	.638	.667	.670									
BIC	1612.765	1590.199	1600.220	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use the first lag of Trade as an instrument for its own level and correspondingly, to avoid the endogeneity problem of Trade and Income we instrument Income with its own second lag.

Table 21: Dependent Variable (Y) - HFC/PFC/SF6 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\hat{Trade}$	−1.866	−6.032***	−4.844*	−.156	−.957	−.849	−1.866	−6.032**	−4.844**	−.392	−.899	−.943
$\hat{Trade}$ × RKL	.178	4.550	2.479	2.810	2.357	1.973	.178	4.550**	2.479	−.741	−.299	−.776
$\hat{Trade} \times (RKL)^2$	.975	−.157	−.077	−.510	−.319	−.231	.975*	−.157	−.077	.823**	.547	.573
$\hat{Trade}$ × RI	.280	−2.855	−.476	−1.257	−1.582	−.402	.280	−2.855	−.476	−.653	−.879	−.625
$\hat{Trade} \times (RI)^2$	1.910	3.649***	3.072**	2.519**	2.708**	2.472**	1.910*	3.649***	3.072***	.924	1.057*	1.006
I	.008**	.015***	.015***	.008**	.008**	.006	.008**	.015***	.015***	.003	.003	.004
I^2	−.000**	−.000***	−.000***	−.000***	−.000***	−.000***	−.000***	−.000***	−.000***	−.000***	−.000***	−.000***
KL	−.001**	−.002***	−.002***	−.001	−.001	−.001	−.001***	−.002***	−.002***	−.000	−.000	−.000
$(KL)^2$	.000	.000**	.000	.000	.000	.000	.000**	.000***	.000**	.000	−.000	−.000
KL × I	−.000	−.000	.000	.000	.000	.000	−.000	−.000	.000	.000	.000	.000*
Poor=1 × $\hat{Trade}$	.574	.576	.322	−.197	−.318	−.352	.574	.576	.322	.594	.956	1.041
$\hat{Trade}$ × RLPC		.164	1.048		2.056	1.656		.164	1.048		.336	.683
$\hat{Trade} \times (RLPC)^2$		.396	.044		−.124	−.062		.396	.044		.598	.520
FDI/K		.111**	.126**		−.015	.012		.111**	.126***		.047*	.048*
LPC		4.351***	5.168***		.066	.075		4.351***	5.168***		−.297	.110
$(LPC)^2$		−.250***	−.291***		−.006	−.006		−.250***	−.291***		.017	−.004
English=1 × $\hat{Trade}$			−2.781**			−.545			−2.781***			−.648
Sea=1 × $\hat{Trade}$			−1.073			.571			−1.073*			−.476
Euro=1 × $\hat{Trade}$			−.040			−.423			−.040			.169
Y(t-1)										.909***	.918***	.916***
Constant	.123*	−18.447***	−22.479***	.014	−.072	−.154	.175**	−18.635***	−22.770***	.004	1.310	−.694
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.221	.273	.282				.706	.725	.728	.898	.900	.900
R2 adj.	.138	.187	.193									
BIC	−1330.450	−1339.795	−1328.188	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use an instrumental variable approach where we instrument trade with a set of exogenous variables including lagged income, exchange rate, capital to labor ratio, price of export, price of imports, land per capita, and four dummies for whether a country uses euro, has access to the sea or ocean, whether it uses English as its official language, and whether it was a poor country at the start of the analysis period, respectively. We classify a country as poor if at the start of the sample its income was less than that of the European Average.

IV with Poor Dummy

Table 22: Dependent Variable (Y) - NO2 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\hat{Trade}$	–20.727**	3.464	20.237*	–8.523	13.901	35.629***	–20.727**	3.464	20.237*	–17.721***	–8.934	–2.501
$\hat{Trade}$ × RKL	58.101***	51.873***	27.012**	58.086***	52.493***	38.818***	58.101***	51.873***	27.012*	20.709***	15.308**	7.887
$\hat{Trade} \times (RKL)^2$	–10.840*	–10.081	–8.854	–11.116*	–7.924	–8.006	–10.840*	–10.081*	–8.854	–4.921*	–3.077	–2.882
$\hat{Trade}$ × RI	–105.315***	–89.538***	–56.678***	–111.153***	–97.128***	–70.931***	–105.315***	–89.538***	–56.678***	–22.675***	–17.132**	–7.494
$\hat{Trade} \times (RI)^2$	40.741***	37.359***	29.467***	42.539***	38.614***	31.745***	40.741***	37.359***	29.467***	8.275***	7.105**	5.069*
I	.132***	.108***	.095***	.135***	.123***	.093***	.132***	.108***	.095***	.037***	.028***	.025***
I^2	.000	.000	–.000	.000	.000	–.000	.000	.000	–.000	.000*	.000	–.000
KL	–.021***	–.020***	–.015***	–.020***	–.020***	–.016***	–.021***	–.020***	–.015***	–.006***	–.005***	–.004***
$(KL)^2$	.000***	.000***	.000***	.000***	.000***	.000***	.000***	.000***	.000***	.000***	.000***	.000**
KL × I	–.000***	–.000***	–.000***	–.000***	–.000***	–.000***	–.000***	–.000***	–.000***	–.000***	–.000***	–.000*
Poor=1 × $\hat{Trade}$	–24.352***	–18.426***	–22.838***	–30.845***	–24.466***	–31.224***	–24.352***	–18.426**	–22.838***	1.147	3.266	1.043
$\hat{Trade}$ × RLPC		–56.790***	–50.112***		–68.061***	–64.228***		–56.790***	–50.112***		–24.378***	–22.894***
$\hat{Trade} \times (RLPC)^2$		25.358***	21.835***		29.191***	25.622***		25.358***	21.835***		14.747***	13.739**
FDI/K		.091	.314		.106	.288		.091	.314		–.087	–.004
LPC		12.013**	18.354***		2.023	.236		12.013***	18.354***		.039	2.239
$(LPC)^2$		–.510*	–.820***		–.059	.040		–.510**	–.820***		.029	–.077
English=1 × $\hat{Trade}$			–33.553***			–17.795***			–33.553***			–11.179***
Sea=1 × $\hat{Trade}$			–6.982			–4.584			–6.982***			–2.308
Euro=1 × $\hat{Trade}$			–2.918*			–6.033***			–2.918**			–1.204*
Y(t-1)										.835***	.817***	.798***
Constant	5.030***	–62.439**	–94.591***	4.620***	–9.323	–1.796	4.195***	–63.494***	–96.452***	.776***	–2.043	–13.518
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.545	.591	.621				.938	.944	.948	.984	.985	.985
R2 adj.	.496	.543	.574									
BIC	577.553	543.873	516.499	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use an instrumental variable approach where we instrument trade with a set of exogenous variables including lagged income, exchange rate, capital to labor ratio, price of export, price of imports, land per capita, and four dummies for whether a country uses euro, has access to the sea or ocean, whether it uses English as its official language, and whether it was a poor country at the start of the analysis period, respectively. We classify a country as poor if at the start of the sample its income was less than that of the European Average.

Table 23: Dependent Variable (Y) - CH4 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\hat{Trade}$	.111	4.446	7.155**	4.283	8.000**	10.813***	.111	4.446	7.155**	–4.153***	–2.278**	–1.314
$\hat{Trade}$ × RKL	7.887**	5.350	2.656	8.773**	10.342**	14.095***	7.887	5.350	2.656	2.898**	2.067*	.789
$\hat{Trade} \times (RKL)^2$	1.547	2.527	2.275	1.218	.323	–1.199	1.547	2.527	2.275	.082	.000	.077
$\hat{Trade}$ × RI	–37.497***	–33.674***	–31.095***	–37.890***	–36.932***	–39.085***	–37.497***	–33.674***	–31.095***	–4.045***	–2.903**	–1.188
$\hat{Trade} \times (RI)^2$	15.104***	13.404***	12.664***	15.462***	15.258***	15.543***	15.104***	13.404***	12.664***	1.040	.619	.225
I	.045***	.040***	.044***	.041***	.035***	.035***	.045***	.040***	.044***	.010***	.007***	.006***
I^2	–.000**	–.000*	–.000**	–.000***	–.000***	–.000***	–.000**	–.000**	–.000***	.000	.000	.000
KL	–.005***	–.004***	–.004***	–.004***	–.004***	–.004***	–.005***	–.004***	–.004***	–.001***	–.001**	–.000
$(KL)^2$	.000***	.000***	.000***	.000***	.000***	.000***	.000***	.000***	.000***	.000**	.000*	.000
KL × I	–.000***	–.000***	–.000**	–.000***	–.000**	–.000**	–.000***	–.000***	–.000***	–.000***	–.000**	–.000
Poor=1 × $\hat{Trade}$	–10.535***	–8.192***	–8.916***	–11.931***	–11.450***	–13.011***	–10.535***	–8.192***	–8.916***	.575	1.012	.716
$\hat{Trade}$ × RLPC		–12.646***	–9.438**		–2.571	2.026		–12.646***	–9.438**		–1.228	–1.009
$\hat{Trade} \times (RLPC)^2$		6.964***	5.792**		.515	–1.804		6.964***	5.792***		.708	.559
FDI/K		.109	.129*		.176**	.190**		.109	.129		.021	.034*
LPC		–5.819***	–3.802**		–1.208*	–.727		–5.819***	–3.802***		–.549*	–.322
$(LPC)^2$		.316***	.212**		.078**	.050		.316***	.212***		.045**	.034*
English=1 × $\hat{Trade}$			–3.620**			4.066***			–3.620**			–1.743**
Sea=1 × $\hat{Trade}$			–4.330***			–4.032***			–4.330***			–.225
Euro=1 × $\hat{Trade}$			.181			–.781			.181			–.214
Y(t-1)										.936***	.933***	.930***
Constant	1.672***	28.088***	18.426**	1.558***	5.852*	3.776	1.033***	27.781***	17.847***	.086**	1.315	.102
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.599	.620	.631				.970	.971	.972	.997	.998	.998
R2 adj.	.556	.576	.586									
BIC	–936.009	–936.959	–935.530	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use an instrumental variable approach where we instrument trade with a set of exogenous variables including lagged income, exchange rate, capital to labor ratio, price of export, price of imports, land per capita, and four dummies for whether a country uses euro, has access to the sea or ocean, whether it uses English as its official language, and whether it was a poor country at the start of the analysis period, respectively. We classify a country as poor if at the start of the sample its income was less than that of the European Average.

Table 24: Dependent Variable (Y) - SO2 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\widehat{Trade}$	140.913	–25.293	120.959	280.057	–25.013	14.336	140.913	–25.293	120.959	82.362	29.564	–9.258
$\widehat{Trade}$ × RKL	–410.579	–747.590**	–50.439	–360.984	–531.120*	–175.709	–410.579*	–747.590***	–50.439	9.532	–11.195	93.093
$\widehat{Trade} \times (RKL)^2$	–47.331	149.211	–7.109	–53.035	–8.744	–112.218	–47.331	149.211*	–7.109	.122	8.363	–.794
$\widehat{Trade}$ × RI	359.719	367.281	–482.712	178.710	155.682	–382.932	359.719	367.281	–482.712*	–191.713*	–215.908**	–342.568***
$\widehat{Trade} \times (RI)^2$	14.828	–37.144	126.380	68.675	75.772	150.557	14.828	–37.144	126.380	115.000***	127.130***	155.342***
I	–1.821***	–1.600***	–.919**	–1.511***	–1.522***	–.714*	–1.821***	–1.600***	–.919**	.110	.129	.136
I^2	–.017**	–.013*	–.005	–.020***	–.020***	–.013**	–.017***	–.013**	–.005	–.008***	–.008***	–.006***
KL	–.014	–.046	–.174***	.010	.011	–.097	–.014	–.046	–.174***	–.012	–.017	–.037
$(KL)^2$	–.000**	–.000**	–.000	–.000**	–.001***	–.000**	–.000**	–.000**	–.000	–.000	–.000	–.000
KL × I	.007***	.007***	.003*	.008***	.009***	.007***	.007***	.007***	.003**	.002***	.002***	.001**
Poor=1 × $\widehat{Trade}$	–139.541	–215.489*	–332.698***	–217.857**	–299.540***	–316.751***	–139.541*	–215.489**	–332.698***	–61.359*	–88.178**	–85.970**
$\widehat{Trade}$ × RLPC		132.230	501.581*		704.419**	1038.795***		132.230	501.581**		124.825	110.965
$\widehat{Trade} \times (RLPC)^2$		110.966	–25.152		–161.276	–245.170		110.966	–25.152		–31.134	–22.929
FDI/K		–18.626***	–22.144***		–10.662*	–16.210***		–18.626***	–22.144***		–3.061*	–4.035**
LPC		–491.642***	–515.748***		–43.690	–5.907		–491.642***	–515.748***		22.605	–15.888
$(LPC)^2$		22.870***	23.134***		1.467	–.969		22.870***	23.134***		–1.470	.388
English=1 × $\widehat{Trade}$			930.004***			567.546***			930.004***			153.079***
Sea=1 × $\widehat{Trade}$			–578.508***			–613.884***			–578.508***			10.096
Euro=1 × $\widehat{Trade}$			18.216			73.430**			18.216			2.912
Y(t-1)										.944***	.936***	.923***
Constant	56.491***	2639.332***	2844.707***	46.949***	333.544*	207.034	56.155***	2658.235***	2859.975***	.239	–81.394	119.571
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.268	.343	.438				.810	.829	.854	.977	.978	.978
R2 adj.	.189	.266	.369									
BIC	4364.015	4329.911	4254.312	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use an instrumental variable approach where we instrument trade with a set of exogenous variables including lagged income, exchange rate, capital to labor ratio, price of export, price of imports, land per capita, and four dummies for whether a country uses euro, has access to the sea or ocean, whether it uses English as its official language, and whether it was a poor country at the start of the analysis period, respectively. We classify a country as poor if at the start of the sample its income was less than that of the European Average.

Table 25: Dependent Variable (Y) - Municipal Waste Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\widehat{Trade}$	3021.297**	1993.435	1646.454	3163.664**	596.547	1519.707	3021.297**	1993.435	1646.454	1695.065*	1467.187	1298.979
$\widehat{Trade}$ × RKL	–1836.250	–3114.955	–3855.397*	–1369.902	–1261.777	–2287.160	–1836.250	–3114.955*	–3855.397**	–1324.310	–1933.582	–2547.508*
$\widehat{Trade} \times (RKL)^2$	–1193.198	–489.013	–474.816	–1095.087	–1360.731	–1157.357	–1193.198*	–489.013	–474.816	–569.446	–394.138	–354.751
$\widehat{Trade}$ × RI	2740.962	2412.069	2304.054	2184.627	1454.123	1309.635	2740.962	2412.069	2304.054	–171.451	–120.631	97.267
$\widehat{Trade} \times (RI)^2$	–1306.750	–1738.204*	–1713.181*	–980.719	–925.658	–1078.474	–1306.750	–1738.204**	–1713.181**	–280.751	–520.599	–573.490
I	–2.804	–1.829	1.351	–2.169	–1.527	.710	–2.804	–1.829	1.351	–.372	–.642	.915
I^2	.033	.067	.053	.014	.025	.024	.033	.067*	.053	.060**	.071**	.060**
KL	.402	.367	.305	.529	.534	.427	.402	.367	.305	.262	.352	.355
$(KL)^2$	–.001	–.001	–.002	–.001	–.002	–.002	–.001	–.001	–.002*	–.000	–.001	–.001
KL × I	.010	.006	.010	.010	.015	.015	.010	.006	.010	–.005	–.003	.000
Poor=1 × $\widehat{Trade}$	–3179.067***	–3692.498***	–3399.649***	–2741.386***	–3322.562***	–3353.017***	–3179.067***	–3692.498***	–3399.649***	–2070.441***	–2335.760***	–2182.219***
$\widehat{Trade}$ × RLPC		4081.362*	5047.127**		7178.579***	7604.691***		4081.362**	5047.127**		2317.591	2812.982
$\widehat{Trade} \times (RLPC)^2$		–1886.143	–2079.614*		–3489.960***	–3457.270***		–1886.143	–2079.614*		–1044.892	–1144.019
FDI/K		–57.973	–62.291		1.005	–31.871		–57.973*	–62.291*		–22.726	–24.300
LPC		–3836.683***	–2849.186***		–586.658**	–757.290***		–3836.683***	–2849.186***		–1500.966***	–972.057*
$(LPC)^2$		189.963***	139.268***		27.740**	36.207**		189.963***	139.268***		77.294***	50.273*
English=1 × $\widehat{Trade}$			–956.067			–579.293			–956.067			–782.519
Sea=1 × $\widehat{Trade}$			–1380.927**			–1582.827**			–1380.927***			–660.039*
Euro=1 × $\widehat{Trade}$			537.605**			582.401**			537.605***			282.263*
Y(t-1)										.599***	.574***	.566***
Constant	390.237***	19507.124***	14792.090***	348.269***	3430.040***	4309.365***	436.554***	19706.801***	14869.457***	197.691***	7482.608***	4881.028*
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.298	.350	.362				.860	.870	.873	.914	.916	.916
R2 adj.	.222	.273	.283									
BIC	6670.578	6655.911	6663.701	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use an instrumental variable approach where we instrument trade with a set of exogenous variables including lagged income, exchange rate, capital to labor ratio, price of export, price of imports, land per capita, and four dummies for whether a country uses euro, has access to the sea or ocean, whether it uses English as its official language, and whether it was a poor country at the start of the analysis period, respectively. We classify a country as poor if at the start of the sample its income was less than that of the European Average.

Table 26: Dependent Variable (Y) - SOx Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\hat{Trade}$	15.112	537.190	150.466	32.469	203.912	–283.963	15.112	537.190	150.466	204.481	372.270	94.820
$\hat{Trade}$ × RKL	736.851*	109.694	981.445**	823.215*	532.755	1144.359**	736.851**	109.694	981.445**	251.250	75.183	419.562
$\hat{Trade} \times (RKL)^2$	–624.381***	–371.228*	–463.907**	–621.019***	–533.253**	–614.976***	–624.381***	–371.228**	–463.907***	–163.879**	–95.673	–108.748
$\hat{Trade}$ × RI	–278.494	238.455	–941.694*	–226.937	64.417	–965.452**	–278.494	238.455	–941.694	–519.574	–355.224	–802.913**
$\hat{Trade} \times (RI)^2$	–6.946	–229.500	37.737	–.295	–84.981	140.938	–6.946	–229.500	37.737	215.837*	156.513	262.158*
I	–1.144*	–1.739***	–.986	–1.387**	–1.686***	–.441	–1.144	–1.739**	–.986*	.290	.091	.199
I^2	.010	.014	.030***	.009	.008	.020**	.010	.014	.030***	–.007	–.006	.002
KL	.047	.113	–.063	.042	.084	–.076	.047	.113	–.063	.030	.047	–.019
$(KL)^2$	–.000	–.000	.000	–.000	–.000	.000	–.000	–.000	.000	–.000	–.000	.000
KL × I	.002	.002	–.004	.002	.003	–.001	.002	.002	–.004	.001	.001	–.001
Poor=1 × $\hat{Trade}$	–66.167	96.623	177.488	26.636	94.434	209.192	–66.167	96.623	177.488	–82.356	–31.041	51.819
$\hat{Trade}$ × RLPC		–1368.371***	–1341.353***		–770.981*	–677.859		–1368.371***	–1341.353***		–500.157	–654.624*
$\hat{Trade} \times (RLPC)^2$		875.475***	900.968***		518.079*	563.152**		875.475***	900.968***		314.331	393.392*
FDI/K		–10.400	–17.707*		–.759	–7.337		–10.400	–17.707***		–3.618	–7.067
LPC		–684.820***	–804.631***		–105.328	–40.670		–684.820***	–804.631***		–123.905	–235.334
$(LPC)^2$		36.383***	41.759***		6.009*	2.235		36.383***	41.759***		6.703	12.274
English=1 × $\hat{Trade}$			1174.463***			855.650***			1174.463***			464.688*
Sea=1 × $\hat{Trade}$			–124.046			–247.819*			–124.046			157.619**
Euro=1 × $\hat{Trade}$			109.405*			165.227***			109.405*			45.522
Y(t-1)										.752***	.745***	.729***
Constant	61.355***	3247.792***	3903.412***	59.805***	514.142*	259.437	38.233***	3262.794***	3931.152***	–6.510	567.605	1136.098*
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.539	.556	.585				.842	.848	.858	.939	.940	.942
R2 adj.	.490	.504	.533									
BIC	4889.047	4898.758	4877.429	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use an instrumental variable approach where we instrument trade with a set of exogenous variables including lagged income, exchange rate, capital to labor ratio, price of export, price of imports, land per capita, and four dummies for whether a country uses euro, has access to the sea or ocean, whether it uses English as its official language, and whether it was a poor country at the start of the analysis period, respectively. We classify a country as poor if at the start of the sample its income was less than that of the European Average.

Table 27: Dependent Variable (Y) - NOx Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\hat{Trade}$	1087.354***	1137.115**	555.519	778.509**	619.365	164.784	1087.354***	1137.115**	555.519	211.610	73.261	–127.478
$\hat{Trade}$ × RKL	–1063.123**	–1435.337**	–1183.773**	–1295.562**	–1126.112**	–1049.496*	–1063.123**	–1435.337***	–1183.773***	122.359	20.138	137.750
$\hat{Trade} \times (RKL)^2$	655.681***	846.564***	910.238***	798.466***	717.107***	774.890***	655.681***	846.564***	910.238***	38.630	187.350	209.150
$\hat{Trade}$ × RI	–887.895	–761.011	–1169.145*	–513.134	–709.261	–1113.970*	–887.895**	–761.011*	–1169.145***	–317.299	–298.927	–534.686
$\hat{Trade} \times (RI)^2$	377.464	229.245	352.809	270.972	329.487	452.070*	377.464*	229.245	352.809*	184.711	113.516	176.603
I	2.269***	2.268***	2.285***	1.972***	2.078***	2.636***	2.269***	2.268***	2.285***	.634*	1.060*	1.202**
I^2	–.026**	–.019	–.009	–.026**	–.026**	–.022*	–.026	–.019	–.009	–.022	–.016	–.012
KL	.217*	.219*	.161	.185	.194	.150	.217**	.219*	.161	–.123*	–.200*	–.228**
$(KL)^2$	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	–.000	.000	.000
KL × I	–.001	–.002	–.005	–.001	–.000	–.002	–.001	–.002	–.005	.003	.000	–.001
Poor=1 × $\hat{Trade}$	62.234	40.270	248.503	214.251	171.935	317.533	62.234	40.270	248.503	108.029	122.474	196.765
$\hat{Trade}$ × RLPC		64.839	–331.377		678.351	454.094		64.839	–331.377		–425.984	–521.101*
$\hat{Trade} \times (RLPC)^2$		–22.513	158.461		–346.527	–218.080		–22.513	158.461		204.725	255.537*
FDI/K		–10.823	–15.118		3.557	–.819		–10.823	–15.118**		–3.697	–5.824
LPC		–814.742***	–953.121***		1.825	3.268		–814.742***	–953.121***		–583.812**	–623.513**
$(LPC)^2$		41.083***	48.364***		–.147	–.217		41.083***	48.364***		27.110**	29.167**
English=1 × $\hat{Trade}$			347.605			87.200			347.605**			191.882
Sea=1 × $\hat{Trade}$			524.778***			297.391			524.778***			126.615
Euro=1 × $\hat{Trade}$			87.186			150.231**			87.186*			45.107
Y(t-1)										.883***	.905***	.891***
Constant	–17.234	3974.374***	4631.831***	–3.282	–8.688	–9.024	–47.632***	3980.077***	4659.438***	6.194	3098.849**	3296.999**
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.295	.315	.328				.869	.873	.876	.904	.908	.909
R2 adj.	.219	.234	.245									
BIC	5121.309	5135.918	5142.777	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use an instrumental variable approach where we instrument trade with a set of exogenous variables including lagged income, exchange rate, capital to labor ratio, price of export, price of imports, land per capita, and four dummies for whether a country uses euro, has access to the sea or ocean, whether it uses English as its official language, and whether it was a poor country at the start of the analysis period, respectively. We classify a country as poor if at the start of the sample its income was less than that of the European Average.

Table 28: Dependent Variable (Y) - SF6 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\hat{Trade}$	–1102.338**	–1072.048**	–61.866	–413.807	–236.345	179.137	–1102.338***	–1072.048**	–61.866	–361.686**	–511.641**	–431.760**
$\hat{Trade}$ × RKL	–531.802	–778.543	–1348.162**	–139.200	–784.966	–789.498	–531.802	–778.543*	–1348.162***	–305.879*	–157.596	–199.562
$\hat{Trade}$ × $(RKL)^2$	511.828*	657.422**	585.815**	281.425	512.381*	360.624	511.828***	657.422***	585.815**	170.291**	114.080	103.630
$\hat{Trade}$ × RI	–77.817	–43.248	907.451	–459.760	–263.280	165.300	–77.817	–43.248	907.451*	154.079	41.057	77.210
$\hat{Trade}$ × $(RI)^2$	262.534	288.552	26.159	437.326*	322.028	165.805	262.534	288.552	26.159	15.332	61.151	48.629
I	3.197***	3.332***	2.877***	2.436***	2.435***	1.947***	3.197***	3.332***	2.877***	.139	.283	.396
I^2	–.011	–.010	–.028**	–.016	–.011	–.012	–.011	–.010	–.028***	–.005	–.006*	–.008**
KL	–.219*	–.308**	–.166	–.130	–.159	–.126	–.219***	–.308***	–.166**	.016	.013	.015
$(KL)^2$	.000	.000	–.000	.000	.000	.000	.000	.000	–.000	–.000*	–.000	–.000*
KL × I	–.003	–.004	.002	–.002	–.002	–.001	–.003	–.004	.002	.002	.002	.002*
Poor=1 × $\hat{Trade}$	207.237	40.402	–317.115	52.303	–184.348	–301.105*	207.237	40.402	–317.115	159.667	165.004	137.262
$\hat{Trade}$ × RLPC		–235.563	288.494		129.641	487.703		–235.563	288.494		219.921	311.743
$\hat{Trade}$ × $(RLPC)^2$		101.229	–165.866		–171.353	–360.932		101.229	–165.866		–83.122	–118.007
FDI/K		–28.850**	–20.036*		–37.486***	–36.787***		–28.850	–20.036		6.065	6.324
LPC		395.617	569.040**		–42.208	–78.940*		395.617**	569.040***		40.311	87.733
$(LPC)^2$		–22.286*	–31.242**		1.713	3.614		–22.286**	–31.242***		–2.488	–4.983
English=1 × $\hat{Trade}$			–783.441***			–34.163			–783.441***			–52.541
Sea=1 × $\hat{Trade}$			–662.600***			–482.809***			–662.600***			–129.803*
Euro=1 × $\hat{Trade}$			–199.514***			–160.199**			–199.514***			1.035
Y(t-1)										.857***	.860***	.856***
Constant	38.994***	–1681.992	–2528.203**	17.502*	271.358	446.203**	79.001***	–1661.958**	–2536.270***	15.987**	–145.241	–374.369
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.193	.216	.255				.639	.649	.666	.922	.923	.923
R2 adj.	.106	.124	.163									
BIC	5190.243	5204.141	5192.588	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use an instrumental variable approach where we instrument trade with a set of exogenous variables including lagged income, exchange rate, capital to labor ratio, price of export, price of imports, land per capita, and four dummies for whether a country uses euro, has access to the sea or ocean, whether it uses English as its official language, and whether it was a poor country at the start of the analysis period, respectively. We classify a country as poor if at the start of the sample its income was less than that of the European Average.

Table 29: Dependent Variable (Y) - NH3 Results

Estimation Method	Fixed Effects			Random Effects			Cross Section Dependance			Serial Correlation Effects		
Specification	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\hat{Trade}$	52.836*	144.193***	170.568***	99.291***	172.779***	203.010***	52.836*	144.193***	170.568***	–17.192	21.499	44.384**
$\hat{Trade}$ × RKL	–74.565**	–132.854***	–156.625***	–76.666**	–112.642***	–108.886***	–74.565*	–132.854***	–156.625***	24.608	–12.064	–31.378
$\hat{Trade}$ × $(RKL)^2$	64.841***	80.118***	82.973***	64.800***	79.888***	73.150***	64.841***	80.118***	82.973***	–1.202	13.258	14.472
$\hat{Trade}$ × RI	–152.716***	–87.610**	–35.577	–179.347***	–137.089***	–101.358**	–152.716***	–87.610**	–35.577	–58.791***	–29.670	3.968
$\hat{Trade}$ × $(RI)^2$	57.185***	38.913**	26.848	64.537***	52.566***	45.325**	57.185***	38.913*	26.848	24.572**	11.670	3.566
I	.150***	.040	–.045	.187***	.127**	.037	.150***	.040	–.045	.088***	.050*	.010
I^2	.002*	.002*	.001	.001	.001	.000	.002*	.002*	.001	–.000	.000	–.000
KL	–.015*	–.008	.001	–.012	–.010	–.003	–.015**	–.008	.001	–.011***	–.008**	–.003
$(KL)^2$	.000***	.000***	.000***	.000***	.000***	.000***	.000***	.000***	.000***	.000*	.000*	.000
KL × I	–.001***	–.001***	–.001***	–.001***	–.001***	–.001***	–.001***	–.001***	–.001***	–.000	–.000*	–.000
Poor=1 × $\hat{Trade}$	–16.380	–5.905	–16.000	–48.987***	–38.267**	–56.702***	–16.380	–5.905	–16.000	13.239	18.497**	10.498
$\hat{Trade}$ × RLPC		–162.880***	–177.232***		–157.713***	–148.483***		–162.880***	–177.232***		–71.607**	–72.259***
$\hat{Trade}$ × $(RLPC)^2$		79.380***	80.146***		69.161***	56.726**		79.380***	80.146***		35.101**	32.830**
FDI/K		–1.725**	–1.324*		–1.238	–.488		–1.725*	–1.324		–.794	–.531
LPC		22.457	11.268		8.331	6.802		22.457	11.268		–28.902***	–30.328***
$(LPC)^2$		–.760	–.157		–.247	–.160		–.760	–.157		1.597***	1.686***
English=1 × $\hat{Trade}$			–32.821**			–8.604			–32.821**			–25.212***
Sea=1 × $\hat{Trade}$			24.259*			13.984			24.259***			2.558
Euro=1 × $\hat{Trade}$			–14.407***			–20.638***			–14.407***			–7.870***
Y(t-1)										.772***	.759***	.753***
Constant	12.848***	–130.296*	–80.142	11.120***	–45.371	–40.260	11.831***	–131.215	–79.633	3.112***	134.024***	139.110***
N	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000	609.000
R2	.636	.683	.691				.962	.967	.968	.989	.990	.990
R2 adj.	.597	.645	.653									
BIC	1868.714	1817.809	1819.906	.	.	.	.	.	.	.	.	.

***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively. M1, M2, and M3 correspond to the three models outlined in equations (1), (2), and (3), respectively. Cross represents a fixed effects regression where we allow for cross-section dependence among countries. Serial correlation effects denote a fixed effects regression setting where we add one lag of the dependent variable (i.e., Y(t-1)) to account for the first order serial correlation effect. In all regressions, a second lag does not appear to yield a significant coefficient. We use an instrumental variable approach where we instrument trade with a set of exogenous variables including lagged income, exchange rate, capital to labor ratio, price of export, price of imports, land per capita, and four dummies for whether a country uses euro, has access to the sea or ocean, whether it uses English as its official language, and whether it was a poor country at the start of the analysis period, respectively. We classify a country as poor if at the start of the sample its income was less than that of the European Average.