University of Lausanne
HEC / MSE
Term Paper
Academic Year 2002-2003

A Simple Test for the Pollution Haven Hypothesis

Course: Applied Econometrics

Author: Nicole Andréa Mathys

Professor: Marius Brülhart

Assistant: Aleksandar Georgiev

Date: May 2003

Contents

1. INTRODUCTION 2

2. THE POLLUTION HAVEN HYPOTHESIS 3

3. ECONOMETRIC ISSUES 5

3.1 Missing Data 5
3.2 Unbalanced Panel (Estimation with Randomly Missing Data) 7

4 DATA AND RESULTS 9

4.1 Data Description 9
4.2 Data Preparation 10
4.3 Regressions 13

5 CONCLUSION 22

APPENDIX 26

1. Introduction

People are more and more concerned about the environment and fearful about the environmental consequences of globalisation. The clash is frequent between policy makers promoting their trade liberalisation programmes and globalisation opponents crying their slogans. But what is the real impact of trade liberalisation on the environment? In this work one of the possible effects, namely the implication predicted by the pollution haven hypothesis (PHH) will be tested empirically. The strength of this work is that it bases its estimates on a large number of countries over more than ten years. Also, it investigates each "polluting industry" separately, in order to take into account the differences between them.

The aim of the present work is twofold: first, to test the PHH, and second, to deal with missing data problems, and discussing which methods may be used in order to overcome the latter problem.

The paper is organised as follows. In the next section, the basic idea of the pollution haven hypothesis is presented in a Heckscher-Ohlin framework. Section three treats with econometric concerns: the problem of missing data and, as a special case, the unbalanced panel estimation. Section four applies the methodology to real data, in order to identify the pollution haven effect. Finally, section five draws the conclusions and points at possible extensions of the work.

2. The Pollution Haven Hypothesis

The pollution haven hypothesis (PHH) is a fundamental concept in the trade and the environment literature. Several definitions have been used, but the one that will be retained for the present empirical investigation is based on Liddle (2001). For this author the PHH is verified if low environmental standards become a source of comparative advantage and therefore drive shifts in trade pattern. To be more precise, what one has in mind in this context is the following: assume developed countries are severe concerning environmental regulation and developing countries are less strict.[1] This leads to a comparative advantage in polluting products (products that are classified to be relatively polluting, see section 4.1) for developing countries. In this line of ideas, one could fear a “Race to the bottom”, which predicts that countries will mutually compete environmental standards down.

An early study on the PHH is Tobey (1990), who tests in a Heckscher-Ohlin-Vanek (HOV) framework (explained below) the impact of domestic environmental policies on trade patterns. More precisely he regresses trade in a specific “polluting” commodity[2] on country characteristics. Tobey uses two approaches. The first one has environmental stringency as an explanatory variable in the equation (23 countries in the sample), while the second one is a so called omitted variable test (58 countries), where he examines the signs of the estimated error terms. In no case, even when extending the basic HOV model of international trade with non-homothetic preferences or scale economies and product differentiation, he finds that the introduction of environmental control measures has caused a deviation of trade patterns from the HOV predictions.

The HOV model is an extension of the HO model which simply predicts that a country should export goods which use intensively the factor of production that is relatively abundant in this country. Mani and Wheeler (1999) and Cole and Elliott (2002) show that polluting industries are typically capital intensive. One easily accepts that developed countries are relatively capital abundant compared to developing countries and would therefore specialise in polluting industries. Hence, the HOV prediction of trade flows is the exact opposite of the PHH. This

[1] This is consistent with the widely confirmed property that increased GDP per capita leads to a stronger concern about the environment. See for example Mani and Wheeler (1999).
[2] Polluting industries are identified in function of US abatement costs.

work tries to figure out whether the coefficient on environmental stringency is significant and has the right sign when controlling for endowment (HOV) effects.

In summary, the following estimation will be run for each polluting sector[3]:

$$ne_{it} = \beta_0 + \beta_1 Labour_{it} + \beta_2 Capital_{it} + \beta_3 Land_{it} + \beta_4 Envstring_{it} + \varepsilon_{it}$$

where ne: net exports
i: country i
t: year t

In contrast to Cole and Elliott (2003) the preferred specification will estimate a separate regression for each polluting industry. Earlier work (in particular Grether and de Melo (2002) and Mathys (2002)) suggests that an aggregate analysis hides specific patterns in each industry. If there is indeed a PHH story in the data, it is more likely to be found at the disaggregated level.

[3] Note that in this simple specification no country-mean correction is included. This is a general equation which must be modified for the different panel estimation procedures.

3. Econometric Issues

3.1 Missing Data

Datasets are rarely complete. When working with panels it is even more likely that some variables and/or some years are missing for the given countries[4]. First of all, one has to know whether there are some reasons underlying the missing data-points. In fact, three types of missing data can be distinguished:

- **Missing Completely at Random (MCAR)**: There is no difference between complete cases and incomplete cases; this would be obtained if a researcher arbitrarily discards some raw data.

- **Missing at Random (MAR)**: Cases with incomplete data on variable "A" differ from cases with complete data and the missingness is related to another variable (i.e. "B") in the database.

- **Non-ignorable**: The pattern of missing data of variable "A" is not random and is not related to other variables in the database, but to the very variable "A".

Assume data is MCAR (or at least MAR), then one may use a method from the list below to deal with missing data:

- **Complete Case approach**: Use only countries where all variables in the database are known (disadvantage: loss of information may be important).

- **Available Case analysis:** use all countries where the variables of interest (for each computation) are present (disadvantage: changing sample bases make comparisons more difficult).

[4] The enconometric issues will be presented in the context of the PHH, namely a database on countries, over years.

- **Model based procedures**: incorporating the missing data into the analysis (i.e. EM (Expectation Maximisation) approach, which is an iterative two stage approach).

- **Imputations Methods**: the missing value is estimated by using other values of the variables and/or cases in the sample (disadvantage: “seductive and dangerous”).

Furthermore, the imputation methods can be broken down into the following approaches:

- **All-available approach:** missing values are not replaced, but distribution characteristics are imputed.

- **Replacement** of missing data:

    - **Case substitution:** replace sampled country with another country not yet in the sample.

    - **Mean substitution:** replacing missing data points with mean value of the variable (disadvantages: variance gets underestimated, actual distribution is distorted, depresses the observed correlation).

    - **Cold Deck Imputation:** Substitute a constant value from external source (disadvantages: see mean substitution).

    - **Regression Imputation:** using the relationships between the variables in the dataset (disadvantages: reinforces relationships already in data which means less general results, variance is underestimated if no error term is added, assumes variable with missing data has strong correlation with other variables, if no constraints computed values may fall outside the valid range for a variable).

    - **Multiple Imputation:** composite estimation based on several methods

This list points at the most important techniques but is far from being exhaustive. Section 4.2 will take up two methods to deal with missing data.

3.2 Unbalanced Panel (Estimation with Randomly Missing Data)

This subsection links together the missing data problem with the panel data estimation procedures[5]. The fixed and the random effect estimators can both be extended to the case where the number of years per country in the data is not identical. Then one has to compute means over the available observations.[6] “Available means” are defined in the following way:

$$\bar{y}_i = \frac{\sum_{t=1}^{T} r_{it} y_{it}}{\sum_{t=1}^{T} r_{it}} \quad \text{and} \quad \bar{x}_i = \frac{\sum_{t=1}^{T} r_{it} x_{it}}{\sum_{t=1}^{T} r_{it}}$$

where r_{it} is the indicator variable taking 1 if (x_{it}, y_{it}) is observed and 0 otherwise.

The fixed effect estimator becomes:

$$\hat{\beta}_{FE} = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} r_{it} (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)' \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} r_{it} (x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i)$$

Hence, one must just make sure that the sums are taken over the available observations only.

The random effect estimator can be obtained form the following equation (note that the definition of the Greek letters is slightly different compared to the random effects presentation in appendix A):

[5] For a summary on panel data estimations read appendix A.
[6] Note that each country should at least report data for two years.

$$\hat{\beta}_{GLS} = (\sum_{i=1}^{N} \sum_{t=1}^{T} \kappa_{it} + \sum_{i=1}^{N} \lambda_i)^{-1} \bullet (\sum_{i=1}^{N} \sum_{t=1}^{T} \varpi_{it} + \sum_{i=1}^{N} \theta_i)$$

where $\kappa_{it} = r_{it}(x_{it} - \overline{x}_i)(x_{it} - \overline{x}_i)'$

$$\lambda_i = \varphi_i T_i(\overline{x}_i - \overline{x})(\overline{x}_i - \overline{x})'$$

$$\varpi_{it} = r_{it}(x_{it} - \overline{x}_i)(y_{it} - \overline{y}_i)$$

$$\theta_i = \varphi_i T_i(\overline{x}_i - \overline{x})(\overline{y}_i - \overline{y})$$

$$\varphi_i = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + T_i \sigma_\alpha^2}$$

$T_i = \sum_{t=1}^{T} r_{it}$ (number of periods country i is observed)

Thus, in fact one simply has to replace T by T_i and therefore take sums and means over the available data.

Fortunately stata7 uses the extended estimators and is consequently insensible to unbalanced panels. Hence in the practical part these issues need not be taken up again.

4 Data and Results

4.1 Data Description

Data covers 13 years (1983-1995) for over 50 developed and developing countries.[7] Basically there are three different categories of data. Firstly, the explained variable is net exports (exports-imports)[8] of the five most polluting industries. The classification of polluting industries has been elaborated by Mani and Wheeler (1999) and they take into account emission intensities per unit of output in three different domains (conventional air pollutants, water pollutants and heavy metals). Based on the 3-digit-ISIC classification they found the following five most heavily polluting industries:

Table 1: Categories of polluting products

ISIC code	Description
341	Paper and products
351	Industrial chemicals
369	Other non-metallic mineral products
371	Iron and steel
372	Non-ferrous metals

Then there are two groups of explanatory variables. One group contains variables relative to the classical Heckscher-Ohlin-Vanek (HOV) trade model, while the other group captures the pollution haven hypothesis. The variables that account for HOV theory are relative factor endowments of capital, human capital, labour force and land.[9] More precisely the following formula has been used to compute the relative factor endowment:

$$re = \frac{ce/we}{sy} = \frac{ce}{we * sy}$$

where: re: relative endowment of a given factor

ce: country i's endowment of this factor

we: world endowment of this factor

sy: country i's share in world GDP

[7] Appendix C lists the countries in alphabetical order.
[8] Trade data is extracted from the World Bank's Trade and Production database. It is available on the following website: www.worldbank.org/research/trade
[9] Endowment data is extracted from Sandeep Mahajan (PRMEP), World Bank 2001.

In words, the relative endowment in each factor has been defined as the ratio between the country's share of endowment of the factor and the share of the country in world GDP. Equivalently, it is the ratio between actual endowment and theoretical endowment. This is very similar to the relative endowments defined by Vanek but it has the advantage that it is comparable over factors.

Finally, the variable of interest in this work is clearly the one capturing environmental stringency. Unfortunately it is difficult to get a good measure of environmental stringency and even more so, if one wants the data to have a panel structure. Here the average maximum lead content of gasoline has been used. The database has been elaborated by Grether and Mathys (2002) on the basis of Octel's Worldwide Gasoline Survey. More precisely the average has been worked out by using different types of gasoline and weighting them by their market share. Therefore, the proxy constructed takes into account the importance of the different types of gasoline in the overall market. If one admits that it is generally more costly to produce gasoline with low lead contents, the selected variables represents not only the maximum lead content observed, but also, and this is the important feature, in some sense the enforced legal limit of lead content in gasoline. Since it is impossible for the moment to get a good global index of environmental stringency, the average maximum lead content represents at least one of the most important environmental policies. Note also that Damania et al (2000) qualified the lead content in gasoline as the "most viable dynamic consumption proxy" for environmental stringency at the country level.

4.2 Data Preparation

The preparation of the three different variable-types will be discussed in turn. The database containing the maximum average lead content has been purified completely. As the data has been entered by students, some checks based on simple error structures have been done. Then, the market share was missing in some cases. Appendix E indicates the two step procedure used to impute the 78 missing data points (out of 4332).

Concerning endowments, several countries report missing data. Table 2 represents the number of missing values summed over either years or countries for a given endowment variable.

Table 2: Missing values summed over years and over countries
(countries are listed in appendix B, variables are defined in appendix C)

	recp	**rel1**	**rehc**	**reln**	**real**	**reil**	**repl**
ETH				10	10	10	10
GER	5	5	5	5	5	5	5
HKG	13	13	13				
IRL						13	
KWT	13	13	13				
MAC	13	13	13		13	13	13
MAR	13	13	13				
NOR							13
POL	6	6	6				
SGP						13	
SWE							13
Total *	63 (1.6%)	63 (1.6%)	63 (1.6%)	15 (0.4%)	28 (0.7%)	54 (1.4%)	54 (1.4%)
1983	4	4	4	1	2	4	4
1984	4	4	4	1	2	4	4
1985	4	4	4	1	2	4	4
1986	4	4	4	1	2	4	4
1987	4	4	4	1	2	4	4
1988	4	4	4	1	2	4	4
1989	4	4	4	1	2	4	4
1990	5	5	5	1	2	4	4
1991	6	6	6	2	3	5	5
1992	6	6	6	2	3	5	5
1993	6	6	6	1	2	4	4
1994	6	6	6	1	2	4	4
1995	6	6	6	1	2	4	4

Note: * reports total number of missing values and in parenthesis % of missing values.

Fortunately, the data used is not based on a survey and one is allowed to declare the missing values to be MCAR. This simplifies matters considerably. To complete the database, regression imputation techniques have been used. More precisely, all variables in the dataset (except net exports) have been used to impute the missing values. The stata-command allowing such a computation is "impute". Table 3 shows descriptive statistics of the old and the new series and the variance of the imputation.

Table 3: Regression imputations on endowment variables
(variables are defined in appendix C)

Variables	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
recp	3540	.9498284	2.255159	2.04e-07	13.7076
nrecp	3880	.965547	2.155313	2.04e-07	13.7076
varrecp	3880	.460179	1.485373	0	5.370513
rel1	3540	3.727832	6.724835	.1565195	54.64182
nrel1	3880	3.56399	6.473195	.1443815	54.64182
varrel1	3880	.2866038	3.559082	0	44.49282
rehc	3540	3.066917	4.596006	.2012101	31.61267
nrehc	3880	2.948767	4.429369	.2012101	31.61267
varrehc	3880	.1901035	1.663179	0	20.71146
reln	3805	2.764517	5.667744	.0006407	42.38218
nreln	3880	2.913262	5.782409	.0006407	42.38218
varreln	3880	.5403159	3.859275	0	30.78699
real	3740	2.603697	4.012287	.0002493	37.93413
nreal	3880	2.757344	4.317819	.0002493	37.93413
varreal	3880	.1996071	1.383604	0	15.93506
reil	3610	2.887009	5.563285	.001538	37.56516
nreil	3880	2.933035	5.427382	.001538	37.56516
varreil	3880	1.640807	6.031847	0	30.66069
repl	3610	4.346591	5.92741	0	33.47644
nrepl	3880	4.31615	5.750986	0	33.47644
varrepl	3880	1.899409	6.988018	0	34.79837

Note: example for the first variable:
recp: old variable, without any changes (containing missing values)
nrecp: newly computed variable including the imputations
varrecp: variance of the prediction

One sees that maxima and minima stay basically the same, before and after imputation. Means and standard deviations change slightly. In general the imputations look sensible, which is certainly also due to the fact that only really small fractions of the database are missing.

For trade-flow data the complete case approach will be used. In other words, only countries, without missing data for imports and exports in all five industries will be kept.

4.3 Regressions

First of all one wants to know whether the data has indeed a panel structure. For that reason it is interesting to look at the summary statistics which decompose the overall variation into the between and the within variation (these results can be found in appendix F). The listed variables report variation between countries as well as variation for each country over the different years. This clearly points at panel techniques. To be more exact, the Breusch-Pagan test-results are shown in table 4. The Breusch-Pagan test for poolability strongly rejects the null of no panel dimension for all polluting industries pooled, and for every polluting industry considered separately.[10]

Table 4: Test statistics for the Breusch-Pagan poolability-test and the Hausman specification effect (p-values are reported)

Industries/ Tests	Pooled	341	351	369	371	372
Breusch-Pagan Test	0.000	0.000	0.000	0.000	0.000	0.000
Hausman Test	0.04	0.945	0.000	0.000	0.294	0.000
Suggestion:	FE /RE	RE	FE	FE	RE	FE

Note: Breusch Pagan test for poolability (Ho: No panel-dimension in data)
Hausman specification test (Ho: difference between FE and RE estimators is not significant)

Next, one is interested whether the fixed or the random effect specification should be used. As can also bee seen in table 4, industry 351, 369 and 372 as well as the pooled sample show indeed a correlation between the individual effect and the other regressors (FE should be used). On the other hand, industries 341 and 371 do not reveal any significant difference between the two estimators (RE is more efficient).

Fixed effect and random effect regressions include 632 observations belonging to 52 countries. For industries 341 and 372 separately, the variables are not significant at all. The random effect results for 371 and the fixed effect results for 351, 369 and pooled industries are shown in table 5.

[10] Simple OLS regressions based on the whole sample period or on means from the beginning and the end of the period do report a significant and positive coefficient on the lead content variable only for industry 372. This can also be seen as a sign that the appropriate estimation procedure must be a panel method.

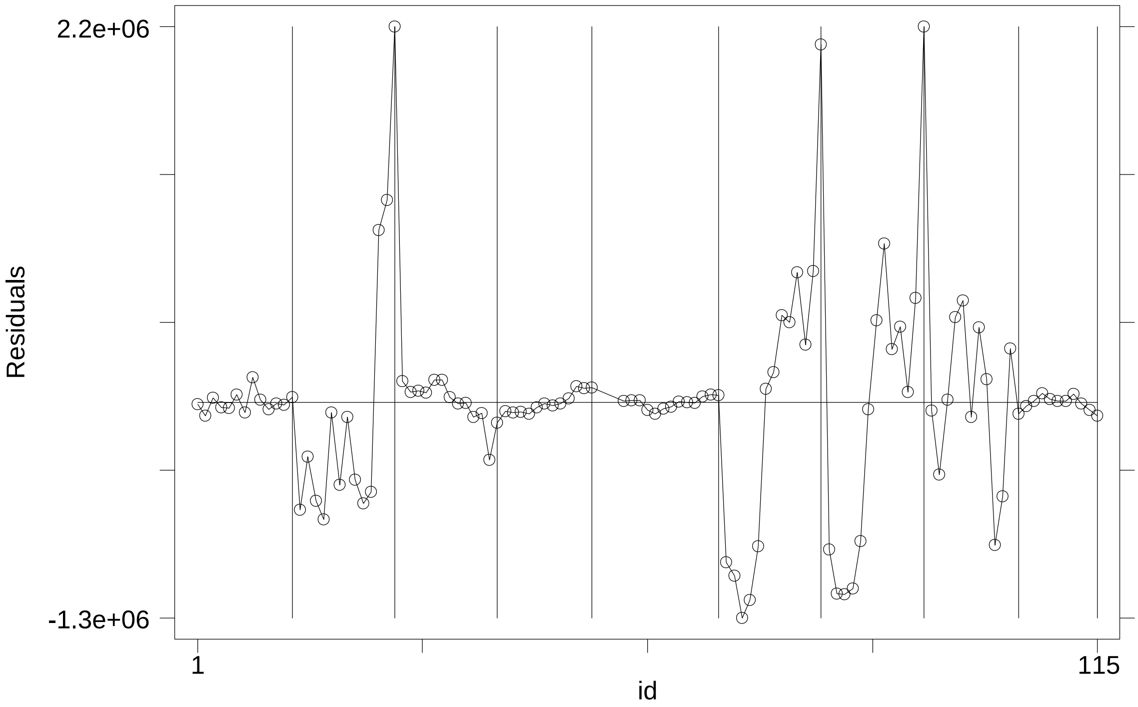
Table 5: Regresion results from FE and RE estimations (variables are defined in appendix C)

Explanatory Variable	Pooled-FE[1]	351-FE	369-FE	371-RE
lead	1578017**	1092036**	-86083	432604**
recp	NS	NS	-91426**	NS
rel1	NS	NS	NS	-160509
rehc	NS	-456608*	84132	NS
real	373921*	166300*	NS	104478*
reil	NS	NS	NS	NS
repl	NS	NS	NS	NS
R^2 within	.05	.08	.06	.04
R^2 overall	.001	.001	.2	.01

Note: the sample includes 632 observations from 52 countries.
NS: not significant.
No symbol: significant at the 10% level.
* significant at the 5% level.
** significant at the 1% level.
[1] RE estimates are similar and thus not presented.

The coefficient on the maximum lead content is significant. However, the sign is not always the same, more precisely, results suggest that 351 and 371 increase net exports as environmental stringency goes down (in favour of PHH) and the opposite is true for 369 (against PHH). Additionally in industry 351, increased relative endowment of skilled labour decreases net exports and increased relative endowment of arable land increase net exports. In industry 369 increased capital endowment leads to fewer net exports. Finally industry 371 decreases net exports with higher unskilled labour endowment and increases the dependent variable with higher arable land endowment. However, the interpretation of the endowment coefficients is not straightforward. The HOV variables are included in order to control for endowment effects but the coefficient of interest is clearly the one on environmental policy. In sum, these regression results are not really convincing (look also at the R^2). The problem could be due to the violation of the homoskedasticity assumption, which sounds sensible when thinking about the large differences between the countries in the sample. Heteroskedasticity implies that the estimators are no longer “best” nor “minimum variance”. In fact when looking at the residual-graph of a FE regression (see graphic 1), it appears clearly, that assuming homoskedastic error terms is wrong.

Graphic 1: Residual graph for industry 372 for 9 selected countries



Therefore, GLS estimations allowing for heteroskedasticity have been computed. Results are reported in table 6. However, as the data set contains few years compared to the number of countries, FGL estimations are likely to lead to "overconfidence". Nevertheless, some time will be spent on these results.[11]

[11] Note that similar works using roughly the same number of countries and time periods also use the FGLS estimation method. See for example Damania et al (2000).

Table 6: Regression results

(variables are defined in appendix C)

	Pooled	**341a**	**341b**	**351**	**369**	**371a**	**371b**	**372a**	**372b**
lead	591413** *583297***	74933** *76119***	75776** *75420***	455070** *455711***	NS *NS*	177330** *162734***	121476** *128496***	27680** *29157***	22489** *28643***
recp	NS *NS*	20863* *22842**	23790* *21481**	NS *NS*	-21131** *-22555***	NS *NS*	NS *NS*	NS *NS*	NS *NS*
rel1	NS *134230***	26036** *17251***	19226** *9888**	81014** *NS*	-34720** *-19643***	-47877* *-40027***	-69057** *-59652***	NS-*1039**	-27826** *-25316***
rehc	NS *107190*	-46835** *-36313***	-41320** *-26375***	-213937** *-66727*	51416** *31455***	68453* *59901***	81647* *69494***	NS *NS*	26437* *24254**
reln		13595 *6168***			NS *NS*	NS *NS*		9473** *5434***	
real	162297** *105175***		14093** *8650***	114076** *53265***			33456** *30859***		21030** *18162***
reil							32850** *21639***		NS *NS*
repl							-10633* *NS*		NS *NS*
Log Likelihood	-10156 *-11232*	-8997 *-9914*	-8995 *-9917*	-9694 *-10723*	-8414 *-9267*	-9298 *-10270*	-8587 *-10278*	-8869 *-9774*	-8169 *-9777*
Observations/Countries	684 / 56 *757 / 62*	684 / 56 *757 / 62*	684 / 56 *757 / 62*	684 / 56 *757 / 62*	684 / 56 *757 / 62*	684 / 56 *757 / 62*	632 / 52 *757 / 62*	684 / 56 *757 / 62*	632 / 52 *757 / 62*

Note: All models use FGLS with mean-correction for each country.
Coefficient in first row: unbalanced panel data, second row coefficients: imputed data.
NS: not significant.
No symbol: significant at the 10% level.
* significant at the 5% level.
** significant at the 1% level.

All coefficients on the lead variable (except for industry 369) are positive and significant at the 1% level. This clearly supports the PHH; a higher maximum lead content and therefore more lenient regulation leads to higher net exports in these polluting industries.

Capital endowment is only significant for industries 341 and 369. The higher the endowment, the higher net exports for 341 and the contrary for 369. This poor result is quite surprising as it was argued that polluting industries are capital intensive and should therefore strongly depend on that endowment.

Unskilled labour endowment has a positive coefficient for the pooled regression and the industries 341 and 369. The remaining industries report a negative effect of this endowment. How could one interpret a negative coefficient on endowments? A possible explanation would be that an increase in total unskilled labour force has a positive effect on the remuneration of the factor which is intensively used in this industry and by this bias leads to a decrease of the comparative advantage and therefore a lower level of net exports.

Skilled labour is non-significant for the pooled regression and has a negative coefficient for industries 341 and 351. The other industries report positive coefficients.

Total land is most of the time not significant. When splitting the different types of land , the significant and also positive coefficient is attributed to arable land.

The second row in the result table (table 6) reports the coefficients when imputed data (see section 4.2) have been used. Results differ only slightly. For the pooled industries skilled and unskilled labour endowment become significant. On the other hand, for industry 351 unskilled labour and for industry 371 the coefficient on permanent cropland becomes non significant. In general, the magnitude of the coefficients is unchanged for the environmental stringency proxy, but the coefficients are smaller for the endowment variables.

To point out the differences between the five so called polluting industries with respect to their sensibility to environmental regulations, elasticities have been computed[12] (see table 7).

Table 7: Elasticities of polluting net exports with respect to the maximum lead content

Industry	Elasticity
Paper and products (341)	3.11
Industrial chemicals (351)	0.44
Other non-metallic mineral products (369)	Not significant
Iron and steel (371)	0.53
Non ferrous metals (372)	0.06
All polluting industries	1.81

The differences between sectors are enormous a simple pooled regression will not reveal the true story. While industry "Other non metallic mineral products" does not change its exports in function of environmental regulation, "Paper and products" reacts strongly, with an elasticity of 3.11. The remaining industries and the pooled sample show smaller but significant effects.

As the results between FGLS and the RE or FE methods differ, in addition two other estimation procedures have been used. The first is again FGLS but allowing not only for heteroskedasticity but also for panel specific autocorrelation (ar1). To be able to compute autocorrelations, the panel need to be balanced. Therefore these results, represented in table 8 are only based on the balanced subset of the data (536 observations from 42 countries).

[12] These computations are based on the data without imputations.

Table 8: Results from GLS regression
(with heteroskedasticity and panel specific autocorrelation (ar1), variables are defined in appendix C)

Explanatory Variable	Pooled	341	351	369	371	372
lead	257613**	37104**	229029**	NS	58745*	17169*
recp	NS	24970*	NS	-20825**	NS	NS
rel1	NS	NS	NS	-32387**	-67702**	-39786**
rehc	NS	NS	NS	65350**	97931*	44660*
real	176414**	27638**	126789**	-11237**	32261	35589**
reil	NS	NS	-28236	NS	NS	NS
repl	NS	NS	21029*	NS	NS	NS
Log Likelihood	-7755	-6887	-7361	-6338	-7111	-6976

Note: a balanced panel with 536 observations from 42 countries has been used, see also note table 6.

The coefficient on the maximum lead content has in all but one case the expected sign and is significant at least at the 5% level. Only industry 369 reports no significant coefficient. Again the coefficient on capital endowment is not significant except for industries 341 (with a positive sign) and 369 (with a negative sign).

Finally the last estimation procedure uses maximum likelihood random effects estimates. Computations are based on 632 observations from 52 countries. Industries 341 and 372 do not report any significant variable at all.

Table 9: Maximum Likelihood Panel Estimations
(Variables are defined in appendix C)

Explanatory Variable	Pooled	351	369	371
lead	1483896**	1017830**	-88903	432529**
recp	NS	NS	-46432*	NS
rel1	NS	NS	NS	-160401
rehc	NS	-334765	NS	NS
real	325938*	124964	NS	104462*
reil	NS	NS	NS	NS
repl	NS	NS	NS	NS
Log Likelihood	-10065	-9686	-8774	-9461

Note: estimations are based 632 observations from 52 countries, see also note table 6.

These results broadly confirm the output from the fixed and random effects estimations.

Table 10 summarises all the results obtained. The pooled regression shows in any method a positive and significant coefficient on the environmental policy variable. Also, the higher relative endowments of arable land, the higher net exports. Industry 341 shows only in the FGL regressions a PHH effect. It has a positive coefficient on relative capital and arable land. Then industry 351 shows PHH effect throughout and has a positive coefficient on relative arable land and a negative coefficient on relative human capital.

Table 10: Synthesis of Regression Results
(variables are defined in appendix C)

Industry		FE / RE	FGLS	FGL (with ar1)	MLE-RE
Pooled	**Lead** [1]	+ ve	+ ve	+ ve	+ ve
	+ HOV [2]	real	real	real	real
	- HOV [3]	-	-	-	-
341	**Lead**	-	+ ve	+ ve	-
	+ HOV	-	recap, rel1, real	recp, real	-
	- HOV	-	rehc	-	-
351	**Lead**	+ ve	+ ve	+ ve	+ ve
	+ HOV	real	rel1, real	real, repl	real
	- HOV	rehc	rehc	reil	rehc
369	**Lead**	- ve	-	-	- ve
	+ HOV	rehc	rehc	rehc	-
	- HOV	recp	recp, rel1	recp, rel1, real	recp
371	**Lead**	+ ve	+ ve	+ ve	+ ve
	+ HOV	real	rehc, real, reil	rehc, real	real
	- HOV	rel1	rel1, repl	rel1	rel1
372	**Lead**	-	+ ve	+ ve	-
	+ HOV	-	rehc, real	rehc, real	-
	- HOV	-	rel1	rel1	-

Note: [1] Reports the sign of the significant coefficient on the lead content variable.
[2] Reports the variables that have a significant positive coefficient.
[3] Reports the variables that have a significant negative coefficient.

Industry 369 shows rather the contrary of the PHH and it reacts in the opposite direction to endowment changes compared to industry 351. Industry 371 reports again strong evidence for the PHH. In addition, it has a positive coefficient on arable land and a negative coefficient on the labour force. Finally, industry 372 shows evidence for the PHH in two out of four regressions and has a positive coefficient on arable land and human capital and a negative coefficient on the unskilled labour force.

To sum up, there is strong evidence for the PHH for all industries qualified as polluting except “Other non-metallic mineral products”.

5 Conclusion

Evidence based on a panel of 52 countries over more than 10 years suggests that in four out of five polluting industries there exists indeed a pollution haven hypothesis effect. This means that lower environmental standards increase (through revealed comparative advantages) net exports in polluting sectors.

However, the method used to test the PHH is fairly simple. The only thing it does, is controlling for endowment driven trade (HOV). The test could be improved in several directions. First of all it has been shown by Ederington and Minier (2003) that environmental stringency is in fact itself endogeneous and therefore a simultaneous equation estimation (with and additional equation explaining environmental policy by political economy variables) would be more appropriate.

Secondly, regressions would certainly be improved when controlling for Ricardian differences. More precisely, HOV assumes that all countries have the same technologies; which is clearly not true in reality. The method used by Trefler (1995) could give better results.

Thirdly, in order to get a clear-cut contrast between "dirty" and "clean" sectors, it would be helpful to apply all the estimations also to the five cleanest sectors.

Fourthly and finally, on the data side, some improvements would be welcome. Relying on alternative data sources would increase the confidence one can have in the conclusions drawn on this problematic.

References

Antweiler, W., B. R. Copeland and M. S. Taylor (2001), "Is Free Trade Good for the Environment?", *The American Economic Review*, Vol. 91(4), pp. 877-908.

Arellano, M. (2000), "Panel Data Econometrics", Draft handed out at a Summer-Course at the Studienzentrum Gerzensee 2002.

Birdsall, N. and Wheeler (1993), "Trade Policy and Industrial Pollution in Latin America: Where are the Pollution Havens?", *Journal of Environment and Development*, Vol.2, 1, pp. 137-150.

Brülhart, M. (2003), "Panel Data Models"; lecture handout for Applied Econometrics.

Cole, M.A: (2000), "Air Pollution and « Dirty » Industries : How and Why does The Composition of Manufacturing Output Change with Economic Development?" *Environmental Resource Economics*, Vol. 17, pp.109-123.

Cole, M.A. and R.J.R Elliott (2000), "Do Environmental Regulations Influence Trade Patterns? Testing Old and New Trade Theories", mimeo, University of Birmingham.

Cole, M.A. and R.J.R Elliott (2002), "FDI and the Capital Intensity of "Dirty" Sectors: A Missing Piece of the Pollution Haven Puzzle", mimeo, University of Birmingham.

Cole, M.A. and R.J.R Elliott (2003), "Determining the Trade-Environment Composition Effect: The Role of Capital, Labour and Environmental Regulations", *Journal of Environmental Economics and Management*, forthcoming.

Copeland, B.R. (2000), "Trade and environment: policy linkages", *Environment and Development Economics*, Vol. 5, pp. 405-432.

Copeland, B.R. and M. S. Taylor (1994), "North-South Trade and the Environment", *The Quarterly Journal of Economics*, Vol. 109, pp. 755-787.

Copeland, B.R. and M. S. Taylor (2001), "International Trade and the Environment: A Framework for Analysis", NBER N°8540.

Damania, R., P.G. Fredriksson and J.A. List (2000), Trade Liberalization, Corruption and Environmental Policy Formation: theory and Evidence, Centre for International Economic Studies, Discussion Paper No. 0047, Adelaide University, Australia.

Dijkstra, B.R. (1999), The Political Economy of Environmental Policy, Edward Elgar, Cheltenham, UK.

Ederington, J. and J. Minier (2003), Is Environmental Policy a Secondary Trade Barrier? An Empirical Analysis, *Canadian Journal of Economics* (forthcoming).

Greene, W. H. (2000), Econometric Analysis, Prentice-Hall, New Jersey.

Grether, J.-M. and J. de Melo (2002), "Globalization and dirty industries: do pollution havens matter?", Paper presented at the CEPR/NBER International Seminar on International Trade "Challenges to Globalization" in Stockholm.

Grether, J.-M. and N. Mathys (2002), Lead content of gasoline 1983-1995, original data taken from "Worldwide Gasoline Survey" published annually by OCTEL (GB).

Liddle, B. (2001), " Free trade and the environment-development system", Ecological Economics, Vol. 39, pp.21-36.

Low, P. (1992), International Trade and the Environment, World Bank, Washington D.C.

Low, P. and A. Yeats (1992), "Do "Dirty" Industries Migrate?", In Low, P. (Ed), International Trade and the Environment, World Bank.

Mani, M. and D. Wheeler (1999), "In Search of Pollution Havens? Dirty Industry in the World Economy, 1960-1995, in P. G. Fredriksson (ed), Trade, Global Policy, and the Environment, Discussion Paper, N°402, Washington D.C.: World Bank.

Mathys, N. (2002), "In Search of Evidence for the Pollution Haven Hypothesis", Mémoire de Licence, Université de Neuchâtel.

Nicita, A. and M. Olarreaga (2001), "Trade and Production, 1976-1999", Paper that accompanies Trade and Production Database (httpp://www.worldbank.org/research/trade).

Nordström, H. and S. Vaughan (1999), "Trade and Environment", Special Studies 4, World Trade Organisation, Geneva.

Olson, M., (1965), The Logic of Collective Action, Harvard University Press, Cambridge.

Tobey, J. (1990), "The Effects of Domestic Environmental Policies on Patterns of World Trade : En Empirical Test", *Kyklos*, Vol. 43 (2), pp. 191-209.

Trefler, D. (1993), "Trade Liberalization and the Theory of Endogenous Protection: An Econometric Study of U.S. Import Policy", *Journal of Political Economy*, Vol. 101 (1), pp. 138-160.

Trefler, D. (1995), "The Case of Missing Trade and Other Mysteries ", *American Economic Review*, Vol. 85, pp. 1029-1046.

Van Beers, C. and C. van den Berg (1997), "An empirical multi-country analysis of the impact of environmental regulations on foreign trade", *Kyklos*, Vol. 50, pp..

Verbeek, M. (2000), A Guide to Modern Econometrics, John Wiley, Chichester.

Appendix

Appendix A : Panel Econometrics

Introduction

Whenever data has both time-series and cross-sectional variation, it is qualified as panel data. In this case it is possible to look at changes on a "country"[13] level. Arellano (2000) points at two different motivations for panel data estimations. Firstly, panel data allows to control for unobserved time-invariant heterogeneity in cross-sectional models. Secondly, panels enable econometricians to study the dynamics of cross-sectional data sets. These two motivations can directly be related to the two strands in the literature, fixed effects and random effects. The two models are explained next.

Fixed Effects Model

This is a linear model where each country (i) may have his own intercept term (α_i). The model can be written as follows:

$$y_{it} = \alpha_i + x_{it}^{'}\beta + \varepsilon_{it} \qquad \varepsilon_{it} \sim IID(0, \sigma_{\varepsilon}^{2})$$

where i=1, ..., N (country i)

t=1, …,T (time period t)

This model is also obtained by using an OLS regression with a dummy variable for each country. Hence, the estimator for the slope coefficients are known as the least squares dummy variable (LSDV) estimator. One gets also the same results when using a regression in deviations from country-means. This model eliminates thus country effects and can be written in the following way:

[13] Cross-sectional units can be thought of as individuals, households, firms, industries or countries to list just some of the possibilities. According to the empirical part of this work, countries will be referred to.

$$y_{it} - \bar{y}_i = (x_{it} - \bar{x}_i)' \beta + (\varepsilon_{it} - \bar{\varepsilon}_i)$$

where bars indicate non weighted means of the variables.

The latter transformation is the so called within or fixed effect transformation. The corresponding estimator is the following:

$$\hat{\beta}_{FE} = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)' \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i)$$

If all the x_{it} are independent of all ε_{it}, the estimator is unbiased.

Basically, a model with fixed effects gives attention to differences "within" countries. However the initial specification on β implies that a change in the explanatory variables should have the same effect whether this variation changes from one period to the other or from one country to the other. From that the interest of an alternative approach, the random effects model, which relies also on cross-country variation.

Random Effects Model

One possible interpretation of the error term in a regression is that it represents all variables that do presumably affect the dependent variable but are not explicitly introduced as explanatory variables. In this sense, the country specific term (α_i) is a random factor independently and identically distributed over countries. Hence, the so called random effects model can be written as:

$$y_{it} = \mu + x_{it}' \beta + \alpha_i + \varepsilon_{it} \qquad \varepsilon_{it} \sim IID(0, \sigma_\varepsilon^2);\ \alpha_i \sim IID(0, \sigma_\alpha^2)$$

The error term $(\alpha_i + \varepsilon_{it})$ is made up of two components: a country specific component that does not vary over time and a country and time specific component that is assumed to be uncorrelated over time. Moreover, the two components are assumed to be mutually independent and independent of x_{js} (for all j and s). If the assumptions are confirmed, the intercept and slope estimates are unbiased and consistent. However, the structure of the error term implies autocorrelation which leads to incorrect OLS standard errors (except if $\sigma_\alpha^2 = 0$).

The GLS estimator is more efficient because it uses the particular structure of the error covariance matrix (see the lecture handout for the Variance-Covariance matrix).

The random effect estimator is in fact a weighted average of the fixed effect (within) estimator and the between estimator (defined below) where the weight depends on the relative variances of the two estimators. Therefore one can write:

$$\beta_{RE} = \Delta\hat{\beta}_B + (I_k - \Delta)\hat{\beta}_{FE}$$

where Δ is the weighting matrix that is proportional to the inverse of the covariance matrix of $\hat{\beta}_B$.

The between estimator is defined as follows:

$$\hat{\beta}_B = \left(\sum_{i=1}^{N}(\bar{x}_i - \bar{x})(\bar{x}_i - \bar{x})' \right)^{-1} \sum_{i=1}^{N}(\bar{x}_i - \bar{x})(\bar{y}_i - \bar{y})$$

The between estimator ignores any information within countries. In fact it is the OLS estimator in a model for individual means:

$$\bar{y}_i = \mu + \bar{x}_i'\beta + \alpha_i + \bar{\varepsilon}_i \qquad \text{for i= 1, …, N}$$

The GLS estimator can also be written as:

$$\hat{\beta}_{GLS} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\kappa_{it} + \varphi T\sum_{i=1}^{N}\lambda_i\right)^{-1} \bullet \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\varpi_{it} + \varphi T\sum_{i=1}^{N}\theta_i\right)$$

where $\kappa_{it} = (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)'$

$$\lambda_i = (\bar{x}_i - \bar{x})(\bar{x}_i - \bar{x})'$$

$$\varpi_{it} = (x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i)$$

$$\theta_i = (\bar{x}_i - \bar{x})(\bar{y}_i - \bar{y})$$

$$\varphi = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + T\sigma_\alpha^2}$$

The random effect or equivalently, the GLS estimator is more efficient than the OLS estimator. However, it is unbiased only if the explanatory variables are independent of all ε_{it} and all α_i.

For T (the number of time periods) going to infinity, the random and fixed effect estimator are equivalent. However, usually in panels T is rather small, while N (the number of countries) is rather large. Therefore, one is interested in which case fixed effects and in which case random effects should be used. A Hausman test can provide the answer.

Hausman Test for Fixed and Random Effects

In the panel data context the Hausman test compares the fixed and the random effect estimator. The former is consistent under both the null (that x_{it} and α_i are uncorrelated) and the alternative hypothesis, the latter is more efficient but only consistent under the null. If the two estimators are significantly different, this means that the null is not likely to be satisfied. The Hausman test statistic[14] is based on the variance-covariance matrices of the two estimators and has under the null an asymptotic Chi-squared distribution with K degrees of freedom. Whenever the null (the two estimators are not significantly different) must be rejected one has to use the fixed effects estimator to get consistent results. Whenever the null cannot be rejected one can use the random effects estimator to get efficient results.

[14] The formula can be found in the lecture notes of M. Brülhart.

Appendix B: Country List:

	Code	Country		Code (ct'd)	Country (ct'd)
1	ARG	Argentina	32	ITA	Italy
2	AUS	Australia	33	JOR	Jordan
3	AUT	Austria	34	JPN	Japan
4	BGD	Bangladesh	35	KEN	Kenya
5	BGR	Bulgaria	36	KOR	Korea, Republic of
6	BOL	Bolivia	37	KWT	Kuwait
7	CAN	Canada	38	LKA	Sri Lanka
8	CHL	Chile	39	MAC	Macau
9	CHN	China	40	MAR	Morocco
10	CMR	Cameroon	41	MEX	Mexico
11	COL	Colombia	42	MWI	malati
12	CRI	Costa Rica	43	MYS	Malaysia
13	CYP	Cyprus	44	NLD	Netherlands
14	DNK	Denmark	45	NOR	Norway
15	ECU	Ecuador	46	NZL	New Zealand
16	EGY	Egypt	47	PAK	Pakistan
17	ESP	Spain	48	PAN	Panama
18	ETH	Ethiopia	49	PER	Peru
19	FIN	Finland	50	PHL	Philippines
20	FRA	France	51	POL	Poland
21	GBR	United Kingdom	52	PRT	Portugal
22	GER	Germany	53	ROM	Romania
23	GRC	Greece	54	SGP	Singapore
24	GTM	Guatemala	55	SWE	Sweden
25	HKG	Honk Kong	56	THA	Thailand
26	HND	Honduras	57	TTO	Trinidad and Tobago
27	HUN	Hungary	58	TUR	Turkey
28	IDN	Indonesia	59	URY	Uruguay
29	IND	India	60	USA	United States
30	IRL	Ireland	61	VEN	Venezuela
31	IRN	Iran	62	ZAF	South Africa

Appendix C: Variable Definition

Variable Name	Description
netexp	net exports (exports-imports) of polluting products (isic categories 341, 351, 369, 371 and 372)
lead	average maximum lead content calculated using market shares of the different gasoline types as weights
recp	relative endowment of the capital stock
rel1	relative endowment of labour force
rehc	relative endowment of human capital
reln	relative endowment of total land area
real	relative endowment of arable land
reil	relative endowment of irrigated land
repl	relative endowment of permanent cropland

Appendix D: Descriptive Statistic of the Variables

Variables	Number of Observations	Mean	Stdandard Deviation	Minimum	Maximum
netexp	3785	-137081	1849278	-1.17e+07	1.84e+07
lead	3785	.3823354	.2762601	0	1.05
recp	3470	.9671016	2.274477	2.04e-07	13.7076
rel1	3470	3.400013	6.310898	.1565195	54.64182
rehc	3470	2.866743	4.38058	.2012101	31.61267
reln	3710	2.702127	5.714755	.0006407	42.38218
real	3645	2.424578	3.876085	.0002493	37.93413
reil	3515	2.513291	4.924824	.001538	37.56516
repl	3515	4.308754	5.829091	0	33.47644

Appendix E: Preparation of the Lead-Database

The imputation of market shares with missing values followed a two step procedure:

1. Surveys were published every year and contained information on the two most recent years. This information was used to complete the database as follows:

    (a) One year has complete data, one year has missing data: If the market share of all types of gasoline are missing, the same figures have been taken for both years. If however only some values are missing, it was assumed that the missing market shares had the same proportion of the non-missing total as in the non-missing year.

    (b) All values of both years are missing: all market shares are assumed to be identical.

2. Remaining non trivial patterns of missing values (e.i. some values are missing for both years): simple interpolation for a given gasoline type was done based on the whole time period. When no clear time pattern can be observed, the market share was assumed to be constant with respect to the closest year.

Finally, as data is characterized by a time overlap, only the least recent year from each survey has been kept, assuming they are more likely to be updated and thus more reliable.

Appendix F: Panel Statistic

Variables		Mean	Standard Deviation	Minimum	Maximum	Number of Observations
lead	overall	.3823354	.2762601	0	1.05	N = 3785
	between		.2192451	.0008663	.84	n = 62
	within		.1719442	-.1704995	.9866575	T-bar = 61.0484
recp	overall	.9498284	2.255159	2.04e-07	13.7076	N = 3540
	between		2.180139	2.77e-07	10.96848	n = 57
	within		.4745689	-3.344543	5.560019	T-bar = 62.1053
rel1	overall	3.727832	6.724835	.1565195	54.64182	N = 3540
	between		6.294225	.1789423	30.64262	n = 57
	within		2.490936	-10.995	27.72703	T-bar = 62.1053
rehc	overall	3.066917	4.596006	.2012101	31.61267	N = 3540
	between		4.369906	.2382284	17.96533	n = 57
	within		1.611156	-5.283444	16.71425	T-bar = 62.1053
reln	overall	2.764517	5.667744	.0006407	42.38218	N = 3805
	between		6.501227	.0011022	37.01238	n = 65
	within		.9430019	-3.687531	11.46999	T-bar = 58.5385
real	overall	2.603697	4.012287	.0002493	37.93413	N = 3740
	between		5.346093	.0007271	34.79903	n = 64
	within		.9683346	-3.951542	13.32048	T-bar = 58.4375
reil	overall	2.887009	5.563285	.001538	37.56516	N = 3610
	between		5.474963	.0024181	31.74753	n = 62
	within		1.067978	-5.203308	9.472484	T-bar = 58.2258
repl	overall	4.346591	5.92741	0	33.47644	N = 3610
	between		6.721187	.0024809	30.92823	n = 62
	within		1.693379	-5.109624	18.18694	T-bar = 58.2258
netexp	overall	-134164.2	1826588	-1.17e+07	1.84e+07	N = 3880
	between		793117.8	-2409670	2798806	n = 66
	within		1657978	-1.02e+07	1.55e+07	T-bar = 58.7879