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Have Countries with Lax Environmental Regulations a Comparative Advantage in Polluting Industries?

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RESOURCES FOR THE FUTURE

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Abstract

We aim to study whether lax environmental regulations induce comparative advantages, causing the least-regulated countries to specialize in polluting industries. The study is based on Trefler and Zhu's (2005) definition of the factor content of trade. For the econometrical analysis, we use a cross-section of 71 countries in 2000 to examine the net exports in the most polluting industries. We try to overcome three weaknesses in the empirical literature: the measurement of environmental endowments or environmental stringency, the possible endogeneity of the explanatory variables, and the influence of the industrial level of aggregation. As a result, we do find some evidence in favor of the pollution-haven effect. The exogeneity of the environmental endowments was rejected in several industries, and we also find that industrial aggregation matters.

Key Words: comparative advantage, environmental regulation, trade, pollution haven, Porter hypothesis

JEL Classification Numbers: F18, Q56

Contents

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1. Introduction

In the last two decades, environmental concern has emerged as a relevant issue in trade liberalization. The debate has been induced by the fear that countries use less stringent environmental policies to gain a comparative advantage in polluting industries.

We investigate to what extent differences in environmental policy among countries are a source of comparative advantage. The subjacent hypothesis asserts that lax environmental standards extend the availability of environmental inputs in the production process, reducing environmental control costs that increase net exports in pollution-intensive sectors—the so-called "pollution-haven effect" described by Copeland and Taylor (2004). Although some theoretical research supports this proposition (see Chilchilnisky 1994; Copeland and Taylor 1994; McGuire 1982; Siebert 1977; Pethig 1976), empirical studies have not found robust results corroborating the hypothesis.[1]

The Heckscher-Ohlin-Samuelson (HOS) theorem is a natural framework to analyze this issue. Scholars use Vanek's factor-content prediction (HOV) to study input services—say capital, labor, land, or natural resources—included in net exports in a country. In a branch of this literature, Tobey (1990) accommodated the comprehensive empirical study published by Leamer (1984) to analyze whether differences in the stringency of environmental regulations influence the comparative advantages in pollution-intensive industries. These industries were assembled into five groups: paper and pulp products, mining, primary iron and steel, primary nonferrous metals, and chemicals. His research was based on a cross-section analysis of net exports in

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[1] The literature has been reviewed by Jaffe et al. 1995; Rauscher 1997; and recently by Copeland and Taylor 2004.

highly polluting industries, with country measures of factor endowments and a qualitative measure of environmental stringency as the explanatory variables. He did not find evidence that environmental regulation determines the net exports of all industries. This study, however, was constrained by the low number of degrees of freedom (Copeland and Taylor 2004). In response, most contemporaneous studies increased the number of observations in the estimations.[2] The endogeneity of the variable measuring strictness of environmental regulations has also been a concern in the literature, as countries could reduce the stringency of environmental policy when their net exports are being threatened by international competition.[3] As recognized by Cole and Elliott (2003), however, it is improbable that this problem could be serious in Tobey's set up because net exports in a specific industry are not likely to influence the environmental regulation at a country level. Even so, Cole and Elliott (2003) estimated the net exports in a polluting industry and the stringency of the environmental regulation using simultaneous equation. Evidence of pollution-haven effect has not been found in any of these extensions of Tobey either.

In this paper, we follow Tobey's approach, but we aim to overcome what we believe are three weaknesses in his empirical study and those that followed: the measure of environmental stringency, endogeneity due to dissimilarity in the consumption patterns across countries, and the level of aggregation of the industries considered in the analysis.

The first of these issues, measuring the stringency of environmental regulations, is a task faced with many difficulties. Van Beers and Van den Bergh (1997) distinguish two main categories of indicators: input and output oriented. Input-oriented indicators relate to a country's efforts in environmental protection—for example, legislation, expenditures on environmental research, and pollution abatement and control, among others. Output-oriented indicators set out to capture the effect of environmental regulations. According to our knowledge, the empirical research based in the HOV model, for the most part, has been grounded on input-oriented indicators.[4] However, the level of environmental control cost does not only depend on the

[2] For instance, Murrell and Ryterman (1991) include East European economies, and Cole and Elliott (2003) use a more updated dataset that includes 60 countries for 1995.

[3] Governments could use the environmental policy as a second-best trade policy when they face limitations on pursuing trade goals using trade policy (see e.g. Trefler 1993 and Ederington and Minier 2003).

[4] This was the approach adopted in the United Nations Conference on Trade and Development study (Walter and Ugelow 1979) used in the empirical analysis of Tobey (1990) and Murrell and Ryterman (1991). The index developed by Dasgupta et al. (2001), used in the empirical work of Cole and Elliott (2003), is also based almost exclusively on input-oriented indicators.

stringency of regulations "on paper," but also on the form and enforcement of the regulations, the nature of the environmental problem, gains in efficiency (e.g. Porter and van de Linde 1995), and offsetting subsidies supporting pollution-intensive industries (see Baumol and Oates 1988; Eliste and Fredriksson 2002), among other factors. As a result, Jaffe et al. (1995, p. 144) claim that the scarce evidence of pollution haven "…could be due to no more than the failure of the ordinal measure of environmental stringency to be correlated with true environmental control costs." We believe that output-oriented indicators might be a better measure than input-oriented indexes because they take account of not only the stringency but also the enforcement of environmental regulations and of any subsidy or domestic policy offsetting some of the effect of stricter regulations. For these reasons, in our setup, the level of emissions is incorporated directly as a measure of the environmental endowment in the empirical analysis. In our framework, we expect that a more stringent environmental policy will reduce environmental endowments available for use in production and emissions. The lesser availability of environmental services will increase the use of primary factors to control pollution, which will increase the unitary production cost in intensive-polluting sectors, reducing the production and net exports of goods that use environmental services intensively.

The second weakness is related to the research on the factor content of trade (Vanek 1968), which is based on the claim that international trade is an indirect way of exchanging abundant factors. Thus, the factor content of the goods exchanged in the international trade is the difference between the factor content of goods produced and consumed in the country. In this context, Trefler and Zhu (2005) formulated a more general definition of the factor content of trade that allows trade in intermediate input and variation in the technology across countries. The authors showed that this definition is not consistent with Vanek's factor content prediction. In our paper, we use this result to show that even when it is assumed that technology is the same across countries, the less restrictive definition of the factor content of trade includes a dissimilarity consumption term that researchers have not been controlling for. We think that the consumption condition could be positively correlated with the environmental endowment, which could make the parameters estimated using Ordinary Least Square (OLS) downward biased, increasing the possibility of finding no evidence of a pollution haven—or the opposite result. To the best of our knowledge, this source of endogeneity has not been discussed in the literature yet.[5] We introduce Instrumental Variables (IV) estimation to overcome this problem.

The third weakness could be the level of aggregation of the industries considered in the empirical analysis. The empirical literature examines trade in aggregated commodity groups covering the industries with the highest environmental control costs. As these groups include a wide array of industries that might have highly different pollution intensities and levels of environmental control costs, the effect of environmental policy on trade might not be detected because control costs could be canceled out when these heterogeneous units are pooled into the same group. Also the level of aggregation may mask shifts in the division of labor between polluting and non-polluting activities within an industry sector. In the paper, we estimate the empirical specification at a more disaggregated level to analyze the effect that industrial aggregation has in our setup.

Our empirical analysis is based on a cross-section of 71 developed and developing countries in the year 2000.[6] Previously published studies used cross-sections of countries for the years 1995 or 1975 (Cole and Elliott 2003; Murrell and Ryterman 1991; Tobey 1990). The fact that we use more up-to-date data is an important advantage in our study, because in the latest years of the past century, considerable progress have been made in tariff reduction and trade agreements that have reduced barriers to trade around the world. According to the World Trade Organization (WTO) (http://www.wto.org), developed countries have cut their tariff on industrial products by 40 percent between 1995 and 2000. The value of the imported industrial products rose from 20 to 44 percent, and the proportion of imports facing tariff rates larger than 15 percent fell from 7 to 5 percent. This new scenario enhances the importance of trade and comparative advantage as a determinant of the pattern of production and specialization across countries. One way to illustrate this point is by observing a measure of the world's openness to trade: the sum of exports and imports as a percentage of gross domestic product (GDP). In 1975, trade openness was 33 percent of the world's GDP, but in the following 20 years, it increased to 42 percent and in the in the following 5 years, between 1995 and 2000, to 49 percent (World Bank, 2006). We believe that this dramatic increase in world trade should increase the probability of finding evidence of

[5] Although another source of endogeneity could come from the fact of using emissions as explanatory variables, we believe that this problem is not serious because we are considering national emissions as explanatory variable but net export in a particular industry.

[6] Appendix A lists the countries.

pollution havens, especially if polluting industries have been more affected by barriers to trade in the past.

The econometric analysis was conducted in the most polluting industries. These industries have been analyzed in other studies, but here they are examined at a more disaggregated (3-digit) level. The industries were classified according to the Standard International Trade Classification (SITC) revision 3. A description of the industries considered in the estimations is given in Table 1. We estimated a model in which the net exports in the industry were regressed on the endowments of inputs, including two environmental variables based on emissions of sulfur dioxide (SO_2) and emissions of organic matter in wastewater, measured as biological oxygen demand (BOD).

Preliminary analysis of this data at the aggregate level, using OLS, only finds evidence of the pollution-haven effect in the non-metallic minerals sector. Some of the other subsectors even exhibited evidence in the opposite direction. Such positive effects of environmental regulation are known in the literature as the Porter hypothesis, interpreted as the result of technological innovation triggered by regulation (Porter and van de Linde 1995). In this case, the stricter environmental policy increases profitability and net exports for the industries concerned. Several economists find the Porter hypothesis flouts logic since it is not clear why companies fail to undertake profitable improvements before being forced by the regulator (e.g. Palmer et al. 1995). We feel that it is more appropriate to look carefully at the data by disaggregating it and by introducing IV to correct for endogeneity. As we will see, this modifies the results.

In the following section we present the conceptual framework. We link the Trefler and Zhu (2005) paper to the literature on the pollution-haven effect. In the third section, we discuss our empirical strategy. In the last two sections, we present an analysis of the results and conclusions.

2. Conceptual Framework

Trefler and Zhu (2005) showed that if we include intermediate trade inputs and allow technologies to vary across countries, factor services exchanged through international trade will contain differences in endowment and consumption patterns across countries. Equation 1 summarizes this relationship. F_i^{T-Z} is the Kx1 vector of net factor services exported by country i. V_i denotes the Kx1 vector of factor endowments, and C_{ij} is the Gx1 vector of country i

consumption of goods produced in country *j*. Subscript *w* symbolizes the variable aggregated at the world level. ϕ_i is the country *i*'s share on world consumption. The *K*x*G* factor intensity matrix is denoted as A_j. It describes the production technology for a country *j*.[7]

$$F_i^{T-Z} = (V_i - \phi_i V_w) - \sum_{j=1}^{N} A_j (C_{ij} - \phi_i C_{wj}) \quad (1)$$

In general, studies have directly considered emissions of pollutants as one of the factors in the production process. The basis for introducing the environment as an input in the production process comes from a seminal paper written by Ayres and Kneese (1969). The pollution and its control are interpreted as a material balance problem in a closed economy. They added intermediate inputs to the Walras-Cassel general equilibrium model and obtained a specification where the production of residuals or emissions is part of the production and consumption process. Later on, Rauscher (1997) and Copeland and Taylor (2003) elaborated a model in which emissions are inputs in the net production function of the firm. In this model, the firm jointly produces goods and emissions and must assign a proportion of its input to abatement of emissions. Copeland and Taylor (2003) assumed that abatement activities and production activities use inputs in the same proportion and that a convenient relationship exists between abatement activity and emissions.[8] Instead Rauscher (1997) used the material-balance relationships to get a linear relationship between emissions and production.

We use Trefler and Zhu's (2005) definition of the factor content of trade to provide an example of how to interpret the environment endowment in this setting (see equation 2). Let E^z symbolize the environmental services included in country *i*'s net exports and E the endowments of this factor. *e'* denotes the transpose of a *K*x1 vector that contains only zeros, but the *e*th element, the environment, is equal to 1. $\alpha_e^{'}$ denotes the transpose of a *G*x1 vector, which indicates the *environment*-requirements per unit of product *g*.

$$E^z = e^{'} F_i^{T-Z} = (E_i - \phi_i E_w) - \sum_{j=1}^{N} \alpha_{e\,j}^{'} (C_{ij} - \phi_i C_{wj}) \quad (2)$$

[7] The *k*-input requirement per unit of product *g*, denoted α_{kg}, is a generic element of A_j. It includes the direct and indirect factor requirements to produce *g* in country *j*. The direct factor requirements are the primary factors used in the production of *g*, and the indirect factor requirements are the primary factors used in the production of intermediate inputs employed in the elaboration of *g*.

[8] Dean et al. (2005) extend this model to include agglomeration economies.

Then, according to equation 2, a country will be a net exporter of environmental services if and only if $E^z > 0$. This condition requires not only that the country's share in the world environmental endowment must be larger than its share in the world expenditure of income $\left(E_i / E_w > \phi_i\right)$, but it also requires a measure of consumption similarity, the second term in the right hand side of equation 2. Therefore, in this less constrained and more realistic framework, the abundance of environmental endowments does not determine by itself the comparative advantage of a country. The consumption by country *i* of goods produced in foreign countries also plays an important role in the factor content of trade.

Econometric Specification

In this section we show that the empirical specification used in the reviewed studies is consistent with the HOV framework, although in a less restricted set up, it could contain a similarity consumption condition that studies have not been controlling for.

Starting from equation 1, it is possible to get the equation that has been estimated in the literature adding two standard assumptions in HOV model: similar production technology across countries and identical homothetic preferences everywhere. Let us start with the first of these assumptions and assume that countries have similar factor intensity matrices, such that $A_j = \widetilde{A} \;\; \forall j$, to get equation 3. In this equation, T_{ij} is the *G*x1 vector of net exports from country *i* to country *j*.

$$F_i^{T-Z} = \widetilde{A}\sum_{j=1}^{N} T_{ij} = \widetilde{A}T_i^c = \left(V_i - \phi_i\, V_w\right) - \widetilde{A}\left(\sum_{j=1}^{N} C_{ij} - \phi_i \sum_{j=1}^{N} C_{wj}\right) \qquad (3)$$

In addition, if we assume that the number of goods is equal to the number of factors (*G*=*K*) and $\left|\widetilde{A}\right| \neq 0$, then the factor intensity matrix, $\widetilde{A}$, could be inverted. Afterward, the net export of a country can be expressed in terms of excess endowment supplies and deviation from the average in the patterns of country *i*'s consumption such as in equation 4.

$$T_i^c = \widetilde{A}^{-1}\left(V_i - \phi_i\, V_w\right) - \left(C_i - \phi_i C_w\right) \qquad (4)$$

Hence, we obtain the net export of good *g* from country *i*, as in the equation 5, premultiplying T_i^c by the transpose of a Gx1 vector, denoted *t*, that contains only zeros, but the *g*th element is equal to 1.

$$T_{ig} = t^{'}T_i^c = \sum_{k=1}^{K} \beta_{gk}\left(V_{ik} - \phi_i\, V_{wk}\right) - \left(C_{ig} - \phi_i C_{wg}\right) \qquad (5)$$

The elements in the inverted matrix, denoted β_{gk}, are called Rybczynski coefficients. They could be interpreted as the derivative of the product *g* with respect to the factor *k* (see Leamer 1984). According to this equation, net exports of good *g* are a linear function of the excess supply factors plus a factor of adjustment *q* (where $q = C_{ig} / C_{wg} - \phi_i$). *q* represents the deviation of the country *i*'s share in the world consumption of good *g* from the country *i*'s share of the world consumption.

Finally, after some algebraic operations (see Appendix B), equation 5 could be expressed as a linear function of factor endowments as well. The coefficient γ_{gk} can be interpreted as the effect that an increment in the endowment of the input *k* will have on the exports of good *g*, *ceteris paribus*.

$$T_{ig} = \sum_{k=1}^{K} \gamma_{gk} V_{ik} - \left(C_{ig} - \phi_i C_{wg} \right) \qquad (6)$$

As a result, the empirical work can be based on two alternative specifications: Net exports of the good *g*, adjusted by *q*, are a linear function of the excess supply factors on equation 5 or are linearly related to the factor endowments in equation 6. As Leamer (1984) highlights in his book, it is possible that one or more factors might not be observed, or they are being measured imperfectly having errors with finite variance. In this case, empirical estimation based on excess factor endowments can yield biased and inconsistent estimators because the stochastic component of the empirical model could be correlated with the explanatory variables. This is because the remuneration to the inputs is integrated in the consumption share of the country in the world output (see equation 5a in Appendix B), and unobserved inputs might be correlated with the explanatory variables through its effect in this variable. As a result, the empirical equation based in factor endowments (equation 6) should be preferred over equation 5.

If a stochastic component is added to equation 6, apart from the variable included into our endowment of factors that captures the influence of the environmental regulation, this expression will look very similar to the empirical specification that has been estimated in the literature—except for the term capturing differences in patterns of consumption, *q*. This factor has not appeared in previous studies because the assumption of identical homothetic preferences in HOV models is a sufficient condition to make $C_{ig} / C_{wg} = \phi_i$.

But what happens if countries do not fulfill this consumption symmetry condition, and we do not control for *q*? The estimated parameters could be inconsistent if *q* is correlated with some of the explanatory variables. In our problem, we suspect that *q* could be correlated with environmental endowment because we are considering the most polluting industries. In this case, a consumption of final goods in the good *g* higher than the share in the world consumption could generate a higher level of pollution. Then, if environmental endowments and *q* are positively correlated using OLS, we could underestimate the true value of the parameters and the asymptotic bias could be negative. We believe that this shortcoming could increase the possibility of finding no evidence of a pollution haven or finding the opposite result when we use OLS. This will be a source of endogeneity we aim to control for in our paper. Nevertheless, the source of the endogeneity is different here, and, to the best of our knowledge, it has not been discussed in this literature yet.

Industrial Aggregation

In past empirical studies, the most polluting-intensive industries have been assembled in five groups. We suspect that this aggregation has tended to dilute the evidence of pollution havens. To analyze the effect that industrial aggregation has in our setup, we define an industry as a collection of goods. Thus, the industry *I* will be a set that contains every good *g* that belongs to *I*. The equation 7 shows the basic equation 6 expressed at an arbitrary industrial level.

$$T_{iI} = \sum_{g\in I} T_{ig} = \sum_{k=1}^{K} \left(\sum_{g\in I} \gamma_{gk} \right) V_{ik} - \left(\sum_{g\in I} C_{ig} - \phi_i \sum_{g\in I} C_{wg} \right) \tag{7}$$

The coefficient γ_{Ik}, which can be interpreted as the effect that has an increment in the endowment of the input *k* on the exports of the industry *I,* will be the sum of the coefficients associated to each good that belongs to *I*.

For instance, let us assume that in the industry *I* there is one good, $g_1 \in I$, with a large $\gamma_{g_1 k}$ such that the impact of the input *k* in the export of the good g_1 is big. Simultaneously, let us assume that input *k* has a small impact in all the other goods that belongs to *I*, such that γ_{gk} is small $\forall g \in I / g \neq g_1$. In this context, it is not difficult to see that it is perfectly possible that the impact of the endowment *k* in the industrial exports could be small despite the big effect that it has in g_1. In this case, the evidence of pollution haven could remain hidden in the industrial aggregation.

Moreover, we suspect that industrial aggregation is also related to the endogeneity problem discussed in the previous section. Industrial aggregation could reduce the severity of the endogeneity problems when we do not control for dissimilarities in the consumption patterns. In effect, in equation 8, the similarity consumption condition *q* is a function of the consumption at an industrial level that corresponds to an aggregation of goods included in this industrial classification. Therefore, if the similarity consumption condition is not correlated between goods in the same industry, it could cancel out when the different goods are added in the same industry. In this case, it might be possible to expect that the endogeneity problems could be more severe at a more disaggregated industrial level.

3. Empirical Strategy

We estimated the parameters of equation 8, which is based on equation 6, for a subset of highly polluting industries. E_k stands for the variables measuring environment endowments, V_k denotes other endowment variables, and ε is the error term.

$$T_g = \alpha + \sum_{k=1}^{p} \gamma_{gk} V_k + \sum_{k=p+1}^{q} \delta_{gk} E_k + \varepsilon \tag{8}$$

The main hypothesis is that the parameters associated to environmental comparative advantages can be estimated as positive at a reasonable level of statistical significance. We conduct three independent estimations of equation 8. These estimations are based in our view on the weaknesses of previous studies. First, we estimate the empirical specification that has been estimated by previous studies. It will constitute our benchmark. We assume that the error term is iid, normally distributed, with finite and constant variance; therefore, we use OLS on a cross-section of countries to estimate the parameters of the model. Here, we assume that countries fulfill the consumption similarity condition ($q = 0$), or, if they do not, this condition is not correlated with the regressors. In a second stage, we assume that $q \neq 0$ and q is positively correlated with environmental endowments such that the parameters estimated using OLS are inconsistent. We assume that we do not have a variable to control for dissimilarities in the consumption condition. Then we will use IV estimation to get consistent estimations of the parameters in the HOV equations. The estimations in the first two stages will be conducted at an industrial level. In third stage, we follow the previous procedures to estimate the empirical equation at a more disaggregated level.

Environmental Variables

What kinds of indicators are suitable for estimating stringency of environmental regulations? Following van Beers and van den Bergh (1997) we argue that output-oriented indicators, aimed at capturing the effect of environmental regulations, are most suitable for the task at hand. Restricting the discussion to pollutants, a suitable indicator in this setting should at least fulfill the following base criteria: (i) be emitted as a result of production; (ii) be subject to regulation due to its direct effects on humans or the environment; (iii) have well-known abatement technologies available for implementation; and (iv) for econometric purposes have data available for a wide set of developed and developing economies. Two pollutants that satisfy these criteria are atmospheric SO_2 and BOD.

SO_2 is a pollutant responsible for the acidification of soil and water, and it has direct noxious effects on humans, being an important component in urban smog. The main source of SO_2 emissions is combustion of coal and oil, accounting for about 85 percent of global anthropogenic emissions (UNDP 2000, page 64). It is possible to reduce SO_2 emissions by shifting to fuels with lower sulfur content or by using techniques such as desulfurizing of the fuel, fluidized bed combustion, sorbent injection in the combustion process or flue gas scrubbing. Efficient pre- and post- combustion desulfurization technologies are available, but they are costly; in addition, shifting to fuels with lower sulfur content generally increases costs.

As a result, a country's emissions of SO_2 mainly depend on three variables: The amount of coal and oil consumed, the sulfur content of those fuels, and the use of abatement technologies. While the latter two can be argued to reflect active choices, i.e. policies aimed at reducing emissions of SO_2, the former to a larger extent merely reflects country specific factors, e.g. availability of fossil gas or hydropower resources or the choice to base electricity supply on nuclear power, factors that say little about a country's ambition when it comes to SO_2 regulation.

Following this, this study aims to do this by adopting an indicator defined as a country's SO_2 emissions from fossil fuel use, divided by the share of coal and oil in the country's total energy use. This indicator will be accurate in countries that have adopted measures to reduce SO_2 emissions and where the use of low sulfur fuels reflects an active choice. Only in countries that have taken no action to mitigate sulfur emissions and where low sulfur-content fuels are used "unintentionally", or where the a shift from e.g. coal to fossil gas or nuclear power has been driven by environmental considerations, will the SO_2 measure be misinterpreted as stemming from tough regulations. If a country that has adopted no sulfur-control regulations uses high sulfur-content fuels, a high value of SO_2 quite rightly results. Consequently, it seems as if the proposed measure, SO_2, could adequately gauge the stringency of the environmental policy in a country.

Organic matter and chemicals, emitted through wastewater, are by-products of various industrial activities and are a major source of surface water pollution. The released organic material is consumed by naturally occurring bacteria, using up the oxygen dissolved in the water. With high enough releases of organic matter, the oxygen levels in the waters may drop to levels so low that fish and other aquatic organisms perish. This process also leads to the release of ammonium, which, when converted to ammonia, is poisonous to fish. A low oxygen level is often considered the single most important factor when determining the extent of pollution in a water body (Nemerow and Dasgupta 1991, page 4). The rate at which the oxygen is consumed can be measured in various ways; one common method is BOD, which quantifies the amount of organic nutrients in the wastewater. The emissions of organic matter can quite easily be reduced through end-of-pipe treatment of the wastewater. Primary and secondary treatment removes more than 90 percent of original BOD in the wastewater. The technologies for this type of treatment are well developed and readily available, although at noticeable costs. Emissions of organic water pollutants, measured as BOD, then, also seem to meet the requirements of an output-oriented indicator as argued for earlier.

Other Endowment Variables Considered in the Estimation

This study adopts a model with endowments in capital, K, labor, land, and natural resource endowments. We have tried to follow the endowments considered in the basic studies first conducted by Leamer (1984). Labor endowment is split up into three groups based on level of education: illiterate workers, literate workers with secondary education, and professional and technical workers. Information about land is divided into tropical and non-tropical forest areas, and cropland. The natural resource endowments consider production of minerals (copper, iron, lead, and zinc) and solid fuels (coal and liquid and gaseous fuels—i.e. crude oil and natural gas).

A more detailed description of the series and the sources of information are in Table 2. Table 3, on the other hand, contains a summary of the statistics linked to the data set.

4. Results

First, we estimated the parameters of equation 8 using OLS. These results will be compared with estimations that cope with two possible weaknesses in this approach. The first one is the possibility of disturbances correlated with the environmental endowments. In this case, OLS estimations could be inconsistent due to the endogeneity of the explanatory variables. We test the endogeneity of the environmental explanatory variables, introducing IV estimation to deal with this problem. The second weakness addresses the issue of the sensibility of the results to the aggregation level considered in the analysis.

Benchmark Results

We estimated the parameters of equation 8 in each industry using OLS. Table 4 displays the results of these estimations. Because the hypothesis of homocedasticity was rejected in some industries, we used White standard errors to estimate heterocedasticity-robust t statistics.[9]

In our framework, two alternative assumptions are consistent with this method of estimation. On one hand, we could assume that countries fulfill the consumption similarity condition ($q = 0$) such that the net export of a country are determined by the abundance of their endowment factors. Although the assumptions seem restrictive, Trefler and Zhu 2005 showed that there are many models consistent with this condition—e.g. models with taste for variety or ideal variety; North-South models with differences in technology; and models consistent with production specialization as Heckscher-Ohlin, scale returns, and failures of factor price equalization. On the other hand, we could assume that $q \neq 0$, but q is not correlated with the regressors such that it is included in the error term and likely also in the constant if its expected value is different from zero.

Several explanatory variables are highly correlated, and different methods of diagnosis suggested that multicollinearity could be severe in our estimations (e.g. the mean variance inflation factor was 48 and the condition number 68). Part of this problem could be due to the fact that we have redundant variables characterizing the skills of labor force. One of these variables is the number of literate non-professional workers. This variable was not statistically different to zero in any of our regressions. Moreover, when we drop this variable, we do not observe any change in the signs or the level of significance of the main variables, and the severity of the multicollinearity was considerably reduced (the mean variance inflation is 13 and the condition number 26). Therefore, the reported results do not include this variable. Although multicollinearity could still be worrisome, we do not detect serious statistical problems. The sign of the parameters looks reasonable, and the sign and the significance of the parameters associated to the environmental endowment are robust to changes in the data and in the specification of the regression model. For instance, most of the industries considered in the analysis are based in natural resources, and we should expect that these factors could be a source

[9] The White standard errors were multiplied by $n/(n-k)$. This degrees-of-freedom adjustment, suggested by Davidson and MacKinnon (1993), improves the White estimator for OLS in small samples. Furthermore, this modus operandi guarantees to get the usual OLS standard errors if the variances of the disturbances were constant across observations.

of comparative advantage. This is exactly what we observe in these sectors. The production of iron has a direct influence in the net export of the iron and steel industry. The production of copper and zinc determines a comparative advantage in the nonferrous metals.[10] Finally, the exports in the pulp and paper industry are considerably influenced by the availability of forest (tropical or not tropical) and, of course, negatively influenced by the area occupied by cropland.

The direct influence of capital in net exports of industrial chemical products is another reference point to evaluate our results. Cole et al. (2005) found that chemical and allied products make up one of the industrial sectors with the highest physical capital intensity in United States. As a result, if chemical production is also capital intensive in other countries, as we observed, capital endowments could provide a comparative advantage in this industry. They also pointed out that the pulp and paper industry has the highest human capital intensity in the United States. Consistently, we should expect that a high endowment of skilled workers generate a comparative advantage in this sector. However, in our results, we observe the opposite: The abundance of illiterate workers is the source of comparative advantage. This is perhaps due to the fact that the industry employs different labor intensities in different stages of development. Its primary stages are non-qualified labor intensive, but the following stages of development incorporate labor-saving technology and more qualified workers.

In general, we observed a rather high coefficient of determination in our results despite the fact that we used a cross-section sample. The independent variables explain a high percentage of the variation in the net exports. The exception is the chemical industry, where we can explain only half of the variation in net exports. An analysis of these results by sector shows that industries differ considerably in their sources of comparative advantage. In most cases, net exports are directly influenced by the abundance of unskilled workers and, in others, by the abundance of capital. Summing up, our estimation results look quite reasonable; as a result, they could be a good starting point for analyzing the influence that environmental endowments have in the exports of the most polluting sectors.

Table 4 shows that only in non-metallic minerals did we find evidence of a pollution haven. In this case, the statistically significant positive coefficient associated to BOD suggests that a higher level of organic water pollutant emissions, which is attributable to a lax

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[10] Lead has a counterintuitive sign. However, this is only because different subsectors coexist in nonferrous metals. In a more disaggregate analysis, lead net exports are directly influenced by lead production, although the coefficient is not statistically different to zero.

environmental regulation in our study, will increase the exports in this industry. In the other cases, the parameters show that the availability of the environmental amenities does not influence the export in a country—or that the effect goes in the opposite direction. In effect, emissions of SO_2 in the nonferrous metals, chemical, and pulp and paper industries (as well BOD in the chemical industry) negatively affect industrial exports. This evidence of the Porter hypothesis suggests a more strict environmental policy that reduces SO_2 will increase the net exports in these industries.

Endogeneity and IV Estimation

We aim to control the possible endogeneity of the environmental endowments. Nevertheless, here the source is different from the literature and, to the best of our knowledge, it has not been discussed yet.[11] We consider the possibility that previous studies have tested an incorrect HOV equation. If countries do not fulfill the consumption symmetry condition, and we do not control for q, then the estimated parameters could be inconsistent if q is correlated with some of the explanatory variables. In our problem, we suspect that q could be correlated with environmental endowment because we are considering the most polluting industries. In this case, a consumption of good g higher than the share in the world consumption could generate a higher level of pollution. Then, if environmental endowments and q are positively correlated using OLS, we underestimate the true value of the parameters, and the asymptotic bias could be negative. We believe that this shortcoming increases the possibility of finding no evidence of a pollution haven or the opposite result when we use OLS. Our crucial hypothesis at this point is to assume parameters estimated using OLS are inconsistent. In response, we will use IV estimation to get consistent estimations of the parameters in the HOV equations.

Our candidate instruments are the number of fish species (fishno), the number of fish species threatened (fishthrea), total road network (road), and the number of vehicles per thousands people (vehicles).[12] In a first step, we evaluated the relevance of the instruments using the first-stage regressions reported in Table 5, and their tests associated. The Shea partial R^2 could suggest, however, that the instruments have the adequate relevance to explain all the

[11] We believe it is highly improbable that flow trade could be influencing the environmental regulation and the availability of environmental inputs, due to the level of disaggregation of the industries considered in the analysis.

[12] The instruments were highly correlated with environmental endowment. In some cases, they could reflect the effect that high levels of pollution can have on biodiversity and in the other the influence that mobile sources of pollution have on our environmental endowments. We tried another instruments as well, but they were irrelevant.

endogenous regressors, and the Anderson canonical correlation likelihood-ratio test indicates that we reject the hypothesis that the model is underidentified.[13] The comparison of the Cragg-Donald statistic with the critical value reported in Stock and Yogo (2004, Table 2) does not allow us to reject the null of weak instruments. As a consequence, weak instruments could result in size distortion of at least 20 percent (*ibid.*).

Therefore, to overcome the weakness of our instruments, we use a Limited Information Maximum Likelihood estimator (LIML) instead of Two Stages Least Squares (2SLS), because LIML has shown to be less affected due to weak instruments. In our analysis, the maximal size distortion is below 10 percent when we use LIML (Stock and Yogo 2004, Table 2).[14]

The lack of consistency in OLS estimations when we suspect that some of the repressors are endogenous has to be balanced with the loss of efficiency when we use IV. A common practice is to check the endogeneity of the regressors. We tested the hypothesis that BOD and SO_2 are exogenous, making use of different versions of Durbin-Wu-Hausman's test of endogeneity. The outcomes were robust to the choice of the statistic.[15] The results of one of these tests are in the penultimate row of the Table 6. In chemical and pulp and paper industries, and in non-metallic mineral production, it was not possible to reject the exogeneity of the environmental explanatory variables.

Furthermore, in choosing the estimator, we must consider whether the assumption of homoskedasticity is valid or not, because the Generalized Method of Moment (GMM) provides a more efficient estimation in the presence of heteroskedasticity of unknown form. If the variance is not constant, IV estimators will be consistent, but less efficient, and OLS will be less efficient than GMM. Therefore, if we reject the hypothesis of homoskedasticity and the regressors are endogenous, we will make use of the orthogonality conditions to estimate the GMM generalization of the LIML estimator to allow for heteroskedasticity. It is called "continuously-updated GMM" estimator (HLIML-GMM). On the other hand, if the regressors are exogenous and heteroskedasticity is present, we estimate a Heteroskedastic OLS estimator (HOLS). It uses the additional moments available to generate the OLS residuals that will constitute the first-step

[13] The rule of thumb in this literature indicates that the instruments are weak to explain all the endogenous variables if the value of the partial R^2 is large, but the Shea partial R^2 is small.

[14] This distortion is lower than the maximal size distortion implicit in many studies when they use the rule of thumb that a first-stage F-statistic of excluded instruments larger than 10 suggests strong instruments.

[15] If we could not reject the assumption of conditional homoskedasticity, a special form of the test was calculated.

in the feasible two-step GMM. Appendix C contains the scheme that we follow to estimate IV with weak instruments.

Table 6 displays the results of our estimations when we consider the possibility of endogenous regressors and apply more efficient methods of estimation when disturbances are not homoskedastic. Only in the iron and steel and nonferrous metals sectors did we reject the hypothesis of exogeneity of the environmental variables. However, in the chemical industry and pulp and paper sector, we employed the HOLS estimator, because when we estimated the HOV equation using OLS we rejected the assumption of homoskedasticity (see Table 4). Overidentification tests suggest that the instruments were valid. They are exogenous—i.e., uncorrelated with the error term.

The results show that as we expected, there is a downward bias in the estimation of the parameters when regressors are endogenous and we employ OLS. We can see this if we compare the parameters associated to the environmental variables in the iron and nonferrous industries in Tables 4 and 6. In almost all the cases, the value of the parameters was larger if we use instrumental variables to control for the endogeneity of the regressors.

Employing these more efficient and consistent methods of estimation we found additional evidence of a pollution haven in the iron and steel sector. Therefore, the net export in the iron and steel industry and in the non-metallic minerals production are directly influenced by lax environmental regulations, while the evidence supporting the Porter hypothesis is now only found in the chemical industry.

Disaggregated Analysis

In this section, we analyze the influence that the industrial level of aggregation has on our results. We follow the same procedure as in the previous section to estimate the HOV equation at a more disaggregated level employing methods that are consistent when regressors are endogenous and more efficient in the presence of heteroskedasticity. The results of the estimations are displayed in Table 7a for the iron and steel industry, Table 7b for nonferrous metals, Table 7c for the chemical industry and pulp and paper sector, and Table 7d for non-metallic minerals manufacturers. Appendix D summarizes the effect of environmental endowments on the net exports in all the industries.

We detected a more extended presence of the endogenous regressors in the analysis. Moreover, we found more evidence of a pollution haven, even in sectors that do not show evidence of pollution haven at an aggregate level. Most of this evidence comes from the variable measuring water pollution, which suggests that more stringent water pollution regulations that are effective in reducing water contamination will reduce the net exports in the industries where the BOD estimated coefficient is positive and statistically different from zero. Only in three disaggregated industries: semi-finished products of iron and steel (672), glassware (665), and pottery (666), did we find evidence that lax air pollution regulations will increase the export in this industries.

Evidence of the Porter hypothesis comes mostly from air pollution regulations. In general, the level of significance and robustness is lower than in sectors with evidence of a pollution haven.

5. Conclusions and Discussion

The main goal of this study was to capture the effect that differences in environmental policy have on trade. Consistent with previous literature, we use cross-section country data on net exports in the most polluting industries and control for the endowments of the country to investigate the hypothesis that lax environmental regulations constitute a source of comparative advantage, causing the least-regulated countries to specialize in polluting industries. The most distinctive aspect of our paper is the link to the literature on factor endowment content, which analyzes missing trade when scholars try to explain global trade using the HOV model, emissions to capture the intensity of the regulation, and estimations made at a more disaggregated industrial level than in our study. We suggest that previous papers have not been controlling for differences in consumption patterns across countries. This fact could make regressors endogenous in our setup. We estimate the parameters using instrumental variables to deal with this trait. Our results indicate that in most cases, the environmental endowments are endogenous and the level of industrial aggregation matters for evidence of a pollution haven.

The preliminary results, from OLS estimations and a more updated dataset than those used in previous studies, show that only in non-metallic mineral sector is there evidence of a pollution haven. In some of the other subsectors, we even found the opposite result. The introduction of IV allowed us to find evidence of a pollution haven in the iron and steel sector as well, while the evidence of an inverse relationship is kept only in the chemical industry.

Our results show that the industrial level of aggregation matters: Analysis at a more disaggregated industrial level showed more extended evidence of pollution haven than our more aggregated analysis. This evidence comes mostly from our measure of water pollution in most of the sectors. Evidence of the Porter hypothesis is mainly linked to the air pollution regulations.

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Appendix A. Countries Included in the Analysis

Algeria, Argentina, Australia, Austria, Belgium, Bolivia, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Denmark, Ecuador, Egypt, El Salvador, Ethiopia, Finland, France, Gabon, Germany, Ghana, Greece, Honduras, Hong Kong, Hungary, Iceland, India, Indonesia, Iran, Ireland, Italy, Japan, Jordan, Kenya, Republic of Korea, Luxembourg, Macau, Madagascar, Malaysia, Mauritius, Mexico, Morocco, Netherlands, New Zealand, Nicaragua, Nigeria, Norway, Pakistan, Panama, Paraguay, Peru, Philippines, Portugal, Senegal, Singapore, Slovak Republic, South Africa, Spain, Sweden, Switzerland, Syrian Arab Republic, Thailand, Tunisia, Uganda, United Kingdom, United States, Uruguay, Venezuela, and Zimbabwe.■

Appendix B. Derivation of Equation 6

Starting from equation 5, the participation of the country in the world income is illustrated explicitly in the equation 5a. ω_k is the remuneration to the input *k*.

$$T_{ig} = \sum_{k=1}^{K} \left(\beta_{gk} V_{ik} - \frac{\sum_{k=1}^{K} \omega_k V_{ik}}{\sum_{k=1}^{K} \omega_k V_{wk}} \beta_{gk} V_{wk} \right) - \left(C_{ig} - \phi_i C_{wg} \right) \tag{5a}$$

Now, we can define the world income, denoted Y_w, as the sum of the rents gained from all world factor endowments and to get the equation 5b.

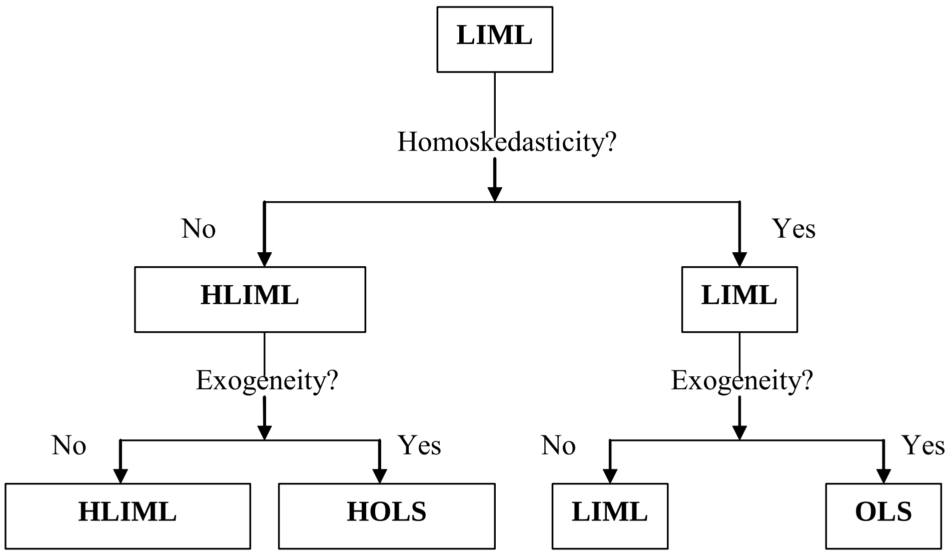
$$T_{ig} = \sum_{k=1}^{K} \left(\beta_{gk} - \sum_{k=1}^{K} \beta_{gk} V_{wk} \frac{\omega_k}{Y_w} \right) V_{ik} - \left(C_{ig} - \phi_i C_{wg} \right) \tag{5b}$$

But we can define $\sum_{k=1}^{K} \beta_{gk} V_{wk}$ as the world output of good *g*, denoted Q_{wg}, arriving to 5c.

$$T_{ig} = \sum_{k=1}^{K} \left(\beta_{gk} - Q_{wg} \frac{\omega_k}{Y_w} \right) V_{ik} - \left(C_{ig} - \phi_i C_{wg} \right) \tag{5c}$$

Finally, equation 6 is obtained when we define $\beta_{gk} - Q_{wg} \frac{\omega_k}{Y_w} = \gamma_{gk}$.■

Appendix C. Outline of IV Estimation with Weak Instruments



where:

HLIML is the heteroskedastic-efficient continuously-updated GMM estimator (it is the GMM generalization of the LIML estimator to the case of possibly heteroskedastic disturbance).

HOLS is the Cragg's heteroskedastic OLS estimator (HOLS) which is more efficient than OLS in the presence of heteroskedasticity. ■

Appendix D. Summary

Effect of the Environmental Endowment on Net Export

Industry	Environmental Endowment		Sub-sector	Environmental Endowment	
	BOD	SO_2		BOD	SO_2
Iron and Steel	+	0	671	++	0
			672	0	+
			673	0	0
			674	0	-
			676	+++	0
			677	+++	--
			678	0	0
			679	+++	0
Nonferrous Metals	0	0	681	+++	0
			682	0	0
			683	+	-
			684	0	--
			685	0	-
			686	+++	0
			687	+++	0
			689	+++	0
Chemical	---	---	512	0	--
			513	0	0
			514	0	--
			581	---	--
Pulp and Paper	0	0	251	--	0
			641	++	0
			642	0	0
Non-metallic Minerals Products	+++	0	661	+++	0
			662	0	0
			663	+++	0
			664	0	0
			665	++	+++
			666	+++	+
			667	++	0

Notes: The sign indicates the impact of the variable on net exports: "+" implies a positive relationship (the so-called "pollution haven effect") and "-" denotes a negative relationship (which could be interpreted as the Porter hypothesis). The number of signs in a cell specifies the level of confidence of the parameter in the econometric analysis: 99%, 95% and 90%. "0" indicates that the variable is not statistically different from zero.

Tables

Table 1: Pollution-intensive Industries Included in the Study (SITC Rev. 3)

Sector	Description
Primary Iron and Steel (67):	Pig iron, spiegeleisen, sponge iron, iron or steel granules, and powders and ferro-alloys, etc. (671); Ingots and other primary forms of iron or steel; semi-finished products of iron or steel (672); Flat-rolled products of iron or non-alloy steel, not clad, plated, or coated (673); Flat-rolled products of iron or non-alloy steel, clad, plated, or coated (674); Flat-rolled products of alloy steel (675); Iron an steel bars, rods, angles, shapes, and sections (including sheet pilling) (676); Rail or railway track construction material of iron and steel (677); Wire of iron or steel (678); Tubes, pipes, and hollow profiles, and tube or pipe fittings of iron or steel (679)
Nonferrous Metals (68):	Silver, platinum and other metals of the platinum group (681); Copper (682); Nickel (683); Aluminium (684); Lead (685); Zinc (686); Tin (687); and Miscellaneous nonferrous base metals employed in metallurgy and cermets (689).
Industrial Chemical:	Organic chemical (51); Inorganic chemical (52); Fertilizers (56); and Chemical materials and products, n.e.s. (59)
Pulp and Paper:	Pulp and waste paper (25); Paper and paperboard (641); and Paper and paperboard, cut to size or shape, and articles of paper or paperboard (642)
Non-metallic Mineral Manufactures (66):	Lime, cement, and fabricated construction materials (except glass and clay materials) (661); Clay construction materials and refractory construction materials (662); Mineral manufactures(663); Glass (664); Glassware (665); Pottery (666); Pearls and precious or semiprecious stones, unworked or worked (667)

Table 2: Definitions and Data

Variable	Definition and Source
Net Export	Thousands U.S. dollars of net export of good *"g"*. Goods are classified according to SITC Rev. 3. United Nations (2000), *UN Comtrade Database*. See Table 1 for details.
Capital	Physical capital stock, millions of dollars of discounted and accumulated investment flows, year 2000. The sum of annual Gross Domestic Investment (GDI) assuming an average life of 15 years and a constant depreciation rate of 13.3%. GDI data from World Bank (2004), *World Development Indicators* 2004.
Labor	Economically active population (thousands), year 2000. World Bank (2004), *World Development Indicators* 2004.
Illiteracy	Illiteracy rate, adult total (% of people ages 15 and above), year 2000.[a] World Bank (2004), *World Development Indicators* 2004.
Tertiary	Professional and technical workers (% of labor force), year 2000 or the closest year with information available. International Labour Office (various years), *Yearbook of Labour Statistics*, and *World Development Indicators* 2004 (labor force with tertiary education).
Qualified Labor	Labor*Tertiary
Illiterate Labor	Illiterate workers (thousands) is calculated as: Labor*(100- Illiteracy)/100.
Tropical	Thousand hectares of tropical forest, year 1996. *World Resources Institute*. *Earth Trends*: The Environmental Information Portal, http://earthtrends.wri.org.
Crop	Square kilometers of cropland, years 1992-1993. *World Resources Institute*. *Earth Trends*: The Environmental Information Portal, http://earthtrends.wri.org.
Nontropical	Thousand hectares of non-tropical forest, year 1996. *World Resources Institute*. *Earth Trends*: The Environmental Information Portal, http://earthtrends.wri.org.
Copper, Iron, Lead, and Zinc	Thousands metric tons of mine production for each of these metals, year 2000. *US Geological Survey*, Commodity statistics and information, 2004.
Coal	Coal production (millions short tons),[b] year 2000.Energy Information Administration (Official Energy Statistics from the US Government), *International Energy Annual* 2003, table 25.
Gasoil	The sum of world production of crude oil, NGPL, and other liquids (thousand barrels per day)[c] and world dry natural gas production (trillion cubic feet), year 2000. It is expressed in million tonnes of oil per year. Energy Information Administration (Official Energy Statistics from the US Government), *International Energy Annual* 2003, table G.1.
BOD	Organic water pollutant (BOD) emissions (kg per day), year 2000. World Bank (2004), *World Development Indicators* 2004.
SO_2	Sulfur emissions divided by share of oil and coal in total energy. Sulfur emissions were compiled by David Stern, "Global sulfur emissions from 1850 to 2000," *Chemosphere* 58, p. 163-175. The data is available on the web at http://www.rpi.edu/~sternd/datasite.html.
Fish-Diversity	Fish species, number, refer to the total number of freshwater and marine fish identified, documented, and recorded in a particular country or region. Total numbers include both endemic and non-endemic species. Most marine fish are excluded from country totals. Years 1992-2003. *World Resources Institute*. *Earth Trends*: The Environmental Information portal, http://earthtrends.wri.org.
Fish-Threat	Fish, number threatened, includes all species of both freshwater and marine fish that are recorded as threatened and that are known to occur in the territory of a given country. Year 2004. *World Resources Institute*. *Earth Trends*: The Environmental Information portal, http://earthtrends.wri.org.

Vehicles	Total number of vehicles per 1000 people. Year 1996. *World Resources Institute*. *Earth Trends*: The Environmental Information Portal, http://earthtrends.wri.org.
Road	Total road network, thousands kilometers, includes motorways, highways, main or national roads, and secondary or regional roads. Year 2000, but they mostly come from 1999. *World Resources Institute*. *Earth Trends*: The Environmental Information Portal, http://earthtrends.wri.org.

[a] For purposes of calculating, a value of 1% was applied in Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Iceland, Ireland, Japan, Luxembourg, Netherlands, New Zealand, Norway, Slovak Republic, Sweden, Switzerland, United Kingdom, and United States.

[b] It includes anthracite, subanthracite, bituminous, subbituminous, lignite, brown coal, and oil shale.

[c] NGPL are natural gas plant liquids, and the “other liquids” category includes alcohol fuels, liquids produced from coal and oil shale, non-oil inputs to methyl tertiary butyl ether (MTBE), orimulsion, and other hydrogen and hydrocarbons for refinery feedstocks.

Table 3. Summary of Statistics, Year 2000

Variable	Observations	Mean	Stan. Dev.	Minimum	Maximum
Capital	71	630128,8	1819032,0	3118,2	1,07e+07
Qualified Labor	71	4605,4	11589,4	17,3	85423,6
Illiterate Labor	71	6464,7	26395,9	1,6	192763,3
Tropical	71	12849,6	39551,8	0	301272,6
Crop	71	144917,4	326383,0	0	1753350,0
Nontropical	71	14198,6	58295,3	0	404313,3
Copper	71	152,9	592,9	0	4602,4
Iron	71	12677,4	42250,2	0	223000,0
Lead	71	41,3	132,1	0	739,0
Zinc	71	112,0	321,5	0	1780,0
Coal	71	56,8	208,4	0	1314,4
Gasoil	71	51,5	124,5	0	902,6
BOD	71	280085,2	795237,9	1886,2	6204237,0
SO_2	71	791,5	1946,2	2,0	12197,0

Table 4: HOV Estimation Results using Robust Ordinary Least Square (Dependent variable: thousands of U.S. dollars of net export in 2000)

	Iron and Steel		Nonferrous Metals		Industrial Chemical		Pulp and Paper		Non-metallic Minerals Products	
Capital	1,2	(0,24) ***	-0,40	(0,16) **	0,63	(0,21) ***	-0,12	(0,14)	0,27	(0,27)
Qualified Labor	-105,4	(96,9)	-39,1	(68,7)	140,1	(139,5)	-30,9	(42,6)	-212,6	(119,4) *
Illiterate Labor	42,1	(19,0) **	10,7	(10,7)	-34,7	(38,3)	44,5	(16,3) ***	19,6	(11,1) *
Tropical	-1,1	(6,4)	-10,8	(5,3) **	-42,4	(24,0) *	21,0	(9,0) **	2,5	(6,4)
Crop	-3,7	(2,4)	-0,71	(1,2)	2,3	(3,6)	-5,1	(1,9) ***	0,25	(1,4)
Nontropical	-2,4	(5,0)	0,80	(5,6)	-45,7	(30,7)	60,3	(12,8) ***	1,2	(6,4)
Copper	98,3	(220,7)	1573,8	(190,0) ***	864,1	(343,1) **	526,0	(156,0) ***	-191,8	(280,9)
Iron	27,3	(7,3) ***	31,3	(7,4) ***	45,8	(27,7)	-1,4	(10,5)	-4,0	(11,2)
Lead[a]	-5,7	(6,9)	-15,2	(8,1) *	-75,6	(41,0) *	13,6	(15,3)	3,7	(10,4)
Zinc[a]	1,5	(2,6)	6,7	(3,0) **	27,6	(16,4) *	-6,9	(5,7)	-0,53	(3,8)
Coal[a]	-1,7	(4,6)	5,5	(3,9)	27,3	(8,8) ***	4,0	(4,6)	-7,5	(5,5)
Gasoil[a]	-4,0	(2,1) *	4,7	(2,7) *	6,3	(5,1)	-5,6	(3,8)	-2,7	(1,7)
BOD	0,35	(0,77)	-0,72	(0,57)	-4,8	(2,6) *	0,95	(1,0)	2,3	(0,77) ***
SO_2	-540,8	(560,5)	-1395,8	(482,8) ***	-2549,6	(907,2) ***	-1098,0	(374,0) ***	322,2	(755,3)
Const[a]	215,4	(185,5)	310,0	(106,4)	572,9	(347,0)	373,1	(221,2) *	100,7	(163,6)
R^2	0,85		0,91		0,48		0,76		0,84	
Observations	71		71		71		71		71	
Homocedasticity[b]	0,03		4,32**		34,88***		8,60***		0,08	

Notes: Heterocedasticity-robust standard deviation is reported in parenthesis. *, **, and *** denote the level of confidence: 90%, 95% and 99%, respectively. [a]Coefficients and standard deviation are expressed in thousands. [b]It reports the Breusch-Pagan/Cook-Weisberg test for heteroskedasticity (with one degree of freedom), the null hypothesis (H_0) is constant variance.

Table 5: First-stage Regressions of Instrumented Variables BOD and SO_2

	(1) OLS BOD			(2) OLS SO_2		
Capital	0,154	(0,034)	***	-0,000	(0,000)	
Qualified Labor	15,867	(10,771)		0,047	(0,027)	*
Illiterate Labor	2,906	(4,225)		-0,002	(0,006)	
Tropical	-1,718	(1,152)		-0,002	(0,003)	
Crop	1,061	(0,249)	***	0,001	(0,000)	**
Nontropical	-2,344	(1,349)	*	-0,003	(0,001)	**
Copper	12,540	(9,767)		0,417	(0,019)	***
Iron	-0,292	(4,439)		0,004	(0,008)	
Lead	-4589,863	(2164,351)	**	-6,409	(2,652)	**
Zinc	1620,756	(661,570)	**	2,217	(0,742)	***
Coal	3373,482	(509,876)	***	4,334	(0,928)	***
Gasoil	327,748	(267,292)		1,880	(0,782)	**
Fish-Diversity	41,416	(46,327)		-0,449	(0,096)	***
Fish-Threat	543,695	(1067,886)		8,007	(3,375)	**
Road	-794,917	(137,011)	***	0,276	(0,200)	
Vehicles	267,968	(106,295)	**	-0,0392	(0,155)	
Constant	-34058,340	(23544,630)		36,104	(51,649)	
Observations	69			69		
Partial R^2	0,59			0,33		
Shea Partial R^2	0,54			0,30		
Anderson canonical correlation likelihood-ratio test[a]	21,2***					
Test of weak instruments[b]	4,7					

Notes: Heterocedasticity-robust standard deviation is reported in parenthesis. *, **, and *** denote the level of confidence: 90%, 95% and 99%, respectively. [a]Distributed Chi-sq(3). [b]Cragg-Donald statistic (critical values are reported in Stock and Yogo 2004).

Table 6: HOV Estimation Results under Hypothesis of BOD and SO_2 Endogenous (Dependent variable: thousands of U.S. dollars of net export in 2000)

	Iron and Steel		Nonferrous Metals		Industrial Chemical		Pulp and Paper		Non-metallic Minerals Products	
Method	**LIML**		**LIML**		**HOLS[e]**		**HOLS**		**OLS**	
Capital	0,98	(0,22) ***	-0,57	(0,20) ***	0,64	(0,21) ***	-0,12	(0,12)	0,27	(0,27)
Qualified Labor	-38,3	(96,5)	-26,2	(89,2)	103,0	(98,5)	-60,8	(54,5)	-212,6	(119,4) *
Illiterate Labor	31,7	(16,7) *	16,6	(14,8)	-24,6	(18,8)	53,3	(18,9) ***	19,6	(11,1) *
Tropical	11,5	(8,9)	-0,30	(6,2)	-35,3	(10,9) ***	23,6	(7,9) ***	2,5	(6,4)
Crop	-4,0	(2,2) *	-1,9	(1,4)	1,5	(2,2)	-5,6	(1,7) ***	0,25	(1,4)
Nontropical	4,2	(6,3)	10,7	(6,0) *	-36,8	(12,2) ***	61,0	(9,6) ***	1,2	(6,4)
Copper	59,8	(302,6)	1409,9	(243,7) ***	770,4	(290,1) **	341,9	(158,9) **	-191,8	(280,9)
Iron	50,2	(15,3) ***	35,6	(14,3) **	36,4	(14,4) **	-5,6	(22,5)	-4,0	(11,2)
Lead[a]	-1,5	(9,1)	-1,9	(10,0)	-63,0	(15,6) ***	18,7	(14,4)	3,7	(10,4)
Zinc[a]	-1,9	(3,7)	1,2	(3,5)	22,8	(6,3) ***	-8,2	(4,6) *	-0,53	(3,8)
Coal[a]	-7,4	(5,4)	-2,5	(4,4)	24,4	(5,0) ***	0,19	(4,2)	-7,5	(5,5)
Gasoil[a]	-5,2	(2,3) **	3,4	(2,8)	5,4	(4,7)	-6,5	(3,0) **	-2,7	(1,7)
BOD	1,3	(0,69) *	0,56	(0,68)	-4,0	(1,0) ***	0,96	(0,88)	2,3	(0,77) ***
SO_2	-584,9	(729,4)	-1004,1	(605,9)	-2310,5	(740,9) ***	-502,7	(361,9)	322,2	(755,3)
Const[a]	86,7	(187,8)	148,8	(118,1)	521,1	(193,4) ***	146,2	(137,8)	100,7	(163,6)
Centered R^2	0,85		0,91		0,48		0,76		0,84	
Observations	69		69		69		69		71	
Overidentification[b]	1,06		0,16		0,34[h]		2,43[h]			
Exogeneity[c]	13,45***		18,47***		0,40		1,13		1,05	
Homocedasticity[d]	8,41		5,54		14,61		7,27		8,62	

Notes: All the estimations have a correction due to small samples. Heterocedasticity-robust standard deviation is reported in parenthesis. *, **, and *** denote the level of confidence: 90%, 95% and 99%, respectively. [a]Coefficients and standard deviation are expressed in thousands. [b]Anderson-Rubin statistic of overidentification of all instruments [chi-sq (2)]. Superscript h indicates that Hansen J statistic was reported instead. [c]C-statistic, test of exogeneity/orthogonality of suspect instruments [chi-sq (2)]. [d]IV heterocedasticity test, Pagan-Hall general test of homoskedastic disturbance using levels of IVs only [chi-sq (16)]. [e]It uses fishno and road as additional moment conditions.

Table 7a: HOV Estimation Results under Hypothesis of BOD and SO_2 Endogenous (Dependent variable: thousands of U.S. dollars of net export in 1996)

Sector	***Primary Iron and Steel***							
Subsector	**671**	**672**	**673**	**674**	**676**	**677**	**678**	**679**
Method	**LIML**	**LIML**	**LIML**	**LIML**	**OLS**	**OLS**	**HOLS[d]**	**HOLS[d]**
Capital	-0,06	0,07	0,21 **	0,18 ***	0,14 ***	0,01 ***	0,02 **	0,15 ***
Qualified Labor	-40,5	-38,5	22,9	20,7	-24,8	-0,63	-2,7	-17,1
Illiterate Labor	6,5	3,8	11,18 *	5,7	6,0 ***	0,23	1,4 *	-0,87
Tropical	4,2 *	2,1	1,6	0,19	-0,07	-0,16 *	0,49 *	0,97
Crop	-1,0 *	-0,44	-1,4 *	-0,6	-0,42 **	-0,02	-0,13	0,16
Nontropical	2,3	-0,38	0,49	0,5	0,89	-0,01	0,47	0,41
Copper	-66,2	-142,6 **	179,2	122,4 *	-6,8	3,7 *	-6,8	-49,8
Iron	2,0	6,8	9,2	5,0	2,0	0,13	1,03	2,9
Lead	2306,9	239,5	-268,0	-848,1	720,4	-46,2	253,2	833,4
Zinc	-1247,1	-166,5	-327,5	11,9	-155,8	31,6	-142,5	-497,7
Coal	4,9	-3379,6 **	733,8	860,1	-1550,2 *	-15,3	-369,3 *	-2094,9 ***
Gasoil	112,2	-217,3	-403,3	-143,4	-900,0 *	-55,8	-163,8	-1647,7 ***
BOD	0,40 **	0,18	0,12	-0,05	0,44 ***	0,03 ***	0,04	0,37 ***
SO_2	152,3	359,9 *	-508,3	-369,1 *	-50,5	-13,5 **	8,6	82,2
Constant	-1086,0	-85011,1 **	54567,3	62786,8	12321,1	986,5	-4425,0	-22709,2
Centered R^2	0,66	0,62	0,64	0,65	0,79	0,65	0,60	0,77
Observations	69	69	69	69	71	71	69	69
Overidentification[a]	1,78	2,16	1,44	1,25			2,81 [h]	5,87 [h]
Exogeneity[b]	20,29***	8,69**	11,13***	7,86**	1,87	0,54	2,74	3,11
Homoskedasticity[c]	3,51	7,33	7,62	6,50	14,64	6,47	3,80	8,03

Notes: All the estimations have a correction due to small samples. For reasons of space, heterocedasticity-robust standard deviations have not been reported. Instead *, **, and *** denote the level of confidence: 90%, 95% and 99%, respectively. [a]Anderson-Rubin statistic of overidentification of all instruments [chi-sq (2)]. Superscript h indicates that Hansen J statistic was reported instead. [b]C-statistic, test of exogeneity/orthogonality of suspect instruments [chi-sq (2)]. [c]IV heterocedasticity test, Pagan-Hall general test of homoskedastic disturbance using levels of IVs only (chi-squared with 16 degrees of freedom). [d]The Breusch-Pagan/Cook-Weisberg test rejected the hypothesis of conditional homoskedasticity in OLS.

Table 7b: HOV Estimation Results under Hypothesis of BOD and SO_2 Endogenous (Dependent variable: thousands of U.S. dollars of net export in 1996)

Sector	*Nonferrous Metals*							
Subsector	**681**	**682**	**683**	**684**	**685**	**686**	**687**	**689**
Method	**HLIML**	**LIML**	**LIML**	**LIML**	**OLS**[f]	**LIML**	**OLS**	**LIML**
Capital	-0,35 ***	0,17 **	-0,07 **	-0,24 ***	0,00	-0,02	-0,03 ***	-0,04 ***
Qualified Labor	6,9	-5,6	0,26	-3,5	0,09	-7,0	-0,17	-4,3
Illiterate Labor	-2,7	17,4 ***	1,2	-0,25	0,26	1,9	-0,31	0,03
Tropical	-0,17	1,8	-0,51	-3,3	-0,15	0,16	0,94 ***	0,15
Crop	-0,12	-1,8 ***	-0,16	0,39	-0,07	-0,30 *	-0,01	-0,05
Nontropical	0,52	1,4	2,3 **	3,9	0,24 *	1,6 **	0,15	0,65 **
Copper	59,0	1123,9 ***	63,4	245,0 *	7,38	-18,4	16,1 *	-14,8
Iron	4,4 **	10,3 **	3,7	14,9	0,35 *	3,2 *	-1,1 ***	0,12
Lead	-87,2	-1280,0	1115,3	-3710,2	23,47	402,8	399,2	434,4
Zinc	174,0	365,1	-233,9	1197,0	59,28	101,4	-69,0	-141,9
Coal	-1677,7	-1746,2	-452,3	3824,0	183,91 **	-1257,5 ***	58,9	-258,0
Gasoil	376,6	-1221,4 *	1003,8 *	3775,8 **	-82,24	-127,9	30,8	-149,5
BOD	0,50 ***	-0,11	0,20 *	-0,52	0,02	0,23 ***	0,13 ***	0,10 ***
SO_2	-129,3	-112,1	-181,4 *	-746,4 **	-22,54 *	9,7	-28,1	30,0
Constant	20346,5	12232,1	-18,8	129669,6 **	3254,34	-4707,8	-3314,0	1174,5
Centered R^2	0,94	0,93	0,79	0,89	0,79	0,86	0,81	0,88
Observations	69	69	69	69	71	69	71	69
Overidentification[a]	1,74 [h]	3,85	1,55	2,98	13,59***	1,89		0,35
Exogeneity[b]	10,78***	13,78***	17,84***	6,77**	1,90	21,61***	2,75	6,91**
Homoskedasticity[c]	4,69[e]*	8,64	10,11	13,43	9,57	9,43	2,57	14,55

Notes: All the estimations have a correction due to small samples. For reasons of space, heterocedasticity-robust standard deviations have not been reported. Instead *, **, and *** denote the level of confidence: 90%, 95% and 99%, respectively. [a]Anderson-Rubin statistic of overidentification of all instruments [chi-sq (2)]. Superscript h indicates that Hansen J statistic was reported instead. [b]C-statistic, test of exogeneity/orthogonality of suspect instruments [chi-sq (2)]. [c]IV heterocedasticity test, Pagan-Hall general test of homoskedastic disturbance using levels of IVs only (chi-squared with 16 degrees of freedom). [e]The test used fitted value and its square (it is distributed chi-sq (2)). [f]This estimator is employed because the result of the overidentification test rejected the hypothesis that excluded instruments are uncorrelated with the disturbance in the structural equation.

Table 7c: HOV Estimation Results under Hypothesis of BOD and SO_2 Endogenous (Dependent variable: thousands of U.S. dollars of net export in 1996)

Sector	*Industrial Chemical*				*Pulp and Paper*		
Subsector	51	52	56	59	25	641	642
Method	HLIML	OLS	LIML	OLS[f]	LIML	HOLS[d]	LIML
Capital	0,24	-0,14 ***	-0,01	0,33 ***	-0,11	-0,03	-0,01
Qualified labor	141,4	0,65	-3,0	74,8 *	-7,7	-49,2	23,3
Illiterate labor	-10,2	-11,3 **	8,7 **	-26,1 **	14,3 **	34,6 **	-3,1
Tropical	-33,6 **	-3,2	0,19	-7,4	0,96	19,3 ***	0,23
Crop	1,3	0,37	-0,97 ***	2,5 *	-1,4 **	-3,6 **	0,13
Nontropical	-28,6 *	-1,7	6,4 ***	-14,1 **	17,7 ***	38,5 ***	1,1
Copper	1047,1 **	88,3	99,9 **	287,6 *	289,6 ***	63,3	136,7
Iron	27,1	3,4	-7,3 *	6,9	-2,8	0,69	1,2
Lead	-45267,5 *	-4915,6	1326,7	-18615,2 **	-610,2	16364,1	-2373,8
Zinc	17665,0 **	1574,9	-367,5	5725,1 *	80,2	-6977,2 *	475,5
Coal	15359,1	2494,1 *	2668,6 ***	12517,7 ***	2998,1 *	-4192,8 *	3254,3 *
Gasoil	5944,1	644,8	720,0	2336,2	-8,1	-4448,6 *	-579,2
BOD	-1,5	0,14	-0,11	-2,0 ***	-0,61 **	1,5 **	-0,06
SO_2	-2874,7 **	-186,0	-252,6 **	-891,4 **	-199,0	-280,7	-384,2
Constant	540371,6 **	5539,1	29260,2	36155,0	44363,9	27372,5	62387,0
Centered R^2	0,52	0,67	0,84	0,82	0,91	0,63	0,10
Observations	69	71	69	71	69	69	69
Overidentification[a]	0,29[h]		0,34	7,68**	2,85	2,65 [h]	1,74 [h]
Exogeneity[b]	7,02**	3,35	11,13***	3,88	5,22*	0,85	13,22***
Homoskedasticity[c]	11,96[e]***	6,36	8,18	6,95	7,91	7,39	9,88

Notes: All the estimations have a correction due to small samples. For reasons of space, heterocedasticity-robust standard deviations have not been reported. Instead *, **, and *** denote the level of confidence: 90%, 95% and 99%, respectively. [a]Anderson-Rubin statistic of overidentification of all instruments [chi-sq (2)]. Superscript h indicates that Hansen J statistic was reported instead. [b]C-statistic, test of exogeneity/orthogonality of suspect instruments [chi-sq (2)]. [c]IV heterocedasticity test, Pagan-Hall general test of homoskedastic disturbance using levels of IVs only (chi-squared with 16 degrees of freedom). [d]The Breusch-Pagan/Cook-Weisberg test rejected the hypothesis of conditional homoskedasticity in OLS. [e]The test used fitted value and its square (it is distributed chi-sq (2)). [f]This estimator is employed because the result of the overidentification test rejected the hypothesis that excluded instruments are uncorrelated with the disturbance in the structural equation.

Table 7d: HOV Estimation Results under Hypothesis of BOD and SO_2 Endogenous (Dependent variable: thousands of U.S. dollars of net export in 1996)

Sector	***Non-metallic Mineral Manufactures***						
Subsector	**661**	**662**	**663**	**664**	**665**	**666**	**667**
Method	**OLS**[f]	**LIML**	**LIML**	**OLS**	**HLIML**	**LIML**	**LIML**
Capital	-0,02	0,11	0,12 ***	0,12 ***	0,02 ***	-0,07 ***	-0,07
Qualified labor	-52,9 *	-35,0	-6,5	-3,5	-25,2 *	-13,2	-75,7
Illiterate labor	2,9	-5,6	3,8 *	2,9	-1,1	0,38	18,0 **
Tropical	1,9	-1,1	0,82	1,5 **	2,5 **	1,0	8,4
Crop	0,19	0,79	-0,48 **	-0,32	0,26	-0,29 *	-1,2
Nontropical	2,6	-3,7	1,2	-0,50	0,67	0,57	4,8
Copper	-113,9	-162,7	11,5	37,0 **	-110,4 ***	-63,1 **	-189,1
Iron	-3,6	3,5	3,0 *	-1,3 *	0,04	2,2	15,6 *
Lead	3663,5	-4296,9	662,5	570,7	2174,1	1487,4	3193,4
Zinc	-1185,8	1565,4	-307,9	-251,9	-893,0	-581,9	-1822,1
Coal	-2848,3 **	-1247,9	-1499,9 **	751,3 *	-2529,6 ***	-2263,5 ***	-6113,1 **
Gasoil	-484,9	-1132,6	-113,1	-195,2	-907,6 **	-492,1 ***	-2279,9 **
BOD	0,63 ***	-0,28	0,42 ***	-0,01	0,27 **	0,65 ***	0,75 **
SO_2	252,5	349,6	-65,6	-69,8	269,7 ***	122,7 *	418,6
Constant	2030,3	21354,2	-15185,9	2361,2	-52581,3 ***	-19279,3	-24513,0
Centered R^2	0,74	0,20	0,91	0,70	0,59	0,96	0,88
Observations	71	69	69	71	69	69	69
Overidentification[a]	5,18*	3,77	1,64		2,74	2,54	2,63
Exogeneity[b]	2,36	11,69***	9,78***	1,20	6,00**	31,25***	7,26**
Homoskedasticity[c]	9,93	12,29	5,16	6,29	9,58[e]***	8,43	3,92

Notes: All the estimations have a correction due to small samples. For reasons of space, heterocedasticity-robust standard deviations have not been reported. Instead *, **, and *** denote the level of confidence: 90%, 95% and 99%, respectively. [a]Anderson-Rubin statistic of overidentification of all instruments [chi-sq (2)]. Superscript *h* indicates that Hansen J statistic was reported instead. [b]C-statistic, test of exogeneity/orthogonality of suspect instruments [chi-sq (2)]. [c]IV heterocedasticity test, Pagan-Hall general test of homoskedastic disturbance using levels of IVs only (chi-squared with 16 degrees of freedom). [e]The test used fitted value and its square (it is distributed chi-sq (2)). [f]This estimator is employed because the result of the overidentification test rejected the hypothesis that excluded instruments are uncorrelated with the disturbance in the structural equation.