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Environmental Regulation and Industry Location in Europe

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Abstract This paper estimates the effect of environmental regulation on industry location and compares it with other determinants of location such as agricultural, education and R&D country characteristics. The analysis is based on a general empirical trade model that captures the interaction between country and industry characteristics in determining industry location. The Johnson–Neyman technique is used to fully explicate the nature of the conditional interactions. The model is applied to data on 16 manufacturing industries from 13 European countries. The empirical results indicate that the pollution haven effect is present and that the relative strength of such an effect is of about the same magnitude as other determinants of industry location. A significant negative effect on industry location is observed only at relatively high levels of industry pollution intensity.

Keywords Pollution haven hypothesis · Comparative advantage · Industry location

1 Introduction

Does environmental regulation have a significant negative impact on industry location? This question is at the heart of the trade and environment debate. A positive answer to this question might give grounds to concerns regarding a host of interrelated issues: the emergence of 'pol-

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lution havens' in environmentally lax countries, harm to competitiveness in environmentally strict countries, and a consequent attempt by jurisdictions to undercut each other's environmental standards. Such issues have served as an additional impediment to the conclusion of the latest round of WTO trade liberalization that started in Seattle in 1999 (Ederington et al. 2004; Wolfe 2004). Industrialists in the EU are also worried about the extent to which the EU Emissions Trading Scheme impairs their competitiveness (Reinaud 2004). Similarly in the US, competitiveness concerns were raised during the debate on the impact of North American Free Trade. Critics argued that differential environmental standards across Canada, Mexico and US would result in massive capital flight to Mexico which would cause more overall pollution.

These issues have received considerable attention in the academic literature and much of the studies are collected under the denominator of the so-called Pollution Haven Hypothesis (PHH).[1] This hypothesis purports that changes in environmental regulation results in a relocation of dirty goods production from countries with stringent environmental regulation to those with lax environmental regulation. While the hypothesis is intuitively plausible, reviews of the empirical literature have concluded that the evidence is mixed or that the correlation between environmental regulation and industry performance is weak (see, for e.g., Copeland and Taylor 2003; Jaffe et al. 1995; Raspiller and Riedinger 2008). Supported by evidence from a meta-analysis of 11 studies, Jeppesen et al. (2002) show how empirical specification, data issues, definition of the regulatory variable, and the control variables included all have a considerable influence on the empirical results. In particular they find that the smaller the geographical area of study, the larger the estimated influence of regulation. They also find that the often reported results that pollution and non-pollution intensive industries are affected similarly may be a repercussion of pooling industries that are in fact heterogeneous. Taylor (2004) has further pointed out that empirical work on the PHH has been troubled by, among other things, the fact that researchers at times mistake a pollution haven effect for the pollution haven hypothesis. Pollution haven *effects* occur if differences in the levels of environmental regulatory stringency affect the inter-jurisdictional distribution of polluting industries. Such effects, if present, are only one determinant of industry location. The PHH however postulates that the interaction between environmental regulation and pollution intensity is the most important determinant for firm location, or at least more important than other determinants, such as the availability of capital and skilled labor. This leads—it is hypothesised—to a "race to the bottom", where jurisdictions have incentives to lower environmental standards to maintain or increase their share of those industries most affected by such standards.

The differential stringency of environmental regulation is only one of several motives for firms' location choices and hence there have been recent calls in the literature for empirical work weighing the relative strength of these different motives[2] (Taylor 2004). Our aim is to present a way of undertaking such an assessment. The analysis in this paper complements those of Becker and Henderson (2001), Greenstone (2002), and List and McHone (2000) who have documented evidence of the pollution haven effect using county level plant data for the US and New York state, respectively. Becker and Henderson study four pollution intensive industries, Greenstone uses dummies for dirty as opposed to clean industries,

[1] See, for example, a recent edited volume dedicated to the Pollution Haven Hypothesis (Fullerton 2006).

[2] Such calls also remind us of a seemingly trivial but a more general point about hypothesis testing. Strictly speaking, the question of how accurate a hypothesis is necessitates an explicit statement of an alternative hypothesis with which the maintained hypothesis is to be compared. In the absence of an alternative hypothesis, normal statistical methods of inference are not applicable and rejection/acceptance of the maintained hypotheses is a matter of mere judgment (Leamer 1984, pp. 45–47).

and List and McHone compare the location decisions of polluting new plants in attainment (stringent) and non-attainment (lax) counties.[3] We propose an alternative approach by explicitly including a continuous variable of pollution intensity per industries so that we can address the question: ‘how polluting must an industry be to be adversely affected by environmental regulation?’, a refinement of the typical question in the literature: ‘are polluting industries affected by environmental regulation?’. Also, we include other determinants of firm location so that we can compare the different determinants and distinguish between the pollution haven hypothesis and the pollution haven effect. In this sense, this paper also complements Levinson and Taylor’s (2008) study which, like this paper, uses a continuous measure of pollution intensity as an explanatory variable but it does not compare environmental policy with other location determinants. Our paper further complements the paper by Cole et al. (2005) which analysed US’s revealed comparative advantage to examine the hypothesis of a decline in US’s specialisation in pollution-intensive industries. The authors did not find a support for the hypothesis and gave the explanation that such industries were also intensive in physical and human capital which US is endowed with relatively well.[4]

Our paper contributes to the literature in three ways. First, we integrate two strands of literature; one from economic geography and one from environmental economics. We employ a general empirical trade model that has recently appeared in the new economic geography literature but has not previously been used in the pollution haven literature. The model analyzes the joint role of country and industry characteristics in determining industry location. Specifically, it estimates how high and low levels of country characteristics interact with high and low intensities of the corresponding industry attributes in location decisions. The model allows us to supplement and expand recent findings in the empirical PHH literature that the impact of environmental regulation tends to be “heterogeneous both spatially and across industry” (Millimet and List 2004. p. 261; Mulatu et al. 2004). The model complements the analyses by Cole and Elliott (2003a) and Chintrakarn and Millimet (2006) as it uses explicit variables for environmental policy and pollution intensity as a driver of location, rather than studying the pollution haven effect indirectly by regressing emission levels against trade intensity, income, the capital/labor ratio, and their various interaction effects.

Second, we elaborate on the interpretation of the conditional effects associated with the interactive terms in our empirical model. The most common method for probing interactive effects is to test significance of coefficients at specific levels of the predictors. In our case, the standard approach would be to test significance for location dependence on environmental policy stringency, given a specific level of the industry’s pollution intensity. We, more broadly, present the dependence relation over the whole range of industry’s pollution intensity and employ the Johnson–Neyman technique to calculate regions of significance and confidence bands for evaluating the conditional effects.

[3] Our paper also complements papers in a related strand of the literature such as List and Co (2000); Keller and Levinson (2002) and Xing and Kolstad (2002) who focus, respectively on US inbound and outbound FDI. Each of these papers compares regression results for dirty and clean industries (or all manufacturing) and obtains some evidence of the pollution haven effect.

[4] Broadly speaking, our paper is also related to that of Cole and Elliott (2003b) which distinguishes between two somewhat different questions examined, respectively in the Heckscher–Ohlin and in the ‘new’ trade models: does environmental regulation affect net exports of pollution-intensive goods?; and does environmental regulation, like the traditional factor endowments, play a role in the composition of trade? Again, however, the paper does not compare environmental policy with other location determinants.

Third, as we apply our approach to data on manufacturing industries from European countries, the analysis focuses on intra-EU heterogeneity and its consequences for firm location. The dataset includes pollution intensive industries such as Industrial Chemicals and 'clean' industries such as Radio, TV & Communication and covers countries with stringent environmental regulation such as Finland and Sweden as well as countries with relatively lax environmental regulation such as Greece and Belgium. A disadvantage of a narrow country selection is lack of variability in country characteristics, which will make the empirical tests harder to prove significance. On the other hand, an advantage of a narrow country sample is that it reduces the possibilities of omitted variable bias, as these countries share much of their history, geography, and many institutions. There is no need to suspect colonial history, climate conditions, or large differences in cultural attitudes to affect the results. In general, working with a homogeneous sample for an empirical study makes it hard to find significant results, but if these are found, they are more reliable. In previous studies, it has been shown that environmental policy within the EU is not homogeneous: within the EU-15 substantial differences exist (Pellegrini and Gerlagh 2006a). Furthermore, we have to bear in mind that for countries in the EU-15, still more than half of manufacturing imports and exports remains within this group of countries, so that policy's effects on industry location is of substantial importance.[5]

The results indicate that the *pollution haven effect* can be uncovered, and that the relative strength of such an effect is of about the same magnitude as other determinants of industry location. Further investigation of the conditional effects indicates that a *significant* negative effect on industry location is observed only at relatively high levels of pollution intensity. Thus, the focus on environmental stringency in this literature is only half the story: both stringency of environmental regulation and industry pollution intensity matter. The findings we report suggest that for the PHH literature the interaction between the differential stringency of environmental regulation and differences in industry pollution intensity is an essential element.

The rest of the paper is organized as follows. Section 2 presents the econometric model. Section 3 describes the data. Section 4 discusses the empirical results and Sect. 5 concludes.

2 Theory and Empirical Model

The model aims to investigate the relevance of various factors in industry's location. In particular, we want to know why some countries attract a high share of certain industries, while other countries have a much lower share. Formally, we search for the determinants of the share of country i in the total manufacturing production of industry k, that is $s_{i,k}$ defined as $s_{ik} = z_{i,k}/\sum_{i'} z_{i',k}$, where $z_{i,k}$ measures the size of industry k in country i, and the country label with prime (i') is used to sum over all countries.

Trade theorists' discussions of industry location are informed by two strands of literature. Comparative advantage arguments based on the role of factor endowments can be derived from Heckscher–Ohlin (HO) models. Recent theoretic work has extended the standard HO models to accommodate environmental factors where cross-country differences in the stringency of environmental regulation play a role in trade patterns. (e.g. Antweiler et al. 2001; Copeland and Taylor 1994, 1995, 2003).

[5] We notice also that much of previous literature has studied competition between US states, and between US and Canada.

New economic geography (NEG), by contrast, stresses the importance of increasing returns, market access and upstream and downstream linkages. NEG predicts that while activity will be dispersed when transport costs are either 'very high' or 'very low', clustering of industries occur when transport costs are 'intermediate'.[6] The HO and NEG theories should be regarded as complementary and their relative importance for industrial location outcomes is thus an empirical issue.

Recently, Midelfart-Knarvik et al. (2000b) developed an empirical model for the location of European industry that incorporates both types of effects, i.e. comparative advantage and market access. They estimate a model that takes account of the HO arguments by relating the factor intensities of industries to the factor endowments of countries. The NEG story is captured by examining how the share of intermediates in costs, the share of sales to industrial users, and scale economies interact with market potential in determining location.

We extend Midelfart-Knarvik et al. (2000b) econometric model and include environmental factors. Countries are heterogeneous in various characteristics such as endowments of natural resources and skilled labor, and proximity to markets. We add to these country characteristics the relative stringency of environmental regulation. Similarly, industries differ in their various attributes such as the intensity of use of production factors like skilled labor, and their reliance on intermediate inputs. We add to these attributes the pollution intensity of the industry. In equilibrium we expect that industries that highly value a regional characteristic locate there. All else equal, a technology intensive industry will locate in a region with abundant skilled labor, while pollution intensive industries will be attracted to countries with a relatively lax environmental regulation. In the context of the PHH literature, the relevant empirical question is how strong the interaction is between environmental regulation and pollution intensity, relative to the interaction between other country and industry characteristics.

Central in the model are the potential interaction channels, indexed j. For each interaction channel, we have a vector of associated country characteristics x^j, and a vector of associated industry attributes y^j. For the skilled-labor interaction channel, x^j measures countries' skilled labor abundance, while y^j measures the industries' skilled labor intensity. For the pollution interaction channel, x^j measures the countries' stringency of environmental regulation (or its inverse, the laxity), while y^j measures the industries' pollution intensity. For each interaction channel, there is a neutral country characteristic level χ^j, also referred to as a cut off point, such that a country with this characteristic does not specifically attract industries with high or low levels for the associated industry attribute. Similarly, there is a neutral industry attribute level γ^j, or cut off point, such that an industry with this attribute level does not consider the associated country-characteristic in the selection of its location. Using these parameters, Midelfart–Knarvik et al.'s model can be written as a reduced form equation:

$$\ln(s_{i,k}) = c + \alpha \ln(pop_i) + \sum_j \beta^j (x_i^j - \chi^j)(y_k^j - \gamma^j) + \varepsilon_{i,k}, \tag{1}$$

where pop_i is the population living in country i, α is a scale coefficient, and β^j measures the strength of interaction effect j. The country characteristics and industry attributes are chosen such that the interaction coefficients β^j are expected to be positive. Expanding the equation we obtain the estimating equation as follows:

6 See, e.g., Krugman and Venables (1995).

$$\ln(s_{i,k}) = c' + \alpha \ln(pop_i) + \sum_j (\beta^j x_i^j y_k^j - \gamma'^j x_i^j - \chi'^j y_k^j) + \varepsilon_{i,k}, \quad (2)$$

where $\gamma'^j = \beta^j \gamma^j$, $\chi'^j = \beta^j \chi^j$, and $c' = c + \sum_j \beta^j \chi^j \gamma^j$. After we have estimated β, χ', and γ' from (2) we can inverse the procedure and calculate the parameters χ and γ in (1).[7]

We specify seven interaction channels. The first three interaction channels are associated with the traditional HO trade model.[8] The fourth interaction channel is the environmental variable which is the main concern in this paper. The last three interaction channels represent the NEG concerns of the model, namely the pull of centrality interacting with scale economies, and forward and backward linkages. In full, the interaction channels are: (i) Agricultural production as percentage of GDP times industry agricultural input intensity;[9] (ii) Secondary & higher education as percentage population times industry skilled labor intensity; (iii) Researchers & Scientists as percentage of labor force times industry R&D intensity; (iv) Environmental standard laxity times industry pollution intensity; (v) Market potential times industry intermediate input use; (vi) Market potential times industry sale to industry; and finally (vii) Market potential times industry average plant size. The main hypothesis regarding the new economic geography interaction variables is that a firm's location decision involves consideration of market access alongside production costs.[10] In Table 1 we present the country characteristics and their association with the interaction channels, and the data sources. In Table 2, we present the industry attributes and their association with the interaction channels.

3 Interactions and Regions of Significance

Of key interest for the PHH debate is the effect of a country's characteristic on firm location. The question is whether a change in environmental policy, or in another country's characteristic, will make this country more or less attractive to firms, in general, or for specific sectors. From the location model as in Eq. (1), we can directly calculate the change in an industry's share a country attracts as dependent on a change in a country characteristic:

$$\frac{\partial \ln(s_{i,k})}{\partial x_i^j} = \beta^j (y_k^j - \gamma^j) = \beta^j y_k^j - \gamma'^j. \quad (3)$$

Given a positive interaction coefficient β^j, it is immediately clear from Eq. (3) that the increase of characteristic j in a country increases the share of industry k if that industry's level of attribute j exceeds the attribute's cut-off level, that is, if $y_k^j > \gamma^j$. An increase of a country's characteristic j will repel other industries. For example, countries with lax environmental policies may attract pollution-intensive industries and repel clean industries, or stated the other way around, countries with strict environmental policies may attract clean industries and repel pollution-intensive industries. What is considered a clean or a dirty industry is determined by the cut-off value γ^j. An immediately obvious comparison of interest therefore is that between the industry's cut-off points γ^j and the mean, maximum, and minimum

[7] When different interaction effects make use of the same country characteristic or industry attribute, the calculation of the cut-off points χ and γ becomes slightly more complicated. See notes to Table 3.

[8] Capital is ignored because of the assumption of capital mobility across Europe.

[9] Following Midelfart-Knarvik et al. (2000b) the rationale for taking the variable Agricultural production as % GDP instead of the underlying conventional factor inputs such as land is that, since our concern is the pattern of manufacturing, agriculture can be considered as an exogenous measure of the 'endowment of agriculture'.

[10] See, e.g., Venables (1996).

Table 1 Country characteristics

Variable (interaction channel)	Definition	Source	Mean	SD	Min	Max
Population	Share of EU population living in country *i* (average over 1990–1994)	OECD	0.076	0.070	0.014	0.219
Agricultural abundance (1)	Value of agricultural output as a share of GDP (1994)	Midelfart-Knarvik et al. (2000b)	0.047	0.027	0.019	0.125
Skilled labor abundance (2)	Share of population aged 25–59 with at least secondary education (1997)	Midelfart-Knarvik et al. (2000b)	0.602	0.178	0.238	0.821
Research & Development abundance (3)	Researchers per 100 labor force (1996)	Midelfart-Knarvik et al. (2000b)	0.477	0.163	0.200	0.780
Environmental standard laxity (4)	One minus the Environmental Sustainability Index/100 (2001)	World economic forum, Yale center for environmental law and policy, and CIESIN	0.365	0.093	0.195	0.559
Market potential (5, 6, 7)	Indicators of market potential based on own and trading partners' GDP in 00000 £ (around the year 1990)	Midelfart-Knarvik et al. (2000b)	0.086	0.041	0.023	0.133
Instrumental variables (for the environmental stringency variable)						
	Corruption (1995)	Transparency International: http://www.transparency.org/	3.03	2.12	0.68	7.01
	Income per capita in log (1992)	OECD: http://webnet.oecd.org/WBOS/index.aspx	9.78	0.18	9.37	9.96
	Schooling (average schooling years of people over 25 years of age in 1990)	CID (Harvard):http://www.cid.harvard.edu/ciddata/ciddata.html	7.97	1.61	4.15	10.01
	Urbanization (% of people living in urban areas in 1997)	Eurostat: http://epp.eurostat.ec.europa.eu/portal/page/portal/product_details/dataset?p_product_code=LFSA_PGAUWS	0.95	0.11	0.61	1.00

Notes: The 13 countries with the values of their respective characteristics are reported in the Appendix in Table 7

Table 2 Industry characteristics

Variable (interaction channel)	Definition	Source	Mean	SD	Min	Max
Log Industry shares	Average share of industry k in country i over 1991–1994	OECD STAN industrial database 1998	−3.30	1.32	−7.20	−0.94
Agricultural input intensity (1)	Total use of agricultural input as a share of value of production (weighted average of Denmark, Germany, France and UK for 1990)	OECD input-output table, 1990	0.019	0.057	0.000	0.234
Skilled labor intensity (2)	Average pay in industry relative to the pay in manufacturing as a whole which is one (1990)	OECD STAN indicators database 2005	1.085	0.194	0.706	1.407
R&D intensity (3)	Research & development expenditure as a share of value added (1990)	OECD ANBERD, 1973–1998	0.086	0.113	0.002	0.357
Pollution intensity 1 (4)	Pollution abatement and control costs as a share of the value of industry output in the USA for 1988	Low and Yeats (1992)	0.733	0.581	0.235	2.170
Pollution intensity 2 (4)	Weight of releases of toxic substances (average over 1990–1995 normalized by the value of shipments for 1992)	US environmental protection agency	1.670	1.874	0.122	5.483
Intermediate input use (5)	Total use of intermediates as a share of value of production (weighted average of Denmark, Germany, France and UK for 1990)	OECD input–output table, 1990	0.419	0.155	0.000	0.612
Sales to industry (6)	Sales to domestic industry (as intermediates and exports) as a share of value of production (weighted average of Denmark, Germany, France and UK for 1990)	OECD input–output table, 1990	0.403	0.224	0.000	0.740
Plant size (7)	Indicator of economies of scale: number of employees per plant (1988)	Pratten (1988)	4.769	4.559	0.378	15.000

Notes: The 16 industries (ISIC Rev.2 codes) with the values of their respective characteristics are reported in the appendix in Table 8. The ‘Petroleum & Coal products’ and ‘Other Manufacturing’ industries have been excluded because the former is virtually a natural resource industry and the latter is a ‘residual’ and cannot plausibly be described as a particular industry values of these industry attributes reported in Table 2. If an industry attribute's cut-off point is close to the minimum value of that industry attribute, this means that an increase in the corresponding country characteristic will attract industry activity, for the sample of industries as a whole. If an attribute's cut-off point is close to the maximum value of that industry attribute, this means that an increase in the corresponding country characteristic will repel industry activity, for the sample of industries as a whole. If the cut-off point is in between, an increase in the associated country characteristic implies a more selective firm activity, but not necessarily an overall increase or decrease.

We notice that the country characteristics cut-off levels χ^j do not appear in the analysis of firm location's response to a change in country characteristics (Eq. 3), and thus we will not further discuss them.

The expression in (3) also reveals that the marginal effect of a change in a country characteristic j on the share of an industry located within it is proportional to the interaction coefficient β^j, and the difference between the industry's attribute level y_k^j and the cut-off point γ^j. Estimation of β^j and γ^j therefore permits these marginal effects to be estimated. Substitution of the estimated coefficients $\hat{\beta}^j$ and $\hat{\gamma}'^j$ gives, for any given industry attribute levely_k^j, the variance of the estimated marginal effect in (3):

$$\text{var}[\hat{\beta}^j(y_k^j - \hat{\gamma}^j)] = (y_k^j)^2\text{var}[\hat{\beta}^j] + \text{var}[\hat{\gamma}'^j] - 2y_k^j\text{cov}[\hat{\beta}^j, \hat{\gamma}'^j]. \tag{4}$$

Thus, estimation of $\hat{\beta}^j$ and $\hat{\gamma}'^j$ allows us to plot the marginal effect and associated confidence interval of environmental policy on industry location, as dependent on the industry's pollution intensity. This approach of calculating regions of significance and confidence bands for evaluating conditional effects is known as the Johnson–Neyman (J–N) technique (Huitema 1980). Clearly the J–N technique has advantages over the more common approach which would involve testing the conditional effects at designated levels of environmental stringency (e.g., high, medium, or low (Bauer and Curran 2005)).

Although the focus here is environmental (pollution intensity and the stringency of environmental regulation) the procedure and insights are general. For example, one could estimate the marginal effect of changes in a nation's level of skilled labour on its share of skill-intensive industries.

4 Data

We base our analysis on a one-period cross-country cross-industry sample. The sample includes 13 countries and 16 industries. The choice of the period (average of 1990–1994) was dictated by availability of most of the explanatory variables.[11] Descriptions of the variables and data sources are presented in Tables 1 and 2. The discussion here is limited to some relevant issues not contained in the table and a further description of the main variables of interest in this paper, i.e. the environmental variables. Data on each of the country characteristics pertain to around the year 1990 and are obtained from Midelfart-Knarvik et al. (2000b). Input–output data (i.e. agricultural intensity, intermediate input intensity and industry sale) are constructed as (output) weighted averages of the data for Denmark, Germany, France and the UK for 1990. The environmental standard laxity variable is constructed as one minus the *Environmental Sustainability Index* (scaled to [0, 1]) which is constructed jointly by World Economic Forum, Yale Center for Environmental Law and Policy, and Center for

[11] We have also experimented with each of the five individual year values for the left hand side variable. The results are fairly similar.

Table 3 Regression results

Dependent variable: ln(s_{ik})	Model			
	I	II	III	IV
Size variable				
Population	1.04***	1.04***	1.04***	1.04***
Interaction channels (β^j)				
Agricultural abundance × intensity	31.44*	32.10*	35.16**	35.22**
Skilled labor abundance × intensity	1.83	1.81	1.97	1.96
R&D abundance × intensity	4.04**	4.18**	4.66**	4.78**
Environmental laxity × poll. Intensity	1.21**	0.40**	1.20**	0.41**
Market potential × Sales to industry	−5.60	−5.67		
Market potential × Intermediate input use	−4.52	−4.18		
Market potential × Plant size	0.17	0.16		
Country characteristics cut-off points (χ^j)				
Agricultural abundance	−0.02	−0.01	0.01	0.004
Skilled labor abundance	0.95	0.93	0.88	0.80
R&D abundance	0.16	0.15	0.45	0.49
Environmental standards laxity	0.23	0.24	0.21	0.26
Market potential	0.19	0.19		
	0.07	0.09		
	0.17	0.20		
Industry attributes cut-off points (γ^j)				
Agricultural input intensity	0.46	0.45	0.42	0.41
Skilled labor intensity	1.05	1.05	1.04	1.04
R&D intensity	0.03	0.03	0.04	0.04
Pollution intensity	0.87	2.08	0.86	2.04
Sales to industry[a]	0.41	0.41		
Intermediate input use[a]	0.41	0.41		
Plant size[a]	4.09	4.09		
N	208	208	208	208
Adj. R^2	0.84	0.84	0.84	0.84

Notes: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1%

[a] The fifth, sixth and seventh interaction effects all use the same country characteristic Market Potential. As a result, in Eq. (2), $x^5 = x^6 = x^7$, consequently we cannot estimate γ'^5 separately from γ'^6 and γ'^7 to identify the cut off points. Since the first two associated industry attributes (sales, intermediate input use) are of about the same size, while the third attribute (plant size) is about ten times larger (Table 2), we impose $\gamma^5 = \gamma^6$ and $\gamma^7 = 10 \cdot \gamma^5$, and this condition enables us to identify the cut off points

International Earth Science Information Network, Columbia University. This index refers to the year 2001 and is based on a total of 67 underlying variables (such as environmental regulatory stringency, environmental regulatory innovation and number of EIA guidelines).[12,13]

[12] This index is also used in Javorcik and Wei (2004).

[13] We have also experimented with an alternative measure of environmental regulation stringency from the Global Competitiveness Report 2001–2002, published by the World Economic Forum. The main results using

The time frame of the environmental sustainability index raises the issue of endogeneity, as nations' environmental policy might be driven by the industries located within them. It can be argued that environmental policy is unlikely to vary dramatically annually, or at least the ranking across the sample, in the time period considered here. However, to check for an endogeneity problem, we carry out a robustness analysis where we use corruption in 1995, income in 1992, urbanization in 1997, and schooling in 1990 as instruments (based on Pellegrini and Gerlagh 2006a). The results are reported in Table 11 and fully confirm the results of the base analysis. We do not use the instruments for the main analyses in this paper, as this would make our discussion of the implications of real versus possible counterfactual environmental policies unnecessarily opaque.

We use two alternative measures of pollution intensity. The first measure is taken from Low and Yeats (1992) who provide estimates of pollution abatement and control costs as a share of the value of industry output in the USA for the year 1988. The second measure is based on the Toxic Release Inventory (TRI) data compiled by the US Environmental Protection Agency. The TRI data catalogues releases of various types of emissions into air, water, land and underground for each manufacturing industry group in the US. Such emissions measured by weight for the year 1990–1995 are averaged and normalized by the value of industry shipments for the year 1992.[14] The full data on all the explanatory variables are reported in the appendix in Tables 7 and 8.

5 Results and Discussion

Table 3 reports the results of the Ordinary Least Squares Robust Error estimation of Eq. (1) for four different specifications. Models I and II use the full model with the NEG and HO interaction channels, with two different specifications for the industry pollution intensity attribute. Models III and IV use only the first four HO variables, again with alternative measures of the industry pollution intensity attribute. Models I and III use abatement costs, and Models II and IV use industry emissions, as the measure of pollution intensity.

For all models, the estimated coefficients for the interaction channels β reported in Table 3 are expected to have positive signs. The estimations confirm the expectations for the HO channels. Thus, industries with large inputs from agriculture tend to locate in countries with a

Footnote 13 continued
this measure of stringency are reported in the Appendix (Table 9 being the equivalent of Table 3 and Table 10 the equivalent of Table 5). These results confirm our finding of significant positive coefficients for the interaction channel (with the two alternative pollution intensity variables discussed below) but gave a wider uncertainty interval for the marginal effects per industry as in Eq. (4). We have further considered other measures of stringency. One measure is reported in van Soest et al. (2006). This measure is based on the shadow price of energy and is calculated for two sectors: one for primary metals sector and another for food and beverages. The coefficient of correlation between each of these two and our measure, ESI are, respectively, −0.26 and 0.41. Whatever the merit of these two indicators of stringency, they are available for only 9 out of the 13 countries in our sample. There are four more indicators that appeared in the literature and as argued by van Soest et al. (2006) each has shortcomings as a measure of stringency. A practical problem is that most of them are only available for a subset of our countries. Nonetheless each is positively correlated with our measure, ESI.

[14] Our second measure of pollution intensity is also used in Javorcik and Wei (2004). These authors also employ an alternative measure of pollution intensity similar to our first measure, i.e. based on pollution abatement expenditure. A third measure that we considered is based on Greenhouse Gas Emissions in UK manufacturing industries (available from UK Environmental Accounts). We normalised this data for 1990 by the value of output of the respective industry in order to proxy intensity. The resulting measure is positively correlated with our two measures (correlation coefficients of 0.57 and 0.34, respectively). However, we did not pursue this alternative measure because, unlike the other two measures, it is based on GHG emissions only.

large agricultural industries, industries with above-average valued labor input tend to locate in countries with an above-average skilled population, R&D intensive industries tend to locate in R&D rich countries, and indeed, industries that are relatively more pollution intensive (such as Industrial Chemicals and Drugs & Medicines) are attracted to countries which have relatively lax environmental standards. We note that although the β coefficient for skilled labour is not significant in Table 3, we show later that the level of skilled labour supply has a significant positive effect on the share of the most skilled-labor intensive industry (see Table 5).

The additional three NEG variables, however, do not all have the expected sign and are insignificant. A formal test of comparing the full model with the model of only the HO variables (including the environmental variable) amounts to a test of whether the estimates of the coefficients of the NEG variables are jointly zero. If so, the parsimonious model is preferred. The F statistic ($F[7, 187]$) for the hypothesis of an HO model is 1.62 for Model I and 1.81 for Model II which, given a critical value at the 5% significance level of 2.01, indicates that the null hypothesis that the HO model is appropriate cannot be rejected. We therefore omit the NEG variables and confine further analysis to Models III and IV. By comparing models I with III and II with IV, we see that the strength of the pollution interaction effect is robust with respect to the inclusion or exclusion of the NEG channels. For all other interaction effects, we also find robust results. This insignificance of the NEG variables contrasts with the finding of Midelfart-Knarvik et al. (2000a) who report significant estimates for the market potential variable but their findings do not seem to be particularly robust as can be seen from Midelfart-Knarvik et al. (2000a).

Using Eq. (3), a comparison of the industry's cut-off points with the mean value informs us on the effect of the country characteristic on the average industry within our sample. The first remarkable finding is that the cut-off point for agricultural intensity is above the maximum attribute level observed in the sample. Thus, as Eq. (3) predicts, for all industries within the sample, the industry share in a country decreases as agriculture's contribution to that country's GDP increases. For the food processing industry (the most intensive industry), the decrease is relatively modest, whereas for the non-ferrous metal industry (the least agriculture-intensive industry), the effect is very large. An explanation for this finding is that, in general, manufacturing and agriculture are strongly negatively correlated. For all other factor inputs, the cut-off point is between the minimum and maximum industry attribute level, signifying that more intensive industries are attracted by the more resource abundant countries, while less intensive industries typically locate in countries that are less resource abundant for that specific resource. For skilled labor, the cut-off point (1.04) is below the industry's attribute's mean (1.08), which means that within our sample, on average, industries are attracted by countries with higher levels of skilled labor. Regarding R&D intensity, the cut-off point (0.04) is also below the mean (0.087) so that, on average, firms are attracted by R&D-rich countries. For both measures of pollution intensity, the cut-off points (0.86 and 2.04) are above the sample means (0.73 and 1.67) meaning that, on average, firms are not attracted by lax environmental policies, or stated inversely, are not deterred by stricter environmental policy. This result is a first indication that strict environmental policy does not deter manufacturing industries in general. That is, even though the most pollution-intensive industries show a significant smaller share in countries with strict environmental policies, on average, within our sample, industries do not prefer to locate in countries with lax environmental policies.

The coefficients reported in Table 3 do not allow one to assess the relative importance of the various interaction channels. To allow such an assessment of the relative importance of the various interaction effects, the estimated cut-off points from Eq. (2), as presented in

Table 4 Standardized coefficients of interaction effects at the jointly estimated cut off points

	Model	
	III	IV
Agricultural abundance × intensity	0.298*	0.298*
Skilled labor abundance × intensity	0.096	0.077
R&D abundance × intensity	0.071**	0.072**
Environmental laxity × poll. intensity	0.096**	0.103**

Table 5 Marginal effects of country characteristics evaluated for the most intensive industries

	Model			
	III	IV	III′	IV′
Agricultural abundance	−6.365**	−6.351**	−0.131**	−0.131**
Skilled labor abundance	1.912*	1.909*	0.097*	0.097*
R&D abundance	1.470**	1.502***	0.182**	0.185***
Environmental stand. laxity	1.565**	1.408**	0.110**	0.099**

Notes: Columns (III′) and (IV′) present coefficients for normalized dependent and independent variables with unit SD
* Significant at 10% level; ** Significant at 5% level; *** Significant at 1%

Table 3, are substituted in (1) and the dependent variable and independent variables are normalized. Expressed in this manner, the estimated coefficients are standardized and hence are comparable. In other words, we are measuring here the effects on the dependant variable in terms of standard deviation units. The resulting standardized coefficients (which Wooldridge 2009, p.188 refers to as "beta-coefficients") are independent of the scaling of the regressors and are reported in Table 4. That is, the choice for the unit of measurement for the country characteristics and industry attributes does not affect the coefficients reported in Table 4, and thereby the explanatory variables are put on equal footing.

Considering the standardized coefficients reported in Table 4, we note that the agriculture interaction remains the single largest determinant for industry location. The interaction between environmental policy and pollution intensity is of next greatest magnitude but is, in size, not much larger than the skilled labour and R&D interaction effects. The relative importance of the four interaction channels is robust across the four model specifications (although only standardized coefficients from Models III and IV are reported here).

The coefficients reported in Table 4 provide a general measure of the relative importance of the various interaction effects but we are also interested in the more specific strength of the interaction effects for the most intensive industries, that is, we may ask how strongly an abundance of skilled labor attracts the most skill-intensive industries, compared to how strongly a lax environmental policy attracts the most pollution intensive industries. For this, we use Eq. (3). We recall that the marginal effect on the industry share of a change in the country characteristic j is proportional to the interaction coefficient β^j as presented in Tables 3 and 4, and to the distance between the industry's attribute level y_k^j and the cut-off point γ^j. Thus, for industries above the cut-off point, an increase in the country characteristic will increase the industry share, while for industries below the cut-off point, an increase in the country characteristic will decrease the share. Table 5 presents the marginal effects of country characteristics on location for the most resource-intensive industries, that is, Eq. (3) evaluated at the maximum industry attribute level. We only report the HO interaction models (III and IV). For these models, we find that all four country characteristics are significant determinants for location of the most intensive industries, including skilled labour abundance.

Agricultural abundance does not have the expected positive effect on the location of the food processing industry. The sign is negative because the cut-off point is above the maximum attribute level observed in the sample, as discussed above. The magnitude of the three other country characteristic marginal effects appear similar in Columns (III) and (IV), but for a proper comparison, in Columns (III′) and (IV′), we report the marginal effects using the standardized independent and dependent variables. Thus, it can be seen that in Models III and IV, a one standard deviation increase in the skilled labor supply increases the share of the most skilled-labor intensive industry (drugs and medicines) by about 0.1 times the standard deviation. The scale of the environmental policy effect for the dirtiest industry (industrial chemicals) is similar to this skilled labour effect, but the responsiveness of R&D intensive industries to a one standard deviation change of R&D abundance is far greater.

Figure 1 portrays in more detail the importance of a country's environmental policy on its share of particular industries.[15] It is based on Eqs. (3) and (4) and uses results from Model III. It shows the marginal effect of environmental policy on the production share conditioned on the pollution intensity of the industry, with a 90% confidence interval added. The upward slope of the solid line represents the marginal effect of environmental standard laxity for different levels of pollution intensity, as depicted by Eq. (3). The figure shows the cut-off point 0.86, where the solid line crosses the x-axis. For this level of pollution intensity, environmental laxity has no effect on location. For the industries to the left of this point a more stringent environmental policy increases the industry share.[16] To the right of this point a more environmentally lax policy may attract a higher industry share. The 90% confidence intervals around the line permit us to evaluate at which values of pollution intensity environmental standard laxity has a statistically significant impact on production shares.

A lax environmental policy has a statistically significant positive effect on industry share when the pollution intensity level is above 1.86, above which there is only one pollution intensive industry in our sample. On the right side of the figure, we find the pollution intensive industries such as Industrial Chemicals, (with the highest intensity, labelled 'H'). On the left side of the figure, we find the majority of the industries that are less pollution intensive (the average and median value of pollution intensity are shown as 'A' and 'M', respectively). The 'cleanest' industry with the lowest pollution intensity level (Radio, TV and Communication Equipment) is shown by the point labelled 'L'.

The graph indicates that while the pollution haven effect is present its negative effect on industry location is significant only at relatively high levels of pollution intensity. At

[15] This figure was constructed using the web-based tool of Preacher et al. (2003) (http://www.people.ku.edu/~preacher/interact/mlr2.htm), see also Brambor et al. (2006).

[16] Though in this specific case, there are no industries where strict environmental policy has a significantly positive effect on their share, the model does not rule out this possibility. A possible explanation for such a positive relationship is that countries with strict environmental policies also have high levels of attractive characteristics such as good governance or low corruption levels, see Mulatu et al. (2004), Pellegrini and Gerlagh (2006b).

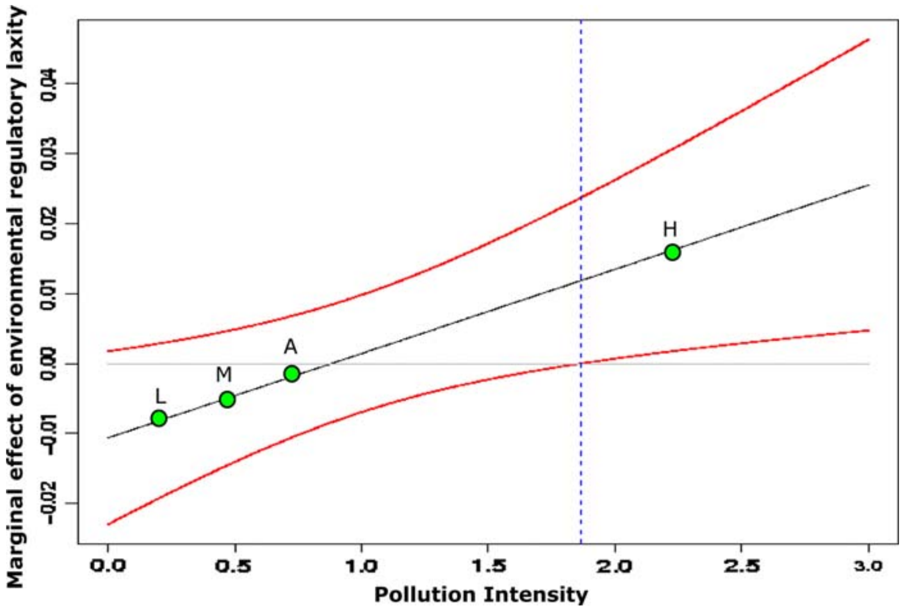

Fig. 1 The marginal effect of environmental standard laxity on production shares

Table 6 Actual, predicted and counterfactual production shares

Most intensive industry	Agricultural input	Skilled labor input	R&D input	Environmental input
	Food, beverages and tobacco	Drugs and medicines	Radio, TV and communication equipment	Industrial chemicals
Actual shares (%)				
1. Most abundant country and its production share	Greece: 1.7	Denmark: 1.7	Sweden: 2.7	Belgium:4.8
2. Least abundant country and its production share	Belgium: 5.6	Portugal: 1.3	Greece: 0.3	Finland: 1.0
Predicted shares (%)				
3. Most abundant country	2.9	1.8	4.1	7.3
4. Least abundant country	4.8	1.3	0.5	0.8
Counterfactual shares when countries would swap abundance values (%)				
5. Most abundant country	5.2	1.2	1.7	3.1
6. Least abundant country	2.7	1.9	1.1	2.0
% point difference between predicted and counterfactual shares				
(3)–(5)	−2.3	0.6	2.4	4.2
(6)–(4)	−2.1	0.6	0.6	1.2

Note: Estimates are based on the regression with pollution intensity variable 1 moderate levels of pollution intensity, the influence of environmental standard would be small compared to other forces, and at low levels of pollution intensity, strict environmental standards are not a deterrent at all.

Finally, in Table 6 we compare our estimated industry shares with observed shares and we calculate counterfactual industry shares: predicted shares if country characteristics (e.g. environmental policy) changed. We do this first by comparing estimated and actual industry shares for the most intensive industries in terms of each of agriculture, skills, R&D and pollution intensity. In each case we compare these actual and predicted shares for the most and least abundant countries in the respective input. We then simulate these shares if, in each case, the most abundant country would become least abundant, and vice versa.

The comparison of the predicted and actual shares gives an idea of the fit of the model. A comparison of the counterfactual with the predicted shares answers the question how important the specific country characteristic is in determining the industry share. If the most abundant country in a particular factor were to have the level of endowment of the least abundant country what would be its share of production? The reverse also holds for the case of the least abundant country. With respect to the environmental factor input, we find that the model predicts a share of 7.3% of the most pollution intensive industry's production (Industrial chemicals) in the country with the most lax environmental standard (Belgium), compared with an actual share of 4.8%. The model predicts a share of only 0.8% in the most environmentally stringent country (Finland) while the actual figure is 1.0%.

If Belgium were to adopt the most stringent environmental regulation from Finland, the model predicts a decline of the share by more than half, that is, 4.2% point. If Finland were to copy the lax standards of Belgium, it would see its share increase by more than a factor two, that is, 1.2% point. A change in R&D country characteristics has a similar effect in the sense that if Sweden would decrease its number of researchers per thousand to the level of Greece, its share of the Communication equipment industry is predicted to halve, while if Greece could copy Sweden's research abundance, it would see its share double. As both countries are fairly small, in absolute terms the change in industry shares would be less compared to the environmental policy change. A change in the abundance of skilled labor has somewhat less substantial consequences.

6 Concluding Remarks

This paper is an empirical analysis of the extent to which environmental regulation influences industry location in Europe vis-à-vis other location determinants, mainly the traditional HO factor endowment forces.

The analysis is based on a general empirical trade model. It has a distinctive feature in that it models the theoretically-emphasized joint role of country and industry characteristics in determining industry location. The model is applied to data on 16 manufacturing industries from 13 European countries. The Johnson–Neyman technique is used to address the interactive terms in the empirical model and to calculate regions of significance and confidence bands for evaluating the conditional effects.

This dataset covers countries with stringent environmental regulation like Finland and Sweden, and countries with relatively lax environmental regulation such as Greece and Belgium. With respect to industries, the dataset includes the most pollution intensive industries such as Industrial Chemicals as well as relatively clean industries such as Radio, TV & Communication Equipment.

The results indicate that the *pollution haven effect* can be uncovered, and the relative magnitude of this effect is about the same as that of other determinants of industry location. This might be interpreted as finding the *pollution haven effect* but failing to support the *pollution haven hypothesis*.

Specifically, we find in our sample that whereas an increase in the skilled labour supply increases the share of an industry with mean levels of characteristics, in contrast, increased environmental regulatory laxity does not result in an increased share of the 'average' industry. However, when the most polluting, rather than the average, industry is considered, increased environmental regulatory laxity does result in a higher proportion of this dirty industry locating there. The approach presented could be developed in a number of ways in future research, for example the issue of endogeneity of environmental policy in this framework, and the use of panel data for more robust estimation.

Appendix

See Tables 7, 8, 9, 10 and 11.

Table 7 List of countries with the values of their characteristics

Country	Population (average, 1990–1994)	Agricultural production as % GDP	Secondary and higher education % population	Research and scientists % labor force	Market potential	Environmental regulation stringency[a]
Austria	2.1	3.2	75.1	34	12303	67.9
Belgium	2.7	1.9	60.6	53	13264	44.1
Denmark	1.4	4.5	82.1	58	6627.8	67
Finland	1.4	6.6	72.6	67	3642.1	80.5
France	15.9	3.5	62.7	60	12380	65.8
Germany	21.9	3	82.1	59	13073	64.2
Greece	2.8	12.5	49.3	20	2335.7	53.1
Italy	15.5	4.1	41.4	32	8715.1	54.3
Netherlands	4.1	4	65.9	46	12840	66
Portugal	2.7	7.3	23.8	31	3193.8	61.4
Spain	10.6	5.4	35.1	32	4993.2	59.5
Sweden	2.4	3.4	76.7	78	5810.5	77.1
UK	15.7	2	55.3	50	12226	64.1

Notes: Definitions of variables and data sources are presented in Table 1

[a] *Environmental standard laxity* is therefore the inverse of these figures

Table 8 List of industries with the values of their characteristics

ISIC Rev.2 codes	Agricultural intensity	Skill intensity	R&D intensity	Pollution intensity 1	Pollution intensity 2	Intermediate input intensity	Industry sales	Plant size
Food, beverages and tobacco	0.2579	90.2	0.0131	0.3275	0.1217	0.6152	0.26	2.23
Textiles, apparel and leather	0.0055	70.6	0.0055	0.3109	0.6337	0.4169	0.2652	0.38
Wood products and furniture	0.0426	75.5	0.0022	0.5273	0.9499	0.4833	0.4002	1.8
Paper, paper products and printing	0.0035	109.6	0.007	0.6031	1.1395	0.4534	0.6878	1.4
Industrial chemicals	0.0005	134.9	0.0658	2.17	5.4826	0.4521	0.4065	5.71
Drugs and medicines	0.0001	140.7	0.2871	1.71	5.4826	0.4131	0.207	5.71
Rubber and plastic products	0.0029	104.8	0.0221	0.442	1.4784	0.3688	0.5971	3.5
Non-metallic mineral products	0.0002	103	0.012	0.8556	0.6576	0.4653	0.7484	0.98
Iron and steel	0.0001	121.7	0.0266	1.61	4.1136	0.5411	0.673	6.26
Non-ferrous metals	0	107.6	0.0265	1.0975	4.1136	0.3945	0.5166	15
Metal products	0.0001	91.4	0.0101	0.4883	0.8901	0.4328	0.5504	0.65
Non-electrical machinery	0.0001	133.8	0.289	0.3827	0.1695	0.4579	0.2144	10
Electrical apparatus, nec.	0.0001	114.1	0.0793	0.332	0.3765	0.429	0.3785	4.67
Radio, TV and communication equipment	0.0001	114.4	0.3566	0.235	0.3765	0.3979	0.2158	14.5
Transport equipment	0.0001	119.5	0.0966	0.3671	0.4287	0.4814	0.1786	3
Professional goods	0.0002	103.6	0.0818	0.2657	0.309	0.3802	0.1704	0.5
Mean	0.02	108.463	0.086	0.733	1.67	0.449	0.404	4.768
Median	0	108.6	0.027	0.465	0.774	0.442	0.389	3.25

Notes: Definitions of variables and data sources are presented in Table 1. The industry classification involves slight modifications from the standard ISIC Rev.2 codes, namely that sub-industries of transport equipment and of non-electrical machinery are aggregated because of missing data for some countries

Table 9 Regression results of the determinants of industry location (with the stringency measure from Global Competitiveness Report 2001–2002)

Dependent variable: $\ln(s_{ik})$	Model			
	I	II	III	IV
Size variable				
Population	1.06***	1.06***	1.07***	1.07***
Interaction channels (β^j)				
Agricultural abundance × intensity	34.48***	34.49***	41.56***	43.17***
Skilled labor abundance × intensity	2.92**	2.88**	3.25**	3.09**
R&D abundance × intensity	3.23*	3.41*	3.60*	3.94**
Environmental laxity × poll. intensity	1.98**	0.67**	2.15**	0.67**
Market potential × sales to industry	−3.29	−2.96		
Market potential × intermediate input use	−4.96	−6.14*		
Market potential × plant size	0.23*	0.27**		

Notes: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1%

Table 10 Marginal effects of country characteristics evaluated for the most intensive industries (with the stringency measure from Global Competitiveness Report 2001–2002)

	Model	
	III	IV
Agricultural abundance	−1.89	−1.54
Skilled labor abundance	2.41*	2.26*
R&D abundance	1.20**	1.29***
Environmental stand. laxity	0.99	0.44

Notes: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1%

Table 11 Interaction effects using instruments

Dependent variable: $\ln(s_{ik})$	Model			
	III	IV	III	IV
Size variable				
Population	0.98***	0.98***	1.02***	1.02***
Interaction channels (β^j)				
Agricultural abundance × intensity	37.7***	38.4***	42.6***	44.1***
Skilled labor abundance × intensity	2.45*	2.32*	3.11**	2.92**
R&D abundance × intensity	4.26**	4.53**	3.70*	4.05**
Environmental laxity × poll. intensity	2.03**	0.62**	2.09**	0.64**
Instrumented variable	Environmental sustainability index (2001)		Environmental regulation stringency (2001)	

Table 11 continued

Dependent variable: ln(s_{ik})	Model			
	III	IV	III	IV
Instruments (only instruments with significant coefficients are used)	Corruption (1995)***		Corruption (1995)***	
	Urbanization (1997)**		Income (1992)***	
			Schooling (1990)**	
R^2 adj first-stage	50%		94%	

Notes: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1%

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