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Why the Grass is not Always Greener: The Competing Effects of Environmental Regulations and Factor Intensities on US Specialization

by

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Abstract

The global decline in trade barriers means that environmental regulations now potentially play an increasingly important role in shaping a country's comparative advantage. This raises the possibility that pollution intensive industries will relocate from high regulation countries to developing regions where environmental regulations may be less stringent. We assess the evidence for this possibility by examining the USA's revealed comparative advantage (RCA) and other measures of specialization. We demonstrate that US specialization in pollution intensive sectors is neither lower, nor falling more rapidly (or rising more slowly) than in any other manufacturing sector. We offer an explanation for this finding. Our analysis suggests that pollution intensive industries have certain characteristics - specifically they are intensive in the use of physical and human capital - that makes developing countries less attractive as a target for relocation. We demonstrate how they appear to oppose the effects of environmental regulations as determinants of US specialization.

JEL codes: Q28, R38, F23

Keywords. Pollution Haven Hypothesis, FDI, Revealed Comparative Advantage, Environmental Regulation.

Outline

- 1. Intoduction
- 2. Specialisation Indices
- 3. Specialization and the Characteristics of US Industry
- 4. Econometric Analysis
- 5. Discussion and Conclusion

Non-Technical Summary

During the last twenty-five years a variety of factors have contributed to the continuous evolution of the structure of US industry. One factor that has been given a great deal of attention is the general reduction in trade barriers - often cited as one of the main causes of the rise in competitive pressures faced by US industries. Alongside this decrease in trade barriers has been an increase in the stringency of US environmental regulations leading to concerns that pollution intensive industries, in particular, are being exposed to some of the fiercest competition from overseas.

The fear of a loss of competitiveness as a result of US environmental regulations is best illustrated by the debate surrounding the US refusal to ratify the Kyoto Protocol climate change treaty. President Bush has stated that since the treaty excludes the developing world from binding emissions reductions, its ratification would cause serious harm to the US economy. Both unions and trade associations have echoed this sentiment. The federation of US unions (the AFL-CIO) has claimed that the Kyoto Protocol would create a powerful incentive for industries to 'export jobs, capital and pollution,' whilst the Business Roundtable has claimed that increased environmental regulations in the US would 'lead to the migration of energy-intensive production - such as the chemicals, steel, petroleum refining, aluminium and mining industries - from the developed countries to the developing countries.'

A number of theoretical studies have provided similar conclusions. As a result of this debate there is a growing body of literature that examines the economic effects of environmental regulations and the extent to which they shape a country's comparative advantage. Whilst it may appear intuitively plausible that environmental regulations will affect US competitiveness, evidence of the migration or displacement of dirty industries from high regulation economies is mixed. As a result, a number of arguments have emerged to explain why clearer evidence of pollution haven pressures has not been For example, it has been argued that environmental regulations may be found. endogenously determined by trade since they may be used as secondary trade barriers i.e. a means of protecting domestic industry. Both of these studies find that US environmental regulations, when treated as an endogenous variable, do influence US trade patterns. Other explanations offered include the fact that environmental compliance costs are likely to form a small proportion of a firm's total costs; the dependence of heavy industries on home markets; the fact that low regulation countries may have certain characteristics which deter inward investment such as corruption, poor infrastructure and uncertain or unreliable legislation; and the possibility that foreign investors may be concerned about their international reputation and do not wish to be perceived to be taking advantage of slack environmental regulations.

In this paper we highlight an additional explanation of why environmental regulations do not appear to have had a widespread impact on trade and investment flows, namely the role played by an industry's human and physical capital requirements. First,

we employ a range of industrial specialization indices to investigate graphically and descriptively whether the effect of the relative stringency of US environmental regulations has resulted in low and/or declining specialization in 'dirty' production as the pollution haven hypothesis predicts. Second, we examine the characteristics of pollution intensive industries and demonstrate that such industries tend to have two common features; (i) they are typically physical capital intensive, (ii) they tend to be relatively human capital intensive, a point not previously demonstrated. Third, we test these assertions by estimating econometrically the determinants of specialization. We demonstrate the statistical and economic significance of a number of key variables and estimate a range of specifications controlling for the potential endogeneity concerns discussed in the recent trade-environment literature.

1. Introduction

During the last twenty-five years a variety of factors have contributed to the continuous evolution of the structure of US industry. One factor that has been given a great deal of attention is the general reduction in trade barriers - often cited as one of the main causes of the rise in competitive pressures faced by US industries. Alongside this decrease in trade barriers has been an increase in the stringency of US environmental regulations leading to concerns that pollution intensive industries, in particular, are being exposed to some of the fiercest competition from overseas.

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A number of theoretical studies have provided similar conclusions (see e.g Pethig 1976, McGuire 1982 and Chichilnisky 1994). Baumol and Oates (1988), for instance, state that those countries that do not control pollution emissions, whilst others do, will 'voluntarily become the repository of the world's dirtiest industries' (p. 265). As a result of this debate there is a growing body of literature that examines the economic effects of environmental regulations and the extent to which they shape a country's comparative advantage (see e.g. Tobey 1990, Copeland and Taylor 1994, Antweiler, Copeland and Taylor 2001, Cole and Elliott 2003, Kahn 2003, Copeland and Taylor 2004).

¹ AFL-CIO Executive Council February 20th 1997.

² From a letter by the President of the Business Roundtable to President Clinton, May 12th 1998.

Whilst it may appear intuitively plausible that environmental regulations will affect US competitiveness, evidence of the migration or displacement of dirty industries from high regulation economies is mixed.³ As a result, a number of arguments have emerged to explain why clearer evidence of pollution haven pressures has not been found. Ederington and Minier (2003) and Levinson and Taylor (2004), for example, argue that environmental regulations may be endogenously determined by trade since they may be used as secondary trade barriers i.e. a means of protecting domestic industry. Both of these studies find that US environmental regulations, when treated as an endogenous variable, do influence US trade patterns. Other explanations offered include the fact that environmental compliance costs are likely to form a small proportion of a firm's total costs; the dependence of heavy industries on home markets; the fact that low regulation countries may have certain characteristics which deter inward investment such as corruption, poor infrastructure and uncertain or unreliable legislation; and the possibility that foreign investors may be concerned about their international regulations.⁴

The aim of this paper is to highlight an additional explanation of why environmental regulations do not appear to have had a widespread impact on trade and investment flows, namely the role played by an industry's human and physical capital requirements. Focusing on the USA, the contribution of this paper is threefold: First, we employ a range of industrial specialization indices to investigate graphically and descriptively whether the effect of the relative stringency of US environmental regulations has resulted in low and/or declining specialization in 'dirty' production as the pollution haven

³ For example, Tobey (1990), Jaffe *et al.* (1995) and Janicke *et al.* (1997) find no evidence to suggest that the stringency of a country's environmental regulations influences trade in dirty products. In contrast, a study of import-export ratios for dirty industries by Mani and Wheeler (1998) found evidence of temporary pollution havens, while Lucas *et al.* (1992) and Birdsall and Wheeler (1992) found that the growth in pollution intensity in developing countries was highest in periods when OECD environmental regulations were strengthened. Antweiler *et al.* (2001) studied the impact of trade liberalization on city-level sulfur dioxide concentrations and found some evidence of pollution haven pressures, a result supported by a complementary study by Cole and Elliott (2003). Van Beers and Van den Bergh (1997) also found evidence to suggest that regulations influence trade patterns, although Harris *et al.* (2002) claim that no such influence is found if fixed effects are included.

⁴ See Neumayer (2001) for a review of these issues.

hypothesis predicts. Second, we examine the characteristics of pollution intensive industries and demonstrate that such industries tend to have two common features; (i) they are typically physical capital intensive, as has recently been recognised (Antweiler et al., 2001, and Cole and Elliott, 2003), (ii) they tend to be relatively human capital intensive, a point not previously demonstrated. It would appear that the industrial processes that require a highly skilled workforce are often those processes that are the most pollution intensive. In contrast, low-skill, labor-intensive processes tend to be relatively clean. Thus, dirty sectors are generally intensive in physical and/or human capital, two factors that appear to be important determinants of US specialization and which explain why relocation to developing countries may be less desirable for such industries. We argue that this explains why US specialization in dirty sectors is neither lower, nor falling more rapidly, than in clean sectors. Third, we test these assertions by estimating econometrically the determinants of specialization. We demonstrate the statistical and economic significance of a number of key variables and estimate a range of specifications controlling for the potential endogeneity concerns discussed in the recent trade-environment literature (Levinson and Taylor 2004 and Ederington and Minier 2003).

The remainder of the paper is organized as follows. Section 2 introduces our measures of specialization, while Section 3 discusses the data and provides some descriptive results. Section 4 provides our econometric analysis examining the determinants of specialization indices, and Section 5 concludes.

2. Specialization Indices

Theories of comparative advantage, such as the traditional Heckscher-Ohlin-Samuelson (H-O-S) model, refer to patterns of pre-trade relative prices that we cannot observe. Applied work uses observable data to infer or 'reveal' what would be the pattern of pre-trade prices. In the H-O-S framework for example, differences in relative factor supplies are characterised in terms of 'abundance' or 'scarcity' where countries are assumed to export those goods whose production makes relatively intensive use of their abundant factors. Several 'specialization' measures, usually based around a country's net exports,

have been used to reveal which of these goods a country has a pre-trade comparative advantage in. This paper examines three such measures.

The starting point for the majority of empirical studies of specialization are measures of revealed comparative advantage (RCA) (originally proposed in an international trade context by Balassa 1965, 1979 and 1986). For a single country, the RCA index is defined as;

$$RCA_{it} = \left(\frac{X_i / \sum_i X_i}{X_{iw} / \sum_i X_{iw}}\right)_t$$
(1)

The numerator signifies the percentage share of a given sector in total exports where X_{it} are exports from sector *i* in year *t*. The denominator represents the percentage share of a given sector in world exports (where subscript *w* denotes world). For a given sector, an RCA index value of one means that the percentage share of that sector is equal to the world average. An RCA value higher (lower) than one indicates specialization or that a country has a comparative advantage (under-specialized or has a comparative disadvantage) in that sector. Changes in RCA patterns are therefore consistent with changes in countries' relative factor endowments and productivity levels.⁵

⁵ A detailed debate on the theoretical interpretation of the Balassa index and the measurement of comparative advantage can be found in a series of papers by Hillman (1980), Bowen (1983, 1985 and 1986), Deardorff (1984) and Balance *et al.* (1985, 1986 and 1987). Hillman (1980) for example, develops a necessary and sufficient monotonicity condition under identical homothetic preferences to investigate the association between the Balassa index and pre-trade prices for different industries across two countries.

For empirical testing however, the Balassa measure implies a risk of non-normality, because it takes values between zero and infinity. Since a value between zero and one represents a lack of specialization, yet a value between one and infinity represents the presence of specialization, regression analyses using RCA give too much weight to values above one.⁶ A solution first suggested by Laursen (1998) is to use a simple transformation of the RCA index providing what Laursen called Revealed Symmetric Comparative Advantage (RSCA) where;

$$RSCA = \frac{RCA - 1}{RCA + 1} \tag{2}$$

Each *RSCA* index lies between minus and plus one (and avoids the problems of an undefined value which can occur in the logarithmic transformation if exports are zero in a given sector). Changes above and below the old RCA value of one are now treated symmetrically (see Larusen 1998 and Dalum *et al.* 1998 for further discussion).

We also use two additional specialization measures that have been widely employed in the literature. The first is the Michaely index (Michaely 1962), defined as;

$$MICHAELY_{it} = \frac{X_{it}}{\sum_{i} X_{it}} - \frac{M_{it}}{\sum_{i} M_{it}}$$
(3)

where X_{it} and M_{it} are exports and imports of sector *i* in year *t* respectively. The Michaely index ranges between plus and minus one. A positive (negative) value means a country is specialized (under-specialized) in that sector.

Our final measure is simply net exports, expressed as a share of each industry's value added.

⁶ One suggested solution is to use the logarithmic transformation of the Balassa index (see e.g. Vollrath 1991, Soete and Verspagen 1994). This solution is however unsatisfactory because of the way it handles small RCA values. A change in the RCA index from 0.01 to 0.02 for example, has the same impact as a change from 50 to 100 (Dalum *et al.* 1998).

$$NETXva_{it} = \frac{\left(X_{it} - M_{it}\right)}{VA_{it}} \tag{4}$$

where VA_{it} is the value added of sector *i* in year *t*. Increasing *NETXva* for a specific industry implies that exports are increasing relative to imports and hence it may be inferred that specialization is increasing within that industry.

Although similar, our three measures are subtly different. RCA indices measure exports for an industry *relative* to its exports from other industries *relative* to other countries' exports from that industry. The Michaely index in comparison takes account of exports within an industry *relative* to imports within an industry, *relative* to total imports and exports with no mention of other countries' exports. Finally, net exports simply reports exports in an industry relative to imports in the same industry and are not expressed relative to other industries, or relative to other countries.

3. Specialization and the Characteristics of US Industry

We begin by computing US RCA patterns at the two and three-digit SIC (Standard Industrial Classification) levels of industry aggregation between 1978 and 1994. Since world trade data are not reported in the US SIC industry classification, all trade data were concorded to SIC from ISIC (International Standard Industrial Classification).⁷

⁷ An ISIC-SIC concordance is available from the authors upon request. Our time series is restricted by the availability of pollution abatement cost data that were not reported between 1995 and 2000. See the Appendix for the sources and additional information concerning these data.

SIC		Ave. 1978-82	Ave. 1983-86	Ave. 1987-90	Ave. 1991-94	Ave. 1978-94
20	Food	0.82	0.79	0.79	0.78	0.79
22	Textile mill products	0.67	0.46	0.39	0.40	0.48
23	Apparel	0.37	0.27	0.26	0.30	0.30
24	Lumber	0.66	0.64	0.83	0.82	0.74
25	Furniture	0.44	0.46	0.39	0.60	0.47
26	Paper	0.88	0.88	0.91	0.97	0.91
27	Printing	1.18	1.32	1.38	1.52	1.35
28	Chemicals	0.93	1.23	1.20	1.14	1.12
29	Petroleum and Coal	0.41	0.55	0.72	0.69	0.59
30	Rubber and Plastics	0.55	0.57	0.61	0.69	0.60
31	Leather	0.24	0.23	0.25	0.24	0.24
32	Stone, Glass, Concrete	0.57	0.56	0.52	0.58	0.56
33	Primary Metals	0.43	0.31	0.43	0.49	0.42
34	Metal products	1.26	1.28	1.34	1.08	1.24
35	Industrial Machinery	1.48	1.48	1.30	1.23	1.37
36	Electronics	1.03	1.03	1.06	1.08	1.05
37	Transport equipment	1.21	1.24	1.25	1.28	1.24

Table 1. The RCA indices of US exports

Table 1 illustrates US RCA indices by broad two-digit categories and shows the large variation in RCA indices across these sectors. Averaged over the full period (1978-94), RCA is greater than one in just six of the seventeen sectors, with the greatest degree of specialization displayed by Printing (SIC27), Chemicals (SIC28), Industrial Machinery (SIC35) and Transport Equipment (SIC37). In contrast, the lowest RCAs are recorded for Leather and Leather Products (SIC31) and Apparel (SIC23).

Before examining RCA indices for the most pollution intensive sectors, it is important to clarify the relative stringency of US environmental regulations. Whilst US environmental regulations are indeed considered to be relatively stringent, comparable cross-country data on such regulations are very limited. Those comparisons that have

been made suggest that the stringency of a country's environmental regulations is highly correlated with its per capita income. For example, an index of environmental regulations developed by Dasgupta *et al.* (1995) indicates that US regulations are amongst the highest in the world and are hence significantly higher than those of many of its trading partners.⁸ This differential between US regulations and those of its competitors has fuelled the arguments of politicians and union leaders and suggests that US specialization in dirty sectors may be lower than in clean sectors. US pollution abatement costs have also increased steadily over time, as Table 2 indicates. Practically all of the dirtiest sectors have experienced positive annual average growth rates in pollution abatement operating costs expressed per unit of value added (*PAOCva*). Averaged across all industries, abatement costs increased by 84% between 1978 and 1994. Unfortunately, there are no comparable time series data for other countries and hence it is unclear whether the differential between US regulations and those of its competitors has increased over time.⁹

⁸ See also Eliste and Fredriksson (2001).

⁹ In recent years the UK and a number of other European countries have started to report industry specific abatement costs. These are unlikely to be comparable with the US data, however, and are typically only reported for one or two years and a selection of ten or fifteen highly aggregated industries

	Sectors	PAOCva	PCI	relPCI	HCI	relHCI
291	Petrol refineries	-5.8	14.1	9.7	3.0	2.8
261-263	Pulp, paper, board	2.4	16.1	13.7	2.4	2.0
281,286	Chemicals	1.9	39.2	37.3	5.8	5.3
331,332	Iron & Steel	12.5	10.7	7.5	3.1	2.7
299	Petrol & coal prods.	-3.7	6.6	4.9	1.5	1.3
333-339	Non-ferrous metals	5.4	4.0	0.6	-0.2	-0.4
282	Resins, plastics	9.4	5.8	2.4	0.9	0.7
311	Leather	10.9	8.6	5.5	1.9	1.7
289	Other chemicals	6.5	3.4	1.2	0.9	0.7
328,329	Non-metallic minerals	2.1	5.4	3.0	1.4	1.0

*Table 2. Average Annual Growth Rates of PAOCva, PCI and HCI, 1978-94, for the Dirtiest Three-Digit Sectors (%)*¹⁰

In Figure 1 we plot RCA indices for the five dirtiest two-digit sectors (as defined by the sectors with the highest *PAOCva*). The five dirtiest sectors are Paper (SIC26), Chemicals (SIC28), Petroleum and Coal (SIC29), Stone, Clay and Glass (SIC32) and Primary Metals (SIC33), respectively. There are two main observations. First, of the five dirtiest industries only Chemicals (SIC28) records an average RCA of greater than one, although Paper (SIC26) is very close to one particularly towards the end of the sample (average RCA for Paper for 1992-1994 was 0.99). This would suggest that, of the five dirtiest sectors, the US has a revealed comparative advantage in two at the most. Second, we note that for the dirtiest sectors there has been no systematic reduction in RCA over time. Indeed, all but one (Chemicals) recorded a higher value in 1994 than in 1978 suggesting

¹⁰ The dirtiest sectors are those with the higher values of *PAOCva*. The variables *rePCI* and *relHCI* express each industry's *PCI* and *HCI* relative to the average for all industries. ISIC sectors do not always perfectly map into single US SIC sectors and hence some of our observations are for groups of two or three SIC industries. See the entry for *RCA* in the Appendix for further information.

that the US increased its specialization in dirty sectors even in the face of an increase in environmental regulations.¹¹

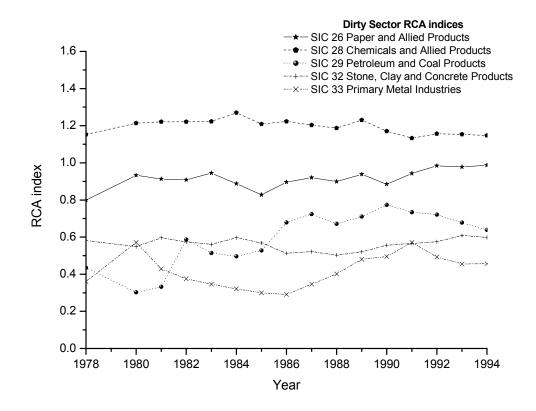


Figure 1. RCA Indices of US 'Dirty' Sectors.

Table 3 considers RCA, the Michaely index and net exports at a greater level of disaggregation. For the ten dirtiest *three-digit* industries our specialization indices are reported for the first and last years in our sample (1978 and 1994), with the change over this period highlighted. We find that the seven dirtiest three-digit industries all experienced an increase in RCA between 1978-1994. Similarly we find that the Michaely and net export measures record increases for six out of the ten industries. Our results therefore indicate that there is no systematic tendency for US specialization to

¹¹ Plotting the Michaely index and net exports over time for the dirtiest industries yields very similar trends to those in Figure 1. Specifically, both indicate a significant level of specialization in the Chemicals industry (SIC 28), with no notable 'despecialization' across dirty sectors. For reasons of space these Figures were omitted.

decline in pollution intensive industries. If anything, there is evidence that such specialization is actually deepening.

SIC3	RCA	RCA	Δ	Mich.	Mich.	Δ	NetX	NetX	Δ
	78	94	RCA	78	94	Mich.	78	94	NetX
291	0.44	0.58	+	-0.0492	-0.0092	+	-0.35	-0.23	+
261-263	0.76	0.96	+	-0.0140	-0.0003	+	-0.17	0.08	+
281, 286	1.08	1.20	+	0.0161	0.0140	-	0.08	0.09	+
331, 332	0.26	0.31	+	-0.0435	-0.0157	+	-0.10	-0.23	-
299	0.40	1.25	+	-0.0026	0.0010	+	0.10	0.19	+
333-339	0.60	0.67	+	-0.0314	-0.0076	+	-0.64	-0.89	-
282	0.85	1.07	+	0.0200	0.0182	-	0.14	0.27	+
311	0.76	0.41	-	-0.0002	0.0001	+	-0.01	-0.20	-
289	1.62	1.29	-	0.0173	0.0104	-	0.07	0.16	+
328, 329	0.72	0.54	-	0.0010	-0.0006	-	-0.04	-0.37	-

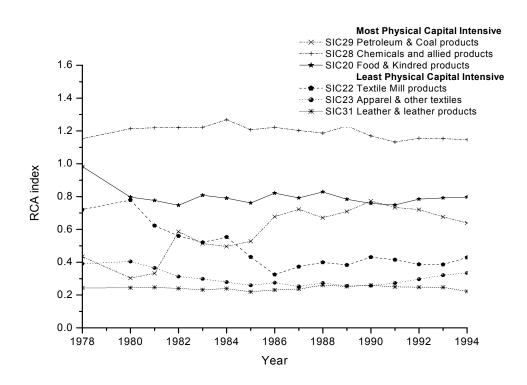
Table 3. The Change in RCA, the Michaely Index and Net Exports 1978-94 for the Dirtiest Three-Digit Industries

Whilst we find no evidence of a reduction in US specialization for the dirtiest industries, we also find no evidence to suggest that dirty sectors have suffered from lower average RCA values than cleaner sectors over our sample period. In fact we find the reverse. For example, the average RCA over the period 1978-1994 for the twenty dirtiest three-digit sectors was 0.93 with an equivalent figure for the twenty cleanest sectors of 0.82.¹² Using industry specific pollution intensity data for 1987 (from Hettige et al. 1994) we also estimate correlations between a range of air pollutants and average RCA 1978-94, RCA for 1987 and the change in RCA 1978-94. All correlations are *positive*, but statistically insignificant. There is therefore no evidence to suggest that US RCA is lower, or falling more rapidly in its dirtiest sectors rather than in its cleanest sectors.

¹² Average RCA is also higher for the dirtier sectors when we compare the cleanest and dirtiest five, ten or twenty sectors.

In order to provide an explanation for these specialization patterns we investigate the role played by the characteristics of US industries, specifically their human and physical capital intensity. We define physical capital intensity (PCI) as the non-wage share of value added and human capital intensity (HCI) as the share of value added that is paid to skilled workers.¹³ Figure 2 plots RCA for the three sectors that have the highest and the lowest physical capital intensity. Notice that the PCI and RCA rankings are matched apart from Petroleum and Coal (SIC29) that has the highest PCI but only the third highest RCA. A Spearman rank correlation between RCA and PCI averaged over our time period at the two-digit level records a value of 0.56 (significant at the 5% level). At the three-digit level the Spearman rank correlation is 0.39 (significant at the 5% level).

Figure 2. US RCA Indices for the Most and Least **Physical** Capital-Intensive Sectors

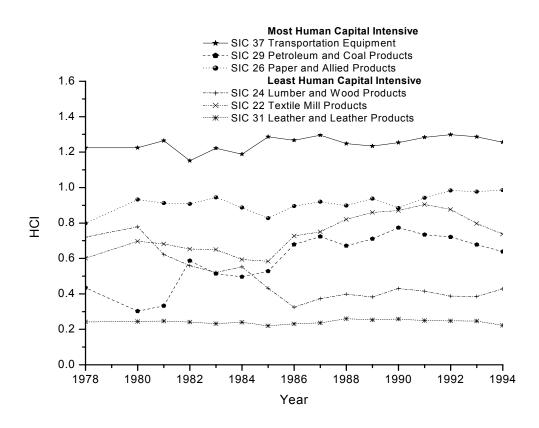


For the US, we also suspect that the human capital requirements of an industry (skills, training, education) have a strong influence on RCA patterns. Indeed, the Spearman correlations of average HCI and average RCA over our period record values of 0.51 and

¹³ The Appendix explains how these variables are calculated.

0.50, significant at the 5% level at the three and two-digit levels respectively. Figure 3 plots RCA for the three sectors that have the highest and lowest human capital intensity. As with physical capital, it can be seen that the human capital-intensive sectors such as Transportation (SIC37) and Paper (SIC26) have higher RCA indices than the least human capital-intensive sectors Textiles (SIC22) and Leather (SIC31). Figures 2 and 3, together with a casual examination of Table 1, therefore suggest, perhaps unsurprisingly, that the USA's revealed comparative advantage in an industry is heavily influenced by the human and physical capital requirements of that industry (see Leamer 1984 for an excellent overview of the relationship between trade and endowments).

Figure 3. US RCA Indices for the Most and Least Human Capital-Intensive Sectors



We believe this finding provides an explanation of why the US is not experiencing low and/or reduced specialization in pollution intensive industries despite having relatively high environmental regulations (particularly compared to US trading partners in

developing regions). Several recent studies have suggested that there exists a correlation between the pollution intensity (or pollution abatement costs) and the physical capital intensity of an industry (Antweiler *et al.* 2001 and Cole and Elliott 2003). Pollution intensive industrial processes are typically those that use heavy machinery reliant on large amounts of energy. In contrast, labor intensive processes are often less dependent on energy and hence are relatively clean. No matter which measure of PCI we use (see the Appendix for alternative definitions of PCI), or whether we use two-digit or three-digit data, we find statistically significant correlations between PCI and pollution abatement operating costs per unit of value added (PAOCva). At the two-digit level for the period 1978-1994 (n = 272), for example, we estimate a correlation of 0.64 between non-wage value added and PAOCva. Using the NBER's measure of total real capital stock per worker we find a correlation of 0.87 with PAOCva.¹⁴

The link between pollution and capital intensity appears to be well grounded. What has not previously been recognised, however, is the fact that there is also a significant correlation between an industry's *human* capital requirements and its pollution intensity. Cleaner industries tend to rely on relatively low-skilled employees whilst the more complex industrial processes that typically depend on greater energy use, tend to require greater amounts of human capital. At the two-digit level we estimate normal correlations of 0.58 between HCI and PAOCva and a Spearman correlation of 0.54 (both statistically significant).¹⁵

To further illustrate the linkages between PAOCva and PCI and HCI, Table 4 summarises the characteristics of our 96 three-digit industries by averaging over time and then ranking by PAOCva. Our industries are then split into approximate quintiles (i.e. dirtiest 20, next dirtiest 20 and so on) and a number of alternative measures of PCI and HCI, as defined in the Appendix, are reported. As each group of industries becomes cleaner,

¹⁴ Spearman correlations are 0.48 and 0.67, respectively. Three-digit correlations are very similar and are all statistically significant. Similarly, significant correlations are found between Hettige *et al.*'s (1994) sectoral pollution intensities and *PCI*.

¹⁵ Statistically significant correlations are also found at the three-digit level and also between PAOCva and alternative measures of *HCI*. A scatterplot of the relationship between HCI and PAOCva provides equally strong evidence of a positive relationship and is available from the authors upon request.

Table 4 reveals that practically all PCI and HCI measures decline. Thus, across a large sample of industries, those industries with above average pollution intensity are also typically characterised by above average physical and human capital intensity.

Table 4. Characteristics of 96 Industries, Each Averaged Over Time and Ranked by PAOCva

Industries	PAOCva	HCI	HCIwage	HCItex	PCI	PCIpw	CAPpw
dirtiest 20	5.71	0.14	26.6	1.88	0.66	65.5	204.1
20 to 40	0.98	0.12	22.0	1.55	0.60	36.3	78.2
40 to 60	0.60	0.11	20.8	1.47	0.59	37.8	63.5
60 to 80	0.40	0.10	20.5	1.45	0.58	33.4	47.1
Cleanest 80 to 96	0.17	0.06	19.9	1.20	0.55	33.7	34.3

Furthermore, as can be seen by referring back to Table 2, although *PAOCva* has been increasing steadily over time for practically all sectors, the same is also true of *PCI* and *HCI*. Thus, any negative impact of abatement costs on US specialization is likely to be offset by the positive relative impact of human and physical capital intensity. Overall, the net effect of these three factors on specialization may be small or even positive. In order to subject these assertions to a more rigorous analysis, we now estimate the determinants of US specialization patterns econometrically.

4. Econometric Analysis

The previous section has revealed that US specialization in pollution intensive sectors does not appear to be low and/or declining. We asserted that a possible explanation is that dirty sectors also tend to be physical and human capital intensive. In order to put this claim to the test we estimate the determinants of US industry specific RCA (RSCA), the Michaely index and net exports. Our data cover three-digit SIC industries for the period 1978-1992.¹⁶ Specifically we estimate the following equation;

¹⁶ Industry specific tariff data proved unattainable beyond 1992, thereby restricting our sample. Also PAOC data were not collected in 1979 or 1987. Although SIC industry classifications changed in 1987, a Chow test performed on our RSCA panel fails to reject the null hypothesis that the coefficient vectors are the same in the pre- and post-1987 periods (test statistic 0.33, p value (0.89)).

$$SPEC_{it} = \gamma_{i} + \tau_{t} + \beta_{1}PAOCva_{it} + \beta_{2}PCI_{it} + \beta_{3}(PCI_{it})^{2}
(-) (+) (-)
+ \beta_{4}HCI_{it} + \beta_{5}(HCI_{it})^{2} + \beta_{6}tariff_{it} + \varepsilon_{it}
(+) (-) (+)$$
(5)

where *SPEC*_{it} denotes RSCA, the Michaely index or net exports and *PAOCva* denotes pollution abatement operating costs per unit of value added. Our measure of physical capital intensity, *PCI*, is defined as the non-wage share of value added. Human capital intensity, *HCI*, is defined as the share of value added paid to skilled workers. *Tariff* denotes import duties per unit of imports within each industry, whilst γ and τ are industry and time specific effects, respectively. Since visual plots of *PCI* and *HCI* against *RSCA*, the Michaely index and net exports suggested the possibility of a quadratic relationship, squared terms are included for *PCI* and *HCI* to allow the possibility of a diminishing effect at the margin.¹⁷ Where both the linear term and the quadratic term are not significant, the quadratic term was dropped. Expected signs are $\beta_1 < 0$, $\beta_2 > 0$, $\beta_3 < 0$, β_4 > 0 $\beta_5 < 0$ and $\beta_6 > 0$ and are indicated below each variable in equation (5).¹⁸

Since RSCA and the Michaely index express each US industry *relative* to other US industries, for these two specialization indices we express each of our independent variables relative to the three-digit industry average for each year. However, since RSCA expresses US trade specialization relative to world trade specialization, the independent variables in equation (5) would ideally be expressed relative to world averages for each industry and year when estimating RSCA. Whilst such data would be difficult to attain for *PCI*, *HCI* and *tariffs*, comparable industry specific *PAOC* are not reported for other countries as we have already noted. Equation (5) is therefore our best attempt to explain US RSCA.

¹⁷ Quadratic terms were also tested for *PAOCva* and *tariffs* but were insignificant in all cases and hence were dropped from our estimations.

¹⁸ See the Appendix for a description and source of each variable.

For each specialization measure, Table 5 provides two sets of estimates, the first based on 'pooled' data with no industry specific fixed effects, the second with fixed effects included.¹⁹

	RSCA		MICH	AELY	NET EX	PORTS
	'Pooled'	FE	'Pooled'	FE	'Pooled'	FE
	no FE (1)	(2)	no FE (1)	(2)	no FE (1)	(2)
PAOCva	-0.027	-0.0095	-0.090	-0.048	-4.65	-4.44
	(4.2)	(2.8)	(5.5)	(2.8)	(15.3)	(9.8)
PCI	0.15	0.33	0.57	0.29	0.45	0.36
	(4.1)	(3.9)	(7.2)	(2.2)	(9.2)	(4.4)
PCI^2	-0.027	-0.22	-0.13	-0.19		
	(3.9)	(7.4)	(5.1)	(3.0)		
HCI	0.12	0.037	0.76	0.22	3.46	3.97
	(2.1)	(1.5)	(3.9)	(7.3)	(10.9)	(9.2)
HCI^{2}					-10.48	-8.53
					(9.6)	(6.4)
Tariffs	-0.045	0.0045	-0.0091	-0.0083	-0.0085	0.013
	(2.8)	(1.2)	(0.8)	(0.5)	(0.3)	(0.3)
R^2	0.12	0.063	0.067	0.058	0.50	0.40
n	806	806	806	806	1115	1115
Hausman	123.5	(0.00)	96.7 (0.00)	177.0 (0.00)

Table 5. The Determinants of RSCA, the Michaely Index and Net Exports

t-statistics in parentheses. 'Within' R² is reported for fixed effects estimates.

In all six estimations we find pollution abatement costs within an industry to be a statistically significant negative determinant of that industry's RSCA, Michaely index or net exports. In contrast, we find the relative human and physical capital intensity of a sector to be positive and significant determinants of RSCA and Michaely, with physical capital intensity having a diminishing effect at the margin. For net exports, we found the quadratic *PCI* term to be statistically insignificant and hence it was dropped from the estimation. Evidence of a quadratic relationship was instead found between net exports

¹⁹ All estimations use heteroscedastic-robust standard errors.

and *HCI*. The Hausman tests all reject the null of a non-systematic difference between the 'pooled' results and the fixed effects results, indicating that industry controls are required.

These results therefore suggest that US comparative advantage in a sector is positively influenced by a sector's physical and human capital intensity and negatively influenced by the level of abatement costs within an industry. Whilst we have noted that, for the RSCA estimates, the independent variables should ideally be expressed relative to world averages, the robustness of our results suggests that US observations are capturing the differential between US industry characteristics and the rest of the world's characteristics quite successfully. This would imply that non-US industrial characteristics have remained relatively stable over time.

However, several recent studies have suggested that an industry's abatement costs may be endogenously determined by its net exports (Levinson and Taylor 2004, Ederington and Minier 2003). We here examine these arguments in more detail and undertake an econometric exercise that enables us to allow for potential endogeneity problems. We limit this more detailed analysis to net exports due to space constraints, concern surrounding the appropriate specification for the RSCA estimates, and the fact that the other studies examining endogeneity in this context also consider net exports, thereby allowing comparison with our results.

The literature to date has suggested two principal sources of endogeneity:

(i) Do imports influence abatement costs?

Levinson and Taylor (2004) suggest that the fact that most analyses are carried out at the three-digit industry level, where each three-digit industry is a heterogenous mix of four-digit industries, can generate an endogeneity problem. An increase in pollution abatement costs may result in an increase in imports of dirty *four-digit* products, a resulting contraction of dirty production from domestic four-digit industries and hence a decline in

the average pollution intensity of domestic production in *three-digit* industries. Thus industries with rapidly increasing regulations are most likely to be imported, which will then reduce measured levels of abatement costs. Furthermore, this change in the composition of three-digit industries could also change other industry characteristics, including physical and human capital intensity.²⁰ An increase in imports can therefore influence the characteristics of three-digit industries.

(ii) Are environmental regulations used as secondary trade barriers?

Such an argument was first tested by Ederington and Minier (2003) who claim that countries may relax environmental regulations in those industries facing the greatest import penetration. They find some evidence for this assertion.

With these potential sources of endogeneity in mind we estimate a number of different model specifications. Table 6 provides the results. As a first step towards controlling for the potential endogeneity of our industry characteristics (*PAOC*, *PCI* and *HCI*), model (3) regresses *NETXva* on time-averaged values of *PAOCva*, *PCI* and *HCI*. Since three-digit industry specific fixed effects now drop out of the estimation due to collinearity, model (3) includes two-digit industry dummies. The sign and significance of our variables of interest continue to concord with our prior expectations. An alternative attempt to control for the possible endogeneity of our industry characteristics is provided by model (4). In this specification *PAOCva*, *PCI* and *HCI* are all lagged by one year thereby removing any contemporaneous relationship between industry characteristics and net exports. Again, we find the same sign and significance patterns as the previous models. The use of two and three year lags provides very similar results.²¹

 $^{^{20}}$ This will be the case as long as all four-digit industries within a three-digit industry do not have identical levels of *PCI* and *HCI*.

²¹ The use of the alternative measures of *PCI* and *HCI* referred to in Table 4 does not change the sign and significance of the *PCI* and *HCI* variables.

	NETXva					
	(3)	(4)	(5)	(6)		
	Ave vars	Lag Vars	Lag Vars	Ave vars		
	2digit FE	FE	IV, FE	IV, 2 digit FE		
PAOCva	-5.34	-5.60	-3.45	-4.15		
	(-8.4)	(-9.9)	(4.6)	(4.0)		
PCI	0.37	0.36	1.93	5.26		
	(3.8)	(4.3)	(2.0)	(3.5)		
HCI	3.88	4.50	3.95	4.66		
	(8.3)	(9.9)	(2.2)	(2.6)		
HCI^{2}	-9.05	-9.78	-10.86	-8.60		
	(-5.5)	(-7.1)	(5.0)	(3.8)		
Tariffs	0.018	-0.26	4.9	-0.41		
	(0.3)	(-1.5)	(8.8)	(1.8)		
R^2	0.48	0.66	0.52	0.41		
n	1249	1167	1167	1249		
Sargan test			1.72	2.00		
			(0.78)	(0.73)		

Table 6. The Determinants of US Net Exports, Controlling for Endogeneity

t-statistics in parentheses

Finally, models (5) and (6) use instrumental variables to control for the potential endogeneity of *PAOCva*. If trade flows are influencing industry characteristics, as was argued above, then it becomes very difficult to find suitable instruments for abatement costs. Any alternative industry characteristics that are correlated with abatement costs may themselves be influenced by trade flows. In order to overcome this problem, we utilise a set of instruments based upon the geographical dispersion of industries across US states as recommended by Levinson and Taylor (2004). Since most US environmental regulations are set at the state level, the location and concentration of industries will provide information regarding the abatement costs that they face.

The instruments we use are based on the premise that the marginal damage of pollution is an increasing function of the level of pollution. Thus, an industry concentrated in a polluted state may face stricter regulations than an industry in a less polluted state. Using Hettige *et al.*'s (1994) estimates of pollution intensity (pollution emissions per dollar of value added) for each industry together with the level of each industry's valued added in each state, we estimate the total level of emissions in each state, for a range of pollutants. Note that we exclude each industry's own emissions from its own instrument. In our instrument the level of emissions is then weighted by each industry's value added in each state in the base year (1978) of our analysis. By weighting our instrument, IV, is calculated for 6 different types of air pollution, providing us with 6 instruments in total.

$$IV_{it} = \frac{\sum_{s=1}^{48} \left(\left(\sum_{i} E_{ist} \right) * \left(VA_{is1978} \right) \right)}{VA_{i1978}}$$
(6)

Where E refers to emissions from industry i in state s at time t. A high value of IV would suggest that an industry is located in a state with a large amount of pollution being generated by other industries.

As Levinson and Taylor (2004) point out, a valid instrument has to be correlated with abatement costs but uncorrelated with the error term in the net trade regression. Any variables that are related to industry location within the US and are correlated with the unobserved determinants of net trade would therefore pose a problem for our instruments. Levinson and Taylor claim that the most likely example would be border effects. For example, if industries locate near to Mexico in order to trade with Mexico then we may expect pollution to increase within the border region. If, in response, regulations are then increased with this region, we may observe a spurious positive correlation between net exports to Mexico and pollution costs. Since we are concerned with total US net trade (with the rest of the world), such border effects are likely to be diluted. Nevertheless, we do experiment with dropping those states that border Mexico and Canada when calculating our instruments. Our estimation results were indistinguishable from those

where border states were included.²² Finally, we note that a Sargan test of overidentifying restrictions fails to reject the null that our instruments are uncorrelated with the error term and that our specification is correct.

Whilst the use of these instruments controls for the potential endogeneity of *PAOCva*, we also have to allow for the fact that *PCI* and *HCI* may be endogenously determined. Levinson and Taylor (2004) simply drop these variables from their estimations, presumably relying on the fixed effects to capture the effects of *PCI* and *HCI* on *NETXva*. This would appear unsatisfactory since the fixed effects obviously cannot control for any industry specific characteristics that change over time. In this paper, *PCI* and *HCI* are, along with *PAOCva*, the variables of central interest and hence model (5) in Table 6 includes all three by instrumenting *PAOCva* and using one year lags of *PCI* and *HCI* and includes two-digit industry dummies. In both estimations we find the instrumented *PAOCva* to be a statistically significant negative determinant of *NETXva*, whilst lagged and time-averaged *PCI* and *HCI* remain statistically significant positive determinants.

A statistical relationship alone, however, cannot explain why the US does not appear to have experienced low and/or declining specialization in dirty industries. In order to provide such an explanation we need to consider the economic significance of these variables. Table 7 reports the estimated elasticities for our key independent variables.²³

²² A Hausman test failed to reject the null of no systematic difference between the two sets of results. Note also that the possibility of polluting industries relocating to states where environmental regulations are lax does not cause a problem for our instruments. Take the example of an increase in Californian regulations. If industries do not relocate to lower regulation states then California's increase in standards, relative to other states, is valid instrument and there are no problems. But if industries do relocate then they must be incurring higher costs in some aspect of their activities or else the industry would have relocated there in the first place. So, again, the increase in Californian regulations will have imposed a higher cost on the industry (reflected in lower international comparative advantage) and hence provides a valid instrument. Thus, since the industrial composition (the weights used in calculating our instrument) is fixed at the base year, an increase in California's regulations will impose cost on its industries, either in the form of higher costs due to relocation to a less profitable location.

²³ Although not reported for reasons already outlined, the estimation of models (3), (4), (5) and (6) for our other two specialization measures, RSCA and the Michaely index, yields results which support those from our reported models. More specifically, our key variables are statistically significant, with *PAOCva* negatively signed and *PCI* and *HCI* positively signed. Similarly, the estimated elasticities are consistent with those reported in Table 7 with elasticities for *PCI* and *HCI* generally larger than those estimated for *PAOCva*. Furthermore, the elasticities for *PAOCva* are larger when instrumental variables are used.

Dep. Var.	Model	PAOCva	PCI	HCI
RSCA	(1)	-0.1	0.8	0.6
	(2)	-0.05	1.8	1.2
Michaely	(1)	-1.1	6.7	0.9
	(2)	-0.8	4.5	3.6
NETXva	(1)	-0.8	2.5	3.9
	(2)	-0.8	2.0	4.5
	(3)	-0.6	1.4	2.7
	(4)	-0.8	1.7	4.3
	(5)	-1.8	3.8	1.2
	(6)	-2.8	3.6	1.5

Table 7. Estimated Elasticities for PAOCva, PCI and HCI

The differences in our specialization measures and the variety of specifications used inevitably result in a range of different estimated elasticities. Elasticity estimates for RSCA appear to be the smallest in magnitude. The elasticity of net exports with respect to *PAOCva* varies between -0.6 and -2.8 across the six models. In Levinson and Taylor's (2004) study of US trade with Mexico and Canada, the equivalent elasticities ranged from 0.17 to 0.67. Table 7 also indicates that instrumenting *PAOCva* (models 5 and 6) does increase the magnitude of the estimated elasticity of net exports with respect to *PAOCva*. This finding is also made by Levinson and Taylor (2004) and Ederington and Minier (2003) in similar studies of US net exports. It would therefore appear that pollution abatement costs are subject to endogeneity concerns.

Of clear significance to this paper, however, is the finding that within each model the estimated elasticities for *PCI* and *HCI* are considerably larger than those estimated for *PAOCva*. This finding holds for the RSCA and Michaely estimations and for all of the net export estimations. The elasticity of net exports (including the change in net exports) with respect to *PCI* varies between 1.4 and 3.8 whilst the equivalent elasticities for *HCI* lie between 1.2 and 4.5. Thus, whilst *PAOCva* does exert a negative influence on net

exports (and RSCA and Michaely) *ceteris paribus*, this is outweighed by the positive influence of *PCI* and *HCI*. Since those sectors that are pollution intensive also tend to be skill and physical capital intensive as Section 3 demonstrated, it is therefore not surprising that we do not observe particularly low levels of net exports, RSCA and Michaely, nor a systematic reduction in such measures of specialization, within pollution intensive industries.

5. Discussion and Conclusions

Despite the fears of US politicians and the predictions of some theoretical models, the widespread relocation/displacement of pollution intensive industries from high regulation countries has failed to emerge. This is reflected in the specialization patterns of US pollution intensive industries. Although environmental regulations in the US are rising and appear to be high relative to those in many developing countries, specialization in US 'dirty' industries does not appear to be lower, nor declining more rapidly (or increasing more slowly) than in other US sectors.

This paper has demonstrated that the characteristics of dirty sectors can go some way towards explaining this finding. We illustrate in a variety of ways that pollution intensive industries are typically more intensive in the use of physical and human capital than cleaner industries. These factor intensities appear to be important determinants of US specialization patterns, suggesting that factor intensities and environmental regulations have a competing influence on revealed comparative advantage. We demonstrate econometrically that this is indeed the case. Whether we estimate RSCA, the Michaely index or net exports, we find that physical and human capital intensities are statistically significant negative determinant. Furthermore, estimated elasticities indicate that the effects of a 1% increase in physical or human capital intensity on specialization are likely to be larger than the effects of a similar increase in abatement costs. If those sectors facing high abatement costs are indeed more intensive in the use of physical and/or human capital then this would explain why we do not see low and/or falling specialization in dirty industries.

For dirty industries, pollution abatement costs per unit of value added have increased over our sample period, as Table 2 indicates. However, since PCI and HCI have also increased over this period (again, see Table 2) the net change in specialization has not been negative. But what if abatement costs were to increase further, for example due to the implementation of the Kyoto Protocol? If PCI and HCI continue to increase then we could expect this to offset the negative pollution haven effect associated with PAOCva. However, if PCI and HCI cease to increase, then we would expect US specialization to decline as abatement costs continue to rise. There is the possibility, however, that PCI and HCI will actually increase as a result of increasing PAOCva. Faced with high abatement costs firms may decide to invest in new, clean technology to prevent further increases in abatement costs. Such investment would increase PCI. Since the skill requirements of new high-technology equipment are likely to be greater, however, HCI may also rise. This may partially explain why PCI and HCI increased alongside PAOCva over our sample period. An investigation of these possible linkages is outside the remit of this paper.

It may be wise to finish on a note of caution since this paper has made a number of generalisations. In reality, of course, not all dirty sectors are highly physical and human capital intensity. Some may be intensive in one factor but not the other, for example the Primary Metals industry (SIC33) appears to be intensive in physical but not in human capital. Others may use neither of these factors intensively, particularly at the three or four-digit level. Some industries may be intensive in altogether different factors of production such as natural resource endowments that we are unable to control for due to lack of data. Nevertheless, across all industries generalised trends are observable which suggest that pollution intensive sectors do typically use physical and human capital in a relatively intensive manner. Thus, whilst US dirty industries may be attracted to the 'green grass' of low regulation developing countries, such countries may be less attractive to an industry intensive in the use of physical and human capital. We believe this finding provides a partial explanation for the lack of more widespread pollution haven evidence.

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Appendix. Data Information

Variable	Details
RCA	RCA, as defined by equation (1), was calculated using World Bank ISIC export
	data. See; www1.worldbank.org/wbiep/trade/data/TradeandProduction.html
	'World' exports are the sum of all 68 countries for whom export data are
	reported. All export data were concorded from ISIC to US SIC prior to the
	calculation of RCA. Since four-digit ISIC sectors do not always map into
	individual three-digit SIC sectors, we calculate RCA for 61 'sectors', the
	majority of which are individual three-digit SIC sectors, but some are groupings
	of two or three sectors. When estimating the determinants of RCA all industry
	characteristics were aggregated to match these concorded industry groupings.
Michaely	The Michaely index is defined by equation (3). Source: NBER Trade Database
NetXva	Net exports per unit of value added. Source: Trade data from NBER Trade
	Database, VA data from NBER-CES Industry Database.
PAOCva	Pollution abatement operating costs per unit of value added. Source: Current
	Industrial Reports: Pollution Abatement Costs and Expenditures, US Census
	Bureau.
PCI	The non-wage share of value added, calculated as
	(1 – (payroll/VA)). Source: NBER-CES Industry Database.
PCIpw	Non-wage value added per worker, calculated as
	((VA-payroll)/employees). Source: as above.
CAPpw	Total real capital stock / employees. Source: as above.
HCI	The share of value added paid to skilled workers. Defined as
	(payroll/VA) – ((Unskilled wage*employment)/VA) where the unskilled wage
	is that of the Textiles sector. Source: as above.
HCIwage	The average wage in a sector. Source: as above
HCItex	The average wage in a sector, relative to the wage in an unskilled sector such as
	Textiles. Source: as above.
Tariffs	Import duties per unit of imports. Source: NBER Trade Database (extension to
	1992 generously provided by Jenny Minier).
Gross State	Used to calculate instruments . Source: US Bureau of the Census
Product	
Pollution	Used to calculate instruments. Source: Hettige et al. (1994)
intensities	