US Specialization in Pollution-Intensive Industries: Factor Intensities versus Environmental Regulations

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Abstract

The global decline in trade barriers means that environmental regulations now play an increasingly important role in shaping a country's comparative advantage and hence the industrial structure of an economy. The belief that pollution intensive industries will relocate to developing regions where environmental regulations may be less stringent has been shown to be largely unfounded however, despite anecdotal evidence and the predictions of some theoretical studies. 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 sector. Our multivariate estimates suggest that pollution intensive industries have certain characteristics - specifically their physical and human capital intensity - that counter pressures for dirty production to relocate to developing countries. We demonstrate the economic and statistical significance of these factors as determinants of US specialization.

JEL codes: Q28, R38, F23

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 the decrease in trade barriers has been an increase in the relative 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,'[1] 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.'[2]

A number of theoretical studies have provided similar conclusions. Baumol and Oates (1988), for instance, state that their model suggests 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 2002 and Cole and Elliott 2003).

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[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 low-regulation pollution havens is mixed. 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.[3] 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. In an extension of this literature Ederington and Minier (2003) and Levinson and Taylor (2002) specifically consider endogeneity issues, with the former arguing that environmental regulations should be treated as a secondary trade barrier 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.[4]

Aside from endogeneity arguments, several other explanations have been offered as to why more widespread evidence of pollution havens has not been found despite the predictions of many theoretical studies (see e.g. Pethig 1976, McGuire 1982, Chichilnisky 1994, Copeland and Taylor 1994). These arguments 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

[3] Xu and Song (2000) find that trade in embodied environmental factor services does not appear to be influenced by environmental regulations.

[4] Esty and Gerardin (1998) argue that under certain political economy conditions, competitiveness fears may have a greater effect on the regulation of environmental standards than is rational. Some economists believe that governments will attempt to attract foreign direct investment by competitively undercutting each others' environmental regulations (race to the bottom) while environmentalists believe that multilateral trade agreements prevent countries from setting their desired (perhaps higher) level of regulations. Dean (1992) provides a survey of the early literature on the implications of pollution abatement on US industry.

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.[5]

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 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, as has recently been recognised (Antweiler *et al.*, 2001, and Cole and Elliott, 2002), (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. 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 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, 2002, 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.

[5] See Neumayer (2001) for a review of these issues.

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 such as the US, the RCA index is defined as;

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

The numerator signifies the percentage share of a given sector in total US exports where X_{it} are US 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 in the US, 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 that the US is specialized or 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.[6]

[6] 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,

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. One 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). 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;

$$MICHAELY_{it} = \frac{X_{it}}{\sum_i X_{it}} - \frac{M_{it}}{\sum_i M_{it}} \tag{3}$$

where X_{it} and M_{it} are US 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.

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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.

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

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

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, for example, measure US 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 US 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]

Table 1 illustrates US RCA indices by broad two-digit categories and shows the large variation in RCA indices across these sectors. The US has an average RCA of greater

[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.

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. Expressed as a share of value added, US pollution abatement costs (averaged across all industries) 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]

In Figure 1 we plot RCA indices for the five dirtiest sectors (as defined by the sectors with the highest pollution abatement operating costs per unit of value added (PAOCva) as recorded by the US Census Bureau). 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

[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

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 that the US increased its specialization in dirty sectors even in the face of a relative increase in environmental regulations. Figures 2 and 3 illustrate trends in the Michaely index and in net exports per unit of value added, respectively, for the same selection of sectors. Again, both figures indicate a significant level of US specialization in the Chemicals industry (SIC28), with no notable 'despecialization' across dirty sectors.[10]

Table 2 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.[11] 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 decline in pollution intensive industries. If anything, there is evidence that such specialization is actually deepening.

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] There is therefore no evidence to suggest that the US has lower RCA in its dirtiest sectors rather than in its cleanest sectors.

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[10] The marked decline and subsequent recovery in the net exports of Petroleum and Coal and Primary Metals in the 1980s seems to reflect the cyclical effect of the recession in manufacturing in the early 1980s.

[11] ISIC sectors did 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 Appendix for further information.

[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 4 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).

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 0.50, significant at the 5% level at the three and two-digit levels respectively. Figure 5 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 4 and 5, 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).[14]

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

[13] The Appendix explains how these variables are calculated.
[14] Brulhart (2003, 2000) provides a detailed examination of specialization, particularly in advanced market economies.

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, 2002, 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.[15]

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).[16] Figure 6 provides a scatterplot of HCI against PAOCva for three-digit industries over the period 1978-1994. A line of best fit is included.

To further illustrate the linkages between PAOCva and PCI and HCI, Table 3 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, Table 3 reveals that practically all PCI and HCI measures decline.

[15] 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.

[16] Statistically significant correlations are also found at the three-digit level and also between PAOCva and alternative measures of HCI.

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. Any negative impact of abatement costs on US specialization therefore is likely to be compensated 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 first estimate the determinants of US industry specific RCA (RSCA) and Michaely measures of specialization. Our data cover three-digit SIC industries for the period 1978-1994. Specifically we estimate the following equation;

$$\begin{aligned} SPEC_{it} = \alpha + \gamma_i + \tau_t + &\underset{(-)}{\beta_1 relPAOCva_{it}} + \underset{(+)}{\beta_2 relPCI_{it}} + \underset{(-)}{\beta_3 (relPCI_{it})^2} \\ + \underset{(+)}{\beta_4 HCI_{it}} + \underset{(+)}{\beta_5 tariff_{it}} + \varepsilon_{it} & \end{aligned} \tag{4}$$

where $SPEC_{it}$ denotes RSCA or the Michaely index, *relPAOCva* denotes pollution abatement operating costs per unit of value added expressed relative to the industry average for that year, *PCI* and *HCI* are physical and human capital intensity, both also expressed relative to the industry average. *Tariff* denotes import duties per unit of imports within each industry, whilst γ and τ are industry and time specific effects, respectively. A squared term is included for *relPCI* to allow a diminishing effect at the margin. A visual plot of *relPCI* against *RSCA* and the Michaely index suggested the possibility of a quadratic relationship.[17] Expected signs are $\beta_1 < 0$, $\beta_2 > 0$, $\beta_3 < 0$, $\beta_4 > 0$ and $\beta_5 > 0$ and are indicated below each variable in equation (4).[18]

Since RCA expresses US trade specialization relative to world trade specialization, the independent variables in equation (4) 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, and hence equation (4) is our best attempt to explain US RSCA. Despite this concern we find our estimates of *RSCA* to be surprisingly robust, and also relatively close to our Michaely estimates. Table 4 provides two sets of estimates, the first based on 'pooled' data with no industry specific fixed effects, the second with fixed effects included.[19]

In three out of four estimations we find relative pollution abatement costs within an industry to be a statistically significant negative determinant of that industry's RSCA or Michaely index. 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.[20] The sign and significance of the coefficients for *relPAOCva*, *relPCI* and *relHCI* are generally unaffected by the inclusion of industry fixed effects, although the sign on tariffs switches from negative to positive in the RSCA estimates and *relPAOCva* ceases to be statistically significant in the Michaely estimates. These results therefore suggest that US comparative advantage in a sector is positively influenced by a sector's physical and human capital intensity and the degree of tariff protection that it receives 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.

[17] Quadratic terms were also tested for *relPAOCva* and *relHCI* 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.
[19] All estimations use heteroscedastic-robust standard errors.
[20] An interaction term for PCI and HCI was found to be statistically insignificant.

Nevertheless, we now consider our final measure of trade specialization, namely net exports - a variable commonly used in the empirical trade literature (see for example Grossman and Krueger 1993, Levinson and Taylor 2002, Ederington and Minier 2003) - and undertake an econometric exercise that enables us to allow for potential endogeneity problems. Space constraints and concern surrounding the appropriate specification for the RSCA estimates limits this more detailed analysis to net exports. Using data for three-digit SIC industries for the period 1978-1994 we estimate a number of models based around the following specification;

$$\begin{aligned} NETXva_{it} = \alpha + \gamma_i + \tau_t + &\underset{(-)}{\beta_1 PAOCva_{it}} + \underset{(+)}{\beta_2 PCI_{it}} + \underset{(+)}{\beta_3 HCI_{it}} \\ + \underset{(-)}{\beta_4 HCI^2_{it}} + \underset{(+)}{\beta_5 tariff_{it}} + \varepsilon_{it} & \end{aligned} \tag{5}$$

where net exports are scaled by industry value added and *PAOC*, *PCI* and *HCI* are no longer expressed relative to the industry average.[21] It is notable that when estimating net exports we no longer find PCI^2 to be statistically significant, but now find *HCI* to have a diminishing effect at the margin. The insignificant PCI^2 terms were therefore dropped from our estimations. Expected signs are $\beta_1 < 0$, $\beta_2 > 0$, $\beta_3 > 0$, $\beta_4 < 0$ and $\beta_5 > 0$ and are again shown beneath each variable in equation (5).

Our chosen specifications of equation (5) are influenced by recent claims within the trade-environment literature that abatement costs may be endogenously determined. We here provide a brief review of these possible sources of endogeneity.

(i) Do imports influence abatement costs?

Levinson and Taylor (2002) suggest that an indirect pollution haven effect may be in operation whereby a lowering of tariffs increases imports more in dirty industries than in clean industries. Thus, if tariff barriers fall there may be an increase in imports of

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[21] Expressing the independent variables relative to the industry average actually does little to affect their sign and significance as determinants of net exports.

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. Furthermore, this change in the composition of three-digit industries could also change other industry characteristics, including physical and human capital intensity.[22] An exogenous 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. Levinson and Taylor (2002) also demonstrate this argument theoretically.

(iii) Other sources of endogeneity?

Finally, Levinson and Taylor (2002) demonstrate that several other factors may cause abatement costs to change endogenously. These include the possibility that as the size of an industry increases it may face higher pollution taxes (if marginal damage is an increasing function of pollution levels), whilst the increased size of the industry may result in an increase in exports or lower imports. Thus, here, causality no longer moves from abatement costs to specialization, but rather from industry size to abatement costs and specialization. Also, in the context of a small open economy producing a clean good and a dirty good, they demonstrate that a balanced growth of endowments will increase production of both goods. If marginal damage increases with pollution levels, however, (or if the demand for environmental quality increases with income) then pollution taxes should rise. This will lead to a reduction of production of the dirty good relative to the clean good. Thus, although consistent with the pollution haven hypothesis, in this example abatement costs are endogenously determined by capital and labor endowments, yet abatement costs and endowments are typically treated as being *independent* determinants of specialization.

[22] 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.

With these potential sources of endogeneity in mind we estimate a number of different model specifications. Table 5 provides the results. Model (1) begins by estimating a simple panel regression controlling for industry fixed effects. Abatement costs are found to be a negative and statistically significant determinant of US net exports, whilst *PCI* and *HCI* form positive significant determinants, the latter decreasing at the margin. As a first step towards controlling for the potential endogeneity of our industry characteristics (*PAOC*, *PCI* and *HCI*), model (2) 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 (2) 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 (3). 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. [23]

Finally, models (4) and (5) 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 number of instruments based upon the geographical dispersion of industries across US states as recommended by Levinson and Taylor (2002). 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 first instrument we use is a weighted average of Levinson's (2001) state pollution abatement cost index. The index measures actual abatement costs relative to the

[23] Note that in any of the seven models, the use of the alternative measures of PCI and HCI referred to in Table 3 does not change the sign and significance of the PCI and HCI variables.

abatement costs that would be predicted given the state's industrial composition. In our instrument this index is then weighted by each industry's value added in each state. Thus, the greater the concentration in states with high values of the state abatement cost index, the higher the value of the instrument. This instrument is defined below;

$$IV^1{}_{it} = \frac{\sum_{s=1}^{48}\left(\left(Index_{st}\right)*\left(VA_{ist}\right)\right)}{VA_{it}} \tag{6}$$

where *Index* denotes Levinson's state abatement cost index, *VA* denotes value added and *i*, *s* and *t* denotes industry, state and year, respectively.

The second Levinson and Taylor instrument is 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.

$$IV^2{}_{it} = \frac{\sum_{s=1}^{48}\left(\left(\sum_i E_{ist}\right)*\left(VA_{ist}\right)\right)}{VA_{it}} \tag{7}$$

Where *E* refers to emissions from industry *i* in state *s* at time *t*. A high value of IV^2 would suggest that an industry is located in a state with a large amount of pollution being generated by other industries.[24]

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 (2002) simply drop these variables from their estimations,

[24] Levinson and Taylor (2002) use two additional instruments but in their study these were not significant determinants of *PAOCva*.

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 5 includes all three by instrumenting *PAOCva* and using one year lags of *PCI* and *HCI*. Model (6) replaces lagged *PCI* and *HCI* with time averaged *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. Finally, it is notable that our measure of industry tariffs is not significant in any of our five models and is of mixed sign.

As well as the actual level of net exports we are interested in the *change* in net exports. In order to ascertain whether the characteristics of industries influence the change in specialization, models (6) and (7) repeat models (4) and (5) with the change in net exports per unit of value added as the dependent variable. The sign and significance of the estimated coefficients are similar to those of models (4) and (5). The greater the human and physical capital intensity of a sector the greater the increase in net exports, *ceteris paribus*. Conversely, the higher a sector's abatement costs the greater the decrease in net exports.

For our instrumental variables estimates we performed a Sargan test of overidentifying restrictions which tests the joint null that the equation is properly specified and that the instruments are valid (i.e. not correlated with the error term). Unfortunately, the null hypothesis is rejected for our IV estimates, raising a question mark over our choice of instruments. Alternative instruments are not readily available, however. Despite these test results, we believe that the overall picture painted by our results is clear. Whether we ignore endogeneity or attempt to control for it using instruments, lagged values of *PAOCva*, or time-averaged values of *PAOCva*, our results remain relatively stable.

A statistical relationship alone, however, cannot explain why the US does not appear to have experienced low and/or declining specialization in pollution intensive industries. In order to provide such an explanation we need to consider the economic significance of these variables. Table 6 reports the estimated elasticities for our three key independent variables. The differences in our specialization measures and the variety of specifications used inevitably result in a range of different estimated elasticities. Elasticity estimates for the Michaely index appear to be the least stable across models, with the elasticity of the Michaely index with respect to *PAOCva* from model (2) being particularly small reflecting its non-significance in Table 4. Elasticities estimated for net exports and change in net exports appear quite stable with the elasticity of net exports with respect to *PAOCva* varying between -0.52 and -0.83 across the seven models. It can also be seen that instrumenting *PAOCva* (models 4 - 7) and the use of lagged and averaged *PAOCva* (models 2 and 3, respectively) does not have a notable impact on the estimated elasticity of net exports with respect to *PAOCva*. This suggests that *PAOCva* does not appear to be unduly influenced by endogeneity.

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 1.1 and 1.6 whilst the equivalent elasticities for *HCI* lie between 0.91 and 3.5. 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, widespread evidence of the formation of pollution havens has failed to emerge. This is reflected in the specialization patterns of US pollution intensive industries. Although environmental regulations in the US are 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 positive determinants of US specialization, whilst pollution abatement costs are a 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. By this reasoning, for specialization not to have fallen, PCI and HCI must have also increased within these industries. This is indeed the case. Over the period 1978-1994, for example, the five dirtiest industries experienced an average increase in PCI of 35%, HCI of 14% whilst PAOCva rose by 34%. But what if abatement costs were to increase further, for example due to the implementation of the Kyoto Protocol? Across the vast majority of our results, the estimated coefficient on PAOCva is negative and significant indicating that an instantaneous increase in PAOCva, other things being equal, will reduce US specialization in dirty sectors. 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. This raises the possibility that, by raising PCI and HCI, increasing abatement costs generate offsetting pressures which prevent specialization in pollution intensive sectors from falling. If such offsetting pressures are not generated then our results indicate that an increase in PAOCva will, other things being equal, reduce US specialization in pollution intensive production.

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. We believe this finding provides a partial explanation for the lack of more widespread pollution haven evidence.

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Table 1. The RCA indices of US exports

Year	SIC20 Food	SIC22 Textile mill products	SIC23 Apparel	SIC24 Lumber	SIC25 Furniture	SIC26 Paper	SIC27 Printing	SIC28 Chemicals	SIC29 Petroleum and Coal	SIC30 Rubber and Plastics	SIC31 Leather	SIC32 Stone, Glass, Concrete	SIC33 Primary Metals	SIC34 Metal products	SIC35 Industrial Machinery	SIC36 Electronics	SIC37 Transport equipment
1978	0.98	0.72	0.39	0.62	0.38	0.79	1.12	1.15	0.43	0.54	0.24	0.58	0.36	1.154	1.39	1.02	1.22
1980	0.79	0.77	0.40	0.69	0.38	0.93	1.08	1.21	0.30	0.54	0.24	0.54	0.57	1.493	1.43	1.01	1.22
1981	0.77	0.62	0.36	0.68	0.50	0.91	1.19	0.12	0.33	0.58	0.24	0.59	0.42	1.221	1.53	1.01	1.26
1982	0.74	0.56	0.31	0.65	0.50	0.90	1.31	1.22	0.58	0.55	0.24	0.57	0.37	1.188	1.57	1.06	1.15
1983	0.80	0.52	0.29	0.65	0.48	0.94	1.41	1.22	0.51	0.56	0.23	0.56	0.34	1.168	1.51	1.08	1.22
1984	0.79	0.55	0.27	0.59	0.48	0.88	1.39	1.26	0.49	0.55	0.24	0.59	0.32	1.341	1.52	1.07	1.18
1985	0.76	0.43	0.25	0.58	0.47	0.82	1.25	1.20	0.52	0.60	0.22	0.56	0.30	1.350	1.51	0.98	1.28
1986	0.82	0.32	0.27	0.72	0.40	0.89	1.23	1.22	0.67	0.56	0.23	0.51	0.29	1.271	1.39	1.00	1.26
1987	0.79	0.37	0.25	0.75	0.39	0.92	1.25	1.20	0.72	0.59	0.23	0.52	0.34	1.234	1.35	1.02	1.29
1988	0.82	0.39	0.27	0.82	0.44	0.89	1.26	1.18	0.67	0.60	0.26	0.50	0.40	1.451	1.34	1.03	1.24
1989	0.78	0.38	0.25	0.86	0.29	0.93	1.51	1.23	0.71	0.59	0.25	0.52	0.48	1.422	1.27	1.08	1.23
1990	0.75	0.43	0.25	0.87	0.42	0.88	1.49	1.17	0.77	0.66	0.25	0.55	0.49	1.247	1.23	1.11	1.25
1991	0.74	0.41	0.27	0.90	0.54	0.94	1.53	1.13	0.73	0.66	0.25	0.56	0.57	1.089	1.23	1.08	1.28
1992	0.78	0.38	0.29	0.87	0.60	0.98	1.49	1.15	0.72	0.67	0.24	0.57	0.49	1.009	1.22	1.07	1.29
1993	0.79	0.38	0.32	0.79	0.63	0.98	1.56	1.15	0.67	0.69	0.24	0.60	0.45	1.086	1.23	1.08	1.28
1994	0.79	0.42	0.33	0.73	0.63	0.99	1.49	1.14	0.63	0.72	0.22	0.59	0.45	1.145	1.24	1.08	1.25
Ave:	**0.79**	**0.48**	**0.30**	**0.74**	**0.47**	**0.92**	**1.35**	**1.12**	**0.59**	**0.60**	**0.24**	**0.56**	**0.42**	**1.24**	**1.37**	**1.05**	**1.24**

Table 2. The Change in RCA, the Michaely Index and Net Exports 1978-94 for the Dirtiest Three-Digit Industries

SIC3	RCA 78	RCA 94	Δ RCA	Mich. 78	Mich. 94	Δ Mich.	NetX 78	NetX 94	Δ 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. 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

Table 4. The Determinants of RSCA and the Michaely Index

	RSCA		MICHAELY	
Dep. Var. *RSCA*	'Pooled' no FE	FE	'Pooled' no FE	FE
	(1)	(2)	(1)	(2)
relPAOCva	-0.0292	-0.00808	-0.100	-0.0321
	(-4.5)	(-2.2)	(-6.6)	(-1.0)
relPCI	0.141	0.347	0.414	0.135
	(4.0)	(3.9)	(6.0)	(2.5)
relPCI^2	-0.0272	-0.225	-0.0965	-0.153
	(-4.1)	(-4.6)	(-4.5)	(-3.9)
relHCI	0.161	0.0386	0.0588	0.0318
	(3.1)	(1.6)	(3.2)	(4.4)
Tariffs	-0.0424	0.00654	-0.0125	-0.0630
	(-2.6)	(1.7)	(-1.0)	(-1.7)
year	-0.00919	-0.00580	-0.000515	-0.00175
	(-0.04)	(-1.3)	(-0.2)	(-0.2)
R^2	0.13	0.93	0.057	0.67
n	806	806	806	806

t-statistics in parentheses

Table 5. The Determinants of US Net Exports

	NETXva					Δ NETXva	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FE	Ave vars 2digit FE	Lag Vars FE	Lag Vars IV, FE	Ave vars IV, FE	Lag Vars IV, FE	Ave vars IV, FE
PAOCva	-4.44	-4.79	-5.61	-12.88	-9.19	-1.00	-1.84
	(-9.8)	(-7.5)	(-9.9)	(-9.4)	(-10.0)	(-2.2)	(-6.5)
PCI	0.27	0.35	0.29	0.62	0.35	0.041	0.0016
	(3.7)	(4.0)	(3.9)	(6.6)	(3.8)	(1.7)	(3.5)
HCI	3.99	3.94	4.54	3.54	2.45	0.18	0.39
	(10.1)	(8.8)	(11.0)	(12.3)	(15.8)	(3.5)	(2.2)
HCI^2	-8.53	-9.19	-10.29	-8.56	-0.69	-0.23	-2.46
	(-7.4)	(-5.7)	(-8.9)	(-10.1)	(-0.8)	(-0.6)	(-4.2)
Tariffs	0.031	0.035	-0.31	-0.72	-0.061	0.0033	0.019
	(0.6)	(0.6)	(-1.6)	(-0.4)	(1.4)	(0.3)	(0.1)
Year	-0.061	-0.82	-0.15	-0.010	-0.107	0.0017	0.0053
	(-0.6)	(-8.5)	(-1.7)	(-1.6)	(-10.7)	(5.9)	(2.1)
R^2	0.59	0.48	0.66	0.52	0.41	0.074	0.12
n	1909	1909	1803	1803	1909	1803	1803

t-statistics in parentheses

Table 6. Estimated Elasticities for PAOC, PCI and HCI

Dep. Var.	Model	*PAOCva*	*PCI*	*HCI*
RSCA	(1)	-0.053	0.24	0.19
	(2)	-0.012	0.57	0.59
Michaely	(1)	-0.30	0.64	3.1
	(2)	-0.0033	4.6	2.9
NETXva	(1)	-0.76	1.5	3.5
	(2)	-0.52	1.4	2.8
	(3)	-0.81	1.4	3.3
	(4)	-0.58	1.7	1.5
	(5)	-0.60	1.1	1.2
ΔNETXva	(6)	-0.86	1.6	1.0
	(7)	-0.66	1.6	0.91

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

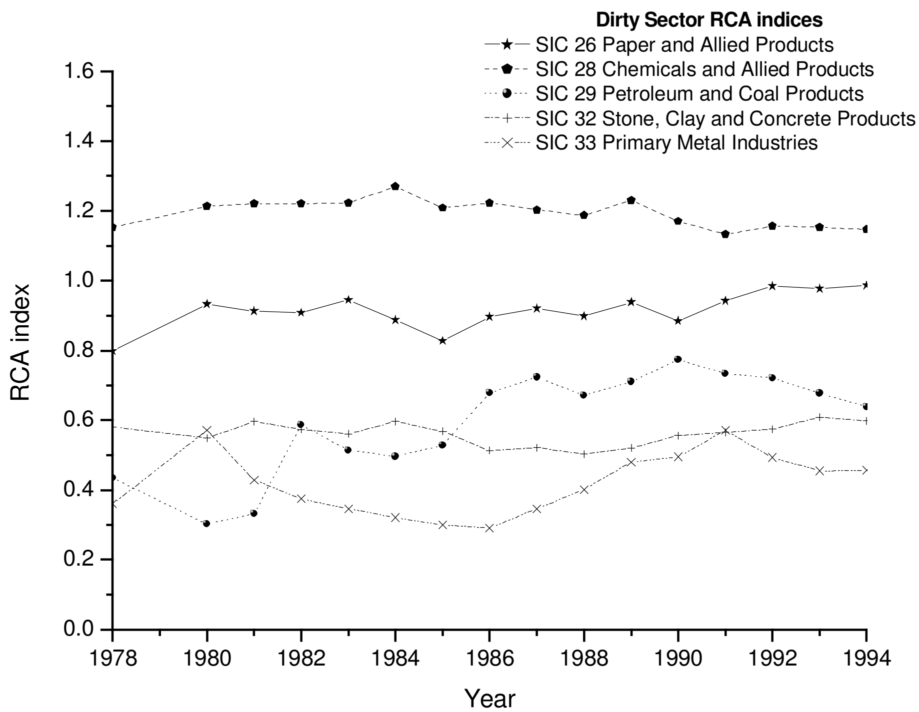


Figure 2. Michaely Indices of US 'Dirty' Sectors.

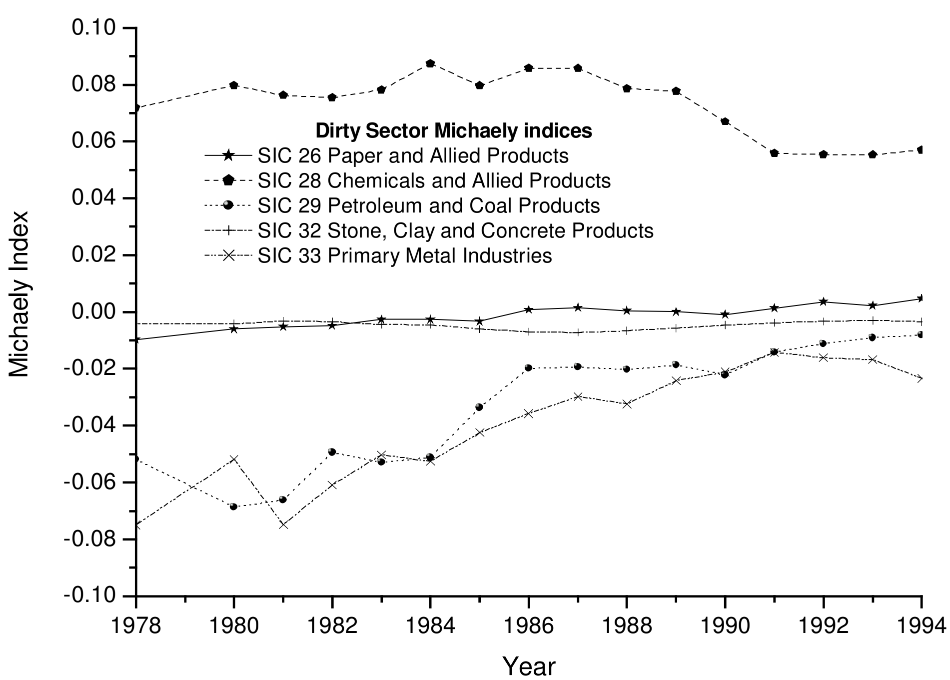


Figure 3. US Net Exports (Per Unit of Value Added) for 'Dirty' Sectors

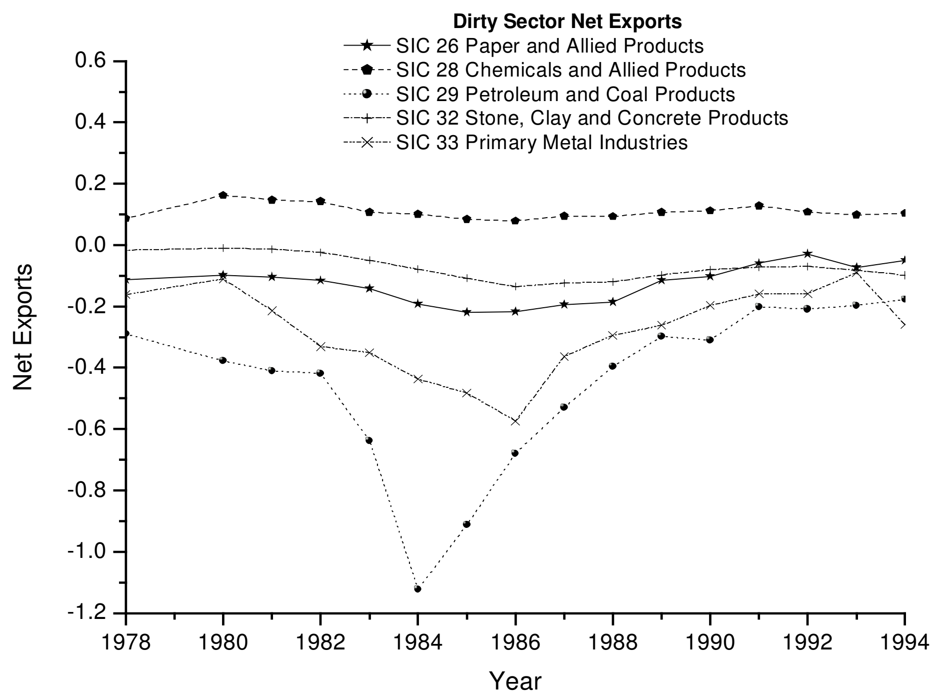


*Figure 4. US RCA Indices for the Most and Least **Physical** Capital-Intensive Sectors*

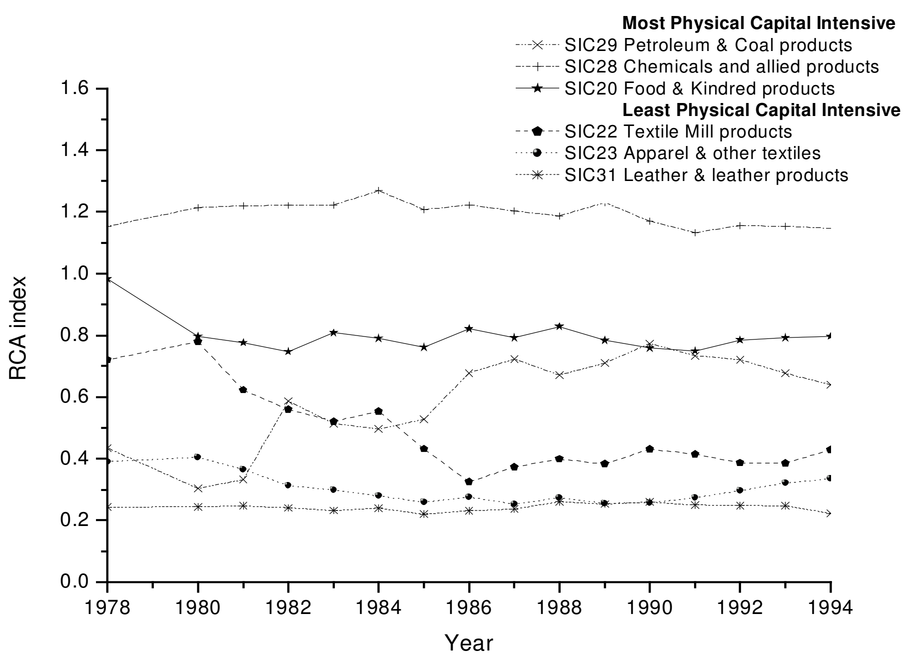


*Figure 5. US RCA Indices for the Most and Least **Human** Capital-Intensive Sectors*

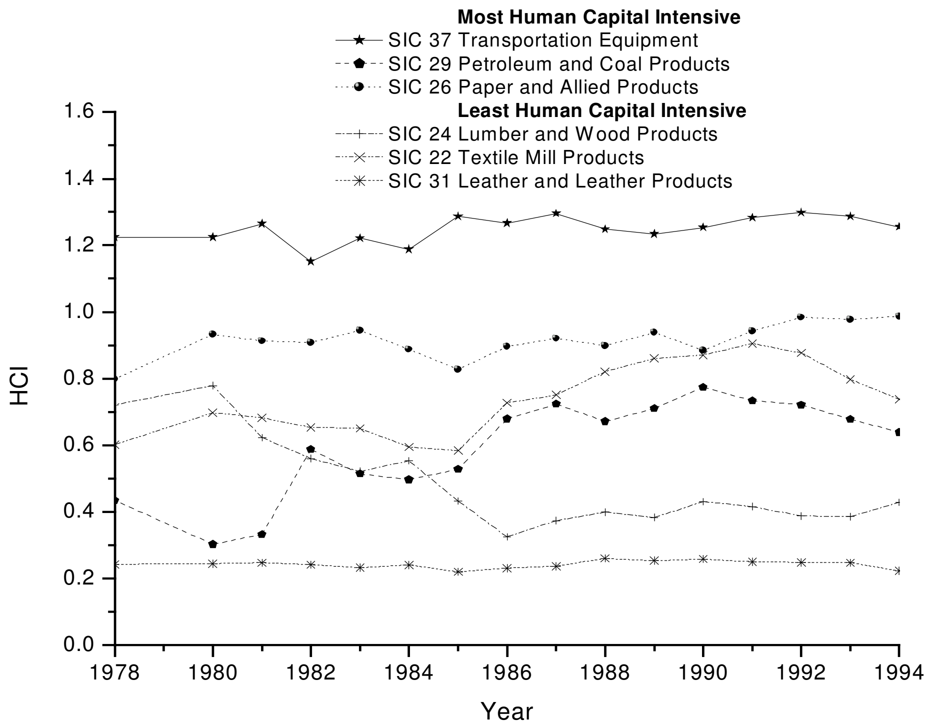
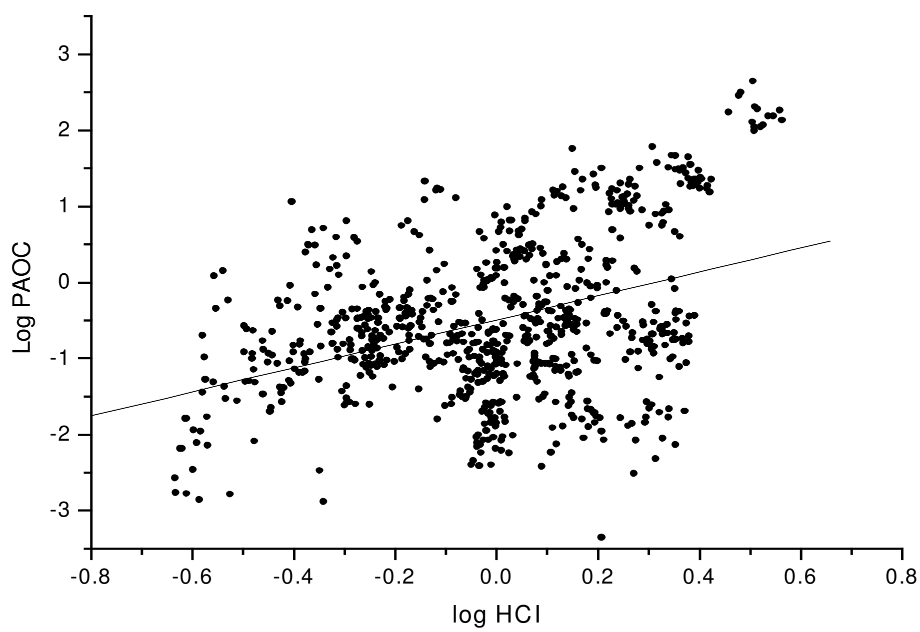


Figure 6. The Relationship Between Human Capital Intensity and Pollution Abatement Costs



Appendix 1. 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. World and US 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 55 'sectors', the majority of which are individual three-digit SIC sectors, but some are groupings of two or three such 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
Gross State Product	Used to calculate Instrument 1. Source: US Bureau of the Census
Abatement Cost Index	Levinson's (2001) Index of State Environmental Compliance Costs
Pollution intensities	Used to calculate Instrument 2. Source: Hettige *et al*. (1994)