

UNMASKING THE POLLUTION HAVEN EFFECT*

BY ARIK LEVINSON AND M. SCOTT TAYLOR¹

Georgetown University, U.S.A.; University of Calgary, Canada

We use theory and empirics to examine the effect of environmental regulations on trade flows. A simple model demonstrates how unobserved heterogeneity, endogeneity, and aggregation issues bias standard measurements of this relationship. A reduced-form estimate of the model, using data on U.S. regulations and trade with Canada and Mexico for 130 manufacturing industries from 1977 to 1986, indicates that industries whose abatement costs increased most experienced the largest increases in net imports. For the average industry, the change in net imports we ascribe to regulatory costs amounting to 10% of the total increase in trade volume over the period.

1. INTRODUCTION

Recent trade and environmental policy debates seem to take as given that regulatory stringency in developed countries shifts polluting industries to the developing world. Although widely believed, this “pollution haven effect” has proven difficult to demonstrate empirically. Some studies examine individual plant location decisions, whereas others study international trade. Until recently, neither approach found significant evidence of a pollution haven effect. But most of these used cross sections of data, making it difficult to control for unobserved characteristics of countries or industries that may be correlated with both environmental regulations and economic activity. A few recent studies have used panels of data and industry or country fixed effects, and have demonstrated small but statistically significant pollution haven effects.² This article employs both theoretical and empirical methods to uncover and estimate the magnitude of the pollution haven effect, while simultaneously arguing that previous efforts suffer from both inadequate accounting for unobserved heterogeneity and from the endogeneity of pollution abatement cost (PAC) measures.

* Manuscript received July 2004; revised September 2006.

¹ This research is part of a project funded by the National Science Foundation grant #9905576. The authors are grateful to Wolfgang Keller, John List, Rod Ludema, Dan Millimet, and Michael Rauscher for comments, and to Akito Matsumoto and Sjamsu Rahardja for research assistance. Taylor thanks the Princeton Economics Department for its hospitality during the time he worked on this article, and the Vilas Trust at the University of Wisconsin for funding. Please address correspondence to: Arik Levinson, Economics Department, Georgetown University, 3700 O Street, NW, Washington, DC 20057, USA. Telephone: 202-687-5571. E-mail: aml6@georgetown.edu.

² See, for example, Becker and Henderson (2000), Greenstone (2002), and List et al. (2003) for recent papers on plant locations, and Ederington and Minier (2003) on international trade. Jaffe et al. (1995) survey the earlier literature, and Copeland and Taylor (2004) and Brunnermeir and Levinson (2004) review the newer studies.

Explanations for the failure to find a pollution haven effect often point to the small fraction of costs represented by pollution abatement. Although it is possible that more stringent environmental regulations have a small effect on firms' costs and international competitiveness, it seems unlikely that more stringent regulations would have no effect whatsoever. This explanation is further undermined by frequent counterintuitive empirical results. Some researchers find larger and more significant pollution haven effects for less pollution-intensive industries. A few even find evidence that industries with relatively high PAC are leading exporters.³ In these cases, the Porter hypothesis—that regulation brings cost-reducing innovation—is often invoked as the explanation for finding a positive link between regulatory stringency and exports.⁴

The current state of empirical work leaves important questions unanswered. Many trade policy analysts express concern that countries may undercut international tariff agreements by weakening environmental regulations to placate domestic protectionist interests.⁵ If this is true, international trade negotiators may need to close this loophole by placing explicit restrictions on domestic environmental policies. This concern, however, rests on the assumption that environmental regulations have significant cost and competitiveness consequences—a disputed empirical point.

In this paper, we reexamine the link between abatement costs and trade flows, using both theory and empirics, in the hope of identifying and accounting for several important econometric and data issues. We believe that these issues—and not the relatively small costs of pollution abatement or the Porter hypothesis—are responsible for the mixed results produced so far.

To do so, we develop a simple, multisector, partial equilibrium model, where each manufacturing sector (i.e., a 3-digit standard industrial classification [SIC] code) is composed of many heterogeneous (4-digit) industries. Sectors can differ in their use of primary factors and in their average pollution intensity; one sector's production could be capital intensive and relatively dirty, whereas another's is labor intensive and relatively clean. To make our point as clear as possible, we assume that industries within a sector differ only in their pollution intensity, and two-way trade within each 3-digit sector occurs because of these differences. We take factor prices and national incomes as exogenous, and make no attempt to make environmental policy endogenous. This simple model serves two purposes.

First, and most importantly, we use the model to show likely sources of bias in previous empirical work. We derive an analytical expression for the measured PAC as a fraction of value added. This statistic is widely used as a measure of regulatory stringency in empirical work estimating the pollution haven effect. We show how this measure is simultaneously determined with trade flows, and demonstrate how unobserved changes in foreign costs, regulations, or domestic industry attributes can produce a spurious negative correlation between the sector-wide PAC and net imports. This correlation is opposite to the direct effect predicted by the pollution

³ See, for example, Kalt (1988), Grossman and Krueger (1993), or Osang and Nandy (2000).

⁴ Porter and Van Der Linde (1995).

⁵ See Ederington and Minier (2003) for empirical evidence of this.

haven hypothesis, and suggests an explanation for the difficulties encountered by earlier studies.

Second, we show how the model relates to a reduced-form estimating equation, linking industry net imports to domestic and foreign measures of regulations, factor costs, and tariffs. The theoretical model enables us to be explicit about the estimating equation's error term and the implications of employing PAC as a proxy for direct measures of regulation. We detail the set of conditions a successful instrument must exhibit, and then construct instrumental variables relying on the geographic distribution of dirty industries around the United States. Geographic location has been used as a source of exogenous variation before (see Frankel and Romer, 1999, in particular), but here it is put to new use in estimating the effect of pollution costs on trade flows.

We then estimate the pollution haven effect using data on U.S. imports in 132 3-digit manufacturing sectors from Mexico and Canada over the 1977–86 period. We are limited in coverage by changes in SIC codes after 1987 and by the discontinuation of the PAC data. Our empirical results consistently show a positive, statistically significant, and empirically plausible relationship between industry PAC and net imports into the United States. This is true for imports from both Mexico and Canada.

In fixed-effects estimations, we find that a 1% increase in PAC is associated with a 0.2% increase in net imports from Mexico (or decrease in net exports), and a 0.4% increase in net imports from Canada. When we instrument for PAC, we find larger effects. The same 1% increase in PAC predicts a 0.4% increase in net imports from Mexico and a 0.6% increase from Canada.

To put these estimates in context, for the average 3-digit U.S. manufacturing sector, PAC as a fraction of U.S. value added approximately *doubled* between 1977 and 1986. At the same time, trade volume (real exports plus imports) grew by over 300% from Canada and over 600% from Mexico.

Before describing the details of these estimates, we need to outline a model of trade and present an estimating equation. Along the way, we will point out the biases that may have affected previous work using similar data.

2. A MODEL OF POLLUTION COSTS AND TRADE

Consider two countries, “Home” and “Foreign,” with foreign attributes denoted by a star (*). The model is partial equilibrium, in the sense that factor prices and environmental policies in the form of pollution taxes (τ , τ^*) are exogenous.⁶ To generate a basis for trade arising from differences in regulation, we assume Home has more stringent regulation than Foreign: $\tau > \tau^*$. Each country produces output in each of N sectors, which we index by i . Empirically, “sectors” correspond to 3-digit SIC codes. Within each sector is a continuum of industries indexed by

⁶ We use emissions taxes (τ , τ^*) here for convenience and clarity, as they provide a direct link between the stringency of policy, competitiveness, and PAC. Other instruments (quotas or restrictions on technology choice) can be and are used by governments. For example, restrictions on emissions per unit output yield a similar relationship between the stringency of environmental policy and measures of PAC.

$\eta \in [0,1]$. “Industries” correspond to 4-digit SIC codes.⁷ We denote output from industry η in the x_i , or i th sector, by $x_i(\eta)$. Production in each sector requires labor and sector-specific capital, but creates pollution as a joint product. Industries within each sector differ only in the pollution intensity of their output. This allows us to demonstrate very clearly how (within sector) trade flows respond to changes in environmental policy across countries. At the same time, since each sector employs sector-specific capital, the pattern of trade (across sectors) is determined by national differences in factor costs together with differences in environmental policy. For simplicity, consumers in each country spend a constant fraction of their incomes on goods from each sector, and spread these expenditures across industries within a sector uniformly. Home and foreign consumers need not have identical tastes.

2.1. *Technologies and Abatement.* Production in sector “ i ” uses labor, L_i , and a sector-specific factor of production, K_i . Production creates pollution as a by-product, but firms allocate part of their factor use to abatement. We denote the fraction of factor use devoted to abatement as θ . Since production is constant returns to scale (CRS), we can write output available for sale in a typical industry, η , as

$$(1) \quad x(\eta) = [1 - \theta(\eta)] F(K(\eta), L(\eta)),$$

where we suppress the i -sector subscript for clarity. Given CRS and free entry, total revenue equals total costs, and since there are no intermediate goods, value added equals total revenues. This implies that $\theta(\eta)$ is the share of PAC in value added in industry η .

Pollution emitted is a function of total activity, F , and the intensity of abatement, θ ,

$$(2) \quad z(\eta) = \phi(\theta(\eta)) F(K(\eta), L(\eta)),$$

where ϕ is a decreasing function of θ . It is useful in our empirical work to be able to rank industries in terms of their pollution intensity and abatement efforts. To do so, we assume $\phi(\theta) = (1 - \theta)^{1/\alpha}$, where $0 < \alpha < 1$. Firms faced with a pollution tax of τ per unit of z , and given prices for labor and capital employed in abatement, choose θ to minimize costs. With relatively low pollution taxes, no abatement will occur, $\theta = 0$, and by choice of units, pollution emitted equals output, that is, $\phi(0) = 1$ and $z = x = F(K, L)$. When pollution taxes are relatively high, abatement is active, $\theta > 0$, and pollution is reduced.⁸

When abatement occurs, we can use Equations (1) and (2) to write output as if it were produced via a Cobb–Douglas function of pollution emitted and

⁷ Technically, 3-digit SIC codes are referred to as “industry groups.” We use the term “sector” for convenience.

⁸ See Copeland and Taylor (2003, chapter 2) for a similar model and further details.

traditional factors,

$$(3) \quad x(\eta) = z(\eta)^{\alpha(\eta)} [F(K(\eta), L(\eta))]^{1-\alpha(\eta)}$$

and by labeling industries appropriately, we obtain $\alpha'(\eta) > 0$: high- η industries are the most pollution intensive. We can also extend this ordering from the primitive $\alpha(\eta)$ to the endogenous variable $\theta(\eta)$, so that the most pollution-intensive industries also exhibit the highest PAC as a fraction of value added.⁹

2.2. *The Pattern of Trade.* To determine the subset of industries in each 3-digit sector produced at home, we compare unit costs across countries. From Equation (3), it is apparent that unit costs at home are

$$(4) \quad c(\eta) = k(\eta)\tau^{\alpha(\eta)}(c^F)^{1-\alpha(\eta)},$$

where $k(\eta)$ is a constant, τ is the cost of emitting one unit of z , and $c^F = c^F(w, r)$ is the unit cost of producing one unit of F using labor and the sector-specific capital with factor prices (w, r) . A similar unit cost function denoted by $c^*(\eta)$ describes foreign costs. Therefore, the home country produces and exports in all industries η such that $c(\eta) \leq c^*(\eta)$, whereas Foreign produces the remainder. Rearranging this condition shows that industry η is produced at Home when

$$(5) \quad \left(\frac{c^F}{c^{F*}}\right) \leq \left(\frac{\tau^*}{\tau}\right)^{\alpha(\eta)/1-\alpha(\eta)} \equiv \Gamma(\eta; \tau, \tau^*).$$

The left-hand side of Equation (5) is independent of η . The right-hand side is declining in η because $\tau > \tau^*$ and $\alpha'(\eta) > 0$. In any sector, $\Gamma(1; \tau, \tau^*) > c^F/c^{F*}$ is inconsistent with full employment of Foreign's sector-specific factor, while $\Gamma(0; \tau, \tau^*) < c^F/c^{F*}$ is inconsistent with full employment of Home's sector-specific factor. Hence, taking Equation (5) with equality defines an interior threshold industry, $\bar{\eta} \equiv g(c^F, c^{F*}, \tau, \tau^*)$.

Figure 1(a) depicts the basic setup for two sectors that we have labeled 1 and 2, which are identical except that production of x_2 in the foreign country is relatively cheaper than x_1 : $c_1^{F*} > c_2^{F*}$. The x_1 sector faces factor costs c_1^F at home and c_1^{F*} abroad, and pollution taxes τ and τ^* , respectively. To the left of $\bar{\eta}_1$, we have $c(\eta) < c^*(\eta)$: These industries are active at Home and their products are exported to Foreign. To the right of $\bar{\eta}_1$, we have $c(\eta) > c(\eta)^*$: These industries are active in Foreign and their products are exported to Home. By construction, within-sector trade flows are driven entirely by differences in environmental policy across countries with the dirtiest industries in any sector produced and exported by the low pollution tax country. From Equation (5), it is apparent that a uniform increase

⁹ Equation (3) is only valid when pollution taxes are high relative to the unit cost of abatement inputs, c^F , so that abatement is worthwhile. Specifically, when $\tau/c^F > \alpha(1) \exp\{[1/(1-\alpha(1))]\}/[1-\alpha(1)]$, abatement is undertaken in all industries and θ is increasing in η . We assume this condition (and its foreign analog) holds throughout.

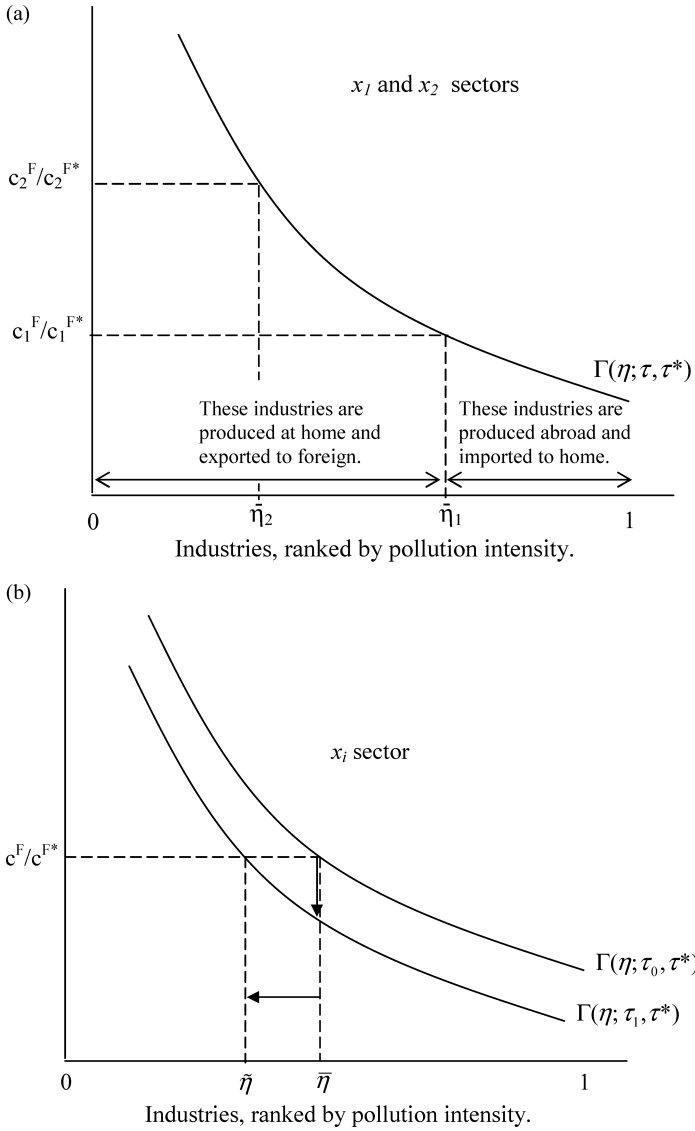


FIGURE 1

(A) UNIT COSTS DETERMINE NET IMPORTS WITHIN A SECTOR AND (B) THE EFFECT OF AN INCREASE IN POLLUTION TAXES ON ABATEMENT COSTS

in $\alpha(\eta)$ makes a sector, on average, more pollution intensive and shifts Γ down. Therefore, the advantage of low pollution taxes is greatest in sectors that are very pollution intensive.

Now consider sector 2, which is also shown in the figure. To avoid clutter, we have assumed that sectors 1 and 2 share the same Γ function (which implies they

have the same pollution intensity in each industry), but as shown $\bar{\eta}_1 > \bar{\eta}_2$. Home exports a smaller range of goods to Foreign in sector 2 than in sector 1. The reason is straightforward: Home's unit costs are relatively high in this sector, and cross-sector variation in trade patterns reflects both differences in the unit cost of conventional factors of production and in environmental policy.

3. FROM THEORY TO ESTIMATION

The vast majority of work in this area estimates specifications only loosely related to theory. Although we do not provide structural estimation either, it is useful to employ our theory to identify the set of assumptions made in generating the typical estimating equation. By doing so, we can illustrate several potential problems and biases present in the literature.

To start with, let b_i and b_i^* denote the fraction of income spent on sector x_i products in the Home and Foreign country, respectively, and I and I^* represent their respective national incomes. Then the value of Home imports from Foreign in the x_i sector are $b_i I [1 - \bar{\eta}_i]$, the value of Foreign imports from Home in the same sector are $b_i^* I^* \bar{\eta}_i$, and the value of Home net imports are

$$(6) \quad \text{Net Imports}_i = b_i I [1 - \bar{\eta}_i] - b_i^* I^* \bar{\eta}_i.$$

Since sectors differ greatly in size, it is common to scale imports by domestic production or value shipped.¹⁰ In our model, these are the same, and since the value of domestic production is equal to $[b_i I + b_i^* I^*] \bar{\eta}_i$, we write net imports in sector “ i ” (scaled by domestic production) as

$$(7) \quad N_i = - \left[1 - \frac{s_i}{\bar{\eta}_i} \right],$$

where s_i is Home's share of world spending in the i th sector. Net imports in sector i are positive if Home's share of world spending exceeds its share of world production: $s_i > \bar{\eta}_i$. Employing our definition of $\bar{\eta}_i$ and approximating Equation (7) with a linear function, we write the determinants of net imports in the x_i sector as

$$(8) \quad N_{it} = \beta_0 + \beta_1 s_{it} + \beta_2 c_{it}^F + \beta_3 c_{it}^{F*} + \beta_4 \tau_{it} + \beta_5 \tau_{it}^* + \varepsilon_{it},$$

where ε_{it} reflects both approximation error and standard measurement error in obtaining data on net imports, N_{it} .

The only component of foreign costs (c^{F*}) that we observe is the tariffs on foreign products, so we include those at the sector level and denote them by T_{it} . We do not observe other components of c^{F*} or foreign pollution taxes (τ^*). To

¹⁰ This is to ensure that any excluded right-hand side variable that is correlated with industry size does not automatically contaminate the error. See Leamer and Levinsohn (1996) on this point.

capture changes in Home's share of world spending, s_{it} , and any other economy-wide change in U.S. propensity to import, we include a set of unrestricted time dummies (D_t) in our estimation. In addition, we add sector dummies (D_i) to control for sector-specific but time-invariant differences in foreign and domestic unit costs and consumer tastes. Since we have a relatively short panel, and the stocks of primary factors, such as physical and human capital, that determine (c^F) and (c^{F*}) are only slowly moving, sector fixed effects may capture most if not all unobserved differences in the ratio of Home to Foreign costs.

Whereas the typical sources of comparative advantage adjust slowly over time, U.S. environmental regulations changed sharply over our sample period. Although we do not observe domestic pollution taxes or other measures of environmental regulation costs to represent τ_{it} , we do observe PAC as a fraction of value added (θ_{it}). Making this substitution yields our estimating equation:

$$(9) \quad N_{it} = a\theta_{it} + bT_{it} + \sum_{i=1}^N c_i D_i + \sum_{t=1}^T d_t D_t + e_{it}.$$

The error term, e_{it} , contains our original measurement and approximation error reported in Equation (8), plus any industry-specific, time-varying element of the ratio c_{it}^{F*}/c_{it}^F not captured by our industry dummies, foreign pollution costs, τ_{it}^* , and measurement error introduced by employing θ_{it} rather than τ_{it} . These observations raise several econometric issues.

3.1. *Econometric Issues.* Environmental regulations take many forms: technology requirements, effluent limits, permitting standards, etc. Sometimes these are strictly enforced, and sometimes they are not. As a consequence, no single measure of environmental stringency can be used in regressions such as Equation (9). Instead, researchers have relied on indirect measures of stringency such as PAC. Although this measure has the benefit of being readily available for many industries and time periods and measures the cost consequences of various regulations, it also suffers from at least three deficiencies that make its use in empirical work problematic.

To be precise about these deficiencies, it is useful to examine the determinants of this commonly used measure within our model of trade and pollution. To do so, note that total revenues (at producer prices) for any industry in the x_i sector are given by $p(1-\alpha_i)x_i$, since pollution taxes account for fraction α of total revenues. PAC are just a fraction of revenues given by $p(1-\alpha_i)x_i\theta$.¹¹ To find the sector-wide measure of PAC, integrate over all industries active in this sector at home:

$$\int_0^{\bar{\eta}} p(\eta)x(\eta) (1 - \alpha(\eta))\theta(\eta) d\eta.$$

¹¹ Producers pay the fraction α of revenues as pollution taxes (recall Equation (4)); hence the producer price, net of tax payments, is $p(1-\alpha)$. From Equation (5) we also have $p(1-\alpha)x = c^F F$. PAC are $\theta c^F F$; hence, PAC can be written $\theta p(1-\alpha)x$. PAC as a fraction of value added are then just θ .

Total PAC as a share of value added (again measured at producer prices) is

$$\int_0^{\bar{\eta}} p(\eta)x(\eta)(1 - \alpha(\eta))\theta(\eta)d\eta / \int_0^{\bar{\eta}} p(\eta)x(\eta)(1 - \alpha(\eta)) d\eta$$

Since aggregate spending on products in the x_i sector by Home and Foreign is given by $[b_iI + b_i^*I]$, we can simplify to write PAC as a share of value added as

$$(10) \quad \theta_i(\bar{\eta}_i) \equiv \frac{PAC_i}{VA_i} = \frac{\int_0^{\bar{\eta}_i} (1 - \alpha(\eta))\theta(\eta) d\eta}{\int_0^{\bar{\eta}_i} (1 - \alpha(\eta)) d\eta},$$

where $\theta_i(\bar{\eta}_i)$ is the fraction of value added in sector x_i that is spent on pollution abatement when the home country produces goods in the range $[0, \bar{\eta}_i]$. Once we introduce time subscripts, Equation (10) is our proxy for τ_{it} in Equation (9). Because this measure was readily available in the United States from the mid-1970s until 1994, it is the measure of regulatory stringency used by numerous studies in examining the effect of pollution regulation.

The first econometric problem arises when variation in $\theta_i(\bar{\eta}_i)$ across sectors reflects unobserved heterogeneity rather than differences in regulatory stringency. To demonstrate, suppose we compare two sectors, x_1 and x_2 , depicted in Figure 1(a). Assume they face the same PAC, are equally dirty, and have identical costs at Home given by $c_1^f = c_2^f$. Since all active industries in sector 1 and 2 have identical costs, they share identical $\theta(\eta)$ terms, industry by industry, and are observably equivalent to the econometrician. But now assume production in sector x_2 in the foreign country is relatively cheaper than in x_1 . That is, $c_1^{f*} > c_2^{f*}$. As a result of this variation in comparative advantage at the sector level, sector 2 has higher net imports and lower PAC. Differentiating Equation (10) shows $d\theta_i/dc_i^{f*} > 0$. The reason is straightforward: The dirtiest industries in sector 2 are imported, and not counted in domestic pollution costs. And since foreign costs are unknown, we only observe that sector x_1 has higher PAC and lower net imports than x_2 —a seeming contradiction of the negative link between environmental control costs and competitiveness.

There is, in fact, some evidence of this in existing work. Grossman and Krueger’s (1993) original study of the North American Free Trade Agreement (NAFTA) found a negative and significant relationship between PAC and imports in some of their cross-section regressions. And several studies have reported a smaller coefficient on pollution cost variables in resource-intensive or dirty industries than in other industries, i.e., coefficients are smaller in just those industries where unmeasured industry-specific factors may loom large in determining production costs. In Section 5, we show evidence of this unobserved heterogeneity in our data.

A second problem arises from unobserved foreign environmental regulation. Although foreign pollution regulations have no direct effect on Home PAC, it is apparent from Equation (10) that θ_{it} is an increasing function of $\bar{\eta}_{it}$, and $\bar{\eta}_{it}$ is itself an increasing function of unobserved foreign pollution regulations, τ_{it}^* . Consequently, the error term, e_{it} , in Equation (9) is almost surely correlated with the

right-hand-side variable, θ_{it} , making estimation by ordinary least squares (OLS) biased and inconsistent. When Foreign PAC rise, Home's measured sector-wide PAC rise but its net imports fall. If foreign pollution costs were the only time-varying determinants of net imports, we could then use the standard omitted variable formula to conclude that β_4 in Equation (9) is biased downward, because β_5 is negative and we have established a positive covariance between the measure of Home stringency and unobserved foreign pollution regulations. Whether this covariance is positive in the data is unknown; nevertheless, our discussion provides a suggestive explanation for the small or even counterintuitive signs found on PAC in previous research.

The final problem introduced by the indirect measure of stringency is an aggregation bias arising from the fact that the unit of observation (3-digit sectors) is a heterogeneous mix of 4-digit industries.¹² This heterogeneity means that when pollution regulations at home raise production costs, some of the industries lose out to foreign competition and shut down. The direct effect of an increase in the pollution tax is that industries at home respond by abating more pollution, devoting a larger share of output to abatement, and increasing $\theta(\eta)$ for each industry η within sector x . There is, however, an additional effect, which is depicted in Figure 1(b). When the increase in the pollution tax shifts the Γ function downward, it produces a new lower threshold industry $\tilde{\eta}$. Goods produced by industries between $\tilde{\eta}$ and $\bar{\eta}$ are now imported from Foreign rather than produced domestically: Therefore, imports and $\theta_i(\tilde{\eta}_i)$ are jointly determined. In fact, since the industries given up to Foreign were the dirtiest in the x_i sector, this second impact of pollution regulations works to lower $\theta_i(\tilde{\eta}_i)$ in Equation (10). Studies seeking to measure the effect of pollution costs on trade inadvertently also capture the effect of trade on measured pollution costs.¹³

To demonstrate the potential importance of this aggregation bias, in Figure 2, we plot pollution abatement operating costs (PAOC) per dollar of value added in U.S. manufacturing sector over 1974–94. These plots compare $\theta_{it}(\tilde{\eta}_{it})$ from Equation (10) with $\theta_{it}(\tilde{\eta}_{i1974})$, where we fix industry composition at its initial 1974 value. Our analysis tells us that rising home pollution regulations lower measured sector-wide costs by altering the composition of the remaining industry. By fixing the composition of industry, we should observe higher sector-wide PAC, as we are then only measuring the impact of rising pollution regulation on a fixed set of industries.

¹² We recognize that 3-digit SIC codes aggregate 4-digit industries that are heterogeneous in many ways, not only pollution intensities. The econometric issues we describe here would apply equally if we were trying to estimate, say, the effect of labor standards or capital costs on trade, and aggregating across industry groups with different levels of labor and capital intensities. We can only hope that differences in these other characteristics are of second order, relative to the changes in pollution regulations that occurred from 1977 to 1986, and that they can be absorbed by the industry fixed effects.

¹³ In general though, the direction of this bias is unclear. In our model, an increase in pollution costs causes the most pollution-intensive industries to move abroad, reducing the average pollution costs of the industries remaining at home, but it is unclear whether this is true in the data. For example, some very dirty natural resource industries may have little or no international mobility, whereas relatively clean assembling operations may move quite easily.

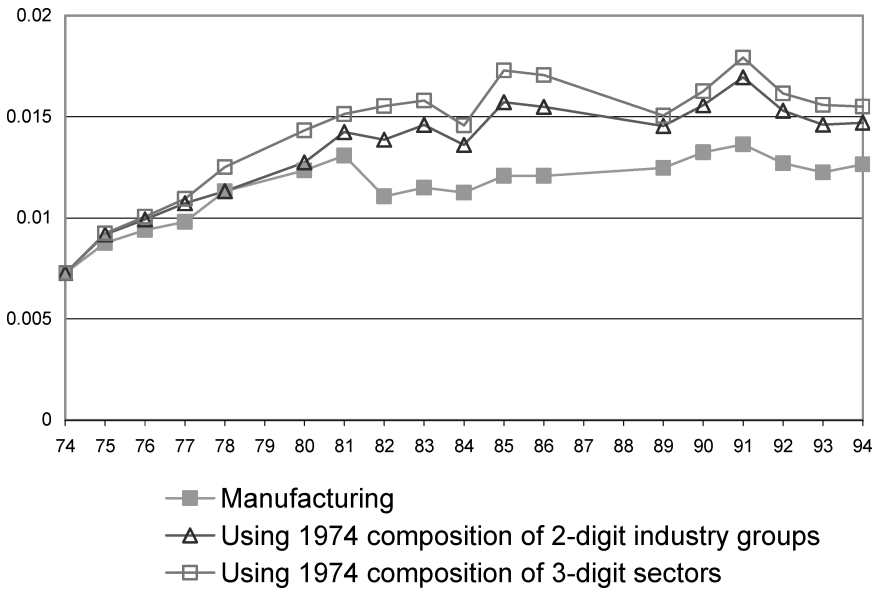


FIGURE 2

POLLUTION ABATEMENT COSTS AS A FRACTION OF VALUE ADDED

The bottom line in Figure 2 shows the aggregate value for all U.S. manufacturing. It rises sharply through the late 1970s, and then remains relatively flat. Note, however, that if the composition of U.S. manufacturing shifted away from polluting industries, this bottom line understates what PAC would have been had all industries remained as they were in 1974. To see this, the second line in Figure 2 plots PAOC, divided by value added, where the composition of U.S. industries by 2-digit SIC code is held constant as of 1974. This line is higher because U.S. manufacturing has shifted toward less polluting 2-digit industry groups. Similarly, the third line holds the industrial composition constant at the 3-digit SIC code level. It is higher still because within each 2-digit group, the composition has shifted toward less polluting 3-digit sectors. We strongly suspect, but cannot prove because of data limitations, that a similar process is at work at the 4-digit level making our 3-digit, sector-wide measures similarly suspect. Furthermore, the problem cannot be solved by disaggregating, because any practical industry definition will include heterogeneous subindustries that differ in their pollution intensities and their propensities to be imported.

Figure 2 suggests why pollution haven effects are so difficult to observe. Aggregate measures of PAC per dollar of value added understate the rise in regulatory stringency in the United States, because the composition of output has become relatively cleaner over time. Although we cannot say that this change in composition is solely due to rising U.S. pollution control costs, the change in composition alone poses a major problem for research on the effect of environmental costs on trade: Industries whose regulations increased most are increasingly likely to be

imported, which then lowers measured increases in pollution costs in the United States. Researchers trying to measure the effect of costs on trade can be misled by the effect of trade on measured costs.

4. INSTRUMENTS

The preceding section has detailed the problems involved in estimating Equation (9): unobserved heterogeneity, unobserved foreign pollution regulations, and aggregation bias. Unobserved heterogeneity is a well-recognized pitfall, and is typically solved by including sector or country fixed effects, depending on the unit of analysis.¹⁴ Given our panel, we include time and sector fixed effects to soak up unobserved sector-specific or time-specific excluded variables. Many of the unobservable sector characteristics are very slow moving, including sources of comparative advantage that attract pollution-intensive sectors: geographic proximity to markets, sources of raw materials, etc. By looking at *changes* in net imports as a function of *changes* in PAC, we can difference out the unobservable effects of sector characteristics that remain constant.

To address the other two problems, we adopt a fixed-effects instrumental variables approach.¹⁵ With fixed effects included, our instrument must have both time and sector variations; it must be correlated with sector-wide PAC measures; and it must be uncorrelated with the sector-specific time varying elements left in e_{it} . Using Equation (10) and recalling $\bar{\eta} \equiv g(c^F, c^{F*}, \tau, \tau^*)$, we write sector-wide PAC as

$$\theta_{it} = \Omega(c_{it}^F, c_{it}^{F*}, \tau_{it}, \tau_{it}^*).$$

Since domestic costs, foreign costs, and foreign regulations are unobserved, any time- and sector-specific component of these is left in our error. Therefore, our instrument must create independent variation in abatement costs by altering the home country's pollution regulation.

To find instruments, we proceed in several steps. First, we note that standard theories of regulation relate the stringency of regulation to the income levels of affected parties, the current level of pollution, and tastes. Hence, variations in income, pollution, or tastes are possible candidates.¹⁶ However, these characteristics vary by region rather than by sector. The second step then is to transform these aggregate regional characteristics into useful instruments with both time and sector variations. To do so, we employ two facts and make one assumption. The first fact is that much of U.S. environmental policy is set by states. As a result,

¹⁴ That implies that researchers have access to a panel of data over many years, something that is not always true. Several researchers have taken this approach, and the results often do support a modest pollution haven effect. See, for example, Ederington and Minier (2003) and Ederington et al. (2005).

¹⁵ Ederington and Minier (2003) also instrument for environmental regulatory stringency in a paper that focuses on environmental regulations as a strategic substitute for trade restrictions.

¹⁶ See, for example, Copeland and Taylor (2003, chapter 2).

variation in state-level regulation will affect PAC. The second fact is that the distribution of manufacturing sectors across states is not uniform: Different sectors are concentrated in different parts of the country. A consequence of these two facts is that some sectors are predominantly located in stringent states and face high PAC; other sectors are located in lax states and face low PAC.

To construct our instruments, for each sector, we take a weighted average of state characteristics (q_s), where the weights are the sector's value added in the various states (v_{is}) at the beginning of the sample period. By using beginning-of-period weights, all variations over time come from changes in state characteristics. More concretely, for the 48 contiguous U.S. states, our instrument for the pollution costs faced by sector i based on characteristic q is

$$(11) \quad \zeta_{it} = \sum_{s=1}^{48} q_{st} v_{is,77} / v_{i,77},$$

where q_{st} is the characteristic of state s in year t , $v_{is,77}$ is the value added by sector i in state s in 1977, and $v_{i,77} = \sum_{s=1}^{48} v_{is,77}$ is the sum of the value added by sector i across all 48 contiguous states in 1977.

To be a good instrument, ζ_{it} must be correlated with the PAC facing the x_i sector, while simultaneously being uncorrelated with the error e_{it} in Equation (9). Take as given that the state characteristic, q_{st} , is strongly related to state-level regulations and hence PAC. And now recall that the error term in Equation (9) contains measurement and approximation errors reported in Equation (8), time-varying sources of comparative advantage, c_{it}^{F*}/c_{it}^F , foreign pollution costs, τ_{it} , and measurement error introduced by employing θ_{it} rather than τ_{it} . Since we have included both time and sector dummies, only the time-varying and sector-specific elements of these unobserved variables remain in our error term. Therefore, whether our instruments are valid relies on there being zero covariance between the remaining sector-specific and time-varying elements of e_{it} and ζ_{it} . Since ζ_{it} is a (fixed) linear function of state characteristics, this simplifies to requiring that at each t we have $\text{cov}(e_{it}, q_{st}) = 0$ for all s . In turn, this requires an assumption:

ASSUMPTION 1. Sector-specific shocks to costs, tariffs, foreign pollution regulations, etc., that alter home sector production are not large enough to induce a change in the stringency of environmental policy in the states in which this sector resides.

This is basically a small industry assumption. If it holds, then sector-specific and time-varying shocks in each sector alter net imports in that sector, but do not affect environmental stringency. A beneficial shock to sector i will raise the demand for its output and its derived demand for pollution; but if this sector's share of emissions is small in this state, then the aggregate demand for pollution is virtually unchanged. Sector-specific shocks then have no effect on pollution demand.

If this sector is also small in providing income to state residents, then the shock will have a negligible effect on state incomes as well, and hence no impact on

marginal damage. Pollution supply is then unaffected by sector-specific shocks. If the sector is small in both of these senses, then environmental stringency is independent of sector-specific shocks.¹⁷

What are the good candidates for the exogenous variation that we need to alter PAC? We exploit two basic sources of exogenous variation. The first arises when a set of sectors (other than the i th) experiences a shock. For example, suppose foreign costs rise in some set of sectors we denote by J , and this stimulates output in those sectors. This shock raises the competitive margin in the set of J sectors, shifts pollution demand to the right, and raises PAC for the i th sector. Abatement costs in the i th sector rise because of the shock in the j th.

To construct this instrument, we need to construct measures of pollutants emitted in each state by all sectors. The World Bank has estimated the pollution emissions per dollar of value added for each manufacturing SIC code in the United States, for 14 different air, water, and solid waste pollutants (Hettige et al., 1994). We use these figures to estimate the total emissions of each of the 14 pollutants in each state, based on each sector's value added in each state in each year. This gives us 14 instruments, where we are careful to exclude sector i 's contribution in its own instrument. Sectors with a high value of this instrument for a given pollutant are located in states with a large amount of that pollutant being generated by *other* 3-digit sectors.

Formally, the instrument works as follows: For a given pollutant E , say airborne particulates, we take the total amount predicted to be emitted in state s by all sectors except sector i . That gives us the amount of pollution in state s at time t due to other sectors. (This is the term in brackets in Equation (12) below.) Then we take a weighted average of all 48 contiguous states, where the weights are sector i 's value added in each state in 1977. That gives us our instrument, a measure of the amount of pollutant E contributed by other sectors in the states in which sector i tends to locate:

$$(12) \quad \zeta_{it}^1 = \frac{\sum_{s=1}^{48} \left(\sum_{j \neq i} E_{jst} \right) \times (V_{is,77})}{V_{i,77}}.$$

Sectors that locate in states with lots of pollution caused by other sectors will have high values of this instrument, and vice versa. Since the World Bank data cover 14 pollutants, we calculate a version of Equation (12) for each.

Our second instrument is based on pollution supply rather than pollution demand. State incomes vary over time because of ongoing technological progress and factor accumulation, which we take as exogenous to developments in sector i . These gains may occur in services, real estate, transportation, mining, agriculture, or in other manufacturing sectors. To the extent that these changes raise state incomes, they will affect the demand for a clean environment (pollution supply).

¹⁷ In the empirical section, we test the sensitivity of the results to the exclusion of industries that are relatively large in particular states or counties.

Formally, we take a weighted average of the incomes per capita in the states, where the weights are sector i 's value added in each state in 1977:

$$(13) \quad \zeta_{it}^2 = \frac{\sum_{s=1}^{48} (\text{Income per capita}_{st}) \times (V_{is,77})}{V_{i,77}}.$$

Sectors located in states whose incomes are growing faster will have values of this instrument that increase over time.

4.1. *When Might the Instruments Fail?* This discussion suggests our instruments can fail in a couple of ways. First, our “small industry” assumption may be untrue if any single sector can have a significant effect on the aggregate demand or supply of pollution. If changes in the sector’s size affect state environmental policy, then the instrument fails. To investigate this possibility, as a robustness test of our instruments, we identify those sectors that represent more than 3% of gross state product in any state, and eliminate those states from the construction of the instruments for those sectors.

Second, the geographic dispersion of sectors in U.S. states may not be exogenous with respect to trade. Trade agreements and falling transportation costs may make locations closer to borders more attractive over time, and manufacturers may move to border states in order to trade with Mexico and Canada. If dirty and clean manufacturers differ in their mobilities, then there may be a dirty-sector-specific but time-varying element to our error term. Since the instruments are constructed using 1977 weights, the movement of sectors to take advantage of proximity is not in itself a problem for our instruments. The problem arises if the movement of sectors is large enough so that states respond by changing environmental policies. In that case, the increase in stringency in border states would be correlated with the improved competitiveness of sectors located there.

To lessen this concern, when studying trade with Mexico, we calculate the instrument using states that do not border Mexico. Similarly, when studying trade with Canada, we calculate the instrument using only those states that do not border Canada.

5. DATA

Data on imports and exports to and from the United States come from the Center for International Data (CID) maintained by Feenstra (1996, 1997).¹⁸ These data are collected by U.S. Bureau of the Census, and are organized by sector according to the international Harmonized Commodity and Coding System. The CID has matched these data with the appropriate SIC codes. Thus, for each sector and for each country with which the United States trades, we know the value of exports, the customs value of imports, and the total duties paid.

Data on PAC come from U.S. Census Bureau’s Pollution Abatement Costs and Expenditures survey (PACE). The PACE data report the annual PAOC by 3-digit

¹⁸ The CID can be found at <http://www.cid.econ.ucdavis.edu>.

sector, including payments to governments. These data are published in Current Industrial Reports: Pollution Abatement Costs and Expenditures, MA-200.

In constructing the data set for this analysis, we confronted two significant obstacles. The first involves the breakdown of published PAC into capital costs and operating costs. The Census Bureau published both, but the capital cost data pose numerous problems. The PACE capital data are for new investment, not for annualized costs. Puzzlingly, abatement capital expenditures declined significantly as a share of value added, from around 0.8% in 1975 to 0.2% in 1984. There are several potential explanations. One is the aggregation bias discussed above. If environmental regulations cause polluting sectors to relocate overseas, then investment in pollution control equipment could easily decline in the United States. A second explanation involves the type of capital. In the early years of pollution laws, most abatement capital consisted of “end-of-pipe” technologies. Over time, however, abatement investment becomes increasingly difficult to disentangle from production process changes that have little to do with pollution abatement. Finally, many environmental regulations grandfather existing sources of pollution, and this has the effect of stifling new abatement expenditures in exactly those sectors that are most strictly regulated. For all these reasons, we focus on PACE operating costs, while noting that this is only an imperfect proxy for the full costs of regulation.

The second significant data problem involves the definition of a sector. In 1987, the SIC codes were substantially changed, making time-series comparisons difficult. Six of the 3-digit codes defined as of 1972 were eliminated, and three new codes were added. The total number of 3-digit SIC codes declined from 143 to 140. Of the 3-digit codes that remained, 37 were altered by changing the definition of manufacturing industries within them.

Some papers attempt to span the change in SIC codes in 1987 by applying published concordances, so that the pre-1987 data are listed according to post-1987 SIC codes, or vice versa.¹⁹ These are typically based on total output as of 1987, when the Census Bureau collected the data using both SIC categorizations. Two major problems arise under this methodology. First, although one may be able to attribute $x\%$ of the output of sector i to sector j using such a concordance, that percentage will not likely apply to pollution abatement expenditures. So converting the post-1987 pollution abatement data to the pre-1987 SIC codes will inevitably attribute some pollution expenditures to the wrong sectors. Second, the 1987 concordance becomes increasingly irrelevant as manufacturing changes over time. So although $x\%$ of sector i 's output may be attributable to sector j in 1987, that will not likely be true by 1994. Consequently, we have limited our study to the 1977–86 period. This is the period of fastest growth in PAOC.

Table 1 presents descriptive statistics of these data. The average 3-digit manufacturing sector spent \$77 million (real 1982) on PAOC per year over this period. In columns 2 to 4, we take averages over time for each of the sectors. This demonstrates the enormous variation across sectors, ranging from \$65,000 (cigars) to

¹⁹ For example, Bartelsman and Gray (1996) maintain such a concordance at <http://www.nber.org/nberces>.

TABLE 1
DESCRIPTIVE STATISTICS 1977-1986

| | Pooled | | Long Averages (Across SIC Codes) | | | Long Differences (Within SIC Codes) | | |
|--|----------------------------|----------------------------|----------------------------------|------------|-------------------------|-------------------------------------|--|--|
| | Mean (Std. dev.) (1) | Mean (Std. dev.) (2) | Min (3) | Max (4) | Diff. (86-77) (5) | Pct change (%) (6) | | |
| Industry Characteristics | | | | | | | | |
| PAOC by U.S. industries (1982 \$M) | 77.0 (201.8) | 66.4 (177.6) | 0.065 | 1546 | 71.96 | 448% | | |
| Value added by U.S. industries (1982 \$M) | 6683 (7172) | 5910 (6295) | 70.8 | 41433 | 5297 | 180 | | |
| Value shipped by U.S. industries (1982 \$M) | 15617 (22,521) | 13706 (19,883) | 157.0 | 151405 | 11176 | 175 | | |
| Pollution abatement cost as fraction of U.S. value added | 0.0122 (0.0215) | 0.0112 (0.0193) | 0.00025 | 0.1180 | 0.0062 | 100 | | |
| Tariff rate | 0.052 (0.038) | 0.053 (0.039) | 0.0046 | 0.176 | -0.018 | -29.6 | | |
| Trade With Mexico | | | | | | | | |
| Manufacturing imports to the U.S. (1982 \$M) | 50.0 (140.2) | 43.9 (103.4) | 0 | 673 | 72.3 | 28,366 | | |
| Manufacturing exports from U.S. (1982 \$M) | 77.0 (147.4) | 66.6 (120.0) | 0 | 838 | 65.6 | 1417 | | |
| Net imports divided by U.S. value shipped (1982 \$M) | -0.0010 (0.0073) | -0.00032 (0.00682) | -0.028 | 0.034 | 0.0014 | -1,706 | | |
| Trade With Canada | | | | | | | | |
| Manufacturing imports to the U.S. (1982 \$M) | 335.8 (1488.8) | 289.6 (1243.5) | 0 | 13,563 | 346.2 | 641 | | |
| Manufacturing exports from U.S. (1982 \$M) | 261.2 (925.1) | 226.9 (798.6) | 0 | 8,920 | 190.2 | 332 | | |
| Net imports divided by U.S. value shipped (1982 \$M) | 0.0056 (0.0527) | 0.0045 (0.0483) | -0.045 | 0.445 | 0.0091 | 4,799 | | |
| Number of observations | 1,015 | | 132 | | 127 | | | |

NOTES: The sample is 1,015 observations on 132 industries over 10 years (1979 is omitted because the PACE data are not available for that year).

\$1.5 billion (petroleum refining). Of course, most of this variation comes from the size of the sectors, which is why our measure of costs, θ_{it} , is abatement costs divided by value added. Average abatement expenditures normalized this way averaged 1.22% of value added, ranging from 0.025% (periodical publications) to 11.8% (primary nonferrous metals). In the last two columns of Table 1, we calculate the “long differences”—simply the 1986 value for each sector minus the 1977 value. This demonstrates the large increase in PAC, even above the increase in industry output. Whereas the average sector’s value added increased 180% over the period, abatement costs increased 448%.

The bottom two panels of Table 1 describe trade patterns with Mexico and Canada that we use to study the effect of the abatement cost increases in the top panel. The average 3-digit sector imported \$50 million worth of manufactured goods from Mexico and \$336 million from Canada. The average sector exported \$77 million to Mexico and \$261 million to Canada. (The largest exporter *and* importer to both Canada and Mexico was SIC 371—motor vehicles and equipment.) Because most of the variation here also results from the sectors’ various sizes, we divide by the size of the industry in the United States. Our dependent variable, net imports per dollar of value shipped, ranges from -2.8% (electric distributing equipment) to $+3.4\%$ (rubber and plastics footwear) for trade with Mexico, and from -4.5% (metal forgings) to $+45\%$ (pulp mills) for trade with Canada.

6. EMPIRICAL RESULTS

Before turning to estimates of Equation (9), it is worth examining evidence for the biases described in Section 3. In the top panel of Table 2, we report that the 20 sectors (3-digit SIC codes) with the lowest PAOC spent 0.12% of their value added on abatement. By contrast, the 20 sectors with the highest PAOC spent 4.8%. But column 2 of the table clearly shows that net imports from Mexico are *higher* in those industries with lower abatement costs, although this difference is not statistically significant. For Canada, the pattern is reversed. Column 3 shows that the U.S. imports from Canada significantly more goods with high PAC.

The top panel of Table 2 thus seems to imply that the United States imports pollution-intensive goods from a rich country (with ostensibly tight regulation) and clean goods from a developing country (with presumably lax regulation), belying a link between environmental control costs and international competitiveness. Most likely, these correlations reflect the fact that Canada has an unobserved comparative advantage in natural resource industries that are relatively pollution intensive, whereas Mexico has an unobserved comparative advantage in labor-intensive and relatively clean industries.²⁰ But this trade pattern prediction is not inconsistent with the result that increases in U.S. PAC, *ceteris paribus*, raise net imports from both countries at the margin: a pollution haven effect.

²⁰ If true, this would fit the results of Antweiler et al. (2001), who argue that other motives for trade, in particular capital abundance, more than offset the effect of pollution regulations, leading rich, developed countries to have a comparative advantage in many dirty-good industries.

TABLE 2
COMPARISONS OF POLLUTION ABATEMENT OPERATING COSTS (PAOC) AND NET IMPORTS: 1977-1986

| | PAOC/ Value Added (1) | Average Net Imports Divided by Value Shipped in the United States | |
|---|-------------------------------|---|------------------------|
| | | Mexico (2) | Canada (3) |
| Cross-Section Comparison of Levels. Averages for 1977-1986 | | | |
| 20 3-digit SIC codes with the lowest average PAOC per dollar of value added | 0.0012* (0.0005) | -0.00021 (0.00545) | -0.00535* (0.00741) |
| 20 3-digit SIC codes with the highest PAOC per dollar of value added | 0.0482 (0.0284) | -0.00159 (0.00845) | 0.04693 (0.10742) |
| Time-Series Comparison of Changes. Average for 1986 Minus Average for 1977 | | | |
| | Change in PAOC/Value Added | Change in Average Net Imports Divided by Value Shipped | |
| 20 3-digit SIC codes for which PAOC share increased least | -0.00054* (0.00114) | -0.00017 (0.00524) | -0.00345* (0.04236) |
| 20 3-digit SIC codes for which PAOC share increased most | 0.02726 (0.02651) | 0.00103 (0.00529) | 0.02662 (0.05582) |

NOTES: The top panel contains average values over the entire 1977-86 period. The bottom panel reports the changes, the difference between the average values from 1986 and the average values from 1977.

*Indicates that the relevant figures for clean and dirty industries are statistically different from each other at 5%. (**Statistically significant at 10%)

TABLE 3
U.S. TRADE WITH MEXICO AND CANADA—SIMPLE BETWEEN AND WITHIN REGRESSIONS

| | "Between" Regressions | | Regression of "Long Differences" 1986–1977 | |
|--------------------------------|--------------------------|-----------------------|---|-----------------------|
| | From Mexico (1) | From Canada (2) | From Mexico (3) | From Canada (4) |
| PAOC per dollar of value added | -0.019 (0.060) | 1.40* (0.60) | 0.077** (0.046) | 1.23* (0.15) |
| Constant | -0.0001 (0.0007) | -0.011* (0.004) | 0.0009 (0.0007) | 0.0015 (0.0023) |
| <i>n</i> | 132 | 132 | 127 | 127 |
| <i>R</i> ² | 0.003 | 0.314 | 0.022 | 0.338 |

NOTES: Heteroskedastic-consistent standard errors in parentheses.

*Statistically significant at 5%.

**Statistically significant at 10%.

To confirm this, in the bottom panel of Table 2, we present the *change* in net imports for the 20 sectors whose PAC *increased least* from 1977 to 1986, compared with those whose pollution costs *increased most*. In contrast to the top panel, the sectors whose pollution costs increased most saw the largest increase in net imports from both Canada and Mexico. Though statistically significant only for Canada, these results suggest a link between higher environmental control costs and increased net imports, whereas the top panel suggested the opposite.

Table 2 only confirms that unobserved heterogeneity drives much of the differences in trade patterns across industries. The problem highlighted by Figure 1(a) is that those unobserved industry differences will bias empirical findings against finding a pollution haven effect.

Table 3 provides somewhat more systematic evidence of the same phenomenon. Columns 1 and 2 use the 132 sector averages to regress net imports on PAC. For Mexico, the coefficient (-0.019) is negative and statistically insignificant, suggesting no pollution haven effect. For Canada, the coefficient (1.4) is large and significant, suggesting a large pollution haven effect. In columns 3 and 4, we run the same regressions using "long differences" rather than the levels. Now the coefficient for Mexico is positive and close to statistical significance, whereas the coefficient for Canada is smaller but still significant.

Taken together, Tables 2 and 3 suggest that Mexico has a comparative advantage in relatively clean goods, whereas Canada has a comparative advantage in pollution-intensive goods. Hence, the United States tends to import from Mexico those goods that face low pollution costs at home, and to import from Canada those goods that face high costs, exactly opposite to the pollution haven hypothesis. However, if we look at changes in costs and trade, some of those sources of comparative advantages are differenced out. Industries that saw a faster increase in PAC saw a faster growth in net imports from both countries—a pollution haven effect.

The first, and simplest, implication of our discussion so far is that cross-section regressions of net imports on PAC may be biased by unobserved heterogeneity. Fixed effects easily solve this.

6.1. *Fixed Effects.* In columns 1 and 2 of Table 4 we present fixed-effects versions of Equation (9). In column 1, the dependent variable is net imports from Mexico divided by value shipped in the United States. The PAC coefficient is large and statistically significant, suggesting that those sectors in which PAC increased also saw increased imports from Mexico. Column 2 presents the same specification, except that the dependent variable is net imports from Canada. In both cases, we find a positive relationship between PAC and net imports. In addition, import tariffs lower net imports, although the coefficients are not statistically significant.

Overall these results are sensible—increases in abatement costs raise net imports and tariffs reduce them. This is a departure from much of the literature that uses cross sections of data and finds no evidence of a pollution haven effect.²¹

To get a feel for the magnitudes involved, note that a 1 percentage-point increase in the share of PAC in a sector leads to a 0.064 percentage-point increase in net imports from Mexico and a 0.53 percentage-point increase from Canada. Although the Canada coefficient is eight times as large as that of Mexico, imports from Canada were seven times imports from Mexico during this period, so the Canada coefficient represents an effect of comparable magnitude.

The average 3-digit sector in the United States imported from Mexico 0.32% of the total value of U.S. shipments, and exported to Mexico 0.49% (resulting in the net import share of -0.1% as reported in Table 1). If the change in net imports measured by the pollution cost coefficient of 0.064 in Table 4 comes entirely from changing gross imports, the relevant elasticity is 0.22 (ξ_1 in Equation (A.2)). On the other hand, if the change comes entirely from gross exports, the relevant elasticity is about 0.17 (ξ_2 in Equation (A.3)). These elasticities are reported at the bottom of Table 4, and their derivations are discussed in the Appendix.

For imports from Canada, the fixed-effects coefficient in column 2 of Table 4 corresponds to an elasticity of 0.45 if the change in trade comes entirely from imports, and of 0.32 if the change comes from exports. Note that for Mexico, the elasticity based on imports is larger than that based on exports ($\xi_1 > \xi_2$), whereas for Canada the reverse is true. This is because the United States is a net exporter to Mexico and a net importer from Canada.

One way to understand the size of this effect is to see that the average industry shipped \$15.6 billion worth of goods per year, and saw its θ (PAC as a fraction of value added) rise by 0.64%. Multiplying the product of these two numbers by the coefficient (0.064) from Table 1 yields \$6.4 million.²² This is roughly the amount

²¹ We have also run cross-section versions of Table 3 without industry fixed effects and reproduced the lack of evidence for a pollution haven effect. Coefficients on pollution costs are either small and statistically insignificant or are negative.

²² To calculate this figure, we used the average value shipped in these industries over the whole time period to convert the change in net imports/value shipped to the change in net imports. Multiply 0.064 (from Table 3) with 0.0064 (the change over the whole sample) times \$15.6 billion (the average value shipped over the sample).

TABLE 4
U.S. TRADE WITH MEXICO AND CANADA

| | Fixed Effects | | 2SLS With Fixed Effects | |
|---|--------------------|--------------------|-------------------------|---------------------|
| | From Mexico (1) | From Canada (2) | From Mexico (3) | From Canada (4) |
| Pollution abatement operating costs per dollar of value added | 0.064* (0.018) | 0.529* (0.045) | 0.144* (0.063) | 0.792* (0.102) |
| Tariffs by two-digit SIC code | -0.017 (0.017) | -0.061 (0.043) | -0.031** (0.016) | -0.083** (0.046) |
| <i>n</i> | 1015 | 1015 | 991 | 1000 |
| <i>R</i> ² | 0.76 | 0.97 | 0.78 | 0.97 |
| F-test of the joint significance of the instruments. | | | 7.6 | 14.4 |
| Partial <i>R</i> ² test | | | 0.12 | 0.20 |
| Cragg-Donald statistic (Stock and Yogo, 2005) | | | 134.1 | 255.4 |
| Sargan overidentification test (The critical value of a Chi-square test with 14 df and $\alpha = .05$ is 23.69) | | | 49 | 180 |
| Elasticity of net imports with respect to changes in pollution costs (derivation in Appendix) | | | | |
| based on exports (ξ_2) | 0.17 | | | |
| based on imports (ξ_1) | 0.22 | | | |
| | | 0.45 | 0.38 | 0.67 |
| | | 0.32 | 0.49 | 0.49 |

NOTES: Heteroskedastic-consistent standard errors in parentheses. All columns contain year and industry fixed effects.

*Statistically significant at 5%.

**Statistically significant at 10%.

that imports from Mexico are estimated to have increased for the average industry as a consequence of its increased PAC in the United States, holding constant other characteristics of the industry including abatement costs in Mexico. That same average industry had average annual imports of \$50 million, and over the 10-year period, saw its two-way trade rise by \$154 million, so the \$6 million increase in imports may not be economically significant. The same calculation for Canada predicts an increase in net imports of \$53 million per year, relative to average imports of \$336 million, and growth in two-way trade of \$601 million.

It is worth remembering, however, that some sectors saw much larger increases in PAC. Table 2 shows that the 20 sectors where PAC increased the most experienced an average increase of 2.7 percentage points.²³ Although it may be inaccurate to apply reduced-form regression coefficients calculated at the means of the data to observations in the tails, doing so will at least illustrate the potential for much larger effects. For the 20 sectors where costs rose most, the 2.7 percentage-point increase in costs translates into an average increase in net imports from Mexico of approximately \$37 million per year.²⁴ Meanwhile, the average sector in these top 20 sectors had an increase in two-way trade of \$143 million. The same calculation for Canada predicts an increase in net imports of \$302 million per year, with two-way trade increasing \$595 million. All of these calculations are summarized in Appendix Table A.2.

While the fixed-effects estimates in Table 4 appear more reasonable to us than the cross-section or pooled estimates in the earlier literature, there are still reasons to believe that the coefficients misstate the true effect of pollution costs on imports. First, the statistical endogeneity of the pollution cost variable, due to its aggregation across different industries, means that even the fixed-effects regressions in Table 4 are likely to be biased against finding a pollution haven effect. Second, the fixed-effects regressions assume implicitly that unobserved sector characteristics that simultaneously affect tariffs, pollution abatement, and imports are fixed over time. Although it is reasonable to imagine that this is true for some sector characteristics (location, geography, and natural resource abundance), for others it is surely false. For these reasons, we turn to instrumental variables estimates of the pollution haven effect.

6.2. Instrumental Variables. Appendix Table A.1 presents first-stage regressions in which PAOC as a share of value added (the right-hand-side variable in Table 4) is regressed on tariffs, year dummies, 130 sector fixed effects, and the instruments. The first column excludes states that border Mexico, the second column excludes states that border Canada, and for comparison, the third column includes all 48 contiguous U.S. states.

Note that because the first stage includes sector and year fixed effects, the coefficients in Table A.1 can be interpreted as the result of changes in the underlying

²³ Only nine sectors experienced increases larger than 2 percentage points: SIC codes 214 (tobacco stemming and redrying), 266 (building paper and board mills), 286 (industrial organic chemicals), 287 (agricultural chemicals), 291 (petroleum refining), 311 (leather tanning and finishing), 331 (blast furnace, basic steel prod.), 333 (primary nonferrous metals), and 334 (secondary nonferrous metals).

²⁴ The calculation is 0.064 (from Table 4) times 0.027 (the change over the whole sample, from Table 1) times \$21 billion (the average value shipped over the sample).

variables. Sectors facing higher tariffs tend to have increasing abatement costs. Sectors concentrated in states whose incomes grew fastest tend to have PAC that grew less fast. (This could be due to, for example, national pollution regulations forcing less stringent states to catch up with the leaders, or due to fast-growing sun-belt states also being those without the fastest-growing environmental standards.) And for the most part, sectors located in states with growing concentrations of other polluting sectors tend to have declining relative PAC, though some of the pollution coefficients are positive.²⁵

Returning to Table 4, columns 3 and 4 contain our central estimates of the pollution haven effect: two-stage least squares (2SLS) versions of the fixed-effects regressions in columns 1 and 2, where the first stage constitutes estimates of θ_{it} as a function of the exogenous variables, from Appendix Table A.1. For Mexico, instrumenting for pollution costs increases the coefficient from 0.064 to 0.144. For Canada, the coefficient increases from 0.529 to 0.792.

As with the fixed effects, one way to understand the magnitude of these estimates is to examine the elasticities, reported at the bottom of Table 4. If the change in trade with Mexico comes entirely from changing gross imports, the relevant elasticity is 0.49 (ξ_1 in Equation (A.2)). If the change comes entirely from gross exports, the relevant elasticity is 0.38 (ξ_2 in Equation (A.3)). For trade with Canada, these elasticities are 0.49 and 0.67.

For the average industry, which experienced a 0.64 percentage-point increase in PAC (θ), the coefficient in column 3 of Table 4 (0.144) implies that pollution costs caused net imports from Mexico to increase by \$14 million—compared with \$50 million in average imports and a \$154 million increase in two-way trade. The Canada coefficient (0.792) implies abatement costs caused a \$79 million increase in net imports—compared with \$336 million in average imports and a \$601 million increase in two-way trade. These calculations are summarized in Appendix Table A.2.

These estimates can no longer be considered economically small. The increase in imports attributed to PAC amount to about 10% of the total increase in two-way trade over this period. Moreover, for the handful of sectors whose PAC rose by much more, the effect on trade would have been larger.

6.3. Robustness Checks. To test the robustness of these estimates, particularly with respect to the instruments, we ran a series of standard tests. First, *F*-tests of the joint significance of all the instruments are high.²⁶ A second measure of instrument relevance is the “partial R^2 ” (Baum et al., 2003). This also suggests that the instruments have explanatory power in the first stage. Third, we report the Stock and Yogo (2005) version of the Cragg–Donald statistic, which

²⁵ The instruments in Table A.1 are highly collinear. Note, for example, that criterion air pollutants (SO_2 , NO_2 , CO, and VOCs) all have correlations greater than 0.9.

²⁶ The Staiger and Stock (1997) rule of thumb is that the first-stage *F*-test should be greater than 10. The *F*-test statistic falls short of this for column (3) but not for column (4). In Appendix Table A.1, we show that the first stage passes this test when the border states are not dropped, and in Table 5, row (6), we show that using all the border states also yields a statistically significant pollution haven effect that is larger than the fixed-effects estimates.

TABLE 5
 ROBUSTNESS CHECKS: ALTERNATIVE INSTRUMENTAL VARIABLES REGRESSIONS OF U.S. TRADE WITH FIXED EFFECTS 1977–1986

| | Coefficients on Instrumented PAOC as a Fraction of U.S. Value Added | |
|--|--|--------------------|
| | From Mexico (1) | From Canada (2) |
| (1) Table 4 coefficients | 0.144* (0.063) | 0.792* (0.102) |
| (2) Without state incomes | 0.103** (0.063) | 0.798* (0.103) |
| (3) Without industries that are >3% of gross state product | 0.300* (0.110) | 1.28* (0.18) |
| (4) Drop state-industry combinations where industry >25% of any one county's output | 0.123** (0.069) | 0.802* (0.101) |
| (5) Construct pollution instruments from industries <i>outside own 2-digit SIC</i> | 0.157* (0.059) | 0.571* (0.113) |
| (6) With border states included in instruments | 0.080* (0.037) | 1.02* (0.11) |
| (7) With oil prices interacted with industry dummies | 0.146* (0.060) | 0.808* (0.102) |
| (8) Limited information maximum likelihood estimator | 0.207* (0.075) | 1.73* (0.25) |

NOTES: Heteroskedastic-consistent standard errors in parentheses. All regressions contain year dummies, industry fixed effects, and tariff levels, as in Tables 3 and 4.
 *Statistically significant at 5%.
 **Statistically significant at 10%.

rejects the null hypothesis that the first stage is underidentified. The standard test of overidentifying restrictions, however, is the Sargan test, in which all these sets of instruments fail.²⁷

For a more intuitive set of robustness checks, in Table 5, we estimate the models with alternate sets of instruments. The original coefficients are reproduced in the top row. Row 2 drops the state incomes from the first stage, relying only on state pollution levels as instruments. The PAC coefficient for Mexico shrinks, but remains much larger than the fixed effects estimate. The Canada coefficient is unaffected by dropping incomes.

We have also tried dropping all the 14 measures of state pollution levels, one-by-one. These results are reported in Appendix Table A.3. The PAC coefficients are all similar to those in the base specification in Table 4, statistically significant, and much larger than the analogous fixed-effects coefficients.

In each case, where we have dropped instruments from the first stage, we have also tried including those dropped variables as regressors in the second stage.

²⁷ This consists of regressing the residuals from the second-stage regression on the set of instruments, and examining the test statistic (nR^2). Under the null hypothesis that the specification is correct and the instruments are uncorrelated with the error term e_{it} in Equation (9), this test statistic is distributed chi-squared.

None of them (income nor any of the 14 pollutants) were statistically significant predictors of trade.

Another concern might be that our “small industry” assumption is violated, and that our instrumental variables results are driven by the few sectors that are highly concentrated in a few states. In that case, the instrumented pollution costs might be endogenous. In row 3 of Table 5, we drop from the instrument stage those state-sector combinations where the sector comprises more than 3% of gross state product.²⁸ If anything, this change renders the pollution coefficients larger than when all sectors are included.

A slightly different small-industry concern is that particular sectors may dominate certain *counties*, which are the enforcement jurisdictions under the 1977 Clean Air Act. To be sure, in row 4, we dropped those state-sector combinations where a single sector amounted to more than 25% of the output in any one of the state’s counties. The coefficients remain statistically significant and larger than their fixed-effects counterparts.

We constructed the pollution instrument for sector i (ζ_{it} in Equation (12)) using the predicted pollution from all sectors except sector i . One might be concerned, however, that 3-digit sectors have closely related pollution characteristics (for example sectors 286 and 287, organic chemicals and agricultural chemicals, respectively). As a check, we recalculated the pollution instruments using only predicted pollution from outside sector i ’s 2-digit industry group. The coefficients in row 5 remain statistically significant and large.

In row 6, we include the Mexico border states in the calculation of the instruments in column 1, and the Canada border states in the calculation in column 2. (Recall that the border states were dropped to alleviate concerns that manufacturers may move to border states in order to trade with Mexico or Canada.) The Mexico coefficient shrinks, but remains large and statistically significant. The Canada coefficient becomes even larger, once the border states are included.

Yet another concern involves the fact that the 1970s and early 1980s saw rising energy prices. Since the United States is an oil importer, and Mexico and Canada are exporters, one might be concerned that polluting sectors are also energy intensive, and that changes in trade patterns that we are attributing to PAC really arise from oil prices. Our 2SLS specification should eliminate this concern, unless state characteristics are affected by oil prices and, in turn, affect state pollution stringency. To be sure, however, in row 7 of Table 5, we have included interactions between average annual crude oil prices and the sector fixed effects. The results hardly differ from the basic specification in row 1.

Finally, in row 8 of Table 5, we estimate the model using limited information maximum likelihood (LIML). Staiger and Stock (1997) show that LIML has a smaller bias than 2SLS, in the case of weak instruments and finite samples. The

²⁸ Of the 132 industries in 48 states, there were 451 cases where the industry was this large, or 7% of the sample.

LIML coefficients for both Mexico and Canada are even larger than the 2SLS estimates in the first row.²⁹

Although the precise estimate of the pollution haven effect varies with the different robustness checks in Table 5, in every alternative specification, the instrumental variables pollution specifications (which include sector fixed effects) are statistically significant and larger than their pure fixed-effects counterparts. Although we cannot assert that we have precisely estimated the structural effect of pollution costs on imports, the regressions in Table 4 demonstrate that simply including industry fixed effects will typically lead to underestimation of the true effect of PAC on trade.

7. CONCLUSION

Recent research on the effects of pollution regulations on trade has generated mixed results. Most studies using cross sections of data are unable to disentangle the simultaneous effects of sector characteristics on both trade and abatement costs. As a result, PAC are often found to have no effect on trade flows; in some cases costs appear to promote exports. This uncertainty is unfortunate because without firm evidence linking environmental control costs to trade flows, it is difficult to know whether governments have the ability, let alone the motivation, to substitute environmental policy for trade policy.

In this article, we use a simple theoretical model to examine the statistical and theoretical sources of endogeneity that confront attempts to measure the effect of environmental regulations on trade flows. We show that for very simple reasons unrelated to pollution havens, PAC and net imports may be negatively correlated in panels of sector-level data. This negative correlation can easily bias estimates against finding a pollution haven effect.

In the empirical work, we first estimate a fixed-effects model and show that those sectors whose abatement costs increased most have seen the largest relative increases in net imports. We then use our model to demonstrate several reasons why the fixed-effects estimates are likely to understate the pollution haven effect. We develop a set of instruments based on the geographic dispersion of manufacturing across U.S. states, and estimate 2SLS versions of the same estimating equation. The 2SLS estimates are consistently and robustly larger than the fixed-effects estimates.

Not only are the estimated effects of pollution costs on net imports positive and statistically significant, they are economically significant too. For each country group studied, for the sectors whose PACs increased most, the increase in net imports due to increased pollution costs represents a considerable fraction of the increase in total trade volumes over the period.

²⁹ One concern we have not addressed here is serial correlation in the error terms. Ignoring serial correlation results in biased but inefficient estimators, so although our coefficient point estimates may be valid, their estimated standard errors may be too small. This concern is partly ameliorated by the fact that in Table 3, we estimate “long differences” of the 1986 values minus the 1977 values. With $T = 2$, serial correlation is no longer a problem, and we still find large and statistically significant effects of pollution costs on imports.

APPENDIX

Magnitudes as Elasticities. The fixed-effect PAC coefficient in column 1 of Table 4 suggests that a 1 percentage-point increase in the share of value added going to pollution costs is associated with a 0.064 percentage-point increase in net imports as a share of U.S. value shipped. Is this large? It is somewhat difficult to think about elasticity calculations for *net* imports. Consider two hypothetical industries: Sector A has gross imports of \$2 million and gross exports of \$1 million; Sector B has gross imports of \$1 billion and gross exports of \$999 million. Each has net imports of \$1 million. An increase in pollution costs that causes net imports in both industries to increase to \$2 million represents a large effect on sector A, and a small effect on sector B. Hence, the elasticity of net imports is not a useful tool for comparing these coefficients.³⁰ We need a unit-free measure of the responsiveness of trade to pollution costs that is not sensitive to the initial size of *net* imports, but is comparable across industries with very different levels of *gross* imports and exports.

The main analysis here, in Equation (9), regresses net imports divided by value shipped (N) on pollution abatement divided by value added and other covariates:

$$N_{it} \equiv M_{it} - X_{it} = \dots + a\theta_{it} + \dots + e_{it}.$$

To interpret \hat{a} , divide it into two terms

$$(A.1) \quad \hat{a} = \frac{\partial N}{\partial \theta} = \frac{\partial M}{\partial \theta} - \frac{\partial X}{\partial \theta}.$$

If we multiply both sides by the average value of θ and divide by the average value of gross imports (\bar{M}) we get

$$(A.2) \quad \xi_1 \equiv \hat{a} \frac{\bar{\theta}}{\bar{M}} = \left(\frac{\partial M}{\partial \theta} \frac{\bar{\theta}}{\bar{M}} \right) - \left(\frac{\partial X}{\partial \theta} \frac{\bar{\theta}}{\bar{M}} \right) = \xi_{M\theta} - \xi_{X\theta} \left(\frac{\bar{X}}{\bar{M}} \right),$$

where $\xi_{M\theta}$ is the elasticity of gross imports with respect to pollution costs, and $\xi_{X\theta}$ is the elasticity of gross exports with respect to pollution costs. Note our prior is that $\xi_{M\theta}$ is positive and $\xi_{X\theta}$ is negative, so the whole expression is positive.

On the other hand, if we divide by the average value of gross exports (\bar{X} rather than \bar{M}) we get

$$(A.3) \quad \xi_2 \equiv \hat{a} \frac{\bar{\theta}}{\bar{X}} = \left(\frac{\partial M}{\partial \theta} \frac{\bar{\theta}}{\bar{X}} \right) - \left(\frac{\partial X}{\partial \theta} \frac{\bar{\theta}}{\bar{X}} \right) = \xi_{M\theta} \left(\frac{\bar{M}}{\bar{X}} \right) - \xi_{X\theta}.$$

³⁰ Worse still, if an industry imports and exports the same amount, net imports are zero, and any measured elasticity will be infinite. Moreover, if the increase in pollution costs at home causes net imports to increase from a large negative number to a small negative number, the measured elasticity of net imports will be negative.

TABLE A.1
 PREDICTED POLLUTION ABATEMENT COSTS 1977–1986

| | Pollution Abatement Operating Costs per Dollar of Value Added | | |
|--|--|----------------------|---------------------|
| | Without Mexico | Without Canada | Using All |
| | Border States (1) | Border States (2) | States (3) |
| Tariffs | 0.025 (0.027) | 0.074* (0.033) | 0.087* (0.033) |
| State-level income per capita (\$millions) | -2.65* (1.30) | 0.76 (1.56) | -2.49** (1.51) |
| State level pollution concentrations: | | | |
| Biological oxygen demand (thousands) | -0.021 (0.069) | -0.466* (0.121) | -0.525* (0.091) |
| Total suspended particulates (thousands) | -0.067* (0.020) | -0.121* (0.023) | -0.049* (0.020) |
| Air toxics (millions) | -0.498* (0.246) | 0.545 (0.382) | 0.091* (0.035) |
| Water toxics (millions) | 0.110 (0.422) | -1.87 (1.14) | -2.73* (1.12) |
| Solid waste toxics (millions) | -0.528* (0.210) | 0.039 (0.150) | 0.014 (0.15) |
| Air particulates (millions) | -0.452 (0.333) | -0.830* (0.342) | -1.10* (0.40) |
| Air CO (millions) | 0.118 (0.120) | 0.692* (0.176) | 0.353* (0.150) |
| Air SO ₂ (millions) | -0.139* (0.148) | -0.701* (0.208) | -0.326** (0.182) |
| Air NO ₂ (millions) | -0.042 (0.272) | 0.342 (0.306) | 0.188 (0.286) |
| Air VOC (millions) | -0.211 (0.154) | -0.371 (0.281) | -0.260 (0.204) |
| Air PM10 (millions) | 1.87* (0.49) | 1.40* (0.43) | 1.41* (0.40) |
| Air metals (thousands) | 0.158* (0.055) | 0.235* (0.039) | 0.117* (0.033) |
| Solid waste metals (millions) | -3.97* (1.75) | -2.72* (1.09) | -2.38* (1.18) |
| Water metals (thousands) | 0.111** (0.060) | -0.045 (0.059) | 0.048 (0.060) |
| <i>n</i> | 991 | 1000 | 1000 |
| <i>R</i> ² | 0.92 | 0.93 | 0.92 |
| <i>F</i> -test of the joint significance of all the instruments | 7.56 | 14.41 | 13.98 |

NOTES: Standard errors in parentheses.

Contains 130 industry fixed effects and 9 year fixed effects.

*Statistically significant at 5%.

**Significant at 10%.

TABLE A.2
MAGNITUDES

| Predicted Change in Net Imports Due to Increased Pollution Abatement Costs (\$1982 millions) | | |
|--|--------------------|--------------------|
| | From Mexico (1) | From Canada (2) |
| Average industry | | |
| Fixed effects | \$6 | \$53 |
| 2SLS | 14 | 79 |
| Average increase in trade volume | 154 | 601 |
| Average of the 20 industries whose pollution abatement costs increased most | | |
| Fixed effects | 37 | 302 |
| 2SLS | 82 | 453 |
| Average increase in trade volume | 143 | 595 |

NOTES: Each predicted change in imports is the coefficient estimate times the increase in pollution abatement costs for the average industry, times the average value shipped. For example, the fixed effects coefficient for trade with Mexico from Table 3 is 0.064. On average, for the 20 industries whose pollution abatement costs increased most, PAC divided by value added increased by 0.028. Those same industries' average value shipped was \$21 billion. Multiply the three numbers to get \$37 million, the figure in column 1.

TABLE A.3
ROBUSTNESS CHECKS: DROPPING POLLUTANTS FROM THE INSTRUMENT

| Coefficients on Instrumented PAOC as a Fraction of U.S. Value Added | | | |
|---|-------------------------------|--------------------|--------------------|
| | | From Mexico (1) | From Canada (2) |
| (1) | Drop biological oxygen demand | 0.147* (0.062) | 0.786* (0.106) |
| (2) | Drop total suspended solids | 0.155* (0.066) | 0.794* (0.110) |
| (3) | Drop air toxins | 0.134* (0.064) | 0.764* (0.103) |
| (4) | Drop water-borne toxins | 0.143* (0.063) | 0.785* (0.103) |
| (5) | Drop land toxic pollution | 0.159* (0.065) | 0.794* (0.102) |
| (6) | Drop particulates | 0.138* (0.063) | 0.692* (0.103) |
| (7) | Drop CO | 0.142* (0.063) | 0.759* (0.106) |
| (8) | Drop SO ₂ | 0.134* (0.063) | 0.817* (0.106) |
| (9) | Drop NO ₂ | 0.144* (0.063) | 0.796* (0.106) |
| (10) | Drop VOC | 0.124* (0.063) | 0.790* (0.103) |
| (11) | Drop PM10 | 0.114** (0.067) | 0.751* (0.104) |

(table continues)

TABLE A.3 (CONTINUED)

| Coefficients on Instrumented PAOC as a Fraction of U.S. Value Added | | | |
|---|----------------------------|--------------------|--------------------|
| | | From Mexico (1) | From Canada (2) |
| (12) | Drop metals in the air | 0.170* (0.065) | 0.794* (0.112) |
| (13) | Drop metals in solid waste | 0.167* (0.064) | 0.769* (0.104) |
| (14) | Drop metals in the water | 0.153* (0.064) | 0.784* (0.102) |

NOTES: Heteroskedastic-consistent standard errors in parentheses.

All regressions contain year dummies, industry fixed effects.

*Statistically significant at 5%.

**Statistically significant at 10%.

Both ξ_1 and ξ_2 approximate the sum of the absolute values of the elasticities of imports and exports with respect to pollution costs. If net imports are positive ($\bar{M} > \bar{X}$), then $\xi_1 < \xi_2$, ξ_1 understates this sum of elasticities, and ξ_2 overstates the sum. If net imports are negative, then $\xi_1 > \xi_2$, ξ_1 overstates the sum of elasticities, and ξ_2 understates it.

The statistics ξ_1 and ξ_2 have several nice properties. They provide bounds for a sensible magnitude with which to interpret the coefficient \hat{a} . They are comparable across sets of countries. And, if $\bar{M} = \bar{X}$, the two statistics are identical and equal to the sum of the import and export elasticities: $\xi_1 = \xi_2 = \xi_{M\theta} + \xi_{X\theta}$

REFERENCES

- ANTWEILER, W., B. R. COPELAND, AND M. S. TAYLOR, "Is Free Trade Good for the Environment?" *American Economic Review* 94 (2001), 877–908.
- BARTELSMAN, E. J., AND W. GRAY, "The NBER Manufacturing Productivity Database," NBER Working Paper T0205, October 1996.
- BAUM, C. F., M. E. SCHAFFER, AND S. STILLMAN, "Instrumental Variables and GMM: Estimation and Testing" Boston College Working Paper 545, 2003.
- BECKER, R. A., AND J. V. HENDERSON, "Effects of Air Quality Regulations on Polluting Industries," *Journal of Political Economy* 108 (2000), 379–421.
- BRUNNERMEIER, S. B., AND A. LEVINSON, "Examining the Evidence on Environmental Regulations and Industry Location," *Journal of the Environment and Development* 13 (2004), 6–41.
- COPELAND, B. R., AND M. S. TAYLOR, *Trade and the Environment: Theory and Evidence* (Princeton: Princeton University Press, 2003).
- , AND —, "Trade, Growth, and the Environment," *Journal of Economic Literature* 42 (2004), 7–71.
- EDERINGTON, J., AND J. MINIER, "Is Environmental Policy a Secondary Trade Barrier? An Empirical Analysis," *Canadian Journal of Economics* 36 (2003), 137–54.
- , A. LEVINSON, AND J. MINIER, "Footloose and Pollution-free," *Review of Economics and Statistics* 87 (2005), 92–9.
- FEENSTRA, R. C., "NBER Trade Database, Disk1: U.S. Imports, 1972–1994: Data and Concordances," NBER Working Paper 5515, March 1996.

- , “NBER Trade Database, Disk 3: U.S. Exports, 1972–1994, with State Exports and Other U. S. Data,” NBER Working Paper 5990, April 1997.
- FRANKEL, J. A., AND D. ROMER, “Does Trade Cause Growth,” *American Economic Review* 89 (1999), 379–99.
- GREENSTONE, M., “The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Acts and the Census of Manufactures,” *Journal of Political Economy* 110 (2002), 1175–219.
- GROSSMAN, G. M., AND A. B. KRUEGER, “Environmental Impacts of a North American Free Trade Agreement,” in P. M. Garber, ed., *The Mexico-U. S. Free Trade Agreement* (Cambridge, MA: MIT Press, 1993) reprinted in R. V. Percival, and D. C. Alevizatos, eds., *Law and the Environment: An Interdisciplinary Reader* (Philadelphia: Temple University Press, 1997).
- HETTIGE, H., P. MARTIN, M. SINGH, AND D. WHEELER, “The Industrial Pollution Projection System,” World Bank Policy Research Working Paper 1431, 1994.
- JAFFE, A. B., S. R. PETERSON, P. R. PORTNEY, AND R. N. STAVINS, “Environmental Regulations and the Competitiveness of U. S. Manufacturing: What Does the Evidence Tell Us?” *Journal of Economic Literature* 33 (1995), 132–63.
- KALT, J. P., “The Impact of Domestic Environmental Regulatory Policies on U. S. International Competitiveness,” in A. M. Spence and H. A. Hazard, eds., *International Competitiveness* (Cambridge, MA: Harper and Row, Ballinger, 1988).
- LEAMER, E. E., AND J. LEVINSOHN, “International Trade Theory: The Evidence,” in G. M. Grossman, and K. Rogoff, eds., *Handbook of International Economics* Vol. 3 (New York: North Holland, 1996).
- LIST, J. A., W. W. MCHONE, D. L. MILLIMET, AND P. G. FREDRIKSSON, “Effects of Environmental Regulations on Manufacturing Plant Births: Evidence From a Propensity Score Matching Estimator,” *Review of Economics and Statistics* 85 (2003), 944–52.
- OSANG, T., AND A. NANDY, “Impact of U. S. Environmental Regulation on the Competitiveness of Manufacturing Industries,” Mimeo, SMU Economics Department, 2000.
- PORTER, M. E., AND C. VAN DER LINDE, “Toward a New Conception of the Environment-Competitiveness Relationship,” *Journal of Economic Perspectives* 9 (1995), 97–118.
- STAIGER, D., AND J. H. STOCK, “Instrumental Variables Regression With Weak Instruments,” *Econometrica* 65 (1997), 557–86.
- STOCK, J. H., AND M. YOGO, “Testing for Weak Instruments in Linear IV Regression,” in D. W. K. Andrews, and J. H. Stock, eds., *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg* (Cambridge, MA: Cambridge University Press, 2005).