Pollution Abatement Costs and Foreign Direct Investment Inflows to U.S. States: A Nonparametric Reassessment

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Abstract

Keller and Levinson (2002, this *Review*, 84(4), 691-703) utilize state-level panel data on inflows of foreign direct investment along with an innovative measure of relative pollution abatement costs to assess the impact of environmental stringency on capital flows. Using standard parametric panel data models, the authors find moderate evidence that capital flows are sensitive to abatement costs. Using recently developed nonparametric methods, we assess the robustness of this conclusion. The nonparametric approach reveals that (i) some of the parametric results are not robust, (ii) the impact of relative abatement costs is heterogeneous across states and generally of smaller magnitude than previously suggested.

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1 Introduction

Stringent environmental regulation has long been perceived as a serious threat to U.S. competitiveness.[1] Empirical evidence surrounding this claim, however, has been mixed. During the early 1990s, Jaffe et al. (1995, p. 157) conclude after an extensive review: "Overall, there is relatively little evidence to support the hypothesis that environmental regulations have had a large adverse effect on competitiveness...". Recent evidence, though, suggests that environmental regulation does alter the spatial distribution of capital. An important paper within this recent literature is Keller and Levinson (2002; hereafter referred to as KL). The authors improved upon the existing literature at the time by utilizing a lengthy state-level panel data set on inflows of foreign direct investment (FDI) to the U.S., as well as an innovative measure of relative pollution abatement costs across states. Applying standard parametric panel data models, the authors find "robust evidence that abatement costs have had moderate deterrent effects on foreign investment" (p. 691). Given the implications of such a conclusion for both environmental and trade policy, assessing the sensitivity of this finding to the relaxation of the parametric assumptions is warranted, especially in light of existing evidence suggesting that empirical studies of the Pollution Haven Hypothesis (PHH) are sensitive to parametric assumptions.[2] Applying recently developed nonparametric techniques to KL's data reveals three findings. First, while some of the parametric results are robust, some are not. Thus, modeling assumptions matter in crucial ways. Second, the impact of greater relative abatement costs (RAC) is not uniform across states, and interesting patterns emerge. Finally, where we do continue to find negative effects of abatement costs on FDI inflows, the effects are generally of smaller magnitude than documented in KL. The remainder of the paper is organized as follows. Section 2 discusses the estimation framework and data. Section 3 presents the results. Section 4 concludes.

2 Empirical Methodology

2.1 Generalized Kernel Estimation

To analyze the determinants of FDI inflows, we utilize Li-Racine Generalized Kernel Estimation (Li and Racine 2004; Racine and Li 2004). To begin, consider the nonparametric regression model

$$y_i = m(x_i) + \varepsilon_i, \qquad i = 1, ..., NT \tag{1}$$

[1]The notion that stricter environmental regulation will shift production to locations with more lax regulation is known as the Pollution Haven Hypothesis.

[2]For example, List et al. (2003) utilize a semiparametric propensity score matching method to analyze the impact of county-level attainment status under the U.S. Clean Air Act on counts of new manufacturing plants in New York State. The authors find a more detrimental effect of non-attainment relative to a fixed effects Poisson model.

where y_i is a measure of FDI inflows for observation i and i indexes state-year combinations. Further, m is the unknown smooth production function with argument $x_i = [x_i^c, x_i^u, x_i^o]$, where x_i^c is a vector of continuous regressors (discussed in the following section), x_i^u is a vector of regressors that assume unordered discrete values (state effects), x_i^o is a vector of regressors that assume ordered discrete values (time effects), ε is an additive error, N is the number of cross-sectional units, and T is the number of time periods. Taking a first-order Taylor expansion of (1) with respect to x_j yields

$$y_i \approx m(x_j) + (x_i^c - x_j^c)\beta(x_j) + \varepsilon_i \tag{2}$$

where $\beta(x_j)$ is defined as the partial derivative of $m(x_j)$ with respect to x^c. If y and x are both in logarithmic form, then $\beta(x_j)$ represents an elasticity.

The estimator of $\delta(x_j) \equiv \binom{m(x_j)}{\beta(x_j)}$ is given by

$$\begin{aligned}\widehat{\delta}(x_j) &= \begin{pmatrix}\widehat{m}(x_j)\\ \widehat{\beta}(x_j)\end{pmatrix}\\ &= \left[\sum_i K_{\widehat{h}} \begin{pmatrix} 1 & \left(x_i^c - x_j^c\right) \\ \left(x_i^c - x_j^c\right) & \left(x_i^c - x_j^c\right)\left(x_i^c - x_j^c\right)' \end{pmatrix}\right]^{-1} \sum K_{\widehat{h}} \begin{pmatrix} 1 \\ \left(x_i^c - x_j^c\right)\end{pmatrix} y_i \end{aligned}\tag{3}$$

where $K_{\widehat{h}} = \prod\limits_{s=1}^{q} \widehat{h}_s^{-1} w\left(\frac{x_{si}^c - x_{sj}^c}{\widehat{h}_s}\right) \prod\limits_{s=1}^{r} l^u\left(x_{si}^u, x_{sj}^u, \widehat{\lambda^u}_s\right) \prod\limits_{s=1}^{p} l^o\left(x_{si}^o, x_{sj}^o, \widehat{\lambda^o}_s\right)$. K_h is the commonly used product kernel (Pagan and Ullah 1999), where w is the standard normal kernel function with window width $h_s = h_s(NT)$ associated with the s^{th} component of x^c. l^u is a variation of Aitchison and Aitken's (1976) kernel function which equals one if $x_{si}^u = x_{sj}^u$ and λ_s^u otherwise, and l^o is the Wang and Van Ryzin (1981) kernel function which equals one if $x_{si}^o = x_{sj}^o$ and $(\lambda_s^o)^{\left|x_{si}^o - x_{sj}^o\right|}$ otherwise. See Li and Racine (2004) and Racine and Li (2004) for further details.

Estimation of the bandwidths $(h, \lambda^u, \lambda^o)$ is crucial in nonparametric estimation. We utilize Hurvich et al.'s (1998) Expected Kullback Leibler (AIC_c) criteria, which chooses smoothing parameters using an improved version of the Akaike Information Criteria. AIC_c has been shown to perform well in small samples and avoids the tendency to undersmooth as often happens under other approaches such as Least-Squares Cross-Validation. The bandwidths are chosen to minimize

$$AIC_c = \log\left(\widehat{\sigma}^2\right) + \frac{1 + tr(H)/NT}{1 - \left[tr(H) + 2\right]/NT} \tag{4}$$

where $tr(H)$ is the trace of H, H is given by $\widehat{y} = \widehat{m}(x) = Hy$,

$$\begin{aligned}\widehat{\sigma}^2 &= \frac{1}{NT}\sum_{j=1}^{NT}\left(y_j - \widehat{m}_{-j}(x_j)\right)^2\\ &= \left(\frac{1}{NT}\right) y'(I-H)'(I-H)y\end{aligned}\tag{5}$$

and $\widehat{m}_{-j}(x_j)$ is the commonly used leave-one-out estimator of $m(x)$.

In comparison, KL estimate a standard parametric model of the form

$$y_i = x_i\beta + \mu_i, \qquad i = 1, ..., NT \tag{6}$$

where y is a linear function of the covariates and μ_i is decomposed into a linear function of state effects, time effects, and an idiosyncratic term. To the extent that (6) is misspecified, the parametric results will be biased; the nonparametric estimation results will differ depending on the severity of the bias.

2.2 Data

The data come directly from KL; thus, we provide only limited details. The data cover the 48 contiguous U.S. states from 1977 – 1994, omitting 1987 due to missing data on abatement costs. The four dependent variables we utilize are the value of gross property, plant, and equipment (PP&E) of foreign-owned affiliates for all manufacturers, as well as just for the chemical sector (1992 – 1994 omitted), and employment at foreign-owned affiliates for all manufacturers, as well as just for the chemical sector (1992 – 1994 omitted).[3,4] The chemical sector is analyzed in isolation given that FDI in these industries is most likely to be responsive to spatial variation in abatement costs given the pollution-intensive nature of production. The primary independent variable of interest is Levinson's (2001) index of state-level RAC (defined as the ratio of actual state-level abatement costs to predicted state-level abatement costs, where the predicted value is based on the industrial composition of the state). Consequently, higher values indicate greater pollution control costs. The index varies over time and across states. The remaining set of controls follow directly from KL: market proximity (a distance-weighted average of all other states' gross state products), population, unemployment rate, unionization rate, average production-worker wages across the state, total road mileage, land prices, energy prices, tax effort (actual tax revenues divided by those that would be collected by a model tax code, as calculated by the Advisory Commission on Intergovernmental Relations). All variables are expressed in logarithmic form with the exception of the unemployment and unionization rates. In addition, we control for state and time effects.

[3]For each dependent variable, the sample represents an unbalanced panel where the number of observations for total manufacturing PP&E (employment) are 811 (814); for chemical sector PP&E (employment), the sample size is 563 (621).

[4]KL also utilize count data on the number of new plants. Given the nature of the nonparametric estimation, we focus on continuous outcomes at this stage.

3 Results

3.1 Relative Abatement Costs

The main results – the elasticity of FDI inflows with respect to RAC – are displayed in Table 1.[5] The table reports the mean elasticity (computed over all state-year combinations), as well as the elasticities at the 25^{th}, 50^{th}, and 75^{th} percentiles (labelled Quartiles 1, 2, and 3). For comparison, we also display the (replicated) parametric results from KL.

For chemical sector PP&E and employment, the mean elasticity with respect to state-level RAC is negative, but statistically insignificant even at the 90% confidence level. At the first quartile, however, the elasticity is -0.322 (-0.300) for PP&E (employment), and statistically significant at conventional levels using PP&E. At the median, the elasticity continues to be negative (-0.105 and -0.134 for PP&E and employment, respectively), although neither is statistically significant. Finally, over 25% of the sample has a positive point estimate, although the estimates are not statistically significant at the 75^{th} percentile. Thus, the results for the chemical sector yield two conclusions. First, there is minimal evidence of a statistically significant, negative impact of abatement costs on FDI inflows, particularly as measured by employment. Second, the effect of greater pollution abatement costs is not uniform across state-year observations; the estimated elasticity is roughly two to three times greater (in absolute value) at the 25^{th} percentile than at the median, and positive for at least 25% of the sample.

Comparing these findings to the results in KL reveals a substantial impact of relaxing the usual parametric assumptions. Using PP&E, the parametric model yields a statistically significant estimate of -0.198 ($s.e. = 0.092$). This falls between the first and second quartiles of the nonparametric estimates, and is roughly two (three) times as large as the median (mean) nonparametric estimate. Using employment, the parametric estimate is -0.397 ($s.e. = 0.072$). This represents an elasticity below the 25^{th} percentile of the corresponding nonparametric estimates, and is roughly three times larger than the median and mean nonparametric estimates. Consequently, while there remains some evidence of a modest deterrent effect of RAC on FDI inflows in the chemical sector, the evidence is much less robust than documented in KL.

Examining FDI inflows aggregated across all manufacturing industries reveals an even larger discrepancy between the nonparametric and parametric results. For both PP&E and employment, the nonparametric model indicates that even at the 25^{th} percentile, the elasticity with respect to abatement costs is positive (albeit statistically insignificant). Moreover, the mean elasticity is 0.251 (0.118) for PP&E (employment) and statistically significant at at least the 90% confidence level; at the 75^{th} percentile, the elasticity is 0.452 (0.221) and statistically significant. In comparison, the parametric approach yields an

[5] All nonparametric calculations are performed using N ©.

elasticity estimate of -0.079 ($s.e. = 0.046$) for PP&E, which is statistically significant at the 90% confidence level, and -0.013 ($s.e. = 0.041$) for employment. Thus, the nonparametric analysis not only overturns the previous parametric evidence supporting the PHH when aggregating across all manufacturing sectors, but even suggests a positive association between RAC and FDI inflows for some observations.

A statistically insignificant impact of pollution abatement costs on FDI inflows is consonant with previous evidence suggesting that foreign firms are not responsive to domestic environmental regulation. List et al. (2004) compare the spatial distribution of new pollution-intensive manufacturing plants across counties in New York State using a semiparametric propensity score matching estimator, finding that the location decisions of foreign-owned (domestic-owned) plants are unaffected (affected) by environmental regulation. The authors argue that foreign-owned firms tend to locate in major industrial locations, regardless of regulatory costs, to overcome informational disadvantages. A statistically significant, positive association between pollution abatement costs on FDI inflows is consonant with the notion that environmental stringency is likely endogenous (e.g., List et al. 2003). For example, regulatory stringency (both in terms of the law itself as well as the degree of enforcement) may be related to bureaucratic corruption (Fredriksson et al. 2003), political climate, or the presence of industry subsidies used to offset the costs of pollution abatement (Eliste and Fredriksson 2002). The presence of such omitted factors, which are unlikely to be time invariant (and thus captured by the state fixed effects) given the length of the panel, would preclude one from interpreting even the nonparametric results in a causal manner.

If the positive elasticities in the nonparametric model are due to the endogeneity of RAC, then it is perhaps striking that the parametric results are predominantly negative despite also treating RAC as exogenous. This apparent discrepancy arises because there are two primary biases that may be at work in the estimation of any model of FDI inflows and RAC: misspecification bias and endogeneity/omitted variable bias. The parametric model potentially suffers from both; the nonparametric model potentially only from the latter. Thus, it is the misspecification bias (and its interaction with the endogeneity bias) that drives the differences across estimation techniques.[6] As evidence of this, we re-estimate the parametric models including a full set of quadratic and interaction terms to approach the flexibility of the nonparametric approach.[7] Examining the distribution of the now observation-specific elasticities, we obtain a *positive* mean elasticity using PP&E for the chemical sector (total manufacturing) of 0.132 (0.057); a negative mean elasticity using employment for the chemical sector (total manufacturing) of -0.136 (-0.068). Moreover, in both models using PP&E, the median elasticity is positive; using employment, the median elasticity is

[6] Nonparametric instrumental variable (IV) methods, still in their infancy, will be examined in future research, enabling one to assess the impact of each type of bias.

[7] The ten quadratic terms and 45 interaction terms are jointly significant at the $p < 0.01$ level in all four models.

positive at the 75^{th} percentile in both models.[8]

Aside from the greater flexibility afforded by the nonparametric approach, an additional benefit is the estimation of observation-specific elasticities. To analyze the variation across observations, Table 2 reports the median elasticity for each state for each of the four measures of FDI inflows, as well as each state's ranking for each measure (where the lowest elasticity is assigned a ranking of one).[9] For individual states, while there is some variation by FDI inflow measure, the elasticities are positively correlated. The correlation between the median elasticity for total manufacturing (chemical) PP&E and employment is 0.53 (0.30), with both being statistically significant at the 95% confidence level. In terms of specific states, Idaho has the lowest median elasticity using total manufacturing PP&E and employment (-0.514 and -0.257, respectively), whereas South Dakota (-1.361) and New Mexico (-0.866) have the lowest median elasticities using chemical sector PP&E and employment, respectively. At the other extreme, Maine (1.190) and Delaware (0.635) have the highest median elasticities using total manufacturing PP&E and employment, respectively; Ohio (0.866) and Montana (0.297) have the highest median elasticities using chemical sector PP&E and employment, respectively.

Furthermore, a cursory examination reveals several significant correlations between various state-level attributes and the observation-specific elasticities. For instance, the correlation between the elasticity for total manufacturing PP&E (employment) and RAC is -0.04 (-0.16), with the latter being statistically significant at the 99% confidence level; the correlation between the elasticity for chemical sector PP&E (employment) and RAC is 0.07 (-0.13), with the latter being statistically significant at the 99% confidence level as well. The predominantly negative correlations suggest that an increase in RAC is associated with a larger detrimental impact of FDI inflows in states with high initial RAC. In addition, in three of the four cases, the correlation between FDI inflows and its corresponding elasticity is positive and statistically significant at the 95% confidence level. Specifically, the correlation between total manufacturing (chemical sector) PP&E and the elasticity of total manufacturing (chemical sector) PP&E with respect to RAC is 0.08 (0.09); the correlation between chemical sector employment and the elasticity of chemical sector employment with respect to RAC is 0.16. These positive correlations are consonant with the presence of positive agglomeration externalities (at least) partially offsetting increases in RAC. Furthermore, the correlations between the elasticity of total manufacturing PP&E, chemical sector PP&E, and chemical sector employment with respect to RAC and Gross State Product and population are positive and statistically significant at the 95% confidence level. Thus, FDI inflows into states that are larger (economically or

[8] The full set of results are available upon request.

[9] We report the median, as opposed to mean, due to concern over sensitivity to outliers. Nonetheless, the results are similar, and available from the authors upon request.

measured in terms of population) are less likely to locate elsewhere when confronted with higher RAC.

The fact that the elasticity of FDI inflows with respect to RAC is significantly correlated (at least in a statistical sense) with several observable attributes, including the level of RAC, indicates that FDI inflows are a non-linear function of RAC, and that important interactions exist between RAC and other state attributes. This underscores the misspecification bias in the parametric models.

Lastly, Table 3 presents the median elasticities by year to assess any changes over time in the responsiveness of FDI inflows to RAC (due to, for example, changes in capital mobility, transportation costs, or agglomeration benefits). In terms of the specific estimates, the median elasticity obtains the sample minimum in 1988 for total manufacturing PP&E and chemical sector employment; for total manufacturing employment (chemical sector PP&E) the lowest mean elasticity occurs in 1977 (1981). The sample maximum occurs in a different year for each FDI measure: for total manufacturing (chemical sector) PP&E in 1983 (1986), and for total manufacturing (chemical sector) employment in 1982 (1981). Nonetheless, the results indicate little variation over time for three of the four FDI measures; chemical sector PP&E is more volatile, but does not follow a trend. Thus, FDI inflows do not appear to be becoming more or less sensitive to changes in pollution abatement costs over the sample period.

3.2 Remaining Covariates

To briefly evaluate the effects of the remaining covariates, Table 4 presents a summary of the various estimates (where the nonparametric results correspond to the mean estimates across state-year observations).[10] For many of the covariates the parametric and nonparametric results are in agreement; for others, discrepancies arise. For market proximity and the unemployment rate, the results are positive and statistically significant in the majority of cases regardless of estimation technique. However, the nonparametric approach does yield a few more instances where the effects of each variable are positive and statistically significant when analyzing total manufacturing PP&E (Panel I). In terms of the effects of the unionization rate, the nonparametric (parametric) approach finds a negative and statistically significant estimate in all four (three of four) models. For total road mileage, the effects are always negative and sometimes statistically significant across the nonparametric and parametric techniques. Finally, regardless of estimation approach, there is only modest evidence that FDI inflows are adversely affected by greater tax effort.

The nonparametric and parametric approaches do yield divergent inferences, however, with respect to the effects of population, average manufacturing wages, land value, and energy prices. In terms of population, the parametric approach finds a statistically significant, *negative* effect of state population

[10] More detailed nonparametric results for the remaining covariates are availble at http://faculty.smu.edu/millimet/pdf/tables_original.pdf.

on employment in foreign-owned affiliates in the chemical sector; insignificant effects in the other three cases. The nonparametric technique, on the other hand, finds a statistically significant, *positive* impact of population in three of four cases (and a positive, but statistically insignificant mean elasticity in the remaining case). Thus, the nonparametric results suggest a strong advantage for more populated states in the attraction of FDI inflows. This is consistent with previous research (mentioned above) that firms tend to avoid more remote areas when locating abroad.

For average wages and land values, the results also differ dramatically across the nonparametric and parametric techniques; whereas the parametric results tend to indicate negative, statistically significant impacts of higher average wages and land values, the nonparametric results suggest a strong, positive association between average wages and land values and FDI inflows. These findings suggest the presence of relevant omitted variables that are correlated with average wages and land values. For example, local public goods may raise the productivity of labor (and thus average wages) and the value of land, as well as increase the attractiveness of such locations. In addition, the results may be due to reverse causation, where FDI inflows raise local wages and land values by increasing demand. As discussed above, omitted variable bias may have differential affects in the parametric and nonparametric model since the parametric model also suffers from misspecification bias.

Finally, while the parametric models fail to find a relationship between energy prices and FDI inflows, the nonparametric technique finds a negative, statistically significant impact of energy prices on FDI inflows in the chemical sector (using both PP&E and employment), as one might expect.

4 Conclusion

Whether capital flows respond to spatial variation in environmental regulation has enormous implications in both a positive and normative sense. As a result, assessing the robustness of previous studies to modeling assumptions is crucial. In this paper, we reassess the impact of U.S. state-level pollution abatement costs on the spatial distribution of FDI inflows. While previous parametric approaches suggest a modest deterrent effect of higher costs, applying recently developed nonparametric techniques yields three conclusions. First, modeling assumptions matter in a statistically and economically meaningful way; the nonparametric approach finds a much less robust adverse impact of higher abatement costs on FDI inflows. Second, the impact of greater abatement costs is far from uniform across states. Finally, where we do continue to find negative effects of abatement costs on FDI inflows, the effects are of considerably smaller magnitude on average than documented previously. Consequently, future investigations into the empirical validity of the Pollution Haven Hypothesis should be wary of the implications of modeling assumptions.

References

[1] Aitchison, J. and C.B.B. Aitken (1976), "Multivariate Binary Discrimination by Kernel Method," *Biometrika*, 63, 413-420.

[2] Eliste, P. and P.G. Fredriksson (2002), "Environmental Regulations, Transfers, and Trade: Theory and Evidence," *Journal of Environmental Economics and Management*.

[3] Fredriksson, P.G., List, J.A., D.L. Millimet, (2003), "Corruption, Environmental Policy, and FDI: Theory and Evidence from the United States," *Journal of Public Economics*, 87, 1407-1430.

[4] Hurvich, C.M., J.S. Simonoff, and C.-L. Tsai (1998), "Smoothing Parameter Selection in Nonparametric Regression Using an Improved Akaike Information Criterion," *Journal of the Royal Statistical Society, Series B*, 60, 271-293.

[5] Jaffe, A.B., S.R. Peterson, P.R. Portney, and R.N. Stavins (1995), "Environmental Regulations and the Competitiveness of U.S. Manufacturing: What does the Evidence Tell Us?" *Journal of Economic Literature*, 33, 132–163.

[6] Keller, W. and A. Levinson (2002), "Pollution Abatement Costs and Foreign Direct Investment Inflows to U.S. States," *Review of Economics and Statistics*, 84, 691-703.

[7] Levinson, A. (2001), "An Industry-Adjusted Index of State Environmental Compliance Costs," in C. Carraro and G.E. Metcalf (eds.) *Behavioral and Distributional Effects of Environmental Policy*, Chicago, University of Chicago Press.

[8] Li, Q., and J. Racine (2004). "Cross-Validated Local Linear Nonparametric Regression," *Statistica Sinica*, 14, 485-512.

[9] List, J.A., D.L. Millimet, P.G. Fredriksson, and W.W. McHone (2003), "Effects of Environmental Regulations on Manufacturing Plant Births: Evidence from a Propensity Score Matching Estimator," *Review of Economics and Statistics*, 85, 944-952.

[10] List, J.A., D.L. Millimet, and W.W. McHone (2004), "Effects of Environmental Regulation on Foreign and Domestic Plant Births: Is There a Home Field Advantage?," *Journal of Urban Economics*, 56, 303-326.

[11] N ©, Nonparametric software by Jeff Racine (http://faculty.maxwell.syr.edu/jracine).

[12] Pagan, A. and A. Ullah (1999), *Nonparametric Econometrics*, Cambridge, Cambridge University Press.

[13] Racine, J. and Q. Li (2004), "Nonparametric Estimation of Regression Functions with Both Categorical and Continuous Data," *Journal of Econometrics,* 119, 99-130.

[14] Wang, M.C., and J. Van Ryzin (1981), "A Class of Smooth Estimators for Discrete Estimation," *Biometrika*, 68, 301-309.

Table 1. Elasticity of FDI Inflows with Respect to Relative Abatement Costs.

	Property, Plant, & Equipment		Employment	
	Chemical Sector	**Total Manufacturing**	**Chemical Sector**	**Total Manufacturing**
Mean	-0.068	0.251	-0.148	0.118
	(0.142)	(0.108)	(0.105)	(0.069)
Q1	-0.322	0.079	-0.300	0.014
	(0.141)	(0.113)	(0.206)	(0.089)
Q2	-0.105	0.257	-0.134	0.102
	(0.158)	(0.104)	(0.107)	(0.072)
Q3	0.250	0.452	0.040	0.221
	(0.218)	(0.084)	(0.154)	(0.085)
KL	-0.198	-0.079	-0.397	-0.013
	(0.092)	(0.046)	(0.072)	(0.041)

NOTES: Other controls included in the models are: state and time fixed effects, market proximity, population, unemployment rate, unionization rate, average wages, total road mileage, land value, energy prices, and tax effort. Models for the chemical sector estimated using data from 1977-1991, except 1987. Models for total manufacturing estimated using data from 1977-1994, except 1987. 1987 is omitted due to lack of abatement data for that year. Q1, Q2, and Q3 refer to first, second, and third quartile, respectively. AICc used for bandwith selection. KL corresponds to parametric results from Keller and Levinson (2002). Standard errors in parentheses.

Table 2. Impact of Relative Pollution Abatement Costs on FDI Inflows by State

	Relative Pollution Abatement Costs	Property, Plant, & Equipment				Employment			
		Chemical Sector		Total Manufacturing		Chemical Sector		Total Manufacturing	
State		**Median Elasticity**	**Rank**	**Median Elasticity**	**Rank**	**Median Elasticity**	**Rank**	**Median Elasticity**	**Rank**
Oklahoma	0.567	-0.458	(8)	0.078	(12)	-0.377	(7)	0.063	(17)
Nevada	0.605	-0.564	(4)	0.887	(47)	-0.300	(14)	-0.006	(8)
Rhode Island	0.619	-0.706	(3)	-0.194	(4)	-0.447	(4)	0.081	(20)
Connecticut	0.628	0.265	(36)	0.584	(44)	0.008	(34)	0.257	(39)
Vermont	0.628	0.588	(45)	0.097	(15)	-0.077	(29)	0.138	(27)
South Dakota	0.642	-1.361	(1)	0.598	(45)	0.094	(43)	0.205	(34)
Minnesota	0.653	-0.014	(27)	0.207	(21)	-0.049	(32)	0.121	(26)
Massachusetts	0.671	0.402	(39)	0.517	(38)	0.098	(44)	0.348	(45)
Wyoming	0.687	-0.076	(25)	-0.070	(8)	-0.223	(18)	0.282	(43)
North Dakota	0.689			-0.134	(5)	-0.422	(5)	0.019	(12)
Kansas	0.723	-0.244	(15)	0.214	(22)	0.023	(36)	0.084	(22)
New Hampshire	0.728	0.063	(31)	0.538	(41)	-0.255	(15)	0.422	(46)
Missouri	0.769	-0.190	(19)	0.021	(10)	-0.154	(23)	0.112	(25)
New York	0.796	0.349	(38)	0.408	(36)	-0.119	(26)	0.191	(32)
North Carolina	0.810	-0.085	(24)	0.295	(31)	-0.223	(17)	0.014	(11)
Nebraska	0.811	-0.372	(10)	-0.121	(6)	-0.353	(8)	-0.003	(9)
Colorado	0.816	0.033	(29)	0.153	(17)	-0.129	(25)	0.038	(15)
New Jersey	0.818	-0.143	(22)	0.281	(29)	-0.073	(30)	0.204	(33)
Ohio	0.818	0.866	(46)	0.538	(42)	0.235	(47)	0.101	(24)
Georgia	0.880	-0.509	(5)	0.266	(27)	-0.254	(16)	0.158	(28)
Wisconsin	0.885	-0.172	(21)	0.279	(28)	-0.198	(19)	0.031	(13)
California	0.902	-0.337	(11)	0.202	(20)	-0.306	(12)	-0.016	(7)
Utah	0.929	-0.508	(6)	0.262	(24)	0.051	(39)	0.257	(40)
Pennsylvania	0.930	0.581	(44)	0.372	(34)	-0.056	(31)	0.180	(31)
Iowa	0.942	-0.309	(13)	0.121	(16)	-0.189	(21)	-0.054	(6)
Illinois	0.949	0.466	(42)	0.525	(40)	-0.097	(27)	0.265	(42)
Virginia	0.970	0.347	(37)	0.264	(26)	0.171	(45)	0.178	(30)
Kentucky	0.988	-0.091	(23)	0.326	(33)	-0.198	(20)	0.248	(36)
South Carolina	0.989	-0.334	(12)	0.075	(11)	-0.318	(11)	0.002	(10)
Michigan	0.993	0.416	(40)	0.387	(35)	-0.152	(24)	0.211	(35)
Tennessee	1.055	0.053	(30)	-0.112	(7)	0.194	(46)	0.257	(41)
Alabama	1.130	0.189	(32)	0.569	(43)	0.014	(35)	0.255	(37)
Indiana	1.140	-0.182	(20)	-0.364	(2)	-0.178	(22)	0.037	(14)
Maryland	1.174	-0.414	(9)	-0.229	(3)	-0.305	(13)	-0.237	(2)
Florida	1.187	0.526	(43)	0.195	(18)	0.050	(38)	0.083	(21)
Oregon	1.188	-0.030	(26)	0.094	(14)	0.069	(41)	0.073	(18)
Arkansas	1.193	-0.860	(2)	0.282	(30)	-0.340	(9)	0.175	(29)
Arizona	1.290	-0.504	(7)	0.262	(25)	0.059	(40)	0.299	(44)
Delaware	1.334	-0.265	(14)	0.801	(46)	-0.045	(33)	0.635	(48)
Washington	1.370	-0.207	(17)	0.516	(37)	-0.084	(28)	0.255	(38)
Texas	1.395	-0.005	(28)	0.309	(32)	0.082	(42)	-0.187	(3)
Mississippi	1.518	-0.190	(18)	0.197	(19)	-0.849	(2)	-0.153	(4)
Maine	1.539	0.233	(35)	1.190	(48)	-0.562	(3)	0.524	(47)
Louisiana	1.557	-0.239	(16)	0.524	(39)	0.044	(37)	-0.057	(5)
Montana	1.580	0.417	(41)	0.083	(13)	0.297	(48)	0.076	(19)
Idaho	1.631	0.225	(34)	-0.514	(1)	-0.414	(6)	-0.257	(1)
New Mexico	1.636			0.000	(9)	-0.866	(1)	0.047	(16)
West Virginia	1.650	0.218	(33)	0.259	(23)	-0.334	(10)	0.084	(23)

NOTES: Relative pollution abatement costs refers to the median over the 1977 - 1994 period (1987 excluded). Property, Plant, and Equipment chemical sector data for New Mexico and North Dakota is censored by the Bureau of Economic Analysis in all years (see Keller and Levinson (2002, footnote 12)).

Table 3. Impact of Relative Pollution Abatement Costs on FDI Inflows by Year.

	Property, Plant, & Equipment				Employment			
	Chemical Sector		Total Manufacturing		Chemical Sector		Total Manufacturing	
Year	Median Elasticity	Rank	Median Elasticity	Rank	Median Elasticity	Rank	Median Elasticity	Rank
1977	-0.078	(12)	0.262	(13)	-0.148	(3)	0.054	(1)
1978	-0.082	(10)	0.254	(8)	-0.147	(5)	0.055	(2)
1979	-0.062	(13)	0.262	(14)	-0.136	(8)	0.101	(6)
1980	-0.082	(11)	0.256	(9)	-0.128	(9)	0.103	(7)
1981	-0.150	(1)	0.258	(12)	-0.085	(14)	0.117	(16)
1982	-0.147	(2)	0.264	(15)	-0.106	(13)	0.129	(17)
1983	-0.112	(6)	0.277	(17)	-0.127	(10)	0.115	(14)
1984	-0.120	(5)	0.254	(7)	-0.141	(6)	0.106	(10)
1985	-0.138	(4)	0.251	(3)	-0.149	(2)	0.116	(15)
1986	-0.029	(14)	0.257	(10)	-0.148	(4)	0.112	(12)
1988	-0.090	(9)	0.245	(1)	-0.152	(1)	0.106	(9)
1989	-0.141	(3)	0.250	(2)	-0.138	(7)	0.114	(13)
1990	-0.109	(7)	0.252	(4)	-0.126	(12)	0.111	(11)
1991	-0.097	(8)	0.252	(5)	-0.126	(11)	0.097	(3)
1992			0.258	(11)			0.098	(4)
1993			0.252	(6)			0.104	(8)
1994			0.267	(16)			0.100	(5)

Table 4. Summary of Covariate Effects on FDI Inflows.

	Independent Variable									
	Relative Abatement Costs	Market Proximity	Population	Unemp. Rate	Union. Rate	Average Wages	Total Road Mileage	Land Value	Energy Prices	Tax Effort
I. Chemical Sector Plant, Property, & Equipment										
NP	-	++	+	++	--	++	--	++	--	--
P	--	++	-	++	--	-	--	--	-	-
II. Total Manufacturing Plant, Property, & Equipment										
NP	++	++	++	++	--	++	--	-	-	-
P	--	+	+	-	--	--	-	--	+	--
III. Chemical Sector Employment										
NP	-	++	++	++	--	+	-	++	--	-
P	--	++	--	++	--	+	--	--	-	+
IV. Total Manufacturing Employment										
NP	++	++	++	-	--	++	--	++	+	-
P	-	++	-	-	+	--	-	--	-	-

NOTES: NP (P) refers to results from the nonparametric (parametric) model. ++ (+) indicates a positive and statistically significant (insignificant) effect at at least the 90% confidence level; -- (-) indicates a negative and statistically significant (insignificant) effect. NP results based on the mean point estimate.