Pollution Incidence and Political Jurisdiction: Evidence from the TRI

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Abstract

Few issues are more contentious for local communities than industrial pollution. When local industries pollute, lawmakers and regulators must balance two primary concerns: economic prosperity and the environment. The role of political pressure is well-documented in environmental policy. What is less clear is the role jurisdictional or boundary considerations play in determining the implementation of environmental laws. Anecdotal evidence suggests that local regulators are more lenient in their treatment of polluters when the incidence of pollution falls partially on those outside the state. One explanation for such behavior is that regulators take actions to maximize political support. This paper tests this jurisdictional model using Toxics Release Inventory (TRI) data from 1987 to 1996. We find that facilities' emissions into the air and water are systematically higher in counties that border other states. These results are consistent with the hypothesis that jurisdictional considerations are an important determinant of pollution incidence

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1. Introduction

In 1983 the state of Tennessee sued the state of North Carolina charging that it had allowed a Canton, North Carolina paper mill to violate the Clean Water Act.[1] Tennessee claimed that the primary reason for its neighbor's inaction was the mill's close proximity to the state line (Bartlett 1985:105); in this case, the location of the Champion Internationals mill was on the Pigeon River twenty-six miles upstream from the Tennessee border. This was not the first time state regulators had been accused of giving lenient treatment to polluters located on or near a state border. In 1987 the Supreme Court heard arguments in a case involving New Hampshire and Vermont (Bartlett 1995).[2] In both situations, a neighboring state alleged that another state's regulators had enforced national pollution laws less stringently, usually by grandfathering high emission levels at older facilities, in order to protect state resident's income rather than reduce pollution that largely affected nonresidents. A similar debate has taken place over acid rain and other types of air pollution (Novello (1992)).

Few issues are more contentious for local communities than industrial pollution. When local industries pollute lawmakers and regulators must balance two primary concerns: economic prosperity and the environment. The role of political pressure is well-documented in environmental policy (Oates (2001), Magat, *et al*. (1986), Hird (1990)). In general the theory suggests that local control is at least as efficient as any other political jurisdiction in dealing with local pollution simply because the median voter receives both the costs and benefits of the policy. What is less clear is the role jurisdictional or boundary considerations play in determining the enforcement of environmental laws. As Oates (2001) explains the strongest case for national standards exists when local public goods (in this case environmental protection) have spillover

[1] State of Tennessee v. Champion International Corporation. 709 S.W. 2d 569 (Tenn. 1986), April 21, 1986.

effects in other jurisdictions. Theoretically at least this can lead to a “race to the bottom.”[3] There is some evidence that suggests that local regulators are more lenient in their treatment of polluters when the incidence of pollution falls not on state residents but on those outside the state. For example, Novello (1992) finds that regulatory stringency is lax when emissions of volatile or organic compounds (VOCs) or nitrogen oxides affect downwind states. Deyle and Bretschneider (1995) show that, in the case of New York hazardous waste production, differing regulations between jurisdictions caused a shifting of risk. Sigman (2000), in a recent paper, finds a 40% increase in pollution in rivers near international borders.

An explanation for this behavior is that regulators take actions to maximize political support (Magat, *et al*. 1986). The costs and benefits associated with the regulators’ actions are assumed to produce responses from external actors. The political jurisdiction in which constituents reside will dictate, in part, a regulator’s behavior. The stringency of pollution abatement will vary with the number of the state’s residents (or voters) who are affected by this pollution. This does not mean that all border communities go unprotected but that border facilities will be less stringently regulated than are plants in the interior of the state.

This paper tests a jurisdictional model using Toxics Release Inventory (TRI) data from 1987 to 1996. The analysis uses establishment-level data form the TRI. The dependent variable is the emission level by TRI facilities (using several standard measures in the TRI) between 1987 and 1996. These results have potentially important implications for regulatory federalism. Specifically we find systematic evidence of free riding by jurisdictions when pollution can be more easily exported to neighboring states.

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[2] International Paper Co. v. Harmel Ouelette, *et al*. 107 S. Ct. 805 (1987).

The paper proceeds as follows. In the next section we present a model of the political determinants of pollution standards. In section 3 we discuss the data. In section 4 we discuss the econometric issues involved in estimating the model. In section 5 we present the results and section 6 offers some concluding remarks.

2. The Model

We start with one of the simplest models of environmental federalism to motivate the specification that follows in section 4.[4] We modify Magat, *et al*.'s (1986) external signals model by introducing an export parameter to capture the proportion of pollution that remains in the jurisdiction.[5] The resulting model, as constructed, is similar to Weingast, *et al*.'s model of federalism (1981).

A jurisdiction contains n citizens and m firms. The Magat model posits that regulators set the stringency of environmental regulations, s, to maximize the sum of external support M (or minimize opposition); for example, $s=0$ is a complete elimination of the hazard. The total damage each citizen suffers from the pollution allowed by that standard is $v(s)$; harm is assumed to increase at an increasing rate ($v'(s) > 0$ and $v''(s) > 0$). The representative citizen's (or median voter) probability of sending a positive (supportive) signal is $f(v(s))$; the probability of support from individuals is assumed to be decreasing and concave in harm ($f'(v(s)) < 0; f''(v(s)) < 0$). The firm's probability of opposition is $h(t(s/m))$, where $t(s/m)$ is the representative firm's cost of compliance. Compliance costs are assumed to decrease in s (less stringent standards) at an

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[3] Baron (1985), for example, shows that national regulation can improve social welfare because local regulation is subject to jurisdictional problems. Ingberman (1995) shows that the location of hazardous waste facilities depends critically on jurisdiction.
[4] Oates (2001) is an excellent survey of the various models and their predictions.
[5] Magat, *et al*.'s (1986) model is based on Peltzman's (1976) model of political competition. The interpretation in Magat, *et al*. – support maximization by regulators rather than vote maximization by elected officials – makes the model somewhat different.

increasing rate ($t'(s/m) < 0; t''(s/m) > 0$); the probability of industry opposition increases in compliance cost at an increasing rate ($h'(t) > 0; h''(t) > 0$). The relative strength of the industry's signal is *e*. We include the proportion (a) of the total harm (*v(s)*) that affects local residents in the regulator's jurisdiction. As a approaches 1, less pollution is exported to non-residents.[6] A national regulator who values all voters equally would set a pollution level would account for the harm done to all voters ($a = 1$).

The local regulator's objective function is to maximize

$$M = nf[a\,v(s)] - meh[t(s/m)] . \tag{1}$$

The first order necessary condition for s^* is

$$nf'[a\,v(s^*)]a\,v'(s^*) - meh'[t(s^*/m)]t'(s^*/m) = 0 . \tag{2}$$

The total differential[7] of (2) with respect to s is

$$na\,(f'v'' + v'^2 f'' a) - e(h'' t'^2 (1/m) + h't'') < 0 . \tag{3}$$

The total differential of (2) with respect to a is

$$nf'v' < 0 . \tag{4}$$

This means that the impact of incidence on stringency is $\frac{\partial s}{\partial a} = -{}^{(3)}\!/_{(4)} < 0$. As expected, an increase in the proportion of pollution damage that is inflicted on local residents causes a reduction in the allowed level of pollution. Figure 1 shows the intuition of the model. As incidence increases, the pollution damage causes more harm to the regulator's base of support and so his marginal political support curve shifts to the right relative to the case where $a = 1$. Second, as the lower panel of Figure 1 indicates, neither the national standard s_F ($a = 1$ by definition) nor

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[6] In Magat, *et al*. (1986) the a parameter is labeled *p* and is included as a shift parameter measuring the impact of changes in pollution damage on s. We have changed the name to reflect change in interpretation.

the local (export) standard s_L are systematically related to the efficient standard s_E; we do not know if local control is more or less efficient. Table 1 presents the other comparative statics.

[Insert Figure 1 about here.]

[Insert Table 1 about here.]

There are alternative models that suggest that the equalization of pollution incidence across jurisdictions. For example, the Coase Theorem (1960) suggests that if transaction costs were low enough cross-border pollution issues could be solved. However, there is every reason to believe that borders between jurisdictions create high transaction costs. Jurisdictions complicate information problems in that the two political jurisdictions must share information in order to attribute pollution to potential emitters (Fesler 1949). For example, if a plant on one side of the state line and a plant on the other side both pollute the same river the downstream regulator would need to know the emission levels at the first plant to attribute responsibility to the second plant. Although there are many reasons, the basic prediction of the literature is that pollution levels will be higher if the incidence of pollution falls on residence of another state.

3. Data

3.1 Dependent variables and hypothesis

Our test environment for this hypothesis is the emission of toxic pollutants by manufacturing and other establishments in the United States. Our data source is the Environmental Protection Agency's Toxic Release Inventory (TRI) for the years 1987 to 1996.[8] The 1984 Bhopal, India disaster heightened awareness of toxic emissions and aided, directly or indirectly, the creation of the 1986 Emergency Planning and Community Right-to-Know Act (EPCRA), which requires

[7] The comparative statics are given in Magat, *et al*. (1986:61-63). We refer the reader to Magat, *et al*. for a derivation of the other derivatives.

disclosure of over six hundred designated toxic chemicals. The TRI tracks emission levels for all establishments producing more than 25,000 pounds of any toxic chemical. Our dependent variables are the amounts released for a reporting facility by four specific pathways for a given year.

Our primary variable of interest is an establishment's border status as a measure of the proportion (a) of the establishment's waste that impacts local residents. We classify every county as being a border county or non-border county; a border county shares a border with another state, Mexico, or Canada. This coding scheme corresponds with the finding that people's aversion to hazardous wastes declines with distance (Mitchell and Carson 1986). When a polluting facility is located in the interior of a state (i.e., the larger the proportion of overall pollution produced inside the state), an in-state resident's utility will be lower and the utility of a neighboring state's resident will be higher. Further, we classify the county as an ocean county if it borders an ocean or one of the Great Lakes. Because the model indicates that exportability increases pollution levels regardless of whether it is fish or people receiving the pollution, we expect pollution levels are higher when bordering an ocean.

Our four pollution pathways are air, water, and land releases and the quantity shipped off-site to treatment, storage and disposal (TSD) facilities within the state (land emissions includes on-site storage in a lagoon or treatment pond). We disaggregate the pathways because the model's predictions should differ by pathway. Both land and off-site transfers affect residents less in a neighboring county than would air or water emissions. Even if spillovers from storage facilities (usually ponds) or accidents in off-site transfers affect out-of-state residents, the relative magnitude should be smaller because these types of accidents are rare events. Spillovers are generally fairly

[8] While there has been some concern that the first two years of TRI data are censored at high levels of emissions

localized, and shipments often cross great distances so accidents would be no more likely to affect neighboring state residents if they originated in a border county. Thus, land emissions and off-site in-state transfers serve as explicit comparison measures for air and water emissions. We expect that facilities in border counties will be marked by elevated pollution levels for the latter two measures because of the greater possibility of migration.

Additionally, we carry out several extensions of the model. Because we do not know the direction of the air or water flow and releases from a border-county plant, which might traverse the state, we examine counties on the eastern edge of the state. According to the model, air emissions should be higher in these counties than for the entire population of border counties because prevailing winds increase the likelihood that air emissions from eastern edge counties will be deposited in the neighboring state. However, we note that not knowing if emissions flow directly into the next state tends to bias our initial coefficient estimates toward zero. Our estimates are lower bounds.

In the second extension, we address the proposition, raised particularly with *maquiladores* factories, that pollution abatement efforts are lower at international borders. Our second extension includes estimating the model excluding counties bordering Mexico and, in a second set of regressions, Canada or Mexico. Last, we also address the fact that U.S. counties vary greatly in size; western counties are much larger than eastern ones. While this is partially accounted for by our estimation technique, we also estimate the model by EPA region.

(Levinson 1999), our results are not sensitive to their inclusion.

3.2 Control Variables

Previous studies and our theoretical model motivate our control variables.[9] First, we include the population of the county (in the theoretical model, n). The model predicts that increases in population will cause decreases in pollution. Second, to capture the likelihood that residents will send a positive signal in response to a given level of pollution ($f(\cdot)$) we include the county in which the facility is resides' per capita income, the percent of the county population in poverty, and the percent of the county population who are black, Hispanic or Native American, and the unemployment rate for the county.[10] The model predicts that factors that increase the probability of positive signal will reduce pollution. Thus we predict that increased income reduces pollution while communities with higher poverty rates and minority communities are less likely to signal. Because unemployment raises the cost of signaling the regulator (due to the implicit job search), we predict higher unemployment rates cause higher rates of pollution. Third, we include the population density as a measure of $v(\cdot)$, the damage caused by allowing a given pollution level, s. We predict that increased population density causes decreased pollution.

Some care should be taken in interpreting the link between demographic characteristics and the model. It is possible, even in the panel context discussed below, that the causation on the demographic variables runs in the opposite direction. That is, rather than counties with a high poverty rate, for example, being less politically active and hence having higher levels of pollution in their community in fact the higher pollution levels may cause wealthier people to leave the community and hence the remaining population has a higher poverty level. Since our primary focus

[9] See for example Hird (1990), Hamilton (1993 and 1995), Gray and Deily (1996), Helland (1998) and Arora and Cason (1999) among others, who find that local communities can be important in determining the level of pollution emitted from a facility.

[10] The poverty and minority percentages are not available for all years and we linearly interpolate the missing values. The results are robust to using the value for the closest year as well.

is not the link between pollution and the demographics of the local community we simply estimate a reduced form equation.

We also include measures related to the environment of the establishments on which our model centers. We include the number of manufacturing establishments as our measure of m in the model. The comparative statics in Table 1 indicate that the greater the number of firms the higher the pollution levels allowed per firm. As a measure of the probability a firm will oppose an allowed pollution level, $h(\cdot)$, we include the percentage of firms with fewer than ten employees; we expect that lobbying is costly to small firms and so the higher the percentage of small firms in the lower the allowed pollution level. As a measure of e, the relative signal strength, we include the number of employees in manufacturing. We believe that e is the relative size of those harmed by pollution to those whose income benefits from pollution – even if they are the same individuals. Thus we expect increases in manufacturing employment are associated with increased pollution.

We note that the predicted sign for these variables for land emissions and off-site in-state transfers depends on the threat of contamination from storage or release during transport. We assume that transport is relatively less likely to release pollution than air and water emissions. Thus we expect that communities with a higher probability of sending a signal will have higher levels of land emissions and off-site in-state transfers as regulators force reductions in other pathways.

We include three variables central to the regulatory environment of firms releasing toxic substances. Because inspections may be endogenous as many of the same factors determine the inspection rate as emissions level (see Helland (1998) and Stafford (2001)), we include the inspection rate of firms in the state regulated under the Resource Conservation and Recovery Act (RCRA). However, as we have no instrument for inspections independent of pollution, we estimate the model with inspections as if they were exogenous. We include two measures of the availability of alternative treatment methods. We include the number of in-state RCRA treatment facilities (TSDs) and the percentage of all hazardous wastes treated nationally treated in the facility's state. We predict that more treatment facilities and a greater percentage of all waste nationwide being treated in state indicate a greater treatment capacity and will reduce air, land and water emissions and lower the cost of off-site in-state transfers.[11]

To account for the fact that counties are not of uniform size, we include the area of the county. We account differences in pollution level caused by industry differences by constructing 78 dummy variables based on the facility SIC code(s).[12] Finally, because we are concerned that emissions have declined overall in the 1987-96 period, we include year intercepts for all years after 1987 to track the overall changes in emissions through the sample period.

Table 2 presents the means and standard deviations from the sample. The mean emission levels for air, water, land and off-site in-state transfers are higher in border counties although the magnitude difference is quite small. In other respects the samples appear similar. The demographic variables between border and non-border counties do not appear systematically different.

[Insert Table 2 about here.]

3.3 Specification

We estimate the model in logs and the coefficients are therefore elasticities. We do not, however, take the natural log of the percentage variables or dummy variables. We also include year intercepts. Our facility-level control variable is the plant's SIC code. Unfortunately, a

[11] The National biennial RCRA hazardous waste report from which these variables are derived is available for 1991, 93, 95, 97 and 99. We utilize the nearest year as we cannot linearly interpolate before 1991. The results are robust to the omission of this variable, too.

number of establishment specific factors we would like to control for are not included in the TRI. We assume, as is usual in panel analysis, that these unobserved establishment level effects are fixed through time. In this case our time frame makes this assumption seem reasonable.[13] The underlying model is

$$\log(W_{ijt}) = f\,border_i + m\,ocean_i + X'b + a\sum_{l=1}^{k} SIC_l + g\sum_{t=1}^{9} year_t + c_i + e_{it} \qquad (5)$$

where W_{ijt} is the toxic release into pathway *j* (air, land, water, and off-site in-state shipments) from establishment *i* in year *t*. *Border* is a discrete variable equal to one if the county in which the facility is located borders another state or country; *Ocean* equals one if the county borders an ocean or one of the Great Lakes. X is the matrix of control variables for year *t* and establishment *i*, b is the matrix of coefficient estimates for control variables, a and g are the coefficient estimates for the SIC and year controls respectively, and c_i are the unobserved establishment level fixed effects. Finally *e* is the random disturbance.

To the extent that we can assume that c_i are uncorrelated with locating on a state border our result will be unbiased. However it seems likely that some unobserved establishment characteristics are correlated with the primary variable of interest, namely border location. For example, manufacturing centers might be located on state borders and hence older plants will also located on borders. In other contexts we would simply include an establishment level fixed effect. Here, though, an establishment's border location does not change and so we need to eliminate the unobserved fixed effect and still estimate the impact of border county status.

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[12] Note that since some industries do not emit toxics via some pathways some SIC codes are not included in certain pathway specifications.

[13] This assumption is not needed for the random effect model although it is required for the Hausman-Taylor model (see below).

4. Econometric Issues

We have two important econometric issues in order to conduct a test of this model: sample selection and the potential endogenity noted above. First, although our data consists of an establishment level panel, not all counties have TRI facilities located in them. In fact, depending on the pathway, over one-third of all counties do not contain a single TRI facility. To control for the fact that the counties represented in our data may not be a random sample, we implement Arora and Cason's (1999) solution and estimate a probit model of the probability that a county has a least one TRI facility utilizing the pathway in question (air, water, land or off-site in-state transfers). We then use the Inverse Mill's ratio, l , as a regressor in our second-stage regressions discussed below to reweight the sample (Heckman 1979). Table 3 presents the results of the first-stage probit. As Arora and Cason (1999) stress it is important not to infer causation from these estimates. Specifically, the presence of toxic releases may be determined by a county's demographic characteristics, but residents may self-select into counties without toxic releases and thus determine the county's demographic composition.

[Insert Table 3 about here.]

The endogenity problem requires additional treatment. A first solution simply would be to estimate the model using OLS and implicitly assume no omitted variable bias. Even if the c_i are uncorrelated with all of the independent variables, OLS still results in incorrect inference because the error terms are serially correlated (Wooldridge 2002). A second solution is to estimate the model using random effects. Unlike a fixed effects model the random effects (RE) model allows us to estimate the border effect, but it also assumes that the unobserved fixed effects are uncorrelated with the other explanatory variables. This may not be a terrible assumption – an establishment's unobserved characteristics may well determine its emission levels but not affect its decision to locate in a border county.

Because a convincing case can be made about the correlation between the unobserved establishment characteristics and border location, we choose to estimate the model so that the fixed effects are removed while still estimating the impact of being located on a border.[14] Our solution is Hausman and Taylor's (HT) (1981) model, which reconstructs equation (5) as

$$\log(W_{ijt}) = z_i g + x_{it} b + c_i + e_{it}, \qquad (6)$$

where z_i are the time-invariant variables (border, ocean, county land area and SIC code) and x_{it} (demographic characteristics, inspections, etc.) are variables which show some time variation. The variables are further subdivided into exogenous variables z_{i1} and x_{it1} (for which $E(z_{i1} | c_i) = 0$ and $E(x_{it1} | c_i) = 0$ for all *t*,) and endogenous variables z_{i2} and x_{it2} (for which $E(z_{i2} | c_i) \neq 0$ and $E(x_{it2} | c_i) \neq 0$). In our model z_{i2} are border and ocean location. All other variables are treated as exogenous and hence x_{it2} is empty.[15] The HT estimator uses the means of the exogenous x_{it1} variables as instruments for the endogenous z_{i2}.[16]

5. Results

5.1. Basic Model

Table 4 presents the results of the estimation of equation (5) for the log of air emissions. Column (1) presents the OLS estimates without controls.[17] Column (2) includes all control variables but not the IMR ratio to correct for sample selection. Column (3) includes the IMR but

[14] Ideally, we need a Hausman-like test (1978) of exogeneity. Yet, the Hausman test compares only the exogeneity of time-varying regressors and hence does not address our concerns.
[15] Estimating the model treating inspections as endogenous does not change the result.
[16] See Wooldridge (2002:325-328) for an excellent treatment of the HT model.

does not correct for serial correlation in the error term. Column (4) contains the random effects model and IMR, which while not accounting for possible correlation between the unobserved establishment effects and border location does control for serial correlation in the error. Finally column (5) contains the HT model estimates.

[Insert Table 4 about here.]

The results from column (1) to (4) estimate a border effect of between 3% and 9.8%. Consistent with the model's predictions, pollution levels are higher when it is possible to export a portion of the pollution incidence to non-residents. In all three cases the border coefficient is statistically significant.

The HT estimates are significantly larger. The border coefficient indicates that establishments located in border counties have air emissions that are 604% more air emissions than establishments located in non-border counties. There are two possible reasons for the large increase in the magnitude of the estimated impact. The first model is miss-specified. However, even when the model is reestimated treating the inspections variable as endogenous, the coefficient remains of similar magnitude. The alternative is that the OLS and random effects estimators seriously underestimate the impact of border status. Because we cannot sort out these explanations we include both sets of estimates.[18] The HT estimate of the ocean effect suggests that ocean counties have air pollution that is 183% higher.

The results for the controls are also largely consistent with the model. In the RE and HT models a 1% increase in per capita income reduces air emissions by 0.35% and 0.75% respectively. While county population and poverty are positive and significant in the OLS estimation, they

[17] Due to missing values of the independent variables it is usually the case that there are more observations in column (1) than the other models.

change sign in the RE and HT models. Minority composition is positive and significant in all specifications; a 1% increase increases pollution by between 0.004% and 0.01%. This is consistent with the model that the decreased likelihood of a signal by residents results in higher pollution. We find a similar effect from unemployment in all models but the HT specification.

The total number of firms is negative and significant in all specifications (elasticity of -0.5) except the HT model; in that case it is positive, implying that a 1% increase in firms increases pollution by 1%. In all models, increases in the proportion of firms with fewer than 10 employees decreases pollution for each firm by about 0.1% to 0.3%. It may be that this measures establishment size rather than political importance. However, the fact that this result holds in the HT specification suggests that the effect measures more than just average firm size because the firm-specific random error should include establishment size.

In all specifications we find that a 1% increase in the fraction of all total waste treated by TSDs in the state causes a 0.014% to 0.044% increase in establishment-level pollution. We find inconsistent evidence on the impact of the number of TSDs in the state. Our proxy of *e*, the total employment in manufacturing in the county, is positive and significant in all 5 specifications with a 1% increase in total manufacturing employment causing a 0.48% to 0.939% increase in an establishment's air emissions.

Table 5 presents the results for water emissions. We find a magnitude of 6% (Heckman) to 55% (HT) for the border county variable (the RE specification is not statistically significant). The coefficient on ocean is significant in all of the specifications (except the OLS without controls), and implies that a being in a county that borders the ocean results in 40% to 70% higher water emissions.

[18] Other studies using HT models find similar increases in the magnitude of estimated coefficients of endogenous

[Insert Table 5 about here.]

Several control variables are also significant. A 1% increase in per capita income causes a 1.6% decrease in water emissions (although this is only significant in the HT model). Consistent with our air results, we find that a 1% increase in the minority population causes a 0.003% increase in water emissions. We also find that unemployment is positively related to water emission and that the number of small firms is negatively related.

Table 6 presents the results for land emissions (storage). The intuition of the model is that border and ocean county status represent a measure of a, the proportion of pollution that impacts local residents in the jurisdiction. As such, we expect that the impact of border and ocean county status to be smaller for land and off-site in-state transfers than for air or water emissions.[19] In all cases the border coefficient on land is either negative or not significant. In the HT model the coefficient statistically significant implying that border facilities have an average of 79% lower land emissions. The ocean coefficient is positive and significant and of comparable magnitude to the air and water coefficients in all specifications.

[Insert Table 6 about here.]

The land emissions model is less well estimated than the air or water regressions. A 1% increase in per capita income decreases land emissions by about 1%. Increased poverty decreases land emissions. However, minority composition increases land emissions. However, generally, the control variables are either not significant or are not the expected sign in the HT model.

Table 7 presents off-site in-state transfers to in-state facilities. We measure only shipments to locations within the state in which the facility is located, so the incidence resulting from

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variables. Hausman and Taylor (1981) find a large increase in returns to schooling relative to OLS estimates.

[19] Because a potential problem is spillovers from storage facilities, the test for land emissions is less clean than for off-site transfers.

treatment and shipping accidents should fall on state residents. We find no relation between border location or ocean location and the amount of off-site transfers.

[Insert Table 7 about here.]

We also find little relationship between county demographics and off-site in state transfers. There is a positive relationship for unemployment and a negative relationship for the number of firms (this is consistent with the model in that as e grows we should see more local disposal). Yet, we find a relationship for the percentage of small firms as that in the air, water and land specifications. This runs counter to the theory and suggests that this measure instead captures establishment size. Several other control variables are consistent with expectations. RCRA inspections are negatively related to emission levels; a 1% increase in the log inspection rate causes a 5% decrease in off-site transfers. Also, an increase in the proportion of all treated waste treated in-state increases off-site transfers, as does an increase in the number of licensed treatment facilities.

These results are generally consistent with the model. Border counties have higher air and water emissions, findings that are consistent with the claim that regulators are lenient when pollution incidence falls on non-residents. We now turn to several robustness tests. For these tests, the HT model presents the most restrictive assumptions and so we will confine our attention to border parameters estimated by that model.

5.2. Extensions

Our first concern is that we do not know the actual migration patterns for air and water emissions. We would like to know, for example, into which river a plant releases its emissions and the direction the river flows. Our data includes over two hundred thousand emitters and mapping the destination of each release is prohibitive.

For air emissions our solution is to examine only those counties on the eastern edge of the state where, due to prevailing winds, the most likely export destination is the neighboring counties. Table 8 presents our estimates using only eastern border counties to classify facilities. We find facilities in counties on the eastern edge of the state have air emission levels that are 194% higher than other border counties. In short, in those border counties where we are more certain that the emissions are being exported to non-residents we find even higher emission by TRI facilities.

[Insert Table 8 about here.]

Our second concern is that the border effect depends on international border status. This would not *per se* contradict the jurisdiction theory; finding that international borders drive the results would indicate that the national government has a role in jurisdictional conflicts. We estimate three specifications (presented in Table 9). The exclusion of facilities located in counties bordering Mexico, Canada, or both does not change the results. In all cases find that air emissions and water emissions are higher in establishments located on state borders while land and off-site transfers are not.

[Insert Table 9 about here.]

Finally, Table 10 provides the results of an HT where each model includes only facilities located in one of the ten EPA regions. The first reason for this is that county size varies greatly across regions. EPA Region IX has an average land area of 4062; Regions IV (south central) and I (New England) have land areas of 502 and 938. A second reason is political. One of the purposes of the EPA Regions is to oversee just the sorts of jurisdiction conflicts created by facilities located in border areas. It is possible that some regions are better at (or more likely to) mitigating these problems than others. Table 10 does not indicate that Region I's counties are driving this result; the border effect is consistently positive and significant in the air emission specification. In those areas where it is not (Regions I, III, and IX) only in Region I do we find a negative and significant coefficient. We find similar evidence for water emissions; in three of the ten Regions the border effect is positive and significant – it is negative and significant in Region 6.

The results are more varied for land and off-site transfers. Only in Region V is the border effect for land emissions significant and positive. For off-site transfers, Regions II, V, and VII have negative coefficients while that for Region IV is positive.

[Insert Table 10 about here.]

There appears to be no consistent pattern form land or off-site transfers. For air releases the pattern seems much clearer. In most Regions, the average facility emits more chemicals if it is located in a county that borders another state. There is still considerable variation in the effect across Regions – a fact we leave to further research.

6. Conclusion

The results presented in this study suggest that jurisdiction matters in determining the level of pollution produced. As Oates (2001) explains, local environmental protection is a public good with spillovers and communities have incentives to export externalities. The benefits of the production in terms of income stay within the state while the costs in terms of pollution are borne (at least in part) by residents of another political jurisdiction. In estimating a model of the determinants of facility emissions, our findings indicate that facilities located in counties bordering other states have significantly higher levels of toxic releases into the air and water. Their releases shipped off-site or stored on land show no systematic significant difference.

It is not clear what if anything could be done to correct this difference. One of the central reasons for a national environmental policy is to avoid externality exporting. In a strong sense, the solution depends on how these externalities are exported. One possibility is that states are less stringent in their enforcement of pollution control laws near the borders of their states. While this is possible, we believe it is unlikely in this case. Because the TRI data are self-reported, facilities out of compliance with their permitted levels of pollution are unlikely to voluntarily report this even if they faced lower regulatory sanctions. Instead, it is more likely that states write less restrictive permits or grandfather near the border.

One wrinkle, however, is that an efficient emission standard would not be uniform as communities almost certainly differ in their willingness to pay. Oates (2001) points out that even if local communities free-ride it is unclear if the deadweight loss created by that free-riding is greater than the deadweight loss created by uniform national standards. In terms of Figure 1 we are not estimating s_E, the efficient level of pollution. Further we have no idea whether the national standard, s_F, is closer to the efficient level than the local standard even if the national standard is not uniform. In sum, we cannot answer Oates' most pressing question,

> "…if there is a race to the bottom, we are left with a choice between to alternatives: suboptimal local decisions on environmental quality or inefficient uniform national standards. And which of these two leads to a higher level of social welfare is, in principal unclear" Oates (2001:9).

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Table 1: Magat, *et al*. comparative statics: effect on the stringency of regulations

Parameter increased	Sign associated with change in s^*
n (number of citizens)	-
m (number of firms)	+
e (relative strength of signal)	+
$h(\cdot)$ (probability of firm support)	+
$f(\cdot)$ (probability of citizen support	-
$t(\cdot)$ (compliance cost)	+
a (pollution damage)	-
Source: Magat, *et al*. (1986:63)	

Table 2: Descriptive Statistics

Variable	All Establishments	Establishments located in border counties
Log(air releases)(1)	8.795889	8.800791
	(2.922354)	(2.914955)
Log(water releases)(1)	6.398296	6.465002
	(3.475193)	(3.485683)
Log(land releases)(1)	7.498625	7.516797
	(3.387659)	(3.375779)
Log(off-site transfers)(1)	8.155332	8.236854
	(2.424001)	(2.396253)
Border	.450201	
	(.4975149)	
Ocean	.1485928	.0832053
	(.3556874)	(.2761936)
Log(Per Capita Income	9.864621	9.866472
	(.2404729)	(.2386215)
Log(land area)	6.481155	6.370419
	(.8428345)	(.7989521)
Log(Population)(2)	12.35937	12.40933
	(1.621046)	(1.515775)
Log(Per Capita Income)(2)	.1226532	.1218319
	(.0502107)	(.051301)
Percent Poverty (2)	.1712438	.1662169
	(.1650395)	(.171952)
Percent minority(2)	5.885378	6.054909
	(1.586308)	(1.669731)
Log(Population Density)(2)	6.481923	6.486475
	(.6566292)	(.658478)
Unemployment Rate(2)	8.623834	8.651642
	(1.696286)	(1.568572)
Log(number of manufacturing establishments)(2)	53.82296	53.68761
	(4.382062)	(4.553181)
Log(number of plants with 10 employees)(2)	-.0588219	-.033929
	(.6807356)	(.6771439)
Log(inspection per plant)(3)	3.922231	2.853796
	(7.757025)	(5.256608)
Percentage of all RCRA hazardous waste treated	4.345126	4.253671
in state	(.9464091)	(.9933635)
Log(total number of in-state RCRA facilities)	11.37031	11.41315
	(1.820805)	(1.705313)

Source:
(1) Toxic Release Inventory
(2)Census and City County Data book and census, various years
(3) RCRA Info
(4) National biennial RCRA Hazardous Waste Report 1991, 93, 95, 97, 99

Table 3: Probability of hazardous waste releases by medium

	Probability of Air Release	Probability of Water Release	Probability of Land Release	Probability of Off-Site Release
Border County	0.035*	0.246***	0.117***	-0.005
	(0.021)	(0.019)	(0.019)	(0.020)
Ocean	-0.242***	0.229***	-0.029	-0.487***
	(0.048)	(0.038)	(0.038)	(0.046)
Log(PCI)	-0.865***	-0.540***	-0.150*	-1.134***
	(0.091)	(0.088)	(0.090)	(0.097)
Log(population)	0.241***	0.299***	0.627***	0.073
	(0.045)	(0.043)	(0.049)	(0.046)
Percent of residents in poverty	-0.036***	-0.017***	-0.013***	-0.035***
	(0.002)	(0.002)	(0.002)	(0.002)
Percent of county residents who are a minority	0.003***	0.003***	0.002***	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Log(population density)	0.126***	0.062***	-0.286***	0.335***
	(0.014)	(0.013)	(0.020)	(0.015)
Percent of county residents who are unemployed	-0.053**	-0.036*	0.160***	-0.262***
	(0.022)	(0.020)	(0.021)	(0.022)
Log(number of manufacturing establishments)	-0.647***	-1.017***	-0.809***	-0.573***
	(0.048)	(0.049)	(0.052)	(0.050)
Percentage of firms with fewer than 10 employees	-0.018***	-0.015***	-0.025***	-0.015***
	(0.002)	(0.002)	(0.003)	(0.003)
Log(inspection rate)	-0.160***	-0.089***	-0.066***	-0.135***
	(0.014)	(0.013)	(0.013)	(0.014)
Percent of all RCRA hazardous waste treated in state	-0.003**	-0.004***	-0.001	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Log(total number of in-state RCRA facilities)-TSDs	0.013	0.038***	-0.001	0.025*
	(0.013)	(0.012)	(0.012)	(0.013)
Log(total employment in manufacturing)	1.042***	1.103***	0.852***	1.025***
	(0.033)	(0.037)	(0.040)	(0.035)
Constant	3.251***	-0.681	-6.262***	7.199***
	(1.107)	(1.049)	(1.086)	(1.164)
Observations	28759	28759	28759	28759

Standard errors in parentheses
All models include year and SIC controls.
* significant at 10%
** significant at 5%
*** significant at 1%

Table 4: The determinates of facility Log(air) emissions

	(1) OLS-no controls	(2) OLS-controls	(3) Heckman	(4) Random Effects	(5) Hausman-Taylor
Border County	0.029**	0.098***	0.098***	0.085***	6.041***
	(0.013)	(0.014)	(0.014)	(0.031)	(0.258)
Ocean	-0.104***	0.315***	0.314***	0.340***	1.835***
	(0.018)	(0.022)	(0.022)	(0.047)	(0.074)
Log(PCI)		-0.122	-0.089	-0.213*	-0.754***
		(0.080)	(0.082)	(0.115)	(0.126)
Log(Land Area)		0.015	0.018	0.174***	1.312
		(0.044)	(0.044)	(0.020)	(2.106)
Log(population)		0.001	0.001	-0.354***	-3.265
		(0.001)	(0.001)	(0.073)	(2.110)
Percent of residents in poverty		0.004*	0.006**	-0.015***	-0.020***
		(0.002)	(0.003)	(0.004)	(0.004)
Percent of county residents who are a minority		0.004***	0.004***	0.003***	0.011***
		(0.001)	(0.001)	(0.0001)	(0.001)
Log(population density)		-0.139***	-0.137***	0.001	0.630
		(0.043)	(0.043)	(0.000)	(2.106)
Percent of county residents who are unemployed		0.448***	0.453***	1.534***	-0.142*
		(0.021)	(0.021)	(0.156)	(0.086)
Log(number of manufacturing establishments)		-0.592***	-0.571***	-0.595***	0.992***
		(0.057)	(0.058)	(0.091)	(0.108)
Percentage of firms with fewer than 10 employees		-0.014***	-0.014***	-0.019***	-0.038***
		(0.002)	(0.002)	(0.003)	(0.003)
Log(inspection rate)		0.009	0.009	0.010	0.003
		(0.011)	(0.011)	(0.011)	(0.014)
Percent of all RCRA hazardous waste treated in state		0.014***	0.014***	0.003**	0.044***
		(0.001)	(0.001)	(0.001)	(0.002)
Log(total number of in-state RCRA facilities)-TSDs		-0.082***	-0.082***	0.018	0.249***
		(0.009)	(0.009)	(0.011)	(0.018)
Log(total employment in manufacturing)		0.482***	0.453***	0.716***	0.939***
		(0.043)	(0.047)	(0.066)	(0.075)
l			-0.087	0.642***	0.161**
			(0.054)	(0.079)	(0.075)
Observations	191697	182231	182231	182231	182231

Standard errors in parentheses
All models include year and SIC controls.
* significant at 10%
** significant at 5%
*** significant at 1%

Table 5: The determinates of facility Log(water) emissions

	(1) OLS-no controls	(2) OLS-controls	(3) Heckman	(4) Random Effects	(5) Hausman-Taylor
Border County	0.134***	0.139***	0.064*	0.059	0.547**
	(0.038)	(0.039)	(0.035)	(0.081)	(0.254)
Ocean	-0.007	0.474***	0.406***	0.480***	0.704***
	(0.053)	(0.063)	(0.066)	(0.119)	(0.193)
Log(PCI)		0.019	0.326	-0.356	-1.699***
		(0.232)	(0.250)	(0.348)	(0.530)
Log(Land Area)		0.001	0.001	0.047	-0.021
		(0.001)	(0.001)	(0.056)	(0.081)
Log(population)		0.311**	0.279**	-0.271	-0.353
		(0.126)	(0.127)	(0.195)	(0.340)
Percent of residents in poverty		0.010	0.022***	0.016	-0.013
		(0.006)	(0.007)	(0.010)	(0.016)
Percent of county residents who are a minority		0.004***	0.003**	0.003**	0.003**
		(0.001)	(0.001)	(0.001)	(0.001)
Log(population density)		-0.060*	-0.078**	0.001	0.001
		(0.033)	(0.034)	(0.000)	(0.000)
Percent of county residents who are unemployed		1.342***	1.376***	2.351***	3.566***
		(0.058)	(0.059)	(0.453)	(0.313)
Log(number of manufacturing establishments)		-0.417***	-0.062	0.307	0.290
		(0.149)	(0.182)	(0.290)	(0.496)
Percentage of firms with fewer than 10 employees		-0.042***	-0.035***	-0.036***	-0.049***
		(0.006)	(0.007)	(0.008)	(0.013)
Log(inspection rate)		0.115***	0.130***	0.027	0.089
		(0.032)	(0.032)	(0.038)	(0.062)
Percent of all RCRA hazardous waste treated in state		0.002	0.002	0.002	0.004
		(0.003)	(0.003)	(0.004)	(0.007)
Log(total number of in-state RCRA facilities)-TSDs		-0.109***	-0.115***	-0.017	-0.022
		(0.027)	(0.027)	(0.037)	(0.066)
Log(total employment in manufacturing)		-0.066	-0.481***	-0.327	-0.083
		(0.114)	(0.168)	(0.255)	(0.459)
l			-0.612***	-0.320	0.037
			(0.182)	(0.267)	(0.237)
Observations	26221	24816	24816	24816	24816

Standard errors in parentheses
All models include year and SIC controls.
* significant at 10%
** significant at 5%
*** significant at 1%

Table 6: The determinates of facility Log(land) emissions

	(1) OLS-no controls	(2) OLS-controls	(3) Heckman	(4) Random Effects	(5) Hausman-Taylor
Border County	-0.041	0.005	-0.035	0.035	-0.789**
	(0.050)	(0.051)	(0.053)	(0.080)	(0.361)
Ocean	0.041	0.486***	0.499***	0.269**	0.323***
	(0.074)	(0.085)	(0.085)	(0.125)	(0.100)
Log(PCI)		-1.112***	-0.923***	-0.343	-0.926***
		(0.295)	(0.303)	(0.374)	(0.344)
Log(Land Area)		0.339***	0.284***	0.216***	0.082
		(0.037)	(0.042)	(0.060)	(0.173)
Log(population)		-0.051	-0.134	0.072	0.000
		(0.149)	(0.152)	(0.213)	(0.000)
Percent of residents in poverty		-0.044***	-0.035***	-0.015	-0.022*
		(0.009)	(0.010)	(0.012)	(0.012)
Percent of county residents who are a minority		0.012***	0.012***	0.009***	0.008***
		(0.003)	(0.003)	(0.003)	(0.003)
Log(population density)		0.001	0.001	0.001	-0.066
		(0.001	(0.001	(0.001	(0.167)
Percent of county residents who are unemployed		0.493***	0.456***	1.857***	0.372
		(0.075)	(0.076)	(0.515)	(0.230)
Log(number of manufacturing establishments)		-0.268	0.046	0.002	0.291
		(0.190)	(0.221)	(0.304)	(0.257)
Percentage of firms with fewer than 10 employees		-0.044***	-0.030***	-0.018*	-0.011
		(0.008)	(0.010)	(0.011)	(0.012)
Log(inspection rate)		0.093**	0.109***	0.063	0.104***
		(0.039)	(0.039)	(0.043)	(0.037)
Percent of all RCRA hazardous waste treated in state		0.010***	0.009***	0.005	0.004
		(0.003)	(0.003)	(0.004)	(0.004)
Log(total number of in-state RCRA facilities)-TSDs		-0.045	-0.039	-0.049	-0.053
		(0.033)	(0.033)	(0.042)	(0.034)
Log(total employment in manufacturing)		0.000	-0.361*	-0.377	-0.665**
		(0.143)	(0.194)	(0.250)	(0.281)
l			-0.663***	-0.282	-1.118***
			(0.239)	(0.316)	(0.417)
Observations	16458	15508	15508	15508	15508

Standard errors in parentheses
All models include year and SIC controls.
* significant at 10%
** significant at 5%
*** significant at 1%

Table 7: The determinates of facility Log(off-site) emissions

	(1) OLS-no controls	(2) OLS-controls	(3) Heckman	(4) Random Effects	(5) Hausman-Taylor
Border County	-0.062***	-0.018	-0.018	-0.040	-0.327
	(0.022)	(0.023)	(0.023)	(0.039)	(0.332)
Ocean	0.029	0.090***	0.091***	0.086	-0.004
	(0.027)	(0.034)	(0.034)	(0.058)	(0.105)
Log(PCI)		-0.023	0.023	-0.493**	-0.094
		(0.139)	(0.143)	(0.204)	(0.187)
Log(Land Area)		0.174**	0.177**	-0.046	0.307
		(0.077)	(0.077)	(0.028)	(1.450)
Log(population)		0.001	0.001	0.077	-0.068
		(0.001	(0.001	(0.117)	(1.459)
Percent of residents in poverty		0.010**	0.012**	-0.018***	-0.001
		(0.005)	(0.005)	(0.007)	(0.006)
Percent of county residents who are a minority		-0.003**	-0.003**	0.005**	0.000
		(0.001)	(0.001)	(0.002)	(0.002)
Log(population density)		0.226***	0.226***	0.001	0.373
		(0.076)	(0.076)	(0.001	(1.450)
Percent of county residents who are unemployed		0.168***	0.176***	1.838***	0.461***
		(0.035)	(0.035)	(0.276)	(0.116)
Log(number of manufacturing establishments)		-0.423***	-0.394***	-0.172	-0.543***
		(0.101)	(0.103)	(0.151)	(0.181)
Percentage of firms with fewer than 10 employees		-0.029***	-0.028***	-0.021***	-0.022***
		(0.004)	(0.004)	(0.005)	(0.005)
Log(inspection rate)		-0.100***	-0.102***	-0.032	-0.052**
		(0.019)	(0.019)	(0.021)	(0.022)
Percent of all RCRA hazardous waste treated in state		0.019***	0.020***	0.011***	0.013***
		(0.001)	(0.001)	(0.002)	(0.003)
Log(total number of in-state RCRA facilities)-TSDs		0.135***	0.134***	0.091***	0.108***
		(0.016)	(0.016)	(0.021)	(0.022)
Log(total employment in manufacturing)		0.155**	0.115	0.093	0.223*
		(0.078)	(0.083)	(0.113)	(0.118)
l			-0.123	0.264**	0.154
			(0.091)	(0.124)	(0.102)
Observations	61075	59211	59211	59211	59211

Standard errors in parentheses
All models include year and SIC controls.
* significant at 10%
** significant at 5%
*** significant at 1%

Table 8: The determinates of facility Log(air) emissions including an eastern border interaction

	Eastern Border Counties
Establishment located in Border County	5.686***
	(0.257)
Establishment located in county on eastern border of the state	1.949***
	(0.268)
Observations	182231

Standard errors in parentheses
All models include year and SIC controls.
* significant at 10%
** significant at 5%
*** significant at 1%

Table 9: The determinates of facility Log emissions excluding counties which border Mexico (Panel A) and Canada and Mexico (Panel B)

Panel A	No Mexican Border
log(air)	5.841***
	(0.243)
Observations	180774
log(water)	0.359**
	(0.146)
Observations	24748
log(land)	-0.691*
	(0.373)
Observations	15363
log(Off-site Transfers)	-0.291
	(0.320)
Observations	58606
Panel B	**No International Borders**
log(air)	6.005***
	(0.249)
Observations	180188
log(water)	0.365**
	(0.145)
Observations	24567
log(land)	-0.582
	(0.377)
Observations	15264
log(Off-site Transfers)	-0.225
	(0.326)
Observations	58515

Standard errors in parentheses
All models include year and SIC controls.
* significant at 10%
** significant at 5%
*** significant at 1%

Table 10: The determinates of facility Log emissions by EPA Region

	(1) log(air)	(2) log(water)	(3) log(land)	(4) log(Off-site)
Region 1	-0.462*	-0.717	-0.012	-0.463
	(0.279)	(0.623)	(0.709)	(0.516)
Observations	12073	1526	639	4036
Region 2	1.766***	-1.367	-0.622	-1.732***
	(0.481)	(0.862)	(0.816)	(0.607)
Observations	13844	1702	778	5258
Region 3	-0.518	-0.007	-0.605	2.190**
	(0.415)	(0.511)	(0.792)	(0.918)
Observations	15912	3119	1366	3479
Region 4	1.752***	0.753***	-0.483	2.104***
	(0.257)	(0.243)	(0.311)	(0.513)
Observations	37190	6231	3683	8167
Region 5	0.949***	0.954**	1.807***	-0.705*
	(0.219)	(0.406)	(0.614)	(0.397)
Observations	52721	5698	3422	21326
Region 6	1.249***	-0.917***	-0.330	1.244**
	(0.314)	(0.350)	(0.534)	(0.578)
Observations	16510	3414	2310	6327
Region 7	2.579***	2.102**	0.481	-1.797*
	(0.679)	(1.034)	(0.717)	(1.048)
Observations	8779	964	982	1389
Region 8	2.956***	1.704	0.424	-0.399
	(0.963)	(1.185)	(0.976)	(1.634)
Observations	4002	402	639	856
Region 9	0.400	3.455	0.332	-0.948
	(0.374)	(2.234)	(1.409)	(0.733)
Observations	15671	806	983	7049
Region 10	2.329***	0.173	-0.370	-0.801
	(0.645)	(0.684)	(0.780)	(1.702)
Observations	5529	954	706	1324

Standard errors in parentheses
All models include year and SIC controls.
* significant at 10%
** significant at 5%
*** significant at 1%

Region 1 - Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont.
Region 2 - New Jersey and New York
Region 3 - Delaware, Maryland, Pennsylvania, Virginia, and West Virginia.
Region 4 - Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, and Tennessee.
Region 5 - Illinois, Indiana, Michigan, Minnesota, Ohio, and Wisconsin.
Region 6 - Arkansas, Louisiana, New Mexico, Oklahoma, and Texas.
Region 7 - Iowa, Kansas, Missouri, and Nebraska.
Region 8 - Colorado, Montana, North Dakota, South Dakota, Utah, and Wyoming.
Region 9 - Arizona, California, Hawaii, and Nevada.
Region 10 Alaska, Idaho, Oregon, and Washington.

Figure 1: Federal, local and economically efficient optimal pollution standards