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ANALYSIS

Power distribution, the environment, and public health: A state-level analysis

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Abstract

This paper examines relationships among power distribution, the environment, and public health by means of a cross-sectional analysis of the 50 US states. A measure of inter-state variations in power distribution is derived from data on voter participation, tax fairness, Medicaid access, and educational attainment. We develop and estimate a recursive model linking the distribution of power to environmental policy, environmental stress, and public health. The results support the hypothesis that greater power inequality leads to weaker environmental policies, which in turn lead to greater environmental degradation and to adverse public health outcomes. © 1999 Elsevier Science B.V. All rights reserved.

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1. Introduction

Environmentally degrading economic activities generate both winners and losers. The winners derive net benefits in the form of producers' and consumers' surplus; the losers bear net costs arising from environmental externalities. Starting with this premise, Boyce (1994) advanced two hypotheses: first, social choices governing environmental degradation systematically favor more powerful agents over less powerful agents; and second, wider inequalities of power tend to result in greater environmental degradation.

The first hypothesis, on the identities of winners and losers, generates the prediction that the distribution of environmental costs will be correlated with other power-related variables such as income, race, and ethnicity. In recent years a substantial literature on such correlations has

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emerged in the USA. Case studies have drawn attention to links between socioeconomic status and pollution exposure in various locations, from Chester, Pennsylvania and Louisiana's 'Cancer Alley' to South Central and East Los Angeles.[1] Pioneering statistical studies by Bullard (1983) and the US General Accounting Office (1983) found correlations between the siting of waste dumps and the racial composition of surrounding communities.[2] Recent studies by Perlin et al. (1995) and Brooks and Sethi (1997) similarly found emissions of airborne toxic pollutants to be correlated with race and ethnicity at the county and postal zipcode levels. In response to concerns that minority and low-income populations bear a disproportionately high share of environmental costs, President Clinton's Executive Order 12898 of February 1994 established an Interagency Working Group on Environmental Justice.

This paper presents a test of the second hypothesis, on the extent of environmental costs as opposed to their incidence. This hypothesis suggests that with greater inequality in the distribution of power, those agents with more power are able to impose higher external costs on those with less power, and that this effect is not fully offset by the diminished ability of the less powerful to impose external costs on the more powerful. If this is so, power inequalities will affect the size of the pollution pie, as well as how it is sliced.

In this paper we test this hypothesis using cross-sectional data for the 50 US states.[3] The choice of the states as the unit of analysis is motivated by two considerations. First, state governments play an important role in the formulation and enforcement of environmental policies. The importance of state policies is increasing as the Federal government devolves greater responsibilities to the states. Second, the possible confounding effects of population movements in response to environmental conditions—for example, the migration of low-income groups to environmentally degraded locales in response to falling property values—are likely to be weaker at the state level than at more disaggregated levels such as the county or postal zipcode area (Been, 1994).

The remainder of the paper is organized as follows. In Section 2 we develop a model linking the distribution of power to environmental policy, environmental stress, and public health. In Section 3 we derive a measure of inter-state variations in the distribution of power and discuss the other data used in our analysis. Section 4 presents the econometric results. Some concluding observations are offered in Section 5.

2. The political economy of environmental costs: A recursive model

This section presents a recursive model running from power distribution to environmental policy to environmental stress to public health outcomes. Each of these links is examined in turn.

2.1. Power distribution and its determinants

Power is difficult to measure. We can construct indirect measures, however, based on power-related variables. In this study we use four variables for this purpose: voter participation, tax fairness, Medicaid accessibility, and educational attainment. Higher voter participation is taken to indicate a more equal distribution of power.[4] Tax

[1] The populations of Chester, Pennsylvania, Louisiana's 'Cancer Alley', and South Central Los Angeles are predominantly African–American; the population of East Los Angeles is predominantly Hispanic. See Janofsky (1996), Bullard (1990), and Kay (1991) for details. See Cole (1992, pp. 621–634), Been (1993, pp. 1009–1013), and Bullard (1994) for further examples.

[2] Subsequent studies have demonstrated the sensitivity of these results to the geographic unit of analysis (Anderton et al., 1994), and have observed that these correlations may also reflect movements of minority and low-income populations in response to the effects of locally undesirable land uses on property values (Been, 1994).

[3] Torras and Boyce (1998) provide a test using international data.

[4] In analyses of the siting of hazardous waste facilities and toxic air pollution, respectively, Hamilton (1993) and Brooks and Sethi (1997) take voter turnout as a measure of the propensity of communities to engage in collective action. At the state level, voter turnout similarly can be interpreted as a measure of the propensity of less powerful social classes to engage in collective action vis-à-vis the more powerful, on the assumptions that the less powerful are (i) less likely to vote and (ii) less able to influence the political process by other means (e.g. via financial contributions).

fairness and Medicaid accessibility are taken to reflect the influence of power distribution on the revenue and expenditure sides of state fiscal policies, respectively. A higher level of educational attainment is taken to indicate a more equal distribution of power, on the assumption that there are important links between information and power.[5] In the next section, we derive a measure of inter-state variations in the distribution of power by means of a principal components analysis of these four variables.

An analysis of determinants of variations in this measure can shed light on its validity and on the origins of power disparities. Following Boyce (1994) and Torras and Boyce (1998), we hypothesize that power distribution (π) is a function of income inequality (G), the level of per capita income (Y), and a vector of non-income determinants ($\mathbf{X}$):

$$\pi = \pi(G, Y, \mathbf{X}), \ \pi_G < 0, \ \pi_Y > 0 \quad (1)$$

where a higher value of π denotes a more equal distribution of power. Greater income inequality is expected to lead, ceteris paribus, to greater power inequality.[6] Building on the suggestion of Kuznets (1963, p. 49) that 'the power equivalents of the same relative income spread show a much wider range when the underlying average income is low than when it is high,' we hypothesize that higher per capita income leads to less power inequality.

Other power-relevant variables, represented by the vector $\mathbf{X}$, include race, gender, ethnicity, and the political framework through which income and other attributes are mapped to power. In the present analysis race and ethnicity are of particular interest; the gender composition of the population varies little from state to state, and all the states operate within the broad political framework based on the U.S. Constitution.

Accordingly, our econometric model of the determinants of power inequality is:

$$\pi = \alpha_1 + \beta_1 G + \beta_2 Y + \beta_3 RACE + \beta_4 ETH + \delta_j RD_j + \mu_1 \quad (1a)$$

where G is the Gini ratio of income distribution and Y is per capita income (both refer to pre-tax income); $RACE$ is the percentage of African–Americans in the state's population; ETH is the percentage of people of Hispanic origin; RD_j are dummy variables which partition the country into four regions to allow for regional differences not captured in the other variables; and μ_1 is an independent, normally distributed error term with zero mean.

A poor fit in the estimation of Eq. (1a) would suggest that our power distribution measure is flawed, or that our hypotheses as to its determinants are incorrect, or both. A good fit, by contrast, would lend support to our analysis on both counts.

2.2. *Power distribution and environmental policy*

The beneficiaries of pollution-generating activities include producers and consumers. Producers receive what Templet (1995, p. 143) terms a 'pollution subsidy', consisting of dollars not spent on pollution control, and consumers reap part of this subsidy via lower prices. In welfare-analytic terms, these benefits accrue via producers' surplus and consumers' surplus. These activities impose external costs on those adversely affected by the pollution. For some individuals, the benefits of the pollution-generating activity exceed the costs. For others, the costs are likely to exceed the benefits.

Let b_i represent the net benefit to the i^{th} individual (net cost if $b_i < 0$) from the pollution-generating economic activity. The normative policy-making rule of benefit-cost analysis is to set the level of pollution so as to maximize aggregate net benefits, that is:

[5] One way in which information may affect environmental outcomes is via effects on preferences. Bergstrom et al. (1990) show that contingent valuations of wetlands are affected by the provision of information about wetland services. Lack of information on pollution and its effects also may increase the effectiveness of propaganda designed 'to make pollution seem palatable or worth the cost' (Galbraith, 1973, p. 9).

[6] Insofar as greater power inequality in turn leads to greater income inequality, the two are mutually reinforcing.

$$\max \sum_i b_i$$

Given declining marginal benefits and rising marginal costs, this rule yields the standard efficiency condition: the optimal level of pollution is defined as the point where the marginal social benefit of an additional unit of the pollution-generating activity equals its marginal social cost.

Boyce (1994, 1996) hypothesizes that actual policy outcomes are better described by a 'power-weighted social decision rule' (PWSDR):

$$\max \sum_i \pi_i b_i$$

where π_i = the power of the i^{th} individual. 'Power' here plays the same role as 'influence' in the model of Becker (1983) of the determination of fiscal policy. Instead of maximizing net benefits, social decisions maximize net benefits weighted by the power of the individuals to whom they accrue.

The positive PWSDR corresponds to the normative benefit-cost rule only in the special case in which all individuals have equal power. When the power of those who benefit from pollution-generating activities exceeds the power of those who bear net costs (that is, when b_i is positively correlated with π_i), the PWSDR predicts inefficiently high levels of pollution. Conversely, when the beneficiaries are less powerful than those who bear net costs (that is, b_i is negatively correlated with π_i), the PWSDR predicts 'excessive' pollution control, in the sense that the marginal social benefit of the pollution-generating activity exceeds its marginal social cost. In the former case, greater power inequality results in more pollution; in the latter, less. In both cases, power inequality drives a wedge between the social costs and benefits of externality-generating activities and the weighted costs and benefits which enter into the political process of decision-making.[7]

The net environmental impact of power inequality hinges, therefore, on the correlation between the net benefits derived from pollution-generating activities (b_i) and power (π_i), summed over all pollution-generating activities. There are reasonable grounds to expect this correlation to be positive. Richer individuals generally reap more producers' and consumers' surplus than do poorer individuals by virtue of the simple facts that they own more productive assets and consume more goods and services. At the same time, richer individuals tend to be more powerful, insofar as purchasing power confers effective demand in 'political markets.' For these reasons we hypothesize that those who receive the greatest net benefits from pollution-generating economic activities will tend, in general, to be relatively powerful. Conversely, those who bear the greatest net costs will tend to be less powerful. If so, the PWSDR predicts that greater power inequality will lead, on balance, to higher levels of pollution.

This is not to say that rich and powerful individuals are not concerned about pollution, or less concerned than anyone else. Indeed, clean air and clean water are quite likely to be 'normal' goods—that is, individual demand for them (measured by willingness to pay) rises with income. The extent to which this demand translates into less pollution is limited, however, by two factors in addition to the well-known free-rider problem. First, clean air and clean water are not pure public goods: those who can afford to do so can reside in relatively unpolluted enclaves, drink bottled water, vacation in pristine locations, and in these and other ways purchase private insulation from public bads. Second, against any greater preference among higher-income individuals for the public-good dimensions of environmental quality, we must weigh their higher price in terms of foregone benefits.

[7] In his analysis of the siting of commercial hazardous waste facilities, Hamilton (1993, p. 122) observes: 'In the 'Coase theorem,' a firm generating externalities ends up locating where, ceteris paribus, its social damage will be the least, because that will be where potential compensation is the least. Yet the differing degree to which groups organize to demand compensation and raise a firm's costs of choosing a particular location drives a wedge between the social costs of its externalities and the costs voiced through the political process of its site selection.' Here we regard 'the differing degree to which groups organize', and differences in the efficacy of their efforts, as reflections of their power vis-à-vis others.

We hypothesize, therefore, that environmental policies will tend to be weaker where power inequality is greater:

$$EP = f(\pi, \mathbf{Z}),\ f_\pi < 0 \qquad (2)$$

where *EP* is an index of environmental policy weakness (i.e. a higher value denotes weaker policies); π is a measure of the distribution of power (where a higher value denotes a more equal distribution); and **Z** is a vector of other determinants of environmental policies. Three other environmental policy determinants are included in our analysis: the manufacturing share of output (*MAN*), urbanization (*URB*), and population density (*PD*). Each of these is expected to generate demand for stronger environmental policies.

Hence we will estimate the following econometric equation:

$$EP = \alpha_2 + \gamma_1\pi + \gamma_2 MAN + \gamma_3 URB + \gamma_4 PD + \mu_2 \qquad (2a)$$

where μ_2 is again an independent, normally distributed error term with zero mean.

2.3. Environmental policy and environmental stress

Weaker environmental policies are expected to lead to greater environmental stress. The next equation tests for this impact:

$$ES = \alpha_3 + \delta_1 EP + \delta_2 MAN + \delta_3 URB + \delta_4 PD + \mu_3 \qquad (3)$$

where *ES* is an index of environmental stress (a higher value denoting greater stress) and μ_3 is an error term with the usual properties. This equation again includes manufacturing, urbanization, and population density as control variables on the right-hand side, since these are expected to lead to greater environmental stress independently of the environmental policies. We test for endogeneity of *EP* in Eq. (3) to examine the possibility that after controlling for these variables greater environmental stress leads to stronger environmental policies (a relationship which would tend to mask the effect of policy on stress, since it would work in the opposite direction).[8]

2.4. Environmental stress and public health

The impact of environmental stress on public health is estimated by a final link in the recursive chain:

$$HEALTH = \alpha_4 + \phi_1 ES + \phi_2\pi + \mu_4 \qquad (4)$$

where *HEALTH* is a measure of public health and μ_4 an error term with the usual properties. We include our power distribution measure on the right-hand side to allow for the possibility that it may affect public health by other avenues apart from environmental stress. Three alternative measures of *HEALTH* are used: infant mortality (*IM*), the premature death rate (*PDR*), and a composite public health index (*PHI*).

Fig. 1 summarizes the structure of our model. In addition to the causal linkages specified here, it is conceivable that environmental policies and outcomes in turn affect the determinants of power inequality. For example, it is sometimes asserted that environmental regulation acts as a brake on economic growth, which over time could lead to lower per capita incomes. It is doubtful, however, that such effects have been either strong enough or rapid enough to have had much effect on the existing income disparities among states.[9] Environmental policies could also affect income inequality. Templet (1995), for example, argues that pollution subsidies (consist-

[8] Stronger environmental policies (here denoted by a lower value of *EP*) are expected to lead to lower environmental stress; therefore, in Eq. (3), we expect $\delta_1 > 0$. If greater environmental stress led to stronger environmental policies, this would downwardly bias our estimate of δ_1. Such endogeneity would therefore increase the risk of a Type-I error (rejection of the true hypothesis that stronger policies lead to lower stress), but would lower the risk of a Type-II error (mistaken acceptance of the hypothesis).

[9] Meyer (1995) examines state-level data and finds no systematic relationship between state environmental policies and state economic performance. Some studies have found negative relationships between environmental regulatory stringency and selected measures of economic activity (notably new plant locations and business start-ups), but the estimated effects tend to be small; for a review of these studies, see Tannenwald (1997).

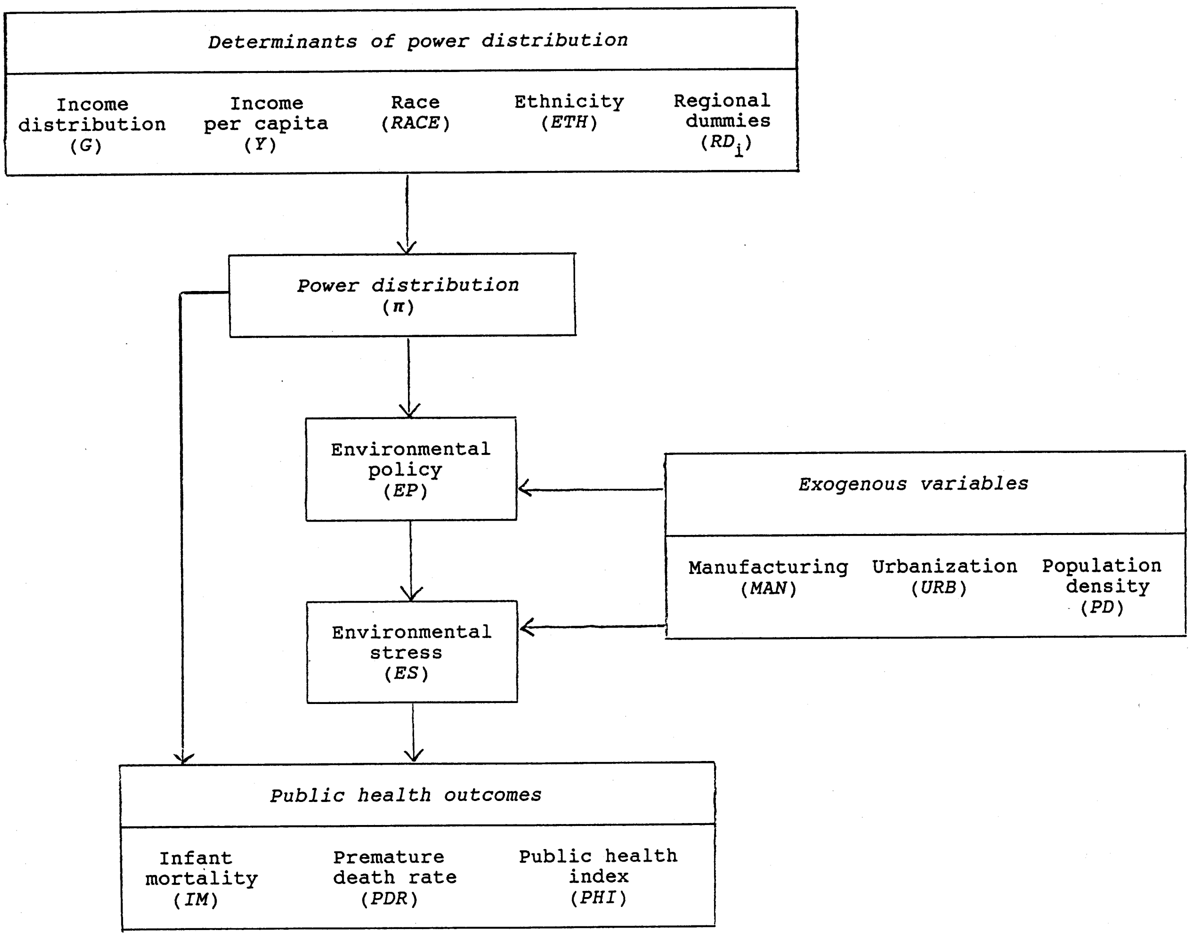

Fig. 1. The model summarized.

ing of unspent pollution control dollars) accrue disproportionately to the higher income classes. In this paper, we confine our attention to the causal relations depicted in Fig. 1, on the assumption that power inequality is a largely exogenous determinant of environmental policies and outcomes.

3. Data

This section derives our measure of inter-state variations in the distribution of power, and discusses the other data used in our analysis. Descriptive statistics for all the variables are presented in Table 1.[10]

3.1. A measure of power distribution

Our measure of inter-state variations in power distribution is based on the premise that voter participation, tax fairness, Medicaid accessibility, and educational attainment levels have something in common: higher levels of these four variables reflect a more equal distribution of power, and lower levels a more unequal distribution. We use the method of principal components to estimate statistically this common feature, here defined as

[10] The complete data file is available from the authors.

Table 1
Descriptive statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Power distribution (π)	0.00	1.00	−1.74	2.32
Gini coefficient (G)	0.37	0.02	0.33	0.42
Income per capita (Y)	40.46	5.73	29.27	53.28
Black ($RACE$)	9.53	9.24	0.25	35.56
Hispanic (ETH)	5.37	7.52	0.45	38.22
Environmental policy (EP)	2200	670	764	3230
Environmental stress (ES)	4175	607	3118	5279
Manufacturing (MAN)	17.39	6.71	3.00	30.40
Urbanization (URB)	66.74	21.68	24.00	100.00
Population density (PD)	166.1	235.2	1.0	1042.0
Infant mortality (IM)	8.79	1.50	5.80	11.80
Premature death rate (PDR)	13.02	1.60	9.78	16.38
Public health index (PHI)	24.99	4.91	17.09	35.09
Voter participation	58.30	7.31	41.90	72.00
Tax fairness	38.25	17.95	6.10	77.73
Medicaid access	56.80	9.02	38.00	75.00
Educational attainment	76.27	5.62	64.40	86.50

the first principal component of this set of variables (which are standardized, that is, measured as the deviations from the means and divided by the standard deviations).

The raw data for construction of this measure are as follows:

Voter participation is measured by the percentage of the voting age population which voted in the 1992 Presidential election, as reported by Scammon and McGillvray (1993).

Tax fairness is a composite measure developed by the Corporation for Enterprise Development (1995). It includes information on the percentage of income spent on sales and excise taxes by the poorest 20% of the state's population, the ratio of the income tax burden of the top 1% of taxpayers to that of the bottom 60%, the state personal income tax threshold, and the corporate tax policies. A higher value indicates a fairer tax structure.

Medicaid access is an index developed by Erdman and Wolfe (1987) to assess inter-state differences in poor people's access to health care through the Medicaid program. We regard this as a proxy for the degree of power inequality on the expenditure side of state fiscal policy. The index is based on eligibility restrictions, the scope of services, the availability of health-care providers, quality of service, and the reimbursement system. A higher value indicates greater access.

Educational attainment is measured by the percentage of the state's population, aged 25 years and older, which has at least graduated from high school according to the 1990 Census of Population (US Department of Commerce, 1995; p. 159).

Our measure of power distribution (π), derived from these four variables, is reported in Table 2.[11] Its mean is zero; a higher value indicates a more equal distribution of power. Minnesota has the most equal distribution of power among the 50 states by this measure, and Mississippi the most unequal distribution. There is a striking regional pattern in that the Southern states display the greatest inequality.

3.2. Determinants of power inequality

Power distribution is expected to be negatively related to the Gini ratio of income distribution, race, and ethnicity, and positively related to per capita income.

[11] The measure's correlations with the four variables from which it is extracted are: voter participation 0.76, tax fairness 0.79, Medicaid access 0.68, and educational attainment 0.80.

Table 2
Inter-state variations in the distribution of power

Minnesota	2.32
Maine	1.65
Wisconsin	1.42
Vermont	1.36
Montana	1.31
Oregon	1.22
Connecticut	1.13
Idaho	0.99
Colorado	0.99
Utah	0.98
Nebraska	0.93
Alaska	0.90
Massachusetts	0.81
Kansas	0.79
California	0.77
North Dakota	0.68
Iowa	0.68
New Hampshire	0.59
Maryland	0.39
Illinois	0.38
Michigan	0.36
Washington	0.27
New Jersey	0.26
New York	0.22
Ohio	−0.07
Rhode Island	−0.08
Pennsylvania	−0.10
Arizona	−0.12
Delaware	−0.16
Wyoming	−0.40
Missouri	−0.45
South Dakota	−0.49
Hawaii	−0.53
Oklahoma	−0.64
Virginia	−0.64
Indiana	−0.66
New Mexico	−0.69
Florida	−0.89
Nevada	−0.91
Louisiana	−0.94
Kentucky	−1.08
North Carolina	−1.11
South Carolina	−1.19
Georgia	−1.19
West Virginia	−1.28
Texas	−1.41
Arkansas	−1.50
Tennessee	−1.52
Alabama	−1.61
Mississippi	−1.74

Note: Higher value denotes more equal distribution of power. For method of calculation, see text.

The *Gini ratio of income distribution* and *per capita income* are calculated from the US Census Bureau's Current Population Survey (CPS) data for 1991–1993.[12] Both variables refer to pre-tax income. A higher Gini ratio indicates greater income inequality.

Race and *ethnicity* are measured by the percentage of the state's population classified as black and Hispanic, respectively, by the Bureau of the Census in 1990, calculated from data reported by the US Department of Commerce (1992, pp. 24–25).

The regional dummy variables partition the states into four regions—the Northeast, Midwest, South, and West—following the classification used by the U.S. Department of Commerce in its annual *Statistical Abstract of the United States*.

3.3. Environmental policy and environmental stress

The *environmental policy index* is a composite measure based on 77 indicators reported by Hall and Kerr (1991, p. 5). Its components include the existence of state policies on recycling, landfills, toxic waste management, air pollution, water quality, agriculture, energy and transportation; ratings of state environmental programs; state spending on environmental programs; and Congressional leadership on environmental issues.[13] The index is reported in Table 3. A lower score indicates stronger environmental policies; among

[12] We are grateful to John Haveman of Purdue University for providing us with calculations of the Gini ratio and per capita income based on the CPS data.

[13] The index is derived by ranking the states from 1 to 50 for each indicator and then summing the rankings. A limitation of this measure is that it is based on ordinal rather than cardinal information: one would ideally like to know not only that policy x is weaker in state A than in state B, but also how much weaker. A second limitation is that all 77 policies are given equal weight, despite the fact that some may be more important than others, and that their relative importance may vary from state to state. The comprehensiveness of the measure dampens noise in the rankings for the individual indicators. Meyer (1993) reports a fairly strong correlation ($r = 0.72$) between this index and an earlier one developed by Duerksen (1983), suggesting that it provides a reasonably robust measure.

Table 3
The Environmental Policy Index

California	764
Oregon	1096
New Jersey	1150
Connecticut	1225
Maine	1246
Wisconsin	1261
Minnesota	1305
New York	1346
Massachusetts	1377
Rhode Island	1384
Michigan	1552
Vermont	1578
Florida	1604
Washington	1606
Maryland	1660
Iowa	1841
Illinois	1865
North Carolina	1873
Ohio	2010
New Hampshire	2054
Pennsylvania	2058
Virginia	2181
Missouri	2182
Hawaii	2239
Delaware	2261
Colorado	2330
Indiana	2332
Kansas	2478
Georgia	2505
Nebraska	2510
Montana	2533
South Carolina	2537
Kentucky	2625
Louisiana	2644
Texas	2659
Idaho	2708
North Dakota	2762
New Mexico	2798
Arizona	2802
Tennessee	2843
Utah	2888
Oklahoma	2913
Nevada	2917
Wyoming	2924
West Virginia	2951
Mississippi	3016
Alaska	3043
South Dakota	3154
Alabama	3212
Arkansas	3230

Source: Hall and Kerr (1991) (p. 5). A higher score indicates weaker environmental policies.

the 50 states, according to this index, California has the strongest environmental policies, and Arkansas the weakest.

The *environmental stress index* is a composite measure based on 167 indicators reported by Hall and Kerr (1991)[14]. The components include measures of air pollution, water pollution, energy use and production, transportation efficiency, toxic chemical releases, hazardous and solid waste production, workplace conditions, agricultural pollution, and the state of forestry and fishery resources. The index is reported in Table 4. A higher score indicates greater environmental stress; among the 50 states, according to this index, Vermont has the least environmental stress, and Indiana the most.

3.4. Control variables

Three variables are included as controls in the environmental policy and environmental stress equations: the manufacturing share of output, urbanization, and population density. These are expected to lead, ceteris paribus, to stronger environmental policies and to greater environmental stress.

The *manufacturing share of output* is the percentage share of manufactured goods in the state's gross domestic product in 1991, calculated from data reported by the US Department of Commerce (1995, p. 455).

Urbanization refers to the percentage of the state's total population residing in metropolitan areas in 1990, as reported by the US Department of Commerce (1992, p. 29).

Population density is the number of inhabitants per square mile in 1990, as reported by the US Department of Commerce (1992, p. 23).

3.5. Health outcomes

Three health measures are used in our final set of equations, permitting us to examine the sensi-

[14] Hall and Kerr (1991, p. 5) present a composite 'green conditions index' based on 179 indicators. Our environmental stress index is recalculated by dropping 12 community health indicators, since we wish to examine public health outcomes separately.

Table 4
The Environmental Stress Index

Vermont	3118
Hawaii	3159
Oregon	3169
Nevada	3334
Maine	3374
South Dakota	3411
Rhode Island	3473
Idaho	3473
New Hampshire	3520
Massachusetts	3562
Minnesota	3575
Colorado	3576
Washington	3623
Maryland	3679
Montana	3688
Alaska	3709
New York	3785
North Dakota	3805
New Mexico	3850
California	3965
Wisconsin	4016
Utah	4065
Connecticut	4126
Arizona	4207
Wyoming	4228
Delaware	4235
Nebraska	4277
Oklahoma	4373
Florida	4402
New Jersey	4420
South Carolina	4451
Missouri	4461
Michigan	4464
Iowa	4501
North Carolina	4505
Virginia	4538
Pennsylvania	4578
Georgia	4598
Kentucky	4643
Arkansas	4711
West Virginia	4726
Mississippi	4774
Illinois	4839
Tennessee	4928
Alabama	4976
Kansas	5057
Ohio	5072
Texas	5195
Louisiana	5261
Indiana	5279

Source: Calculated from data in Hall and Kerr (1991) (pp. 5, 90). A higher score indicates greater environmental stress.

tivity of the results to different specifications of the dependent variable.

The *premature death rate* refers to the rate per 1000 of people who died before age 65 due to illness or injury in the year 1986, as calculated from US Public Health Service data by the Northwestern National Life Insurance Company and reported by Hall and Kerr (1991, p. 89).

The *infant mortality rate* refers to deaths of infants under 1 year of age per 1000 live births in the year 1991, as reported by the National Center for Health Statistics (US Department of Commerce, 1994).

The *public health index* is a composite measure based on 23 indicators reported by Morgan et al. (1994). In addition to infant mortality and the overall death rate, index components include death rates from specific causes, the percentage of low birthweight babies, and other variables not directly influenced by environmental stress such as the percentage of children immunized at age two, the percentage of the population covered by health insurance, and the extent of alcohol consumption and smoking. The index is the average of the sum of state rankings; a higher value indicates better public health.

4. Econometric results

To assess the validity of the measure of power distribution, and in an effort to gain some insight into its determinants, we first estimated Eq. (1a) by ordinary least squares (OLS), with and without the regional dummy variables. The results are presented in Table 5. Regional dummy variables are included for the South, Midwest, and West; hence the intercept term refers to the Northeast, and the coefficients on the dummy variables indicate the intercept shift for the other regions. Tests for heteroscedasticity, including White's test (White, 1980), were carried out for these and the other regressions reported below; in no case did these reject the null hypothesis of homoscedastic error terms.

The adjusted coefficients of multiple determination, 0.52 without the regional dummy variables and 0.57 with them, indicate that the model 'explains' more than half of the variation in power distribution. In each regression the estimated coefficients on the Gini ratio, per capita income, race, and ethnicity have the expected signs: higher income inequality and higher percentages of black and Hispanic minorities are associated with a less equal distribution of power, and higher per capita income with a more equal distribution. The estimated coefficients on the Gini ratio, income, and race are statistically significant at the 5% level. The statistical significance of these coefficients diminishes when the regional dummies are included, but their signs remain unchanged, suggesting that the variables are not simply acting as proxies for omitted region-related variables.[15] Further, the test for the joint irrelevance of the three regional dummy variables was insignificant at the 5% level.[16] These results suggest that our measure successfully captures inter-state variations in the distribution of power. The results are consistent with the hypothesis that income distribution, per capita income, race, and ethnicity are important determinants of the distribution of power in the United States.

OLS estimation of Eq. (2a), analyzing the determinants of environmental policy, gave the following result (absolute t-ratios in parentheses):

$$\begin{aligned} EP = \ & \underset{(14.29)}{3430.9} \ - \underset{(6.99)}{395.85\pi} \ - \underset{(2.86)}{24.15MAN} \\ & - \underset{(3.17)}{10.29URB} \ - \underset{(2.46)}{0.74PD}; \\ \bar{R}^2 = \ & 0.66 \end{aligned} \tag{5}$$

The model 'explains' about two-thirds of the variance in the environmental policy index. The estimated coefficient on the power distribution measure has the expected sign and is statistically significant at the 0.01% level, a result consistent with our hypothesis that greater inequality in the distribution of power is associated with weaker environmental policies. The coefficients on the three control variables also have the expected signs; those on manufacturing and urbanization are statistically significant at the 1% level, and the coefficient on population density is significant at the 5% level.

OLS estimation of Eq. (3) provides evidence that environmental policy in turn has a statistically significant impact on environmental stress:

$$\begin{aligned} ES = \ & \underset{(2.98)}{1319.7} \ + \underset{(4.98)}{0.56EP} \ + \underset{(6.00)}{55.60MAN} \\ & + \underset{(2.70)}{9.84URB} \ - \underset{(0.10)}{0.04PD}; \\ \bar{R}^2 = \ & 0.51 \end{aligned} \tag{6}$$

The model again performs well, 'explaining' roughly half the variance in the environmental stress index. The estimated coefficient on environmental policy has the expected sign and is statistically significant at the 0.01% level, as is the estimated coefficient on manufacturing. The urbanization coefficient is statistically significant at the 1% level. Population density, however, appears to have no statistically significant independent impact on inter-state variations in environmental stress. A Hausman (1978) test for endogeneity of the environmental policy index was negative.

Finally, Table 6 presents the results of OLS regressions of Eq. (4), in which the dependent variables are three measures of public health outcomes. The results indicate that environmental stress is associated with higher infant mortality rates, higher premature death rates, and lower scores on the composite public health index. In the simple regressions, the estimated coefficients on the environmental stress index are statistically significant at the 0.01% level. When the power distribution measure is also included on the right-hand side its estimated coefficients are statistically significant at the 0.01% level; the statistical significance of the estimated coefficients on the environ-

[15] The relatively low t-ratios in the second regression, coupled with the R^2, reflect multicollinearity; in particular, there is a strong correlation between $RACE$ and the dummy variable for the South ($r = 0.72$).

[16] The calculated test statistic was 2.75, less than the critical value of the F-statistic of 2.83.

Table 6
Regression results: Determinants of public health outcomes

Variable	Infant mortality (*IM*)		Premature death rate (*PDR*)		Public health index (*PHI*)	
Intercept	2.93*	5.65*	7.16*	11.40*	46.01*	33.76*
	(2.37)	(4.16)	(5.27)	(8.88)	(11.90)	(9.37)
Environmental stress (*ES*)	1.40×10^{-3}*	7.52×10^{-4}*	1.40×10^{-3}*	3.88×10^{-4}	-5.04×10^{-3}*	-2.10×10^{-3}*
	(4.79)	(2.33)	(4.35)	(1.27)	(5.49)	(2.45)
Power distribution (π)		−0.68*		−1.07*		3.09*
		(3.49)		(5.76)		(5.93)
$\bar{R}^2$	0.31	0.44	0.27	0.56	0.37	0.63

Absolute *t* ratios in parentheses.
* Statistical significance at 5% level.

mental stress index diminishes but they retain the expected sign. These results suggest that environmental stress has serious adverse impacts on public health, and that power inequality has additional adverse impacts apart from those mediated by environmental policy and environmental stress.[17]

Table 5
Regression results: Determinants of power distribution

	Excluding regional dummies	Including regional dummies
Gini	−13.63*	−11.62
(*G*)	(2.02)	(1.74)
Income	5.03×10^{-2}*	2.82×10^{-2}
(*Y*)	(2.60)	(1.32)
Black	-4.70×10^{-2}*	-1.84×10^{-2}
(*RACE*)	(3.52)	(1.09)
Hispanic	-0.98×10^{-2}	-1.22×10^{-2}
(*ETH*)	(0.62)	(0.76)
Intercept	3.52	3.79
	(1.26)	(1.32)
South		−1.00*
		(2.57)
Midwest		−0.13
		(0.40)
West		−0.13
		(0.41)
$\bar{R}^2$	0.52	0.57

Absolute t-ratios in parentheses.
* Statistical significance at 5% level.

[17] The latter finding is consistent with recent studies linking income distribution and mortality in the USA; see Kaplan et al. (1996) and Kennedy et al. (1996).

To summarize, the econometric results are consistent with the set of causal linkages hypothesized in our recursive model. Income inequality, per capita income, race, and ethnicity affect power distribution in the expected directions. A more equal distribution of power is associated with stronger environmental policies, and these in turn are associated with lower environmental stress. Both environmental stress and power inequality are associated with adverse public health outcomes.

5. Conclusions and implications for policy

Our results provide empirical support to the hypothesis that greater power inequality leads to greater environmental degradation. Disparities of power appear to affect not only the distribution of the net costs and benefits of environmentally degrading activities, but also the overall magnitude of environmental degradation. In addition, our results are consistent with the hypothesis that income, income inequality, race, and ethnicity are among the determinants of the distribution of power in the USA. The impacts of environmental stress and power inequality on public health underscore the policy relevance of these findings: for some Americans, the linkages identified here are literally a matter of life and death.

The methodology developed here can assist policy makers in identifying those states most likely to benefit from Federal environmental enforcement assistance. As state responsibility for the implementation of environmental mandates increases, the importance of such information is increasing.[18] If complete and accurate environmental data were available, the identification problem would not exist: environmental protection needs could be assessed directly. The inadequacy of such data, however, is a fundamental part of the enforcement problem—hence the need for diagnostic tools for drawing inferences from other data.

Our findings suggest that Federal enforcement resources can have the greatest impact in states with relatively unequal distributions of power, and that the latter can be estimated from available data. Further refinements—including the analysis of specific subsets of environmental variables, the development of other power-distribution indicators, and studies of inter-state variations within particular geographic regions—could potentially enhance the usefulness and strengthen the predictive power of this methodology.

The broader implication of our analysis is that democratization—in the broad sense of movement toward a more equitable distribution of power—can foster environmental protection. This suggests that democracy-strengthening measures—including public participation, right-to-know laws, and accountability to local communities—are important elements of environmental policy. Such measures can entail short-term costs. Public engagement can complicate the lives of decision makers, and it sometimes produces slower results than a top-down approach. Efforts to strengthen democracy can yield long-run environmental benefits, however, by redressing inequalities of power that invite pollution beyond socially desirable levels.

[18] In November 1996, the US Environmental Protection Agency's top enforcement official called for a nationwide effort to determine the extent of under-reporting of serious environmental violations by state governmental agencies (Cushman, 1996).

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