On Spatial Heterogeneity in Environmental Compliance Costs

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Abstract

This paper examines sub-state variation in the stringency of environmental regulation. In particular, establishment-level data from the U.S. Census Bureau's Pollution Abatement Costs and Expenditures (PACE) survey are used to construct a first-of-its-kind, county-level index of environmental compliance costs. This paper then documents whether counties within a state are statistically – and meaningfully – different from each other (and the state average) in terms of their regulatory intensity, as measured by this index. If they are, this suggests that potentially important spatial variation is lost in state-level studies of environmental regulation.

Results suggest that spatial heterogeneity in environmental compliance costs is indeed real, widespread, and significant. The index constructed here could therefore prove to be quite useful in regulatory analyses, by expanding the research laboratory to include U.S. counties. Among the issues that could be (re)examined using this index are the effects of environmental regulation on industrial location, employment, output, investment (including foreign direct investment), industrial emissions, and ambient pollution levels. Subsequent work will further explore, test, and refine the cost index introduced here in this paper.

Questions:

1. Is there value in such an index?

2. Are there perhaps better empirical specifications for the index? Are there robustness checks that you would like to see?

3. Are there other descriptive exercises that would be illustrative?

4. What recommendations do you have for future research in this area?

1. Introduction

That the stringency of environmental regulation varies spatially in the United States hardly seems a noteworthy point anymore. It is rather well-established that states exercise discretion in their enforcement of federal environmental regulations, and states can of course adopt standards that are more stringent than those promulgated by the federal government. Over the past couple of decades, a number of different proxies that attempt to measure the extent of these regulatory differences between states have been constructed and subsequently used by researchers wishing to explore the impact of environmental regulations on industrial location and industrial activity (see Levinson 2001 and Brunnermeier and Levinson 2004 for reviews).

What is less well-studied and less appreciated is the degree of heterogeneity in regulatory stringency *below* the state level. Duffy-Deno (1992) uses the variation in pollution abatement costs across Standard Metropolitan Statistical Areas (SMSA) to examine the effects of environmental regulations on economic activity, but – with only 63 SMSAs – this analysis is not much richer than a state-level study and it obviously excludes a good deal of economic activity. Berman and Bui (2001) examine the impact on oil refineries of the uniquely stringent air quality regulations of the South Coast Air Basin (i.e., the Los Angeles area) versus those of the rest of California and the rest of the United States. Meanwhile, a growing number of studies have looked at the effects county non-attainment of the Clean Air Act's national ambient air quality standards (NAAQS) have had on manufacturing activity (e.g., McConnell and Schwab 1990, Henderson 1996, Kahn 1997, Becker and Henderson 2000, Greenstone 2002, List *et al.* 2003). While county-level NAAQS non-attainment status may be the best, most geographically-detailed measures of environmental regulation currently available, they cover only six air pollutants, and they are dichotomous (rather than continuous) in nature, thereby cloaking the true variation in regulatory intensity across counties, even within a state.

In this paper, I employ a unique database to measure and examine more fully the extent of variation in regulatory stringency below the state level. In particular, I use fourteen year's worth of establishment-level data from the U.S. Census Bureau's Pollution Abatement Costs and Expenditures (PACE) survey to construct a county-level index of environmental compliance costs. Here, pollution abatement operating costs per unit of economic activity (employment or output) is modeled as a function of plants' industry, size, age, and year — factors known to determine both regulatory scrutiny and environmental expenditures — as well as plants' location. The resulting index is the first measure of its kind, capturing extra-normal environmental costs at a detailed level of geography, due (presumably) to additional environmental regulation faced by industry at the locale.

The paper proceeds as follows. In the next section, I discuss the construction of my county-level index of environmental compliance costs. Section 3 then documents and examines whether counties within a state are indeed statistically – and meaningfully – different from each other (and different from the state average) in terms of their conditional environmental compliance costs. If they are, this suggests that potentially important spatial variation is lost in state-level studies of environmental regulation. Section 4 concludes the paper with a summary of findings and a brief discussion of the potential uses for such an index.

2. A County-level Index of Environmental Compliance Costs

The literature is full of studies that have used pollution abatement expenditure data from the PACE survey to measure geographic differences in the stringency of environmental regulations.[1] At the heart of each of these measures is an estimate of pollution abatement expenditures, divided by some measure of total manufacturing activity, such as gross state product, value added, or value of shipments. In recognition of the inherent variation in the pollution-intensiveness of industries, some measures attempt to adjust for a location's industrial composition (e.g., Bartik 1988, Levinson 1996, Gray 1997, Levinson 2001, Keller and Levinson 2002); others do not (e.g., Duffy-Deno 1992, Friedman *et al.* 1992, List and Kunce 2000, List and Co 2000). With the exception of Levinson (1996), all of these previous studies have used *published* PACE statistics, versus the underlying establishment-level microdata. And with the exception of Duffy-Deno (1992), who analyzed 63 SMSAs, the unit of geography is the state in all of these studies.

In this paper, I use the *establishment-level* data from the PACE survey.[2] For my purposes, these microdata have a few substantial advantages over the published PACE statistics that are commonly used. First and foremost, the location information associated with each establishment allows me to contemplate pollution abatement expenditure at the sub-state level. Second, the industrial classification of establishments in these data is the most detailed available, by *any* level of geography, which is extremely valuable in any effort to explain variation in pollution abatement expenditures. Finally, by merging these PACE microdata to information reported by these same establishments in the Annual Survey of Manufactures (ASM) and the Census of Manufactures (CM), I am uniquely able to control for the size and age of establishments — factors that have been shown to be important determinants of regulatory scrutiny and, hence,

[1] The principal alternatives to such cost-based measures are various indexes and rankings produced by environmental organizations, which are often considered to be subjective in nature. See Levinson (2001) for a review and discussion.
[2] These survey data are confidential, collected and protected under Title 13 of the U.S. Code. Restricted access to these data can be arranged through the U.S. Census Bureau's Center for Economic Studies. See http://www.ces.census.gov/ for details.

establishments' compliance expenditures (e.g., Becker and Henderson 2001; Becker 2005).

Here I use the establishment-level data from the PACE surveys of 1979-1982, 1984-1986, and 1988-1994.[3] As in most of the aforementioned studies, I will employ data on total pollution abatement operating costs (*PAOC*), which includes salaries & wages, parts & materials, fuel & electricity, capital depreciation, contract work, equipment leasing, and other operating costs associated with a plant's abatement of its air and water pollution as well as its solid waste in that calendar year.[4] To this I merge data on these establishments from the ASM or CM, including employment, payroll, value of shipments, four-digit SIC industry, county, and plant vintage (as measured by an establishment's first appearance in the Census of Manufactures). After restricting the sample to cases that had linkable PACE and ASM/CM records in a given year, and after eliminating inactive establishments, plants in Alaska and Hawaii, and those with missing or incomplete data on critical items, there are 200,532 establishment-years of observations for my empirical work. This rather sizable sample contains approximately 49,000 unique manufacturing plants, encompassing virtually all four-digit SIC manufacturing industries and located in 2,514 different U.S. counties.

In harmony with the previous literature, the basis for my index is an establishment's PAOC intensity — that is, its pollution abatement operating costs per unit of economic activity. In this paper, I choose plant employment (*EMP*) for the denominator. This $PAOC_i/EMP_i$ ratio might be said to encapsulate a regulator's implicit choice between environmental protection and jobs.[5]

The degree of regulatory scrutiny faced by a manufacturing plant – and hence its PAOC

[3] Though the collection of these data began with reference year 1973, the establishment-level data from 1973-1978 and 1983 are currently unavailable. A survey for reference year 1987 was not conducted. The PACE survey was suspended over the past decade (1995-1998, 2000-2004), but annual collection has recently resumed, beginning with reference year 2005.

[4] In principle, one could use the separate operating costs on air, water, and solid waste abatement to construct media-specific indexes. I do not do so here in this paper.

[5] I have also performed the analyses that follow using a plant's output – namely, value of shipments – as the denominator.

intensity – is most certainly dependent on the industry it is in (its inherent pollution-intensiveness), as well as the year and its size, and it has been shown that the *combination* of these three factors can affect regulatory intensity (Becker and Henderson 2000). Accordingly, I model PAOC intensity as a function of an industry-year-size quartile effect. In lieu of an overwhelming number of dummy variables (of which there would be over 21,000), I employ the data at hand to compute an estimate of the expected PAOC intensity for each industry-year-size quartile class. In particular, for an establishment in industry *n´*, year *t´*, and size quartile *q´*, the relevant PAOC intensity is assumed to be[6]

$$\sum_{j \in \{n=n', t=t', q=q'\}} PAOC_j \bigg/ \sum_{j \in \{n=n', t=t', q=q'\}} EMP_j \qquad (1)$$

Here, an establishment's size quartile is determined by its position in the employment-weighted plant employment distribution for its industry in that period.[7]

In principle, a plant's age category could be a fourth dimension used in computing an establishment's expected PAOC intensity (above), but this would significantly increase the number of applicable cells and severely reduce the average number of observations per cell. Instead, establishment age is controlled for by a separate series of plant vintage indicators ($\boldsymbol{V_k}$) based on an establishment's first appearance in the CM, with $k \in$ {1963, 1967, 1972, 1977, 1982, 1987, 1992, 1997}. It is therefore assumed that plant vintage has equivalent effects on regulation

[6] Alternatives to this include the PAOC intensity of the mean or median establishment in the set {*n´*, *t´*, *q´*} and/or could involve the weighting of observations.

[7] That is, the inter-quartile cutoffs are drawn so that each quartile contains one-fourth of the industry's employment, rather than one-fourth of its establishments. I conjecture that this grouping more closely approximates the manner in which regulators prioritize their scrutiny of plants within an industry. Because the PACE and ASM sample larger establishments more heavily, the distribution across these size quartiles in this sample is more uniform than it might be, with 18.8%, 26.9%, 29.8%, and 24.5% in the quartiles with the largest to smallest plants, respectively. Data on an industry's plant employment distribution is taken from the prior or contemporaneous CM.

and environmental compliance costs across industry, year, and size classes.[8]

My county-level index of environmental compliance costs is the vector of ϕ_m parameters from the following regression equation:

$$\ln\left(PAOC_i / EMP_i\right) = \alpha + \beta \cdot \ln\left(\sum_{j \in \{n',t',q'\}} PAOC_j \Big/ \sum_{j \in \{n',t',q'\}} EMP_j \right) + \sum_{k \in K}\left(\gamma_k \cdot V_k\right) + \sum_{m \in M}\left(\phi_m \cdot C_m\right) + \varepsilon_i \qquad (2)$$

where observation *i* is an establishment in industry *n´*, year *t´*, size quartile *q´*, and *j* also indexes establishments in the sample. *K* is the set of possible first CM appearances, less one omitted possibility (1963). *M* is the set of U.S. counties, *m* indexes those counties, and C_m is one in a series of county indicator variables, less one omitted county (Washington DC). ε_i is an error term. Note that a comparable state-level index can be computed from a version of equation (2) with $\sum_{s \in S}\left(\phi_s \cdot C_s\right)$ in place of $\sum_{m \in M}\left(\phi_m \cdot C_m\right)$, where *S* is the set of U.S. states, *s* indexes those states, and C_s is one in a series of state indicator variables, less one omitted state (again, Washington DC).[9]

Since the value of the dependent variable is bounded from below for a significant number of observations, the parameters of equation (2) are estimated via a Tobit specification.[10] The parameter α is the estimated constant, representing the omitted group (establishments in Washington DC, observed in existence in the 1963 Census of Manufactures). In estimation, β is restricted to be equal to one, forcing the notion that an establishment is *expected* to have PAOC

[8] Demonstrating whether this is indeed the case is beyond the scope of this current paper. It should be noted that *any* use of plant vintage here is more than has been (or could be) done by any previous study.
[9] Because the same omitted category is used in both regressions (i.e., establishments in the "county" and "state" of Washington DC, observed in existence in the 1963 Census of Manufactures), the county- and state-level indexes are identically scaled.
[10] In particular, establishments are asked to report their expenditures in *thousands* of dollars. Therefore, with rounding, a response of zero reflects expenditures of less than \$500. The *cnreg* (censored normal regression) command in STATA is a generalization of the standard Tobit procedure that allows the censoring point to vary by observation. In this case, left-censoring occurs at $ln(0.5/EMP_i)$ for about 18% of the observations in this sample.

intensity equivalent to the estimate for its industry-year-size class, as specified in equation (1).[11] Deviations from this are explained by differences in plant vintage, as captured by the γ_k parameters,[12] and by differences between counties, as measured by the estimated ϕ_m parameters — my county-level index. The index, assumed here to be time invariant, reveals any extra-normal environmental compliance costs, generally due to above- or below-normal environmental regulation faced by manufacturers at the county level.[13] Exploring the variation in this index is the subject of the next section.

3. On Spatial Heterogeneity in Environmental Compliance Costs

I begin by noting that, according to the respective pseudo-R^2 statistics, the county dummy variables in equation (2) explain 18 times more of the variation in excess PAOC intensity than a version of equation (2) with state dummy variables in their place, relative to a model with no geography variables at all. The R^2 statistics from the analogous OLS regressions tell a similar story. Here, the county dummy variables explain over 16 times more of the variation in excess PAOC intensity than do state dummy variables. Even the *adjusted* R^2 statistics suggest that county variation explains about 14 times more of the variation in excess PAOC intensity than state variation, relative to a model without any geographic controls. These results clearly indicate that, collectively, counties have substantially more explanatory power than do states, on the matter of environmental compliance costs.

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[11] An issue here is when the set {*n*´, *t*´, *q*´} contains just one establishment, particularly if the incidence of such cases is spatially concentrated. Also, if the set {*n*´, *t*´, *q*´} contains any extreme PAOC outliers, this will impact all counties with establishments in that same industry-year-size class. Future work will focus on the sensitivity of the results below to these issues.
[12] Regressions show that, other things being equal, establishments of older vintages have higher PAOC intensity.
[13] The index also includes potential geographic differences in prices related to pollution abatement, such as the salaries of environmental workers, cost of low-sulfur coal, price of electricity, fees for solid waste hauling and disposal, and so forth.

Table 1 begins to illustrate the degree of heterogeneity in regulatory intensity *within* each of the 48 states in scope to this analysis. In particular, I present two statistics here: The first is the difference in the index values between the counties with the maximum and minimum index value in the state (*Max-Min*). The second is the ratio of the maximum county-level index value in the state to the state-level index (*Max/State*). While computing these two statistics, it was necessary for me to ignore the index values of 571 counties, for confidentiality reasons.[14] The measures reported in Table 1 therefore may (will) understate the true degree of heterogeneity observed in the state.[15] Nonetheless, the values presented in Table 1 are fairly correlated with their *true* values (calculated without these suppressions): For *Max-Min* the pairwise and Spearman's rank correlations are 0.6528 and 0.5354, respectively, and for *Max/State* those two correlations are 0.9027 and 0.8960, respectively. A state's rank (highest value = 1) is also shown in Table 1 for each of these two measures.[16]

We see that the state with the highest *Max-Min* is Oklahoma, where the difference in the maximum and minimum county-level index value is over 8 points. In terms of *Max/State*, the state with the highest value is Kansas, where the environmental compliance cost index for the most stringently regulated county is almost 20 times the state-wide index. Meanwhile, Delaware ranks lowest in terms of both *Max-Min* and *Max/State*, followed closely by Rhode Island and Connecticut. These three states are our most geographically compact and have among the fewest counties, which certainly may explain their relative homogeneity.

Among the top 10 manufacturing states (in terms of their employment), California – the largest manufacturing state by any measure – has the largest *Max/State* value, where the

[14] This is in addition to the 600-plus counties that we do not observe at all in this database.
[15] Indeed, 36 of the 48 *true* minima were suppressed, as were 28 of the 48 *true* maxima.
[16] Max/State is undefined for three states – New Mexico, North Dakota, and South Dakota – because their state-level index happens to be negative.

environmental compliance cost index for the most stringently regulated county is nearly 9 times the state-wide index. In terms of *Max-Min*, the largest manufacturing states with the largest values are North Carolina, Michigan, Ohio, and Texas, where the difference in the maximum and minimum county-level index value is over 5 points. On the opposite end, New Jersey is the largest manufacturing state having among the lowest values of both *Max-Min* (a difference of about 1.4 points) and *Max/State* (a factor of 3.4). To help further illustrate the matter, Figure 1 plots the county- and state-level index values for California, Texas, and New Jersey, respectively.

One particularly nice feature of these graphs is their depiction of the confidence intervals around the state and county point estimates. This makes obvious the fact that many of the counties toward the extrema are clearly statistically different from their respective states, in terms of the regulatory intensity and environmental compliance costs faced by their manufacturing establishments.[17] What is less obvious here is whether the many counties with confidence intervals that overlap with their state's are in fact statistically different from their state.

To test for this statistical difference, for county m' in state s', note that the variance of the difference between the estimated county and state index values is given by

$$\text{var}(\hat{\phi}_{m'} - \hat{\phi}_{s'}) = \text{var}(\hat{\phi}_{m'}) + \text{var}(\hat{\phi}_{s'}) - 2 \cdot \text{cov}(\hat{\phi}_{s'}, \hat{\phi}_{m'}) \qquad (3)$$

where $\text{var}(\hat{\phi})$ is the square of the estimated standard error (*se*) associated with the respective index value ($\hat{\phi}$). Here, $\hat{\phi}_{m'}$ and $\hat{\phi}_{s'}$ are equivalent regression coefficients from two different models, estimated on the same sample, where one model contains an additional set of

[17] Note that this is true despite the fact that counties toward the extrema tend to be more imprecisely measured — or rather, counties with more imprecise point estimates tend to define and/or fall toward the extrema. This is somewhat evident in the graphs, but regression analysis (not reported here) more clearly demonstrates this to be the case.

explanatory variables (e.g., indicators for all the other counties in the state). In cases such as this, Clogg *et al.* (1995) – as further refined in their reply to Allison (1995) – demonstrate that (3) becomes

$$\operatorname{var}(\hat{\phi}_{m'} - \hat{\phi}_{s'}) = \operatorname{var}(\hat{\phi}_{m'}) + \operatorname{var}(\hat{\phi}_{s'}) - 2 \cdot \operatorname{var}(\hat{\phi}_{s'}) \cdot (\hat{\sigma}_C^2 / \hat{\sigma}_S^2) \qquad (4)$$

where $\hat{\sigma}_C^2$ and $\hat{\sigma}_S^2$ are the estimated sum of squared errors from the county- and state-based regression models, respectively. The corresponding 90% confidence interval is therefore

$$(\hat{\phi}_{m'} - \hat{\phi}_{s'}) \pm 1.645 \cdot \sqrt{se_{m'}^2 + se_{s'}^2 - 2 \cdot se_{s'}^2 \cdot (\hat{\sigma}_C^2 / \hat{\sigma}_S^2)} \qquad (5)$$

which is easily computed from standard regression output.

Table 2 summarizes the results of this statistical testing. Overall, I find that 1,046 (41.6%) of the 2,513 counties in these 48 states have an environmental compliance cost index statistically different from the index of their respective state. These 1,046 counties contained 52% of U.S. manufacturing employment and 53% of U.S. manufacturing establishments in 2002.[18] I find that 486 (18.6%) of the 2,513 counties have an environmental compliance cost index statistically *higher* than the index of their respective state, while 578 (23.0%) have an index statistically *lower* than the index of their state. These two groups contained 20.4% and 31.3% of U.S. manufacturing employment, respectively. Table 3 lists the largest of these counties (ranked by their 2002 manufacturing employment) and the direction of their difference vis-à-vis their state. Note that this list includes major counties in New York City, Los Angeles, Chicago, San Francisco, Detroit, Dallas, Houston, and other large cities.

Meanwhile, Tables 4a and 4b show the states with the highest and lowest percentage of their counties that are statistically different from the state. As it turns out, New Hampshire,

[18] Note that these states also have about 600 counties not in my sample and therefore without an index value. These counties accounted for just 0.5% of the manufacturing employment in these states.

Rhode Island, and Delaware exhibit no heterogeneity whatsoever (from a statistical standpoint). At the other extreme, two-thirds of New Jersey's counties are different from its state-wide index. Earlier we noted that New Jersey had among the smallest *Max-Min* and *Max/State*, which suggests that the regulatory differences between New Jersey's counties may be relatively narrow but are in fact statistically significant.

A potentially interesting question is whether there is any clustering of "high" and "low" index values within a state. This could arise for a number of reasons — e.g., adjacent counties may share the same set of state regulators and/or nearby counties may regulate themselves similarly, to avoid inter-jurisdictional competition. It has also been shown that environmental regulation may be more lax where exposure to emissions is more likely to fall outside the state, such as in border counties, and particularly those on a state's eastern edge (Helland and Whitford 2003). To examine some of these issues, at least casually, I present county maps for five states that figure prominently in Tables 3 and 4: California, Texas, Illinois, New York, and New Jersey. In particular, in the maps of Figure 2, counties are grouped [and shaded] by whether their index value is statistically smaller than the state's index [light grey], statistically the same [medium grey], or statistically larger than the state's index [black]. Counties with no data or with an index value suppressed for confidentiality reasons are also indicated [stippling].

In California, there is little evidence of any clustering, with the exception perhaps of the above-average expenditure in the counties east of San Francisco. In Texas, on the other hand, it certainly seems that the counties along the gulf coast – including those of the greater Houston area – tend to have significantly higher expenditures than counties elsewhere in the state. Meanwhile, the counties of the Rio Grande basin – or at least the few that actually have data – seem to be significantly less regulated, by Texas standards. In Illinois, Chicago's three main counties have significantly lower expenditures than most counties elsewhere in the state, while there is a cluster of counties southwest of Chicago (toward Peoria) with significantly higher expenditures. In New York, New York City seems to be less regulated, relative to the rest of the state, while New York's other large metropolitan areas (Buffalo, Rochester, Albany, and Syracuse) all appear to have significantly higher environmental compliance costs. And in New Jersey, the counties near New York City are apparently the least regulated while those on the western flank are significantly more regulated. More analysis is needed to determine whether there are any common themes across these (and all the other) states.

4. Discussion

The results presented in the previous section certainly indicate that spatial heterogeneity in environmental compliance costs is real, widespread, and significant. County-level variation is found to explain 14-18 times more of the variation in environmental compliance costs than state-level variation alone. And in terms of variation within a state, manufacturing establishments in the most stringently regulated county are found to have environmental compliance costs that are many multiples of those of manufacturers in other parts of the state, and the state as a whole. Indeed, 42% of the counties (containing 52% of U.S. manufacturing employment) have environmental compliance costs that are statistically different from their states'. All told, there are only three states with counties with homogenous environmental compliance costs (in a statistical sense). These results would suggest that important spatial variation is indeed lost in state-level studies of environmental regulation.

The United States' states have long been used as a laboratory to explore social and economic phenomena, including the impact of environmental regulations on industrial location and industrial activity. The index constructed in this paper could potentially improve such regulatory analyses by expanding the laboratory to include U.S. counties. With this index, one could in principle begin to (re-)explore the effects of environmental regulation on industrial location, employment, output, investment (including foreign direct investment), industrial emissions, ambient pollution levels and so forth *at the county level*. An obvious advantage of this index over the occasionally-used county-level NAAQS non-attainment status is that it encompasses more than just six air pollutants and is continuous (rather than dichotomous or categorical) in nature. And that less than 8% of its variation is explained by county-level factors commonly thought to affect local environmental regulation (see Becker 2004 for list) highlights its usefulness and uniqueness as a measure of local regulatory intensity. Subsequent work will further explore, test, and refine the cost index introduced here in this paper.

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Table 1. Measures of Within-State Heterogeneity in Environmental Compliance Costs

State	Max-Min	(Rank)	Max/State	(Rank)
Alabama	4.412	(13)	11.810	(5)
Arizona	1.011	(45)	3.984	(36)
Arkansas	3.473	(27)	4.360	(33)
California	3.061	(32)	8.740	(13)
Colorado	3.083	(30)	8.885	(12)
Connecticut	0.638	(46)	1.733	(44)
Delaware	0.156	(48)	1.150	(45)
Florida	3.682	(24)	5.826	(26)
Georgia	3.919	(19)	7.903	(16)
Idaho	3.748	(22)	10.027	(10)
Illinois	3.733	(23)	4.293	(34)
Indiana	3.776	(21)	4.501	(32)
Iowa	4.078	(17)	4.749	(30)
Kansas	4.128	(16)	19.970	(1)
Kentucky	2.982	(34)	2.871	(41)
Louisiana	5.122	(10)	2.989	(40)
Maine	2.168	(38)	10.95	(8)
Maryland	2.201	(37)	2.509	(42)
Massachusetts	1.453	(42)	3.176	(39)
Michigan	5.228	(7)	7.462	(18)
Minnesota	3.397	(29)	16.380	(3)
Mississippi	5.508	(5)	8.480	(14)
Missouri	4.229	(14)	8.393	(15)
Montana	3.819	(20)	11.331	(7)
Nebraska	2.983	(33)	7.597	(17)
Nevada	1.580	(41)	6.453	(22)
New Hampshire	1.251	(44)	3.682	(37)
New Jersey	1.355	(43)	3.404	(38)
New Mexico	5.547	(4)	-	-
New York	3.077	(31)	7.386	(19)
North Carolina	5.316	(6)	7.301	(20)
North Dakota	3.493	(26)	-	-
Ohio	5.186	(8)	5.000	(28)
Oklahoma	8.093	(1)	12.433	(4)
Oregon	4.203	(15)	10.875	(9)
Pennsylvania	4.003	(18)	4.868	(29)
Rhode Island	0.398	(47)	1.968	(43)
South Carolina	2.797	(36)	4.262	(35)
South Dakota	3.413	(28)	-	-
Tennessee	6.006	(3)	6.877	(21)
Texas	5.131	(9)	5.386	(27)
Utah	1.762	(40)	11.381	(6)
Vermont	2.830	(35)	5.850	(25)
Virginia	7.372	(2)	6.083	(24)
Washington	4.949	(11)	19.933	(2)
West Virginia	4.801	(12)	4.654	(31)
Wisconsin	3.584	(25)	6.306	(23)
Wyoming	1.944	(39)	9.577	(11)

Table 2. The Extent of Difference in County versus State-wide Estimates of Environmental Compliance Costs

	Number	Percent of U.S. manufacturing employment in 2002	Percent of U.S. manufacturing establishments in 2002
Counties that are significantly **higher** than their state at 90% level	468	20.4%	18.2%
Counties that are significantly **lower** than their state at 90% level	578	31.3%	34.8%
Counties that are **not** significantly different from their state at 90% level	1,467	47.8%	45.8%
Counties that are not in the sample	595	0.5%	1.2%

Table 3. Largest Manufacturing Counties that are Statistically Different from Their State

County	Manufacturing employment in 2002	Index relative to state's index
Los Angeles County, CA	523,293	Lower
Cook County, IL	270,190	Lower
Orange County, CA	187,142	Lower
Santa Clara County, CA	160,734	Lower
Harris County, TX	147,339	Higher
Dallas County, TX	132,968	Lower
King County, WA	106,134	Lower
Cuyahoga County, OH	91,803	Lower
Alameda County, CA	88,262	Higher
Hennepin County, MN	86,103	Lower
Tarrant County, TX	83,010	Lower
Macomb County, MI	75,040	Lower
Oakland County, MI	73,500	Lower
San Bernardino County, CA	66,352	Higher
DuPage County, IL	66,165	Lower
Hamilton County, OH	60,975	Lower
Monroe County, NY	59,260	Higher
Sedgwick County, KS	57,416	Lower
Marion County, IN	57,373	Lower
Erie County, NY	56,473	Higher
St. Louis County, MO	53,255	Lower
Riverside County, CA	52,885	Higher
Dade County, FL	50,568	Lower
Lake County, IL	50,144	Lower
New York County, NY	47,838	Lower

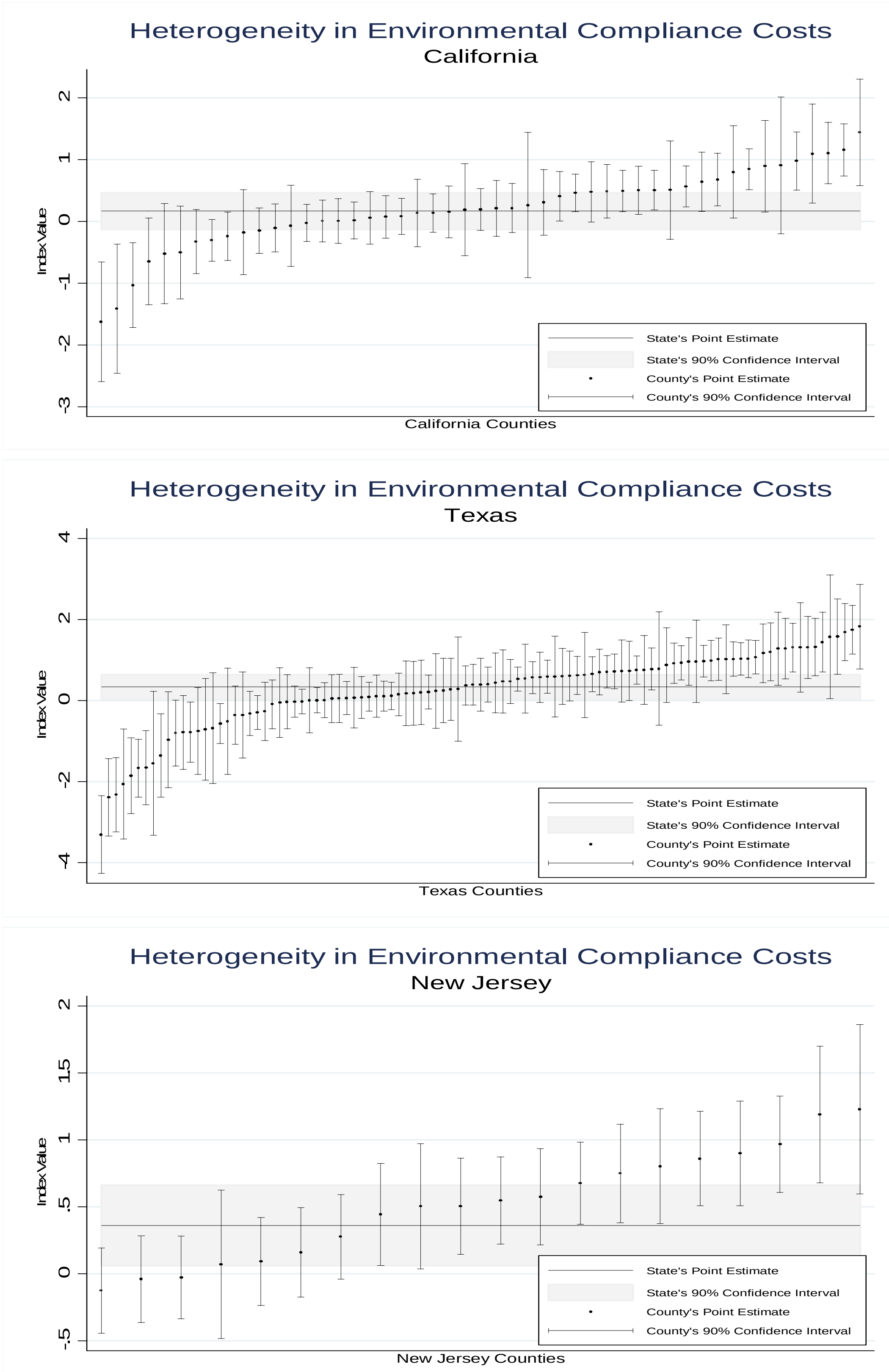
<u>Table 4a</u>. States with the *Highest* Percentage of Their Counties Statistically Different from the State

1.	New Jersey	66.7%
2.	New York	59.0%
3.	Oregon	57.6%
4.	Pennsylvania	54.5%
5.	California	53.7%
6.	Alabama	50.0%
	New Mexico	50.0%
	Vermont	50.0%
9.	Washington	48.6%
10.	Louisiana	48.1%

<u>Table 4b</u>. States with the *Lowest* Percentage of Their Counties Statistically Different from the State

48.	New Hampshire	0.0%
	Rhode Island	0.0%
	Delaware	0.0%
45.	Utah	11.1%
44.	Massachusetts	16.7%
43.	West Virginia	24.4%
42.	Connecticut	25.0%
41.	Colorado	31.0%
40.	Mississippi	32.5%
39.	Arkansas	33.3%
	South Carolina	33.3%
	Nevada	33.3%

<u>Figure 1</u>. Heterogeneity in Environmental Compliance Costs: Three Examples



<u>Figure 2</u>. County versus State-wide Estimates of Environmental Compliance Costs

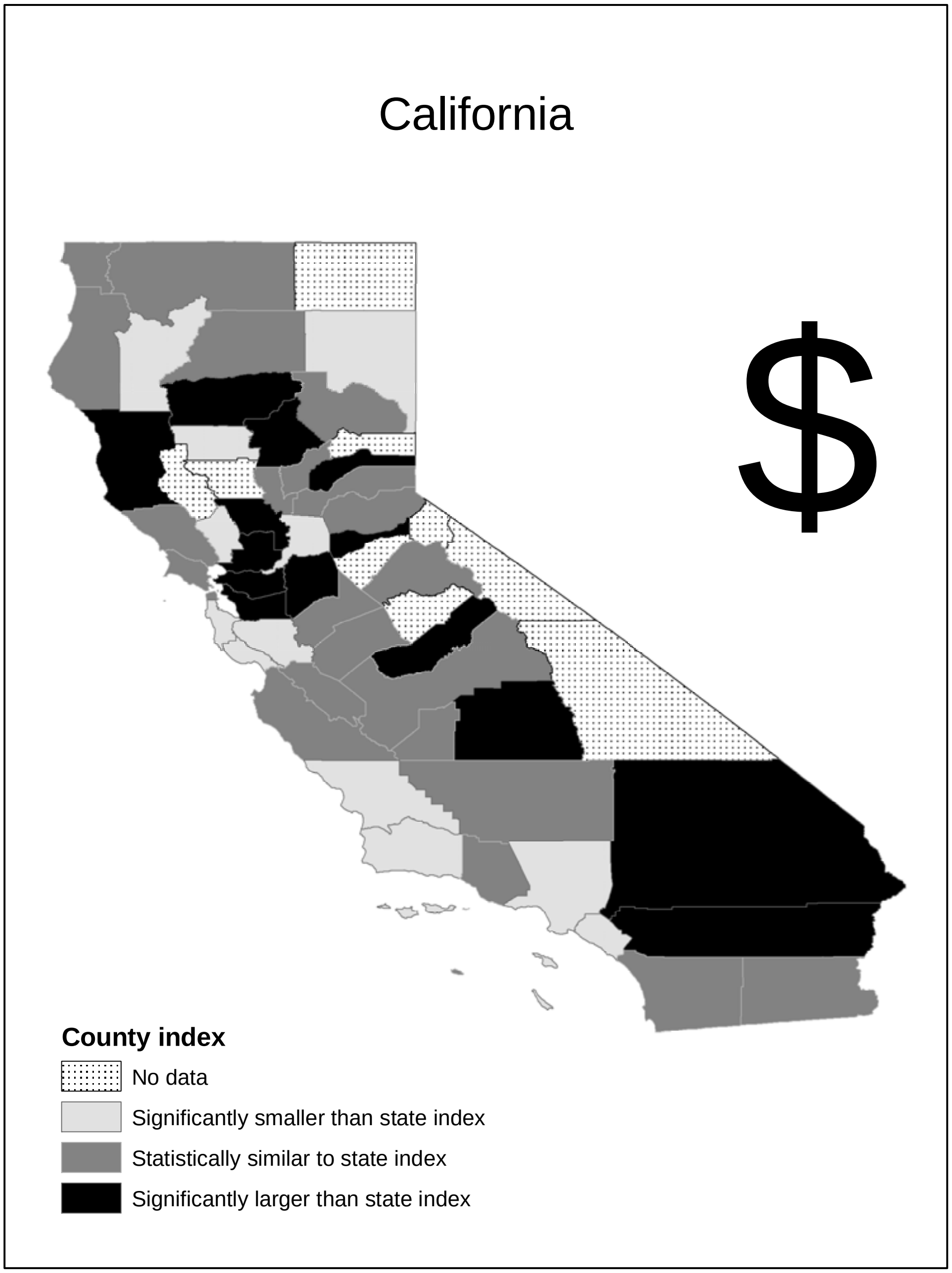
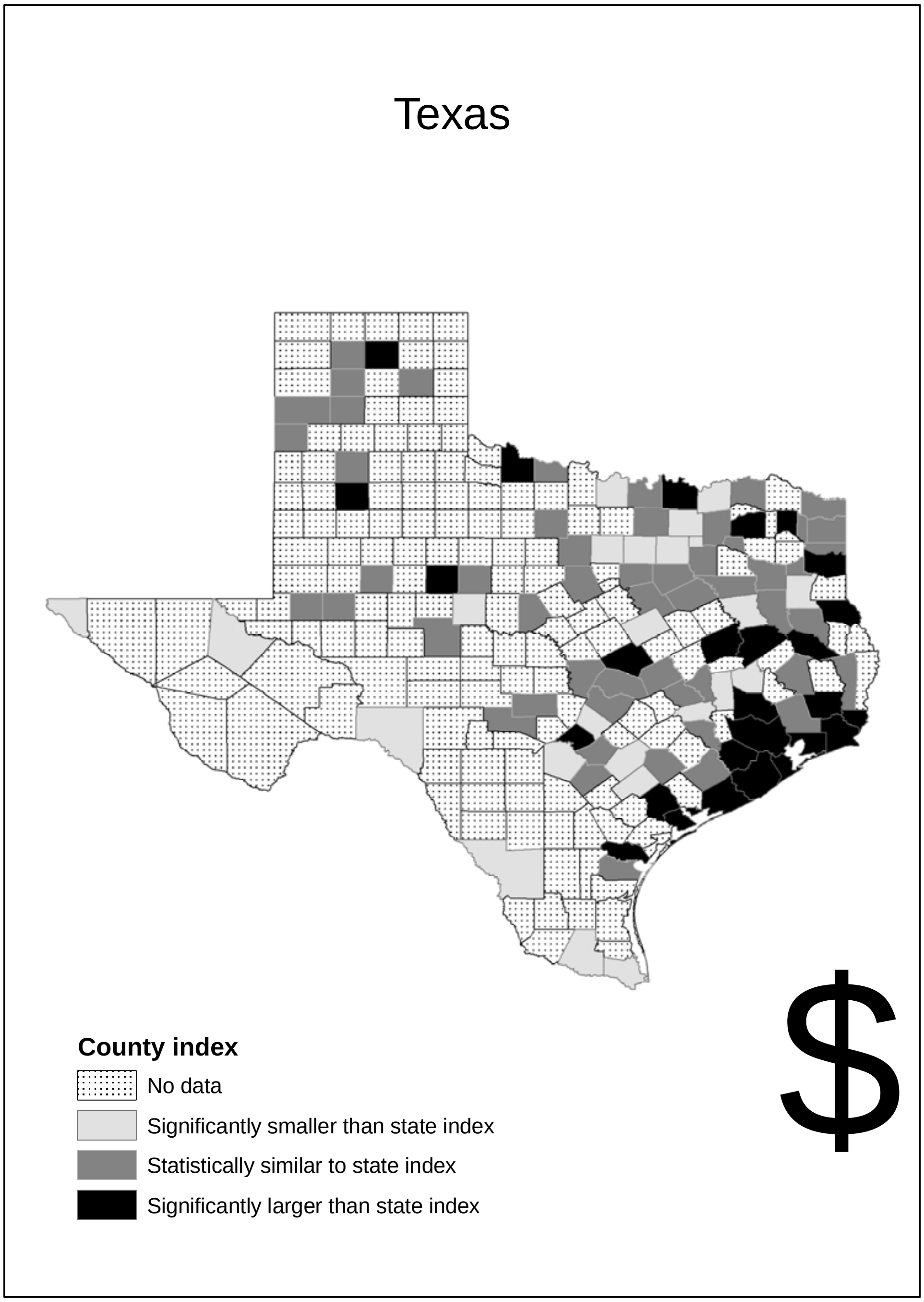
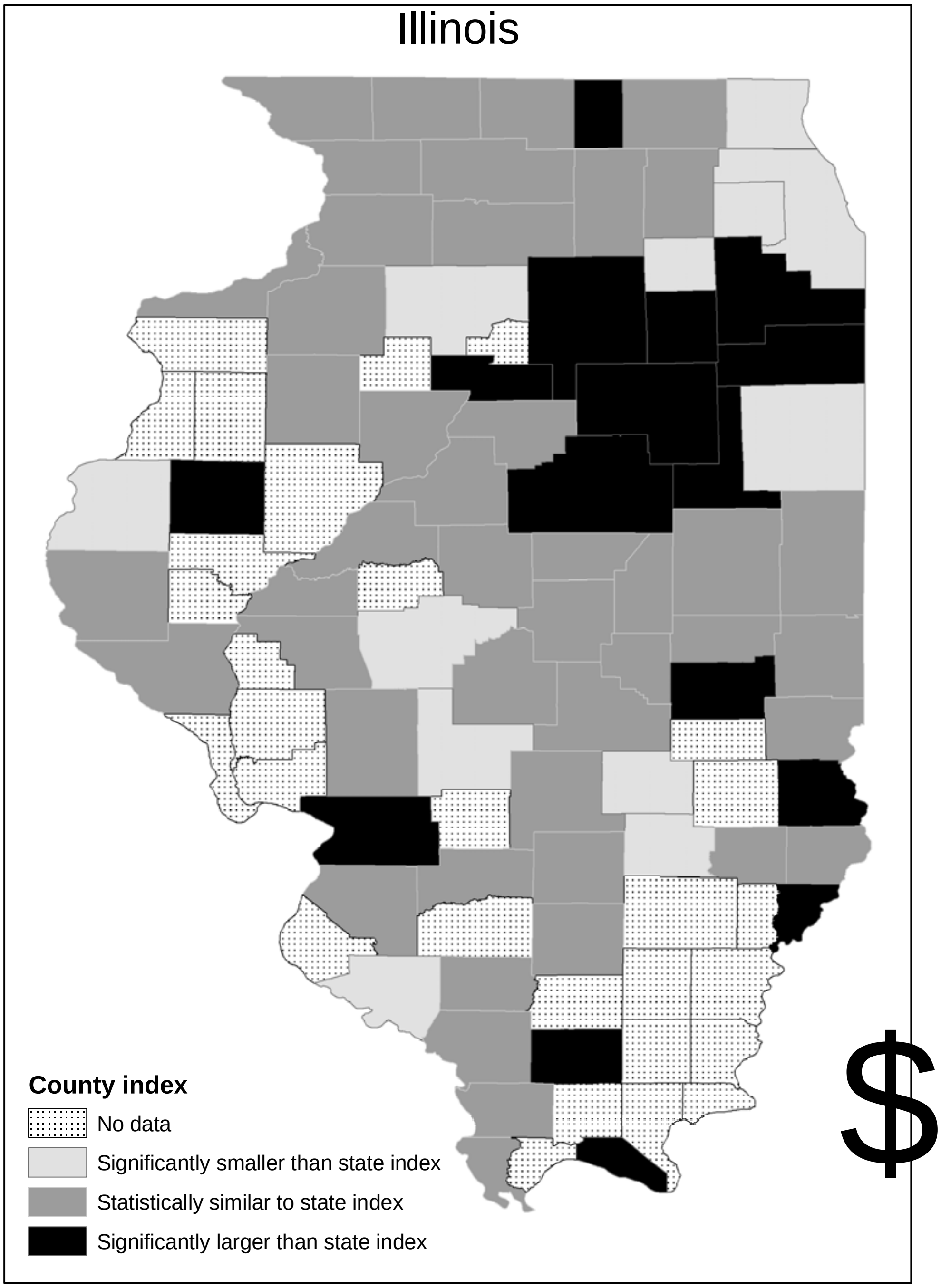


Figure 2 (continued).



<u>Figure 2</u> (continued).



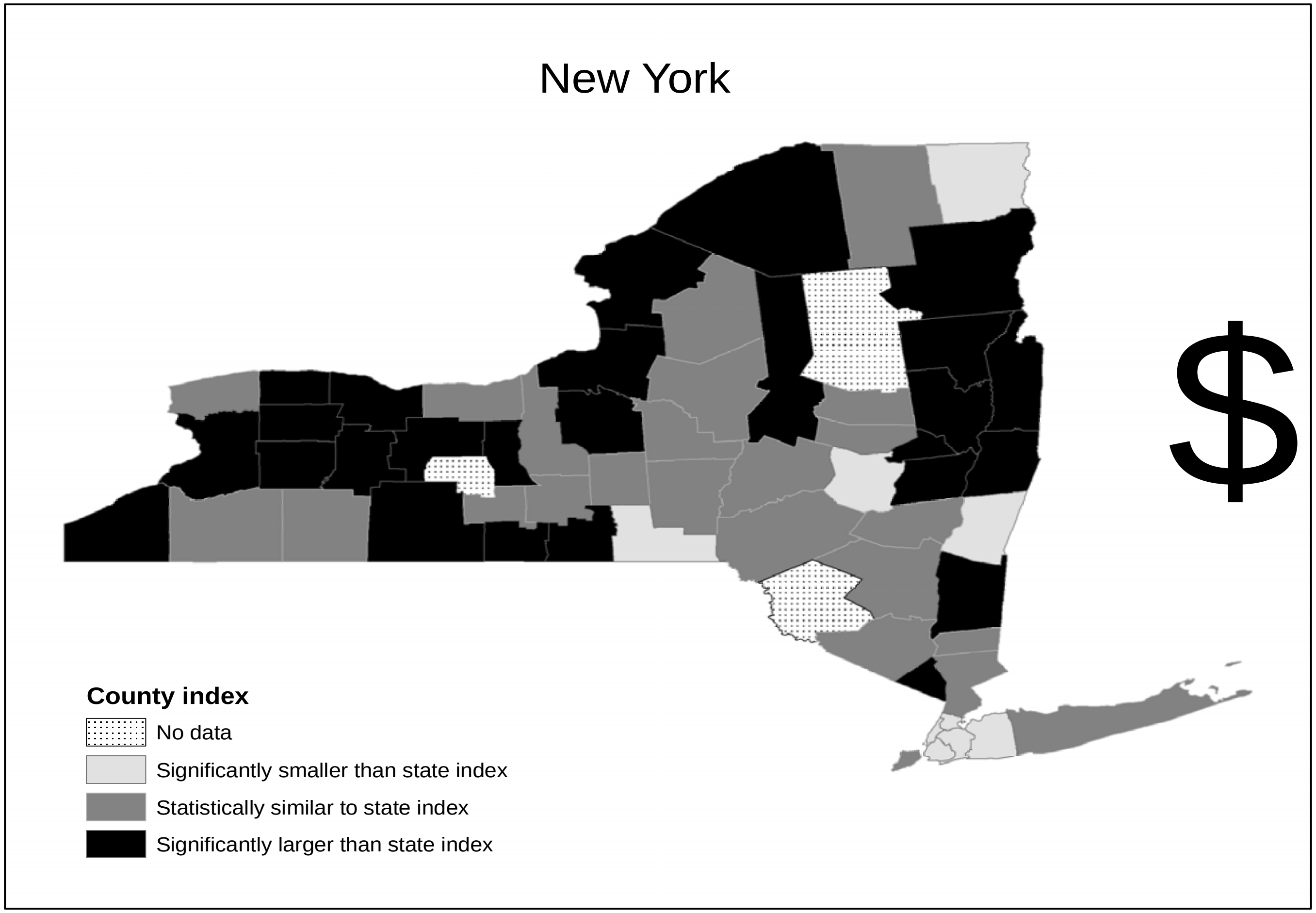

New York
County index
No data
Significantly smaller than state index
Statistically similar to state index
Significantly larger than state index

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Figure 2 (continued).