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Viewing Spatial Consequences of Budgetary Policy Changes

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Abstract

While the research community is often very concerned with the distributional effect of public policy decisions, the geographic distribution of the affected populations is often overlooked. This paper argues that seemingly geographically neutral policies have spatial consequences and that the choice of how to measure them is important. We suggest that maps produced by geographical information systems (GIS) provide a powerful tool for communicating these ideas to policy makers. We further suggest that GIS supplemented by spatial statistics yield geographic information that can perform a valuable function in policy debates. We use the recent proposed changes in Medicaid expenditures in Ohio to illustrate how geographic information provides insights into the spatial consequences of these changes by introducing a simple method to weight the impact of expenditure changes.

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Introduction

Some policies, such as those to close unnecessary military bases, have obvious geographic implications. The decision to close a base can lead to the immediate loss of hundreds to thousands of jobs in a local community. In response to previous base closings, both public and private help has been made available to ease the blow to the affected areas (Murphy, 1993). Other policies, however, may have impacts that are less obviously tied to geography. For instance, changes in Social Security benefits are likely to have disproportionate impacts on communities with more retirees. Such spatial clustering of affected populations can increase the magnitude of the effects of a policy change, and failure to recognize these spatial effects may inhibit consideration of policy responses that address the local implications such as those that accompany base closings.

While any policy targeted at individuals will have spatial implications if people are not randomly distributed, more emphasis is typically placed on the other distributional effects of policy changes. These discussions often focus on distributional effects across economic classes (e.g., Jones and Weinberg, 2000; Piketty and Saez, 2003), such as the examination of changes in tax rates (Petska and Strudler, 2003). Distributional effects across other dimensions are also considered, including the intergenerational implications of tax policy (Heijdra and Ligthart, 2002) or generational implications of budget deficits and health care policy (Auerbach, et al., 1994). Similarly, investments in medical research and accessibility yield variable benefits for males or females or across ethnic or social groups (e.g., Kadar, 1994). However, in studying the distributional effects of policy changes, the effect of geography tends to be underplayed or underestimated.

The geographic distribution of programmatic effects is worth noting because place can have important influences, for instance, on welfare (Berube and Tiffany, 2004). While the role of place is recognized in the literature, and there are numerous polices that explicitly address spatial inequities, there is often a tendency to ignore the spatial distributional effects of programs that are not geographically targeted. For instance, federal policies have important effects on state and local budget sustainability (Lav, 2003). Fiscal need varies across space if people are not randomly distributed across economic, social, and demographic characteristics. Similarly, the cost of delivering the same service varies spatially. Differences in fiscal capacity, the ability of a government to raise revenues, may compound these effects. Thus, even seemingly geographically neutral programs will often have spatial consequences. The spatial disparities in effects are also influenced by the magnitude to which fiscal and decision-making authorities are devolved from federal to state and local governments (Tannenwald, 1999).

This paper highlights that regardless of the nature of the consequences of policy changes, these consequences are likely to be distributed unevenly across space. The paper first argues that because geography matters, it is important to examine geographic distributional effects. We next develop and demonstrate the use of simple techniques for measuring spatial variability. Using a case study of the potential effects of changes in Medicaid expenditures in Ohio, we then show that the spatial consequences of policy changes are non-trivial and vary depending upon choice of measurement. We conclude with some thoughts on how these tools can be applied to help inform policy decisions.

The Role of Place

While the field of geography is premised upon the notion that place is important, the notion is not lost on the other social sciences (Dietz, 2002). It is recognized that there are knowledge spillovers that benefit business firms that locate near other businesses in the same industry (Audretsch and Feldman, 1996). It is also well documented that people are not randomly distributed across space. In the United States, poverty has become increasingly concentrated in the largest cities (Jargowsky, 1997; HUD, 1997), although this trend may have reversed somewhat during the 1990s (Jargosky, 2003). While part of increased economic segregation may be due to market forces, some have argued that it is also the direct result of policy choices (Dreier, et al., 2001; Wilson, 1999). This concentration has fiscal consequences that affect the equitable funding of services such as police protection and school funding (Orfield, 1997); social consequences such as sprawl (Savitch, 2003) and crime (Krivo and Peterson, 1996; Morenoff, et al., 2001); and economic consequences such as labor market activity (Weinberg, et al., forthcoming) and access to vital services such as health care (Chandra and Skinner, 2003). In addition, concentration may create a spatial mismatch between where the unemployed poor live and where employment opportunities exist (Holzer, 1991; Ihlanfeldt, 1994; Kain, 1968).

Some policy has explicitly considered geographic disparity, such as Canada's attempts to equalize per capita tax burdens across provinces (Shah, 1996); regional economic development policy such as the European Union's Structural Funds and the

United States' Regional Commissions (Sweet, 1999); or programs that target economic development incentives to particular distressed areas, such as enterprise zone (Greenbaum, 2004; Peters and Fisher, 2002). Given that spatial inequalities exist, it is still an open question whether policy should explicitly focus on places rather than people (Engberg, 1996; Gyourko, 1998; Ladd, 1994; Mills and Lubuele, 1997).

Rather than add to that debate, we emphasize that even seemingly geographically neutral policies have spatial implications due to clustering of similar populations and spillovers. For instance, Glendon and Vigdor (2003) found that economic outcomes in neighboring counties were spatially correlated primarily because neighbors shared similar industrial characteristics. Thus, exogenous shocks lead to similar outcomes in neighboring counties. They also found some evidence of spillovers across similar industries in neighboring counties. Spillovers between neighboring spatial units implies that economic activity in one place may have a causal relationship with activity in neighboring areas. Examples include the causal relationships between states' expenditures and those of its neighbors (Case, et al., 1993), the influence of negotiated public school teacher salaries on salaries in neighboring school districts (Greenbaum, 2002), and the spatial diffusion of crime across neighborhoods (Cohen and Tita, 1999) and counties (Baller, et al., 2001).

In Ohio, Medicaid expenditure decisions are made at the state level within federal guidelines. However, the impact of these decisions will vary from place to place depending on the needs of the local population and upon the dependence of the local economy on the health care industry. States are required by the federal government to provide an array of basic Medicaid services, but they are also given the discretion to provide additional services or offer coverage to groups not included in the federal guidelines. State funding is matched by federal dollars, sometimes up to two dollars for each dollar spent by the state. Clearly, because of this devolution of authority that allows states to modify and design their own programs, there will be differences across states in the nature and extent of services provided under Medicaid. However, even within a state, there are differences at the local level in the role Medicaid plays in the local economy and in the capacity of the counties to deliver these services.

Most social welfare policies not only attempt to alleviate economic hardship but also have distributional goals. As mentioned above, it is common to study generational and economic distributional issues; we focus here on the spatial unevenness. We explore how, through the use of maps, we can obtain a picture of the spatial variation in the need for and use of Medicaid assistance and consider how this visual perception can be calibrated through the use of spatial statistics.

Spatial variability measures

The standard deviation of a distribution and the variance are common measures of dispersion. The coefficient of variation (CV), which divides the standard deviation by the mean, has the added attraction that it provides some insight into the value of the mean as an estimate for the overall distribution.[1] A more sophisticated measure of spatial variation is the spatial Gini coefficient used by Auderestsch and Feldman (1996) and

[1] For example, a coefficient of variation less than 0.33 would imply that the standard deviation is less than a third of the mean and that in case of a well behaved symmetric distribution, 0 lies at least 3 standard

Krugman (1991) to assess the effects of spatial concentration on product innovation and economic growth. These are, however, overall measures. Geographical information systems offer the ability to actually observe the spatial variability.

Geographic information systems (GIS) provide multi-layered maps of spatial and non-spatial information. A GIS contains digitized geographic information for producing maps. Its database management capabilities also allow a GIS to incorporate other data, oftentimes non-spatial data, such as demographic, economic, social or legal information pertaining to the geographical entities. For example, GIS can be used to display zoning information on a city map superimposed with information regarding various characteristics of the resident population.

While the spatial distribution of any measure can be visualized by displaying the data on a map, the visualization of patterns can sometimes be deceptive (Tufte, 1983). Therefore, it is useful to compute statistics to test whether observations in neighboring spatial units such as counties are associated. One global measure, Moran's *I*, is often used to statistically measure the correlation across spatial units, or spatial autocorrelation (Cliff and Ord, 1981):

$$I = \frac{n\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S_0 \sum_i (x_i - \bar{x})^2} \qquad [1]$$

deviations from the mean. For the mean to be considered a "good" estimate for the distribution, one would want CV to be even smaller.

where n is the number of observations, w_{ij} are the elements of a spatial weights matrix,[2] W, and x represents the measure of interest at locations i and j (with mean $\bar{x}$). S_0 is a scaling constant computed by summing the weights:

$$S_0 = \sum_i \sum_j w_{ij} \qquad [2]$$

Statistical inference regarding the randomness of the spatial distribution of the data can be made based on the standard normal distribution after making the transformation, $Z_I = (I\text{-}E[I])/(V[I]^{1/2})$, where E[I] and $V[I]^{1/2}$ represent the theoretical mean and standard deviation (Anselin,1988; Cliff and Ord, 1981). A common alternative measure of spatial autocorrelation, Geary's *C*, is instead based upon squared deviations from the mean.

The coefficient of variation and the spatial Gini indicate, at an aggregate level, the spatial variation and the unevenness of the variation of the distribution, and Moran's *I* provides a test for whether this variation is random. Another approach to gaining some insight into spatial variation is to determine how local conditions vary from some norm. We construct "dependence" indexes to explore variations in economic conditions across the counties. To provide measures of local dependence, we borrow an expositional tool from the economic geography and economic development literature that regional economists have used for the past 60 years, location quotients (Miller, et al., 1991). Location quotients are often used in the economic development literature as a simple

[2] The spatial weights matrix used in this paper is a geographic contiguity matrix such that each element w_{ij} = 1 if two counties share a border and w_{ij} = 0 if not.

measure of how specialized a particular region is in any particular industry. We create dependence indexes based on the location quotient concept.

A location quotient (LQ) is a ratio of two proportions that provides a relative measure of specialization or dependence. The measure is relative to the overall level of dependence at a more global geographic level, such as the state level. The index is constructed by expressing the proportion of dependence at the local level as a ratio of the same proportion at the state level. For example, a commonly used location quotient measures the dependence of the local economy on employment in particular industrial sectors. The index can be expressed as a ratio of the proportion of the total number of people employed in a *county* that are employed in a sector to the proportion of the total number of people employed in the *state* that are employed in that same sector. More formally, the ratio of the two proportions of employment in any industry sector *s* can be written as:

$$LQ_s = \frac{\dfrac{EMP_{county\_r}}{EMP\_TOT_{county\_r}}}{\dfrac{EMP_{state}}{EMP\_TOT_{state}}} \qquad [3]$$

Where, EMP_{county_r} and EMP_{state} represent employment in industry sector s in county r and for the whole state. $EMP\_TOT_{county\_r}$ and EMP_TOT_{state} measure total employment in county r and for the whole state. Therefore, if LQ = 1, the county is at the state average; if LQ > 1, the county is more dependent than the state; and if LQ < 1, the county is less dependent than the state.

Another way to think of the ratio is that it uses the state's level of dependence as a benchmark for comparison. If the proportion of county employees working in a sector is the same as those at the state level, then the index will be equal to one. Values other than one represent higher or lower levels of dependence on that sector of the economy.

To illustrate the use of these indexes to identify spatial variability across the state, we construct two separate *dependence indexes*. To study the distribution of poverty and to capture the vulnerability of counties in terms of their dependence on public assistance, we construct a poverty index. This index helps provide an indication of the distribution of the population that is most likely to be affected by changes in Medicaid expenditures. The second index focuses on healthcare related activity and can be interpreted to be a measure of a county's dependence on the health services sector. Because Medicaid plays an important role in financing the provision of healthcare, this index helps provide an indication of the distribution of the industry likely to be most affected by any changes in those healthcare expenditures.

Each dependence index (DI), constructed here, is the geometric mean of three related location quotients and can be expressed as

$$\begin{aligned} \boldsymbol{DI}_{Poverty} &= \left(\boldsymbol{LQ}_{Transfer\ payments} \times \boldsymbol{LQ}_{Poverty} \times \boldsymbol{LQ}_{Medicaid}\right)^{1/3} \\ \boldsymbol{DI}_{Health} &= \left(\boldsymbol{LQ}_{Establishments} \times \boldsymbol{LQ}_{Employment} \times \boldsymbol{LQ}_{Payroll}\right)^{1/3} \end{aligned} \qquad [4]$$

The dependence index reflecting poverty, $DI_{Poverty}$, is based upon three measures of poverty in the county, and the health index, DI_{Health}, is based upon economic reliance upon the health services sector of the economy. The poverty index is built using county level data on a) transfer payments, b) number of households with incomes below 100% of the federal poverty level, and c) Medicaid expenditures on county residents. The health services index is built using County Business Patterns data measuring a) the number of establishments in the healthcare sector in each county, b) employment in these establishments, and c) associated payroll in these establishments.

Case study

Medicaid in Ohio

Ohio's Medicaid program began in 1968. Currently, for every dollar Ohio spends on Medicaid healthcare services, the federal government reimburses (federal match) the state just over $0.58 on average (OHP, 2001).[3] Table 1 provides summary information on this program for the three most recent state fiscal years for which data are available.[4]

These 1.7 million Medicaid recipients make up approximately 15% of the 11.35 million residents of Ohio. The recipients are distributed unevenly across the counties (Map 1), ranging from a low of almost 5% to a high of over 30% of the county population. The darker-shaded counties in the southern and southeastern part of the state indicate that those counties have the largest percentage of the population who are Medicaid recipients. The counties with the lightest shading and smallest percentage are concentrated in the northwest part of the state. The Moran's *I* statistic is 0.615 and the

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[3] The federal match in FY 2002 was 50% for administrative services, 58.8% for Medicaid services, and as high as 71.2% for the children's program (SCHIP).
[4] The state fiscal year (SFY) in Ohio is from July 1 to June 30. The federal fiscal year begins on October 1; hence, it is important to identify the year for appropriate accounting. The total expenditures include the federal match of state expenditures on Medicaid.

corresponding Z-value is 9.602 (p-value = 0.000). The statistically significant value of Moran's *I* confirms the visual evidence that the counties with similar percentages of Medicaid eligible populations are clustered together and that this clustering is not even across the state.

The Medicaid program consists of a complex system of interdependent components with multiple categories of aid, delivery systems, categories of services and recipients. There is considerable variety in the cost of services per recipient. Younger adults and children typically incur fewer expenses compared to the recipients who are "aged, blind, or disabled" (ABD). While the ABD population consists of less than a third of the Medicaid recipients, they account for approximately 80% of the expenditures.

In Ohio, as in other states, Medicaid expenditures are the largest item in the state budget after education and therefore are an attractive target for cutbacks during periods of fiscal strain. To explore and to illustrate how apparently spatially neutral policy changes at the state level can have disproportionate effects at the local level, we use a reduction in the growth rate of Medicaid expenditures of $491 million. This is one of the figures originally proposed in the governor's biannual budget submitted to the state legislature in early 2003 (Candisky and Craig, 2003).

Data Sources

Analysis of the impact of Medicaid expenditure changes is conducted at the county level, and the county level data are collected from various state and federal and sources. Each measure used, the source, and the county mean is listed in Table 2. In most cases, we used data from the most recently available year.

Ohio Medicaid expenditure data come from the Ohio Department of Job and Family Services (ODJFS). The Office of Ohio Health Plans, which administers the Medicaid program in Ohio, publishes the Ohio Medicaid Report. This annual report provides county level information on program expenditures, eligible population and funding for different services (OHP, 2001, 2002).

Socioeconomic characteristics of the counties are drawn from the 2000 Decennial Census (US Census Bureau, 2001). Ohio's Office of Strategic Research (OSR, 2002) publishes *County Profiles* that compile demographic and economic information about each county. We draw on the data OSR compiled measuring federal transfer payments to Ohio Counties in 2000 (BEA, 2001). Transfer payments include both means-tested income maintenance transfers as well as Social Security retirement payments and veterans benefits.

Data on the number of jobs, number of business establishments, and their associated payroll[5] come from County Business Patterns (US Census Bureau, 2002). The Census Bureau reports economic activity data for all of the various sectors of the economy. In order to measure the relative dependence of each county on the health services sector, we focus on the "health care and social assistance" sector. This sector includes all public and private healthcare establishments as well as other care facilities.[6]

[5] Data for some of the smaller counties were missing since they had too few establishments to maintain anonymity. We interpolated estimates for these counties based on average per capita figures for the state.
[6] NAICS 62, Health care and social assistance, is comprised of four 3-digit NAICs categories: 221 Ambulatory health care services, 622 Hospitals, 623 Nursing & residential care facilities, and 624 Social assistance. While it would be preferable to exclude NAICS 624 from this analysis in order to isolate health

Analysis

The data report the number of Medicaid recipients in each county rather than the county in which the medical services are provided. It is not clear where recipients obtain their services; hence, it is not possible, without analyzing the detailed claims information, to ascertain the Medicaid expenditures in each of the counties. However, based on where these recipients live, the average expenditures per recipient vary across counties (Map 2) from a low of a little over $3,100 to almost $8,600. This distribution is uneven in the sense that in SFY 2000 the average expenditure for an ABD recipient was approximately $14,000 while that for other recipients was approximately $1,400 (OHP, 2002). This wide range, even in the averages, is indicative of the differences in the nature and extent of Medicaid services and costs. The corresponding coefficient of variation is 0.221 and the Gini Coefficient is 0.116.[7] Taken together, in the aggregate, these measures suggest a fairly tight and even distribution of per capita expenditures.

A more detailed look at the geographic distribution, however, suggests that although the numbers are not distributed over a very wide range, the distribution is not spatially random. The counties with the highest expenditures per recipient are not necessarily the ones with the greatest percentage of the population who are Medicaid recipients. Many of the southern counties with the highest percentages have some of the lowest expenditures per recipient, as indicated by the lighter shading. The Moran's *I*

care establishments, this would reduce the cell sizes in some counties to a level that would induce data suppression to avoid disclosing data for individual firms.

[7] The Gini ranges between 0 and 1, with 0 representing an even distribution.

statistic is 0.122 (Z-value = 2.048 and p-value = 0.041), suggesting once again that the clustering of counties by per capita expenditures is not random.

It is worth noting that while the patterns of clustering of the percentage of the population who are Medicaid eligible residents and the per capita Medicaid expenditures are both non-random, they are not the same. Hence different policies, for instance those that limit expenditures on nursing homes, will have a different effect on counties than policies that change eligibility criteria. It is evident from comparing the two maps (Map 1 and Map 2) that even though the two different polices might have the same initial budgetary effect at the state level, they will not only affect different populations but they would also have differential effects on the local county economies in different parts of the state. Map 1 shows the distribution of Medicaid recipients across the state and can be used to explore consequences in terms of the percentages of the population affected in these counties. Because Medicaid expenditures vary considerably based upon the various services provided, it is also important to examine the distribution of Medicaid expenditures per recipient across the counties, as illustrated in Map 2.

In order to gain a better understanding of why these average expenditures per recipient vary so considerably across counties, it is important to further examine characteristics of the population distributions. MAP 3 shows the distributions of the populations under age 18 and older than age 64. We can see from these maps how two policies, one altering nursing home reimbursement formulas and the other altering eligibility requirements for families with children, could have the exact same fiscal effect at the state level but have very different effects at the local level. Any change in nursing home payments would likely have a larger impact on the east-central counties, which have some of the highest concentrations of elderly residents. Conversely, policies affecting the coverage of children would likely have larger impacts in some of the western counties that have the largest concentrations of children. By examining these age distributions, we are able to get a clearer picture of why the expenditures vary over space. For instance, counties with larger elderly populations are likely to have a more ABD recipients, who are much more costly than child recipients.

County Dependence Indices

The preceding analysis focused primarily on Medicaid expenditures and the potential effects of the proposed reduction of $491 million in state spending growth. Medicaid, however, is only one component of a network of support services available to the poor and economically disadvantaged segments of society. As noted earlier, there are some counties in Ohio where as much as 30% of the population receives some form of Medicaid assistance. Hence, in some of these counties, the dependence on public assistance is substantial and goes beyond healthcare and associated services. Similarly, the size and role that the health services sector plays in the local economy also varies considerably across the counties.

We capture the vulnerability of the counties in terms of their dependence on public assistance and their dependence on the health services sector with the separate dependence indexes defined above (Equation 4). The values for the poverty and heath services indexes range from approximately half to two, providing another indication of the diversity across the state in terms of levels of poverty and extent of the role that healthcare services plays in the local economy. There is a relatively strong linear correlation of 0.71 between these two indexes, indicating that while there is some redundancy in the information, they do capture the different variations across the state in dependence on public assistance and health services.

Map 4 and Map 5 provide a visual depiction of the two indexes reflecting the variation across counties. The message that counties would face differential effects of changes in Medicaid expenditures appears to be repeated in slightly different ways in these two maps. The range of values for both dependence indexes from 0.5 to 2 implies that there are some counties where poverty, as measured by this index, is approximately half that of the overall state. Other places in the state have poverty that is twice as much as the overall state level. The healthcare dependence index also varies over a similar range. There is some overlap in that some of these county economies not only depend considerably on the healthcare sector of the economy, but they are also dependent on public assistance and transfers.

Comparing Map 4 with Map 5, we note that the southern counties are both poor and dependent on the healthcare sector. The Moran's *I* statistics confirm the non-random spatial distribution of the indexes: Moran's $I = 0.572$ for the poverty index (Z-value = 8.933 and P-value = 0.000) and Moran's $I = 0.180$ for the health index (Z-value = 2.932 and Z-value = 0.003).[8] One would expect to see well paying jobs in the health services sector; however, these maps suggest that many of the jobs in the healthcare industry are

[8] We also computed the Geary's *C* measure of spatial autocorrelation. We do not report the results because they concur precisely with the information obtained from Moran's *I*.

not high paying.[9] This reliance on public assistance and the healthcare sector makes these areas of the state doubly vulnerable to the adverse effects of changes in Medicaid funding.

To capture the vulnerability of counties to cuts in Medicaid expenditures, we use the two indexes as weighting factors to estimate the adverse effects of the reductions in Medicaid expenditures. The weighted Medicaid expenditures per resident are displayed in Map 6 and Map 7. By weighting the expenditures by the dependence indexes, we are attempting to capture the dependence of counties on Medicaid.

Consider the poverty index, which varies from approximately one half to almost two. The level of poverty in the county as a whole is much less where the index is a half than where it is close to two; hence, what this analysis suggests is that a loss of a Medicaid dollar in an affluent county will not be felt as severely as it would be in a poor county. That is not to suggest that an individual who has lost Medicaid coverage will suffer any less hardship in one county than in another, but it is possible that in the more affluent counties in which there is typically greater economic opportunity, the individual affected by cutbacks will have greater opportunities to find other sources of support or income. Similarly, counties heavily dependent on healthcare services sector will be proportionately worse off than counties that are less dependent. This situation is analogous to a situation in which a county is dependent upon a particular industry, such

[9] As noted earlier, we used data on healthcare as well as social services assistance jobs. In many instances, Medicaid recipients also receive other social services and their eligibility for these services might be affected by changes in their Medicaid eligibility status.

as steel or mining. If that industry has a downturn, the whole county's economic well-being is adversely affected.

The coefficient of variation shows that, at an aggregated level, the weighted distribution has slightly greater variation than that of the unweighted distribution of Medicaid expenditures across the counties. The coefficient of variation for the unweighted expenditure distribution is 0.221, which increases to 0.345 when the expenditures are weighted by the poverty index and to 0.317 when weighted by the health index. Similarly, the inequality, as measured by the Gini coefficient, increases across the state regardless of which set of weights we consider. The Gini coefficient increases from approximately 0.12 for the unweighted expenditure distribution to approximately 0.17 for expenditures weighted by either index.

However, a more nuanced story emerges when we consider the clustering of these counties. The two maps together show how the counties will experience the burden of the proposed cuts. Based on the Moran's *I*, the distribution of the expenditures weighted by the poverty index ($I = 0.200$, Z-value = 3.239, P-value = 0.001) is more spatially auto-correlated than the distribution of the Medicaid expenditures weighted by the health index ($I = 0.020$, Z-value = 0.480, P-value = 0.631). In spite of the fact that spatial inequality, as measured by the Gini coefficient, increases, the clustering of the poor counties is different from the clustering of those that are dependent on healthcare related activity. In other words, spatial consequences will be more severe in terms of poverty, since these counties are clustered together, whereas, the spatial consequences in terms of healthcare related activity might be mitigated by the fact that nearby counties will not be as severely affected by expenditure reductions. The counties in the northwest are not poor, but some of them do have considerable healthcare services activity. Hence, these counties will suffer some hardship as Medicaid dollars are reduced. However, the effect on these counties will not be as severe as that encountered by the counties in the south and the southeast that are both dependent on healthcare and are poor. Regardless of how we choose to measure, it is apparent that the southern and eastern half of the state will feel the effects of any reductions in Medicaid expenditures more severely than the western half as indicated by the darker shading in the two maps.

Concluding remarks

There is a rich history of distributional analysis across classes of economic, demographic, social and intergenerational categories that examine the consequences of budgetary choices. While social scientists have recognized the importance that geographers place on location and spatial relationships, they have not always explicitly incorporated these notions with the corresponding distributional analyses into their examination of public policy choices. By drawing upon location quotients, maps and associated spatial statistics, we have demonstrated that simple yet effective tools for measuring spatial unevenness and vulnerability are readily available for policy analysis. The appropriate use of these tools can provide powerful insights into the potential for and consequences of spatial inequality due to policies that may not initially appear to have obvious spatial implications. Maps are particularly useful in that they provide, in a single representation, the ability to both analyze and communicate patterns that emerge from the data.

As an example of the implications of the spatial consequences of expenditure changes in a program in which budgetary decisions are made centrally, the paper has reported on an examination of the rate of growth of the Ohio Medicaid program. Although the county governments serve primarily as conduits for the state and federal Medicaid funds, changes in policies at the state level can have profound implications at the local level. If individuals lose access to healthcare or if healthcare institutions lose funding for the provision of that care, the resulting impacts place additional burdens on local governments and local social service organizations. These consequences at the local level vary based on local characteristics and circumstances. For example, because nursing homes represent the largest component of Medicaid expenditures, political attention has focused on them as potential targets for budget cuts. Placing caps on nursing home expenditures will particularly affect counties with larger elderly populations and those with the highest concentration of nursing homes. Reduced expenditures on nursing homes will affect the elderly recipients and their families, and some of the burden of assisting them will transfer from Medicaid to other local agencies and service providers. From a provider's perspective, reduced reimbursements could lead to cutbacks or even closures, resulting in job losses and other secondary economic consequences that have fiscal impacts on local governments.

Hence, the potential implications of different policy choices at the state level will be quite different depending upon local conditions. Constructing indexes such as those developed in this paper would be one way of predicting what the local consequences might be and where their effects will be greatest. As we have shown, choice of the appropriate index is important to correctly characterize the nature of the consequences. Such analysis is useful not only for local administrators, who need to plan for the budgetary implications of statewide policy, but also for state policy makers, who need to be cognizant of how policy affects different parts of the state.

This is not to say that all variation in spatial consequences is bad. In fact, local variability is a primary rationale for devolution of authority and responsibility from federal to state governments and beyond. The jealousy with which local school boards guard their autonomy and differences is indicative of the need and desire for maintaining local diversity. However, court decisions regarding equity in school funding testify to the limits to the amount of variability, particularly fiscal variability that communities are willing to tolerate. As this paper demonstrates, there are non-trivial spatial consequences of policy changes. The challenge for policy analysis is to determine when these differences in consequences are desirable and when they are not.

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Table 1. Comparison Medicaid Data for SFY1999-2001

	SFY1999	SFY2000	SFY2001
Number of recipients	1,387,581	1,409,705	1,676,157
Total Expenditures	$6,988,518,930	$7,638,797,112	$7,975,591,719

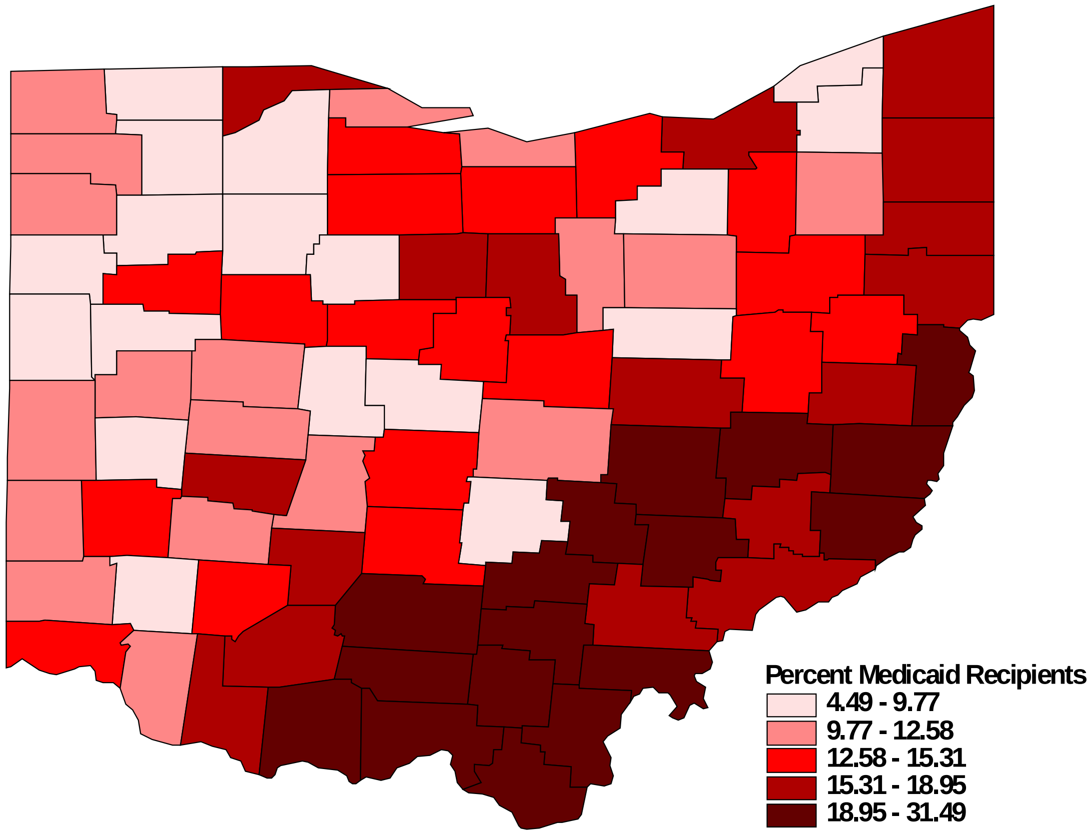
Source: Ohio Medicaid Report: Update April 2002 (OHP, 2002).

Table 2. Data

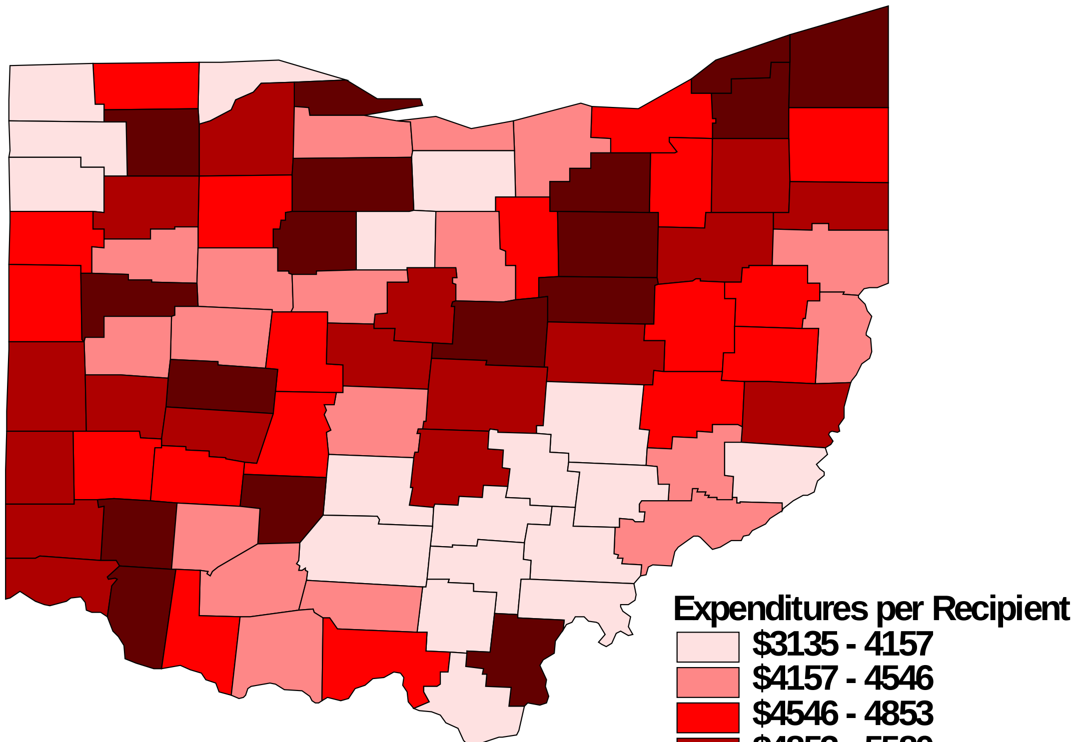
Measure (County-level)	Source	Year	Mean
Medicaid Recipients	ODJFS[a]	2001	19,047.24
Percent Medicaid Recipients	Constructed	2001	15.01
Medicaid Expenditures (millions)	ODJFS[a]	2001	$90.60
Expenditures per Recipient	Constructed	2001	$4,929.83
Residents	Decennial Census	2000	129,013.00
Total Households	Decennial Census	2000	50,529.78
Households in Poverty	Decennial Census	2000	13,303.39
Transfer Payments (millions)	OSR[b]	1999	$486.00
Total Establishments	County Business Patterns	2000	3,073.34
Jobs	County Business Patterns	2000	56,789.20
Healthcare Establishments	County Business Patterns	2000	286.70
Healthcare Jobs	County Business Patterns	2000	7,360.41
Healthcare Payroll (millions)	County Business Patterns	2000	$216.83
Poverty Index	Constructed	2000	1.00
Medicaid Expenditures by Poverty Index	Constructed	2001	$4,880.06
Health Index	Constructed	2000	0.95
Medicaid Expenditures by Health Index	Constructed	2001	$4,634.15

[a] Ohio Department of Job and Family Services (OHP 2001, 2002)
[b] Office of Strategic Research, Ohio Department of Development (OSR, 2002)

Map 1. Percentage of County Residents Receiving Medicaid

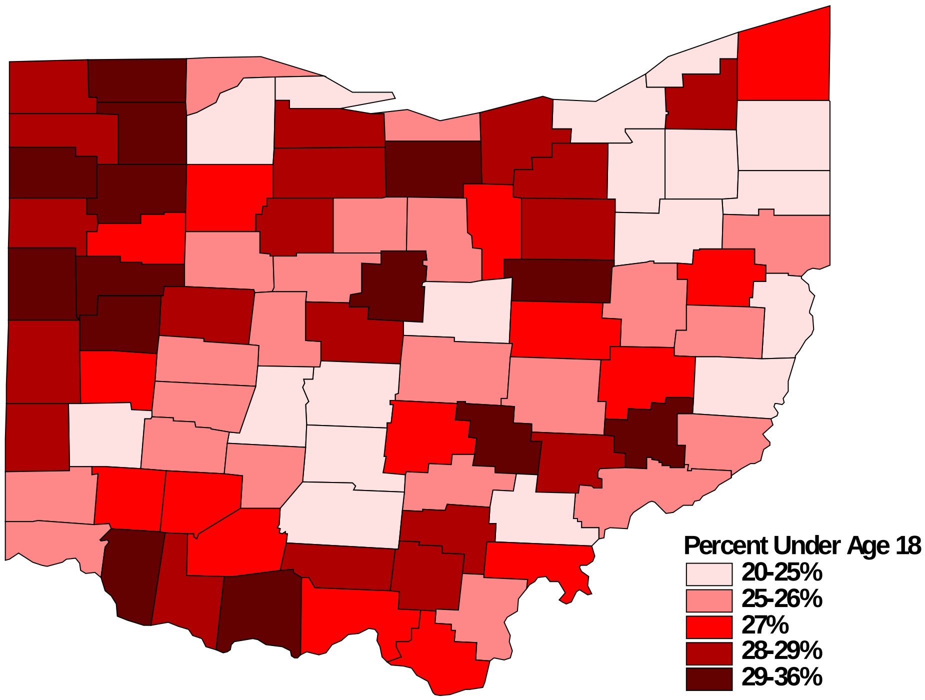


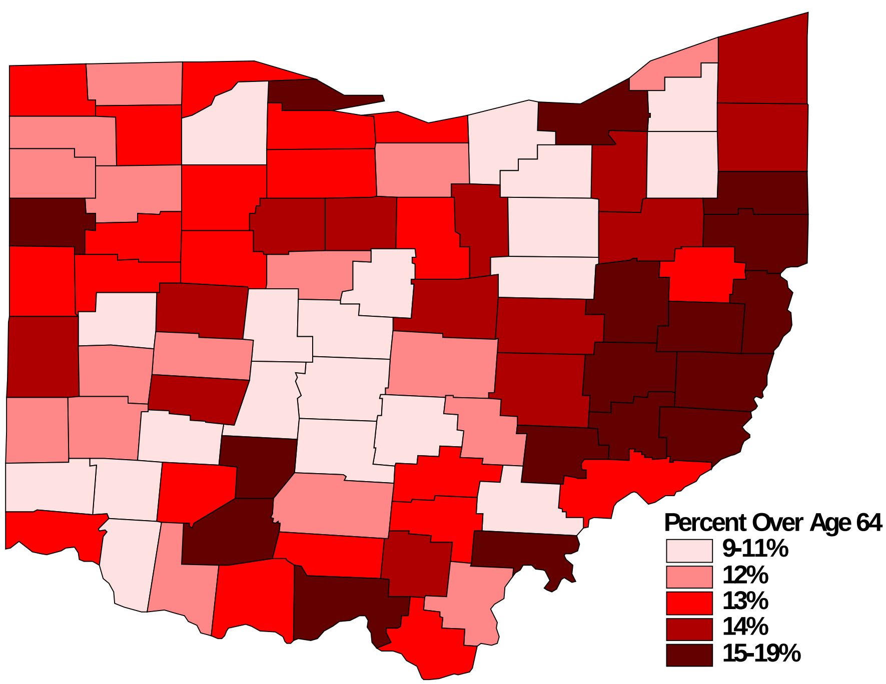
Map 2. Medicaid Expenditures per Recipient



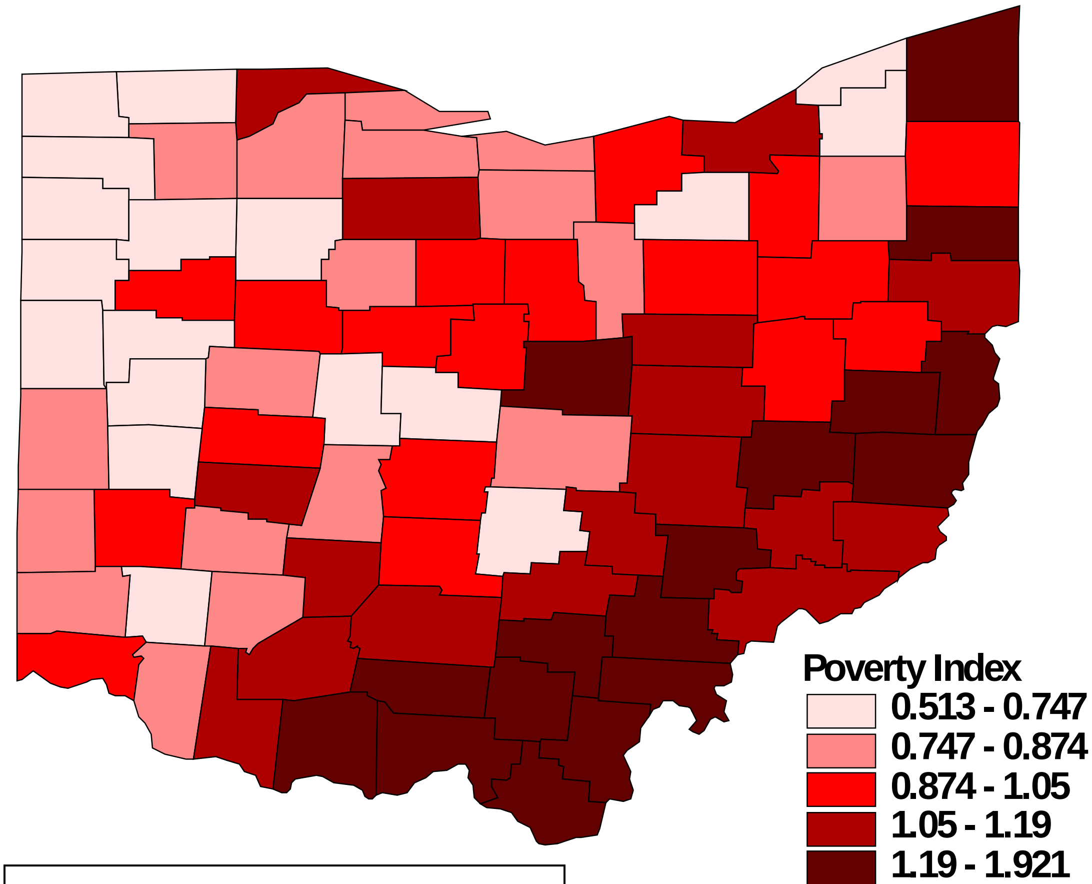
CV = 0.221
Gini = 0.116
I = 0.122

MAP 3. Young and Elderly Populations



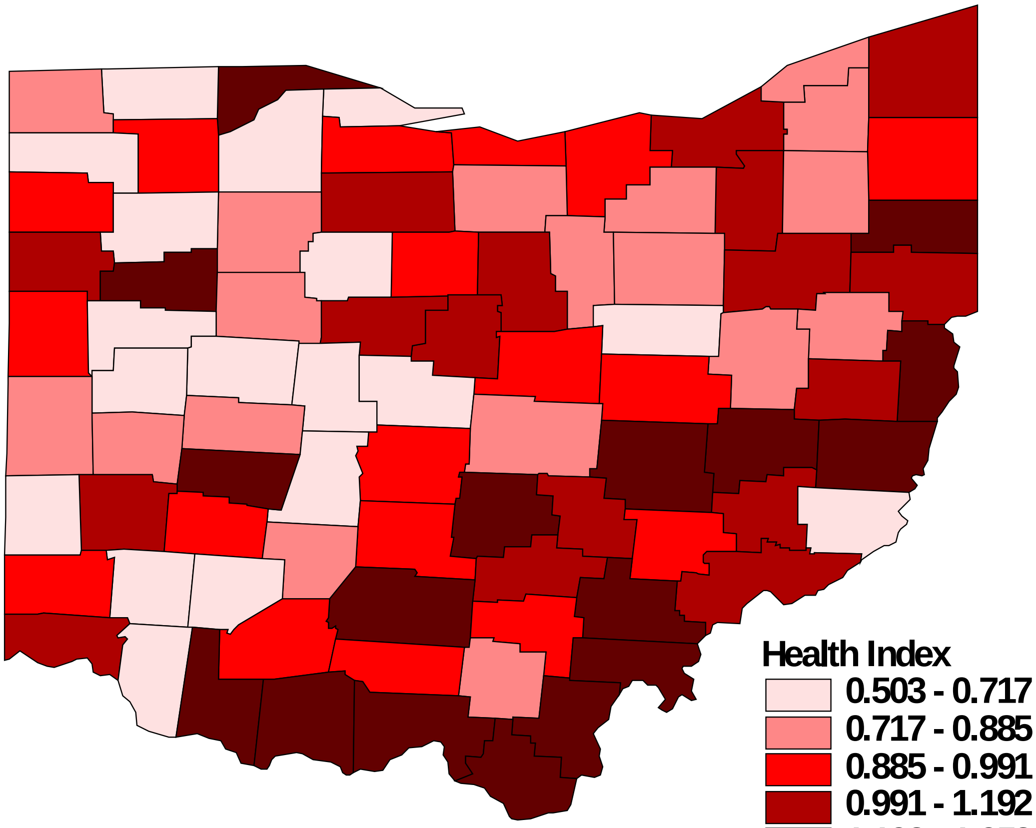


Map 4. Dependence Index – Poverty



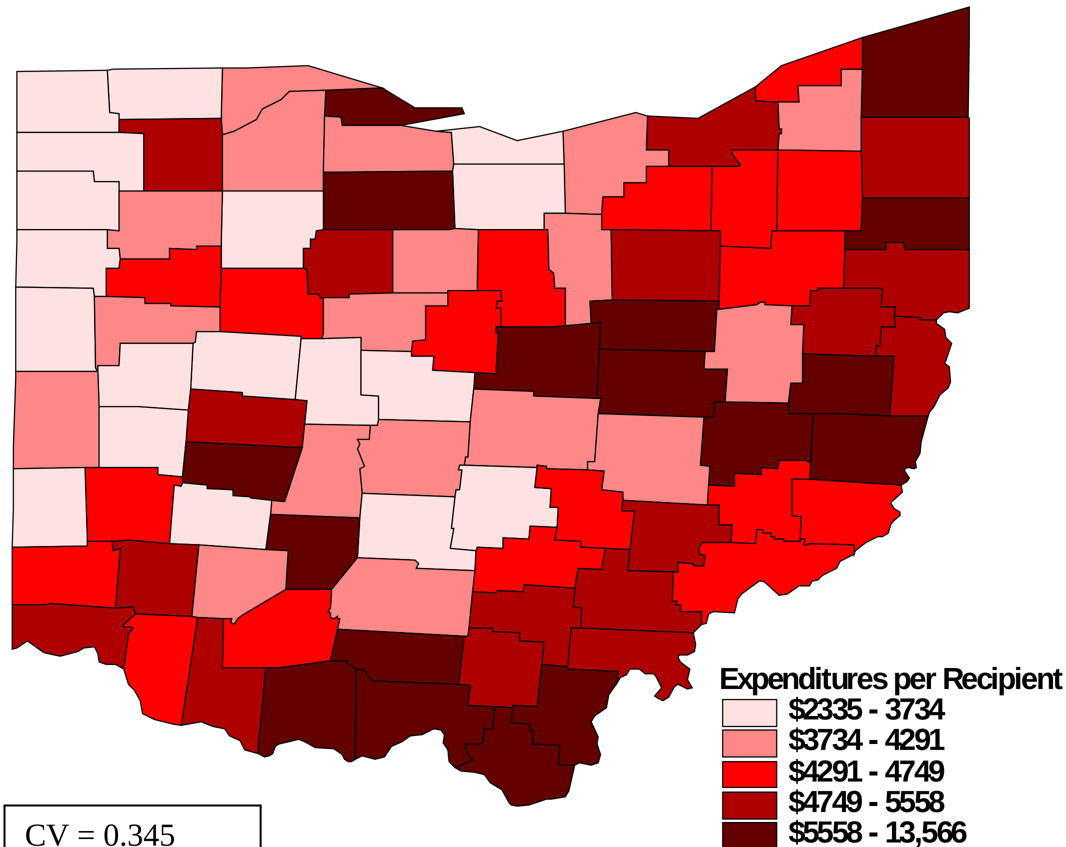
PI = 1 County is at state average
PI > 1 County is more dependent
PI < 1 County is less dependent

Map 5. Dependence Index – Health



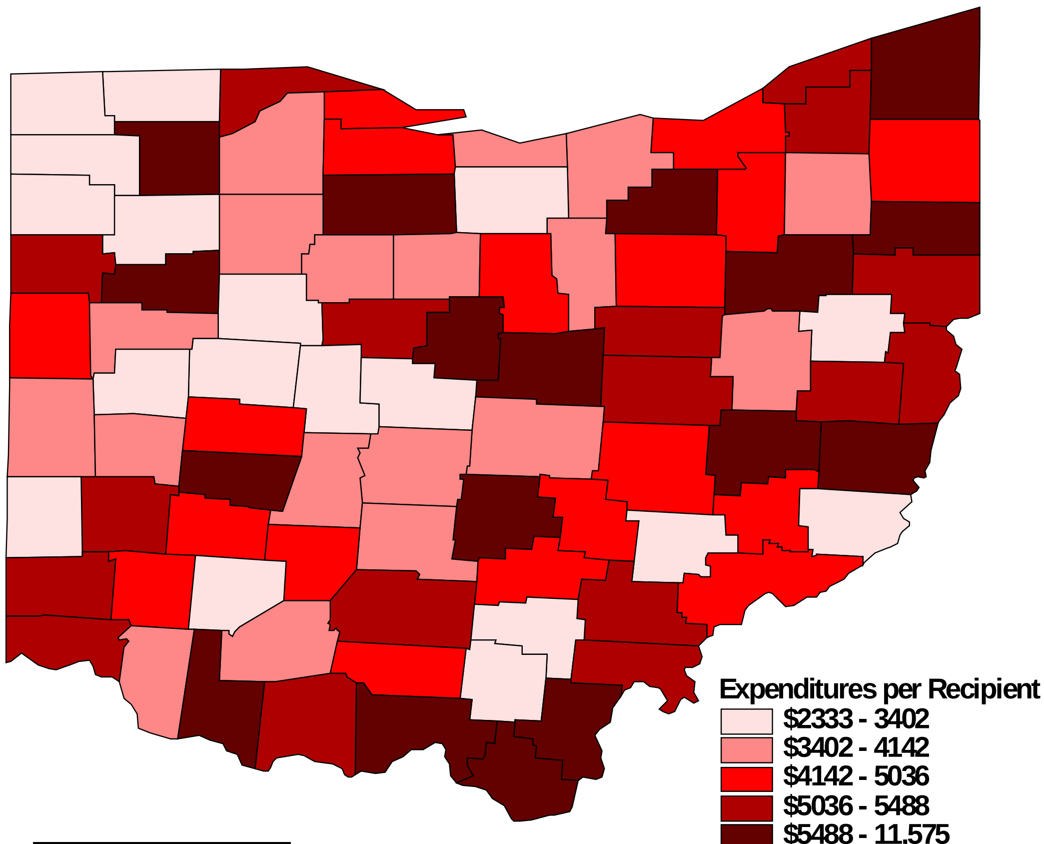
HI = 1   County is at state average
HI > 1   County is more dependent
HI < 1   County is less dependent

Map 6. Expenditures per Recipient Weighted by Poverty Index



CV = 0.345
Gini = 0.168
I = 0.200

Map 7. Expenditures per Recipient Weighted by Health Index



CV = 0.317
Gini = 0.166
I = 0.020