A NEW SUMMARY MEASURE OF YEARLY STATE POLICY SPENDING

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ABSTRACT

In this paper, we develop and test a general measure of state policy expenditures. Our approach is to construct a formal geometric model of state spending across all major policy areas. The advantage of doing so is that such models can be assessed according to a fairly clearcut set of evaluative standards: Parsimony, substantive utility, and explanatory power. Based upon these criteria, the variable created from our model possesses some highly desirable characteristics. And, it compares quite favorably to other measures of state policy activity. The net result is a yearly score for each state which summarizes that state's spending across all major program areas. More generally, we believe that our variable can be interpreted as an empirical representation of state policy priorities. In this capacity, it could occupy an important position within models of state politics.

It is sometimes argued that the evolution of a scientific discipline can be assessed through the quality of the measures used to represent its central concepts (Kuhn 1977). And, by that standard, the field of state politics is developing nicely. There now exists a scholarly consensus on a number of variables that measure state-level political phenomena. These include measures of: Political culture (Elazar 1984; Lieske 1993; Hero and Tolbert 1996); party competition (Dawson and Robinson 1963; Barrilleaux 1986; Holbrook and Van Dunk 1993); legislative professionalism (Squire 1992; Fiorini 1994); judicial decisionmaking (Brace and Hall 1990); public opinion (Erikson, Wright, and McIver 1993); elite ideology (Berry, Ringquist, Fording, and Hanson 1998); gubernatorial power (Beyle 1999); interest group characteristics (Gray and Lowery 1996); and bureaucratic representativeness (Keiser, Wilkins, Meier, and Holland 2002). As this list demonstrates, the currently-existing variables focus largely on political behavior and governmental structure. In contrast, far less attention has been paid to the measurement of state-level public policy. Of course, there has been some work carried out on this topic. But, as yet there is no broadly-based and widely accepted variable that captures for measuring state policy outputs.

In this paper we hope to introduce precisely such a variable. Specifically, we develop and test a general measure of state policy expenditures. Our approach is to construct a formal geometric model of state spending. The advantage of doing so is that such models can be assessed according to a fairly clearcut set of evaluative standards: Parsimony, substantive utility, and explanatory power (King, Keohane, and Verba 1994). Based upon these criteria, our variable possesses some highly desirable characteristics. And, it compares quite favorably to other measures of state policy activity. At the very least, our geometric model provides a yearly score for each state which summarizes that state's spending across all major program areas. More generally, we believe that our variable can be interpreted as an empirical representation of state policy priorities. In this capacity, it could occupy an important position within models of state politics.

BACKGROUND

This paper focuses directly on the program spending patterns of state governments. Expenditures are a clear manifestation of institutional commitments. They represent the "governmental decision agendas" within the respective states (Kingdom 1984); that is, the relative salience that state-level public officials accord to various social and political issues (Baumgartner and Jones 1993). It is important to emphasize that we are focusing on *tangible* distributions of public resources and not merely the *intentions* of politicians and office holders. We contend that this distinction is critical because we want to measure what governments *do* and not what they *plan* to do.

We recognize that program expenditures do not represent the sum total of public policy outputs. Nor do they automatically lead to policy effectiveness in their respective areas. Nevertheless, most observers of the political system understand that adequate financing is a necessary precondition for any meaningful policy activity (Garand and Hendrick 1991). Therefore, expenditures commitments are the targets of those who would influence government (e.g., parties and interest groups, as well as individual citizens). Furthermore, they have a profound effect on the ways that state governments ultimately address issues and ameliorate social problems. In short, policy spending represents a critical concept deserving of attention from political scientists.

Program expenditures are frequently used as the dependent variable in studies of state-level policymaking. A sizable number of analyses focus on spending within a single policy area. While there are far too many to provide a complete listing, this line of work covers a wide range of issues (e.g., Barrilleaux, Holbrook, and Langer 2002; Lewis and Maruna 1999; Goertz 1996; Brown 1995; Plotnick and Winters 1985; Williams and Matheny 1984). The "single-policy studies" are valuable precisely they provide a great deal of detailed information about the ways that state government address particular social problems. However, they are also problematic because virtually all of the states have balanced budget requirements. Therefore, spending within any given policy area is influenced by spending across all other policy areas. This could easily produce biases when expenditure figures are interpreted as a state's level of commitment toward a particular program area.

Recognizing this problem, several other studies have examined program expenditures across multiple policy areas. These analyses typically employ nonrecursive causal models to examine both exogenous influences on budgetary decisions and interrelationships among discrete policies (Garand 1985, 1988; Garand and Hendrick 1991). As such, they seek to provide detailed depictions of the complexities inherent within the policymaking process. But, these “multiple policy studies” intentionally focus on only a few key program areas instead of the complete set of state policy commitments. At the same time, these studies conceptualize program areas as discrete, separate phenomena. In so doing, they fail to consider the possibility that there may be a single structure spanning expenditures across all policy fields. If that is the case, then there should be a way to combine expenditures into a single summary measure for each state.

A third body of research uses data reduction techniques such as factor analysis to summarize many policy indicators simultaneously. Although their exact results differ somewhat, these studies all demonstrate that there is a systematic, coherent framework underlying the ways that states address the myriad array of pressures confronting them. For example, Sharkansky and Hofferbert (1969) found that state policy-making conforms to two underlying dimensions: A “welfare-education” factor and a “highways-natural resources” factor. More recently, Klingman and Lammers (1984) used principal components analysis to develop a “general policy liberalism” factor. And, in a similar vein, Wright, Erikson, and McIver (1987) used factor analysis to justify the construction of a “grand index of state policy;” the variable itself is a simple additive scale which they label “composite policy liberalism.”

The strong points of this analytic strategy have been widely recognized (Hill, Leighley, and Hinton-Andersson 1995; Lascher, Hagen, and Rochlin 1996). But, it is also important to acknowledge that there are some potentially serious problems in the resultant policy measures. The variables employed in the factor analytic studies generally encompass a wide range of governmental activities (e.g., legislative provisions, program adoptions, tax progressivity, etc., as well as program expenditures). These indicators cover many *different* aspects of the public policy-making process, even though the underlying actors, institutions, and dynamics vary markedly between them (Kingdon 1984; Sabatier and Jenkins-Smith 1993).

Furthermore, these studies usually combine data from several time points, spanning periods from seven to fifteen years long. This is problematic because policy considerations almost certainly change over time. Any such temporal variability is lost when the data are combined into a single summary index. For these reasons, it is impossible to say exactly which, if any, specific aspect of the policy process is represented in the final summary measures that are developed in most composite policy studies.

A STRATEGY FOR MEASURING STATE POLICY SPENDING

We want to create a new measure of state policy outputs that overcomes the limitations described in the previous section. We will maintain the focus on government spending precisely because expenditures represent an identifiable and central component of the policy process (Elling 1983; Hansen 1990; Garand and Hendrick 1991; Raimondo 1996). But, we will incorporate spending *across* a very wide range of substantive areas, covering nearly the full range of programmatic commitments by state governments. In addition, we will look at *yearly* state spending, thereby making it possible to evaluate stability and change in state spending priorities over time.

Yearly, policy-specific, spending figures for each of the fifty states will produce an enormous amount of information— probably too much to be usable in its original form. Therefore, we test whether the spending data conform to a common structure. If so, we can construct an abstract representation or "model" of that structure. Such a model would retain most of the variability across states, policies, and years that is contained within the original spending figures. However, it would be more "compact" and, therefore, more comprehensible than the raw data. The modeling process will generate a yearly score for each state encapsulating that state's spending across all policy areas. These scores can be used as empirical variables in subsequent analyses.

Data

The raw data for our analysis consist of yearly state general expenditures in ten policy areas: Corrections; education; government administration; health; highways; hospitals; natural resources; parks and recreation; police and law enforcement; and welfare. The dataset currently covers the time period from 1982 through 2000.

We agree with those researchers who argue that expenditures alone cannot be used to obtain a comprehensive measure of all policy outputs and/or impacts (Walker 1969; Hofferbert 1974; Hanson 1984; Erikson, Wright, and McIver 1989). However, this is simply not a problem for the present analysis. The consensus of scholarly opinion clearly holds that expenditures *across* substantive areas do provide accurate representations of policy *priorities* (Garand and Hendrick 1991). In short, comparative spending levels are the clearest, most unambiguous, indicators of governmental commitments to address various problems (Budge and Hofferbert 1990).

Our analysis seeks to explain the states' *relative* priorities across the different policy areas. We are not interested in examining *how much* states spend on different programs. Instead, this analysis focuses on how states *divide up* their yearly pools of available resources. For this reason, the policy-specific spending values within each state for each year are expressed as proportions of the total policy expenditures for that state across all ten categories for that year. In other words, the ten data values that are actually employed in the analysis will sum to 1.00 for each state in each year. This provides a yearly measure of variability in policy allocations across the states while still effectively controlling for such features as state size, overall spending levels, and the like.

Methodology

Our analysis will construct a specific geometric representation, often called a "spatial proximity model," of the state spending data. The basic idea behind this model is very simple. For each year, the fifty states and the ten policy areas are shown as two sets of points located along a common continuum. The relative positions of the points are determined by the empirical expenditure values. Specifically, state *1's* spending on policy *A* is inversely proportional to the distance between the point representing *1* and the point representing *A*: As spending increases, this distance gets smaller and vice versa. Thus, state points will tend to be located close to the points representing policies for which their relative spending levels are high and far from the points representing policies where their relative spending levels are low.

The overall spatial proximity model for the state spending data is estimated on a yearly basis, and within each year it will consist of two distinct sets of points: One set of fifty state points and a second set of ten policy points. States with similar spending profiles will have points that are located close to each other along the dimension; states with markedly different spending priorities will have larger distances between their points. A similar distance rule applies to the policies themselves: Policies that receive similar proportional allocations in state budgets will be represented by points that fall close to each other along the dimension. Policies that exhibit contrasting spending patterns (i.e., high relative expenditures in one policy area coincide with small expenditures in another) will be shown as widely-separated points. Since the model parameters are estimated separately for each year, the point locations for the states and policies can move over time. To the extent that such movements occur, they should conform to temporal changes in state spending patterns and policy configurations.

Substantive Advantages of the Spatial Proximity Model

Before proceeding, let us consider why the spatial proximity model is a better strategy for studying state policies than the more commonly-used factor analytic approach. There are several reasons. First, our spatial proximity model incorporates a much larger set of programs. For example, Sharkansky and Hofferbert (1969) perform some preliminary analyses in order to isolate a subset of policy variables that produce a "clean" factor solution. Similarly, Klingman and Lammers only examine "... the types of policies ... that ... are associated with ... a liberal position in American politics ... (1984, page 600)." Wright, Erikson, and McIver limit their analysis to those "... policy variables that reflect the usual ideological distinctions between liberalism and conservatism (1987, page 985)." While these steps may produce more easily interpretable analytic results, they inevitably discard or ignore information about state spending and policymaking in a variety of other program areas.

The spatial proximity model avoids this problem by using data that represent almost the full range of substantive concerns that typically confront state governments. Looking across the states, the ten spending categories to be used in our analysis comprise from 80.21% to 86.95 % of total yearly state government general spending, with a mean of 83.70%. Although the data do not cover the states' complete spending profiles, they are the only categories for which complete information is available across the entire time period covered by our analysis. Furthermore, the types of spending omitted from these categories tend to make up only small portions of the states budgets, and they often represent ambiguous classifications. Thus, we are confident that our data encompass the vast majority of state program expenditures, particularly those in the most prominent areas of public policy.

Second, the geometric structure underlying the spatial proximity model is more consistent with the substantive nature of policy-making, than is the factor analytic approach. Factor analysis produces a model of the *correlational* structure in data— the degree to which the values of separate variables "go up and down together." This implies that decision makers focus their attention on simultaneous increases or decreases in expenditures across policy areas (e.g., "we are spending a great deal on welfare, therefore we will also spend a lot on hospitals"). This is an unrealistic, indeed almost nonsensical, depiction of the policy process. In contrast, the spatial proximity model is based upon distance structures— moving closer to one stimulus means moving farther away from another stimulus (e.g., "in order to increase welfare spending, we must cut highway spending"). This is much more consistent with the general give-and-take, trade-offs, and compromises, that invariably occur during the formulation of government budgets (Wildavsky 1964; Wildavsky and Caiden 1997).

Technical Advantages of the Spatial Proximity Model

Along with the preceding substantive advantages, the spatial proximity model also trumps the factor analytic approach for technical reasons. By definition, models are abstract depictions of real-world phenomena. As such, it is inappropriate to say that any model is "correct" or "incorrect." Instead, a model's adequacy should be judged according to the degree to which the empirical data can be reproduced from the components of the model, itself— a property that is sometimes called the model's "explanatory power." And, given two different models with equal levels of explanatory power, the principle of parsimony is usually applied; that is, the simpler model is preferable (e.g., Kaplan 1964; King, Keohane, Verba 1994).

Using the preceding criterion, the spatial proximity model is generally better than the factor analytic model for representing state policy commitments because it produces lower-dimensioned— and hence, simpler— depictions of the data. This contrast between spatial and factor representations of empirical data has long been recognized in the literature on scaling methods and dimensional analysis (e.g., Coombs 1964; Weisberg 1974; Davison 1983; Jacoby 1991; Van Schuur and Kiers 1994). The difference stems from the nature of the respective models and their associated geometry.

The factor analytic model represents linear correlations between columns (or rows) of the data matrix as angles between vectors. If the data contain nonrandom patterns which are also nonlinear in form, then a factor analysis will almost certainly produce "extra" factors in order to account for the nonlinearities. This is not necessarily the case with the spatial proximity model, which represents entries in the data matrix as distances between points. These distances can readily incorporate a variety of nonlinear data patterns.

The higher dimensionality that is virtually inevitable in the factor analytic approach (under certain circumstances) can be demonstrated quite easily, using some simple, hypothetical data. Table 1A shows a data matrix. The rows represent eleven "states" (labeled s_1 through s_{11}) and the columns represent three "policies" (labeled *A*, *B*, and *C*). The cells contain state policy "expenditures," so that entry x_{ij} is the amount state *i* spends on policy *j*.

Table 1B shows the correlation matrix for the policies. Note that the "total variance" in the correlation matrix (represented by the sum of the main diagonal entries) is 3.0, since each of the variables is standardized to a variance of one, and there are three variables. If this correlation matrix is used as input to a factor analysis, it produces two orthogonal factors. Figure 1 shows the resultant factor space and Table 2 gives the factor pattern coefficients, along with the communalities and the eigenvalues. Speaking informally, the communalities give the variance explained in each of the variables, while the eigenvalues give the variance explained by each factor. The sum of the communalities is 3.0, as is the sum of the eigenvalues. Hence, the factor solution accounts for 100% of the variance in the input data. Policies *A* and *C* load at opposite ends of the first factor while Policy *B*, alone, has a large loading on the second factor. For present purposes, the specific configuration of factor coefficients is less important than the fact that it takes two dimensions (or factors) to represent the data.

Now, let us fit a spatial proximity model to the same hypothetical data (i.e., from Table 1A). The rule used to construct the model is simple: Fourteen points (representing s_1 through s_{11}, A, B, and C) are arranged along a continuum such that the distances between state points and policy points (in the unidimensional case, distances can be shown as $d_{ij} = |s_i - p_j|$, where i ranges from 1 to 11, and p_j is either A, B, or C) are inversely proportional to the amounts that states spend on the respective policies. That is, $d_{ij} = k - mx_{ij}$, where m is a constant of proportionality and k is a constant that is at least as large as the maximum value in the original data matrix. For the present example, we will set $m = 1$ and $k = 10$. Figure 2 shows one possible dimension that could be constructed using this modeling approach and Table 3 gives the resultant distances between state points and policy points. Now, the correlation between the distances in Table 3 and the input data values in Table 1A is -1.00; the R^2 value is 1.00. So, the spatial proximity model also accounts for 100% of the variance in the data. But, it does so with a single dimension, rather than the two that were required in the factor analytic approach. This shows that the spatial proximity model produces a simpler, and therefore preferable, geometric depiction of the spending data.

Of course, the results presented here occur as a result of the simulated data employed in the illustrative analysis. So, it is important to ask: Under what circumstances will this difference between the two models be manifested in empirical data? One situation is particularly relevant for the present research context: A data matrix that simultaneously contains bipolarity across certain variables and consensus in others. For example, in Table 1A, states that spend a large amount on policy *A* spend very little on policy *C* and vice versa. But, all states devote at least a moderate amount of resources to policy *B* (the smallest expenditure for *B* is five, while the minimum values for *A* and *C* are both zero). This drives down the correlations between spending on *B* and spending on the other policies.

This kind of situation is very likely to occur in the context of “real” state policy expenditures. States have some discretion to allocate resources selectively across certain kinds of policies. But, there are also some services that *all* states must provide, regardless of other political or socioeconomic factors and preferences. For example, some states spend a great deal of money on natural resources, parks and recreation while others devote relatively few resources to these areas. In contrast, education always comprises the largest segment, by far, within every state's budget (Winters 1999). Thus, state policy spending does exhibit a combination of bipolar and consensual patterns. For this reason, the spatial proximity model is preferable to the factor analytic model for representing state policy spending. Again, it is not that the former is "right" and the latter is "wrong." Instead, the spatial proximity model requires fewer dimensions— i.e., it is a simpler representation— than the factor analytic model.

OPERATIONALIZING THE SPATIAL PROXIMITY MODEL

The input data for the spatial proximity model are yearly state policy expenditures. Each data value, x_{ijt}, represents the i^{th} state's relative expenditure for policy j in year t. The model parameters are estimated on a yearly basis. In other words, a complete geometric representation of the first year's data is constructed, then a complete representation is obtained for the second year's data, and so on, down to the last year in the dataset. Because of this year-by-year strategy, the calculations within any year are completely separate from those for any other year. And, in order to simplify the presentation a bit, we can temporarily drop the "t" subscript from the data values and treat the algorithm as if we are only estimating the model for a single year.

The model, itself, contains two sets of parameters: A set of 50 points representing the states (designated s_1, s_2, ..., s_{50}) and another set of 10 points representing the policy areas (designated p_1, p_2, ..., p_{10}). These two point sets are arrayed along a common unidimensional continuum such that interpoint distances are inversely proportional to state expenditures. Specifically, as state i spends more on policy j, then the distance from the point representing i to the point representing j (designated d_{ij}) gets smaller and vice versa.

For convenience in the discussion below, we will assume that the x_{ij}'s have been "reflected," so that higher spending levels actually correspond to *lower* data values. This is merely done so that distances in the spatial proximity model are now directly proportional to the data values. The reflection is easily accomplished by subtracting all of the data values from a constant. In the present case, it is natural to use a value of one as the constant, since the input data are proportions of total state spending and they accordingly sum to one within every state. The reflected data values will be shown as x_{ij}* below, in order to distinguish them from the original expenditures.

Many specific procedures— usually called "unfolding techniques"— have been developed to estimate the parameters of the spatial proximity model (e.g., Cox and Cox 2000; Borg and Groenen 1997). Our analysis uses a metric, least-squares unfolding method developed by Keith Poole (1984). The overall approach is called "unfolding" because, according to the geometry of the model, a state's profile of (reflected) spending values can be obtained by "folding" the unidimensional continuum at the location of the state's point (Coombs 1964). The scaling task is the opposite of this process: We begin with the folded versions of the dimension (i.e., the input data values) and seek to "unfold" them simultaneously across all states, in order to estimate the dimension itself (i.e., the relative positions of the state and policy points). The method is "metric" because it assumes that the input data are measured at the interval level or higher (many unfolding techniques only assume ordinal or even nominal measurement levels). The method is "least-squares" because its immediate analytic objective is to find the set of state and policy point locations such that the squared errors between distances and data values are minimized. That is:

$$\text{Minimize:} \quad \sum e_{ij}^2 = \sum_{i=1}^{50} \sum_{j=1}^{15} (d_{ij} - x_{ij}^*)^2 \qquad (1)$$

Alternatively, the procedure seeks to maximize the squared correlation between the interpoint distances and the reflected program expenditures. This squared correlation, itself, can be used as a goodness-of-fit measure for the final scale. If the data fit the model exactly, then the errors will all be zero, the squared correlation will be a perfect 1.0, and the reflected data values will be exactly proportional to the interpoint distances on the unfolded dimension.

Readers are referred to Poole's original article (Poole 1984) for theoretical background and technical development on this least-squares, metric unfolding technique. The scaling strategy is quite simple, although the notation and computations can be a bit cumbersome. The remainder of this section contains a brief, largely informal, description of the methodology.

The Conditional Global Minimum Criterion

Let us consider a strategy for estimating the positions of one point set (either state or policy points) conditional upon fixed locations of the other point set (policy or state points, respectively). For this discussion, assume that we are estimating policy points, with fixed state points. Imagine that each state point, s_i has attached to it 10 different vectors— one for each policy. The length of each such vector (say, for the *j*th policy) is equal to the state's (reflected) spending value for that policy, x_{ij}*. Since we are considering a unidimensional model, each of these vectors can only point in one of two directions; either to the left or the right of the state point to which it is attached. In either case, the terminal point of each vector, v_{ij} can be calculated as one of the following:

$$v_{ij} = s_i - x_{ij}^* \qquad (2a)$$

$$v_{ij} = s_i + x_{ij}^* \qquad (2b)$$

Condition (2a) is used when state *i*'s vector for policy *j* points to the left of the state point, and condition (2b) is used when the vector points toward the right. The sum of squared errors for any given policy, *j* can be calculated as:

$$\sum e_j^2 = \sum_{i=1}^{50} (x_{ij}^* - d_{ij})^2 = \sum_{i=1}^{50} (x_{ij}^* - |s_i - p_j|)^2 \qquad (3)$$

In equation (3), the x_{ij}* are the reflected data values and the s_i are fixed by construction; therefore, only the p_j values can be manipulated.

For any given policy, Poole (1984) proved that this sum of squared errors is minimized when the states' vectors are all pointed in the correct direction (i.e., directly toward the location of policy *j*, rather than away from it) and the policy location is estimated as the centroid of the vector terminal points. That is:

$$p_j = \frac{\sum_{i=1}^{50} v_{ij}}{50} \qquad (4)$$

This estimate of the policy point location is called the *conditional global minimum* (CGM). It is a "minimum" in the sense that it is the p_j value which produces the smallest possible value of $\sum e_j^2$. It is “conditional” because the result only holds when the state points, the s_i’s, are held fixed at their current locations. But, within this constraint, it is a “global” minimum: No other value of p_j will produce a smaller squared error.

A Scaling Procedure Based Upon CGM

The preceding result leads to a particularly simple, but exhaustive and computationally-intensive, search procedure for finding the optimal policy location, relative to the currently-fixed state points. The states comprise 50 different locations along the dimension, and their points therefore divide the dimension into 51 distinct intervals. Start by tentatively placing the policy point to the left of the leftmost state point; in this case, all 50 vectors will point to the left, and the v_{ij} values would be calculated according to equation (2a). Use equation (4) to estimate the tentative policy location (designate this $\hat{p}_j$ with the carat indicating that this is only a tentative point location at this stage of the estimation process), and also calculate the variance associated with this tentative position, as follows:

$$\mathrm{var}(\hat{p}_j) = \frac{\sum_{i=1}^{50} (v_{ij} - \hat{p}_{ij})^2}{50} \tag{5}$$

Next, “move” the policy point to the second interval from the left along the dimension (i.e., between the first and second state point locations). Note that, in doing so, one vector reverses direction—the one that originates from s_1, the leftmost state point. Calculate a new value for $\hat{p}_j$ and also a new value for $\mathrm{var}(\hat{p}_j)$. If this latter variance is smaller than the first one, then there is less error associated with this second, tentative policy point location. Therefore, the policy point should be moved to this new centroid.

This process continues, “moving” the policy point into each successive interval between an adjacent pair of state points. After the policy point has been tried in each of the 51 intervals (i.e., it is moved all the way to the right of the rightmost state point), the final policy point location estimate, p_j, is the centroid value ($\hat{p}_j$) that was associated with the smallest value of $\mathrm{var}(\hat{p}_j)$. Again, Poole (1984) proved that this is a global minimum for the amount of error associated with the position of p_j, conditional upon the current, fixed set of ideal points. Hence, p_j is referred to as the “CGM estimate” of the point location.

The “point moving” procedure is repeated for each of the 10 policies in order to obtain the least squares estimate of the point location for each one. Then, the two point sets (policies and states) are interchanged and the search procedure is repeated. In other words, the vectors are now conceived as originating from the policy points and terminating at the various state points. The policy points are held fixed at their current locations, p_1, p_2, ... p_j, ... p_{15}, and each of the 50 state points are tried in each of the 11 resultant intervals along the dimension. As before, each state’s estimated point location is associated with the centroid of vector termini that is associated with the smallest $\mathrm{var}(\hat{s}_i)$ value.

A single iteration of the CGM procedure consists of two complete sets of point movements. The first time through, one set of point locations must be specified by the researcher. In the present case, we will fix the initial state points at certain positions and estimate the policy point positions accordingly; the exact procedure for setting the initial state configuration is discussed in the next paragraph. The CGM algorithm proceeds by moving the policy points contingent upon the fixed state points, and then moving the state points contingent upon the newly-fixed policy points, and so on. The procedure is completed whenever the total sum of squared errors (calculated across all states and policies) converges to a value that does not change across iterations.

The procedure for fixing the initial positions of the state points is straightforward. And, this is where we return to the time-series structure of the data. On the first iteration for the first year’s data (i.e., $t = 1$), the state points are simply located at random positions along the dimension. The state points will be moved during the course of the unfolding procedure, so these initial estimated locations are not taken very seriously (and, tests indicate that the initial locations have little, if any, discernible impact on the final scaling solution). For all subsequent years (i.e., $t > 1$), the state points are initially located at their terminal positions from the previous year. That is, the initial estimate of state *i*’s location at time *t* is simply the s_i that was estimated at time *t*-1.

This yearly initialization strategy is not only convenient for the scaling algorithm; it is also nicely consistent with the substantive nature of governmental spending. The budgetary decisionmaking process within the states always begins with the previous years’ allocation of expenditures (Thompson 1987;

Hansen 1990; Kearns 1993). And, that is precisely what the preceding year's state point represents in the spatial proximity model.

Extensive Monte Carlo testing and several applications to real-world data indicate that Poole's unfolding technique works quite well. The scaling algorithm based upon the CGM criterion converges to a solution very quickly and it provides highly accurate estimates of the point locations. An easy-to-use SAS/IML macro program for performing this type of least-squares metric unfolding is available from the authors, upon request.

EMPIRICAL RESULTS

As explained earlier, models are never "right" or "wrong." Instead, the quality of a model is usually assessed on the basis of three criteria: (1) Parsimony or the degree to which the model simplifies the representation of the original information; (2) explanatory power or the accuracy with which the model represents the original data; and (3) analytic utility or the degree to which the model parameters are substantively interpretable and applicable to subsequent research efforts. By these criteria, the spatial proximity provides an excellent representation of the yearly state spending data.

Parsimony

Models are useful analytic tools because they provide simply depictions of complex phenomena (Kaplan 1964). The parsimonious nature of the spatial proximity model relative to the original data can be established very easily. With 50 states and 10 policy areas across 19 years, the raw data contain 9,500 distinct values. The results from the CGM unfolding algorithm contain 60 elements— 50 state points and 10 policy points— for each of the 19 years, producing only 1,140 total values. As we will see in the next section, the spatial proximity model retains virtually all of the information from the original dataset. But, it achieves an 88% reduction in the number of values that are required to represent this information. This is clearly a much more parsimonious depiction of state government spending patterns over time than the raw expenditure figures themselves.

Explanatory Power

Since models are abstract constructions, it is important to assess their fidelity to the data that they are intended to represent. If the estimated parameters are consistent with the original empirical observations, then the model has explanatory power. In the case of measurement models, such as the one under consideration here, “explanatory power”can be expressed as the validity and reliability of the measured values.

Validity is the degree to which a variable actually captures the phenomenon it is intended to measure (Zeller and Carmines 1980). With many social scientific concepts, validity assessment is problematic because the phenomenon being measured is unobservable (Adcock and Collier 2001). However, that is not the case here. The spatial proximity model is not estimating any sort of latent trait; rather it merely summarizes a set of empirically observable values (i.e., the yearly state policy expenditures). Therefore, validity can be assessed directly: The distances between the policy and state points in a given year should be inversely proportional to the states’ relative spending levels in the program areas for that year. The squared correlation between scaled distances and input spending figures summarizes the strength of the linear relationship between them. Hence, this squared correlation is not only a goodness of fit measure for the spatial proximity model; it is also a direct manifestation of the model’s validity as a summary measure of state policy expenditures.

The unidimensional spatial proximity model provides an excellent representation of the 1982-2000 state spending data. The squared correlation between the scaled interpoint distances (i.e., between states and policies) and the input expenditure figures, across all eleven years, is extremely high at 0.954. The goodness of fit varies somewhat from one year to the next, but only within a very narrow range. The minimum R^2 value is 0.946 in 1985; the maximum is 0.958 in 1990. Thus, even the worst fit is still extremely good. Overall, the scaled array of state and policy points mirrors the empirical data almost perfectly. By any reasonable standard, this extremely strong linear relationship establishes the validity of the point locations as a summary measure of state spending patterns.

Reliability refers to the proportion of variance in a set of scores that is unrelated to error (Zeller and Carmines 1980). In the present context, "error" refers to the part of a state's yearly (reflected) spending on a policy that is *not* reflected in the scaled distance between the state point and the policy point for that year. Thus, for state i and policy j in year t:

$$d_{ijt} = x^{*}_{ijt} + e_{ijt} \qquad (6)$$

The scaled distance can be expressed as the spending value minus the associated error. The total variance of the scaled distances (i.e., across states, policies, and time) can be broken down as follows:

$$\mathrm{var}(d) = \mathrm{var}(x^{*}) + \mathrm{var}(e) + 2\ \mathrm{cov}(x, e) \qquad (7)$$

To get the reliability, any variance due to error is "removed" from the total variance in the spending values. This is accomplished simply by subtracting the last two terms from the first term on the right-hand side of (7). Reliability is then measured as follows:

$$\text{Reliability} = \frac{\mathrm{var}(x^{*}) - \mathrm{var}(e) - 2\ \mathrm{cov}(x^{*}, e)}{\mathrm{var}(d)} \qquad (8)$$

All of the required quantities on the right-hand side of (8) can be calculated directly from the original spending data and the scaled point locations. Doing so produces a reliability value of 0.90. The maximum possible reliability is 1.00, so this result shows that very little of the variance in the scaling results is inconsistent with the proportional relationship between spending and interpoint distances that defines the spatial proximity model. Hence, the latter is not only a valid representation of the spending data; it is also a highly reliable measure as well.

Substantive Interpretation

Parsimony and explanatory power are necessary, but not sufficient, conditions for a useful model. The latter also entails substantive interpretability or the degree to which the model provides insights into the real-world phenomena it represents. Therefore, we need to examine the scaling results to determine what they can tell us about patterns of state policy spending. In so doing, we encounter another practical problem. Even though the spatial model is a simplification of the raw data, it still leaves a large amount of information to be digested. In order to deal with this situation, we proceed by examining graphical summaries of the scaled point locations.

Policy Points. Figure 3 provides shows a dot plot of the mean coordinate point locations (across the nineteen years) for the respective policies. The information in the dot plot is easily interpreted. To find the mean scale value for any particular policy, one merely locates the policy along the vertical axis, scans horizontally to the plotted point within the display, and then scans vertically down to the scale value located along the horizontal axis. Of course the specific values are less important, than the sizes of the differences between the policy points. The solid horizontal lines that appear for several policies in the dot plot are called “error bars.” They extend to the minimum and maximum coordinate values that occurred for each policy across the nineteen year time period. In this manner, the dot plot summarizes both the central tendency and the range of variation in the policy point locations across the entire time period under investigation.

Substantive interpretation of a scaling solution usually proceeds by considering the relative positions of the points to see if there is any systematic pattern in their placement across the dimension. While doing so, it is particularly useful to contrast points that fall consistently at opposite ends of the continuum. In Figure 3, the error bars for five policy areas are either nonexistent or extremely short. Expenditure patterns for these policies are almost perfectly stable over time. And, it is immediately obvious that these “stable” policies fall within two strongly contrasting groups: One combines programs that provide particularized benefits while the other subsumes a variety of collective goods (Jacoby and Schneider 2001). The scaled points for the former group are located near the left side of the dimension. Here, we find two policies that are designed to deal with the social and economic concerns of state constituencies, especially the neediest strata: Health care and welfare. Both of these programs involve government financing of specific benefits to particular groups within the respective state populations. At the opposite end of the continuum in Figure 3, there are several stable policies that represent broad collective goods: Natural resources, highways, and education. Such policies ostensibly benefit all of society rather than particular segments of the population (Savas 1982; Wolf 1988).

The long error bars for the remaining seven points show that relative expenditures for these program areas vary sharply over time. These policies move from one side of the dimension all the way over the other side at least once during the time period. Closer inspection of the scaled points reveals some potentially interesting patterns in the movements. Three of the policy areas— hospitals, parks/recreation, and government administration— usually fall on the particularized benefits side of the continuum, but they move over to the collective goods side for brief periods of time (i.e., no more than three years maximum). The remaining two policy areas— police/law enforcement and corrections— jump back and forth across the dimension more frequently. They also track each others movements fairly closely which is, perhaps, to be expected given the substantive nature of these policy areas.

For the moment, we are hesitant to propose any definitive explanation for these patterns of temporal change. We suspect that the point movements represent a combination of state responses to federal contributions and the ongoing need for states to balance resource allocations across policy areas. Of course, we plan to investigate these changes more closely.

Even though the points for five of the policies move over time, the central tendency in their locations still places them closer to the left, or particularized benefits, side of the scaled continuum. This seems reasonable because all of these program areas have identifiable constituencies— e.g., the law enforcement community for police spending, the recreation industry for spending on parks, government employees for administrative expenditures, and so on. Hence, governmental resources are going to fairly narrow segments of the respective state populations. Thus, the movements that occur in some of the policy point locations do not compromise the basic distinction we find between the two sets of policy areas devoted to collective goods and particularized goods, respectively.

<u>State Points</u>. Figure 4 shows a dot plot summarizing the state positions along the scaled continuum. This is the same dimension that contained the policy points discussed in the previous section. Therefore, states near the left side of the graph spend more on particularized benefits, while those near the right side spend more on collective goods.

Once again, the plotted points represent the mean coordinate for each state from 1982 through 2000, and the error bars extend to each state's maximum and minimum values across that time period. The first, obvious feature in this graph is that nontrivial error bars exist for all of the states. This shows that policy priorities do change over time. For some states, the size of the movement is quite large. This is true for New Hampshire, Michigan, Oklahoma, and Arizona. The spending priorities in these states swing back and forth between collective goods and particularized benefits. In other states (e.g., New York, South Dakota, and Wyoming) the error bars are quite short. In such cases, states maintain the same general "mix" of policy priorities over time. The vast majority of the states fall in between these two extremes. They show some degree of change in their spending patterns, but not enough to signal a major refocusing of their policy priorities over time.

A second interesting feature in Figure 4 is an apparent regional pattern in the state point locations. Northeastern states, like New York and Massachusetts, are located at one end of the dimension, and western states, such as Wyoming and Idaho, at the other. This result is fully consistent with previous research that emphasizes region-based contrasts in American state politics (e.g., Elazar 1984; Garreau 1981; Gray 1999). But, region does not account for all of the differences in state locations. For example, the mean point coordinates for Michigan, California, and Illinois fall among the northeastern states near the left side of the scale, while mean coordinates for Indiana, North Carolina, and West Virginia are located on the right side, among the predominantly western states. And, there are quite a few other anomalous placements like these. This suggests that a regional interpretation of the scale has limited substantive utility. In fact, the relative locations of the state positions correspond more closely to identifiable differences in policy orientations. Therefore, we believe that the scale should be interpreted from this latter, more explicitly political, perspective.

Consider the state points that fall near the left end of the unfolded continuum (or near the lower extreme of the vertical axis in Figure 4). These include virtually all of the states that are commonly identified as innovators or leaders in their policy activities, such as New York, Massachusetts, and Michigan (Nathan, Doolittle, and Associates 1987; Leichter 1992; DiIlulio and Nathan 1994). These states tend to be progressive and highly active in orientation, aggressively taking positive steps to deal with social problems as they arise. In contrast, the states near the right side of the continuum (shown near the upper end of the vertical axis in Figure 4) are usually noted for being more cautious in their orientations toward government involvement in social and economic issues. States such as Wyoming, Idaho, and Utah are less likely to take action in the first place, and when they do so, their steps tend to be relatively narrow and limited in nature.

The states in the center of the dimension exhibit two characteristics. First, some are truly moderate in their policy orientations. For example, Missouri, Florida, and Nebraska do not manifest consistently active or inactive stances in the ways that they address societal concerns (Gray 1973; Erikson, Wright, and McIver 1993). Second, several of these centrally-positioned states are policy innovators, but only within limited substantive areas. For example, Oregon has taken important proactive steps in the field of health care (Neubauer 1992), Minnesota is well-known as a state willing to experiment with education and prison reform (Lewis and Maruna 1999), and Wisconsin was the first state to experiment with “welfare reform” (Corbitt 1995; Mead 2001). But, these states are not particularly active (at least in terms of spending allocations) across the full range of policy areas (Hovey 1996, 1997, 1999, 2002, 2004). Therefore, it seems very reasonable that they are located in central positions between the other states that are more consistent in their orientations toward governmental policy activities.

COMPARISON TO OTHER STATE POLICY VARIABLES

From the results so far, we contend that the spatial proximity model provides an excellent representation of the yearly state spending data; it possesses considerable internal and face validity as a measure of policy priorities. Still, it is imperative that we compare the unfolded state scale scores to the variables obtained from other well-known investigations of public policy-making in the American states. This is useful not only for establishing the convergent validity of the program spending scale, but also for explicating the similarities and differences among the various measures.

For this purpose, we have selected five variables: Walker’s policy innovation scores (1969); Sharkansky and Hofferbert’s “welfare-education” and “highway-natural resources” factors (1969);

Klingman and Lammer's "general policy liberalism factor" (1984); and Wright, Erikson, and McIver's "grand index (of) composite policy liberalism" (1987). These five measures of state policy activity appear very frequently in the research literature. But, they all use different data from the relative spending information that is employed in our unfolding analysis. Therefore, we believe that these variables provide excellent standards of comparison for our results.

Each of the other variables assigns only a single score to each state. In contrast, our unfolded scale provides 19 scores for each state, one for each year from 1982 to 2000. We believe the yearly nature of our measure is one of its major advantages over the alternatives. However, for purposes of comparison, we want to combine the time-series information in order to obtain a single set of state scores. So, once again, we simply use the mean point location for each state.

We also transform our unfolded scale by reversing its direction (so that larger values indicate greater priority on particularized group benefits) and recalibrating the values so that the state scores range from 0 to 100. These changes constitute a linear transformation of the original values. This is fully appropriate, since the unfolded scale is measured at the interval level. In other words, the transformed values do not alter any of the quantitative information contained in the scale. They merely provide measurement units that are more readily comparable to the other variables employed below.

Let us begin with the comparison to Walker's innovation scores. Figure 5 shows the scatterplot between the latter variable (vertical axis) and our policy spending scale (horizontal axis). The graph also contains a nonparametric loess curve to summarize the functional form of the bivariate structure. The relationship between the two variables is far from deterministic, as signaled by the dispersion in the point cloud. This is not at all unreasonable, given that Walker was measuring an ostensibly different concept with data collected more than twenty years earlier than those employed in the present analysis.

Nevertheless, the relationship between innovativeness and the spending scale is positive, monotonic, and nearly linear. The correlation between the two is quite strong at 0.73. This suggests that these two variables are tapping a common phenomenon. Walker's scores are based upon sequential *state* adoptions: “The larger the innovation score, . . . the faster the state has been, on the average, in responding to new ideas or policies” (Walker 1969: 883).

But, Figure 5 shows that this also corresponds to systematic, sequential adoptions of particular types of *policies*. Specifically, innovative states (i.e., those with large values on Walker’s measure) also spend more on particularized benefits for various groups, relative to the collective goods required for maintaining socioeconomic infrastructure (i.e., they have high scores on the unfolded scale). In this way, our measure of policy spending helps clarify the substantive implications of policy innovativeness within the states.

Sharkansky and Hofferbert’s welfare-education factor and the variables created by Klingman and Lammers and by Wright, Erikson, and McIver are all very similar to each other. So, we will examine them together. Figures 6, 7, and 8 show the scatterplots of these variables against the unfolded policy spending scale. The correlations are 0.35, 0.59 and 0.61 respectively. It is important to emphasize that Sharkansky and Hofferbert, Klingman and Lammers, and Wright, Erikson, and McIver all both provide broad summaries of overall state policy outputs. Thus, their variables simply do not measure the same thing as our unfolded scale. Furthermore, Sharkansky and Hofferbert employ data that from more than a decade prior to the earliest spending figures that are used as input to our unfolding analysis. Both of these features undoubtedly help to generate the relatively weak to moderate relationships revealed in the scatterplots.

But, there is a more immediate reason for the low correlations: The functional relationships are simply not linear. The shapes of the nonparametric loess curves in Figures 6, 7, and 8 are very revealing. In each case there is a positive and fairly steep slope in the right side of the plotting region. But, on the left side, the curve reverses direction in two plots (Figures 6 and 7) and becomes nearly flat in the other (Figure 8). This shows that the Sharkansky and Hofferbert, Klingman and Lammers, and Wright, Erikson, and McIver measures do distinguish among states that place their highest priorities on particularized benefits (i.e., those with large values on the unfolded spending priorities scale). However, these variables do not differentiate at all among those states that place greater emphasis on collective goods (i.e., those with small values on the unfolded scale).

This latter feature is perfectly understandable. For one thing, welfare is the main defining characteristic of the Sharkansky-Hofferbert factor, and it is also among the largest of the particularized-benefit policies on our policy spending scale. At the same time, Klingman and Lammers and Wright, Erikson, and McIver both explicitly measure policy *liberalism.* Therefore, they emphasize programs that provide public assistance to needy groups. And, these are precisely the kinds of policies that comprise a major component in our set of particularized benefits.

Finally, Figure 9 shows the scatterplot of Sharkansky and Hofferbert's highway-natural resources factor (vertical axis) and the unfolded policy spending scale (horizontal axis). Here, the loess curve reveals that there is a sharp, negative relationship in the lefthand portion of the plotting region. The slope remains negative, but becomes much shallower in the right side of the graph. States that emphasize highways and natural resources (according to the Sharkansky and Hofferbert variable) also place greater priority on collective goods (they fall near the lower end of the policy spending scale). This is very reasonable precisely because highways and natural resources *are* collective goods. But, once again, this variable fails to differentiate very clearly among the states that place greater emphasis on particularized benefits.

In summary, our program spending variable is related to other prominent measures of state policy activity. And, there are reasonable explanations for the differences that exist across these variables. Accordingly, we believe that the results presented in this section attest to the convergent validity of our measure. Moreover, the precise functional forms of the relationships illustrated in Figures 5 through 8 are revealing in themselves: They are very useful for interpreting and providing more specific meaning to concepts like state innovativeness and policy liberalism. This, in turn, demonstrates the analytic utility of the unfolded spending priorities scale.

CONCLUSIONS

In conclusion, our empirical analysis produces a comprehensive model of state policy priorities. This model is highly parsimonious in that it depicts states and policies as points arrayed along a single unidimensional continuum. It is powerful because the interpoint distances account for virtually all of the variation in relative policy expenditures across the states. And, the model is substantively meaningful: The empirical depiction of state policy priorities has a great deal of internal and face validity; it is also related to other state policy measures in reasonable ways. Thus, our analysis operationalizes successfully a critical aspect of the policy process.

Of course, our spatial proximity model is very different from the factor analyses that appear in most other state policy studies. But, we regard our work as an extension, rather than a refutation or contradiction, of these earlier efforts. The previous research was aimed primarily at *summarizing* the information contained in a large set of policy indicators. But, data reduction never occurs "in a vacuum;" it always involves fitting a model to the data (Coombs 1964; Jacoby 1991). When one recognizes this basic and inescapable fact, it leads easily to a consideration of alternative geometric structures or models. This is precisely how our spatial proximity representation of state policy priorities was generated in the first place.

The scaling approach presented here has a number of advantageous features that should make it a useful analytic tool. First, the spatial proximity model is based upon one specific component of the policy process— program expenditures— rather than a general amalgam of heterogenous policy indicators. This makes it easier to specify exactly which part of the policy process is being modeled than is the case with the other composite measures. Second, the unfolded scale provides a nearly perfect representation of the spending data. It explains a higher proportion of the variance in a larger number of program areas than any of the other policy variables that have been employed in political research. Third, the unfolded scores are available on a yearly basis, thereby enabling analyses over time. This is just not the case with any of the other summary measures of policy outputs. Fourth, the unfolded scale provides empirical scores for both states and policies. This makes possible systematic analyses of variability across policies which would be impossible with the other measures (which focus only on the states). Finally, expenditure allocations represent a relatively central step in the broader policy process. Therefore, our new variable facilitates investigation of both the sources and the consequences of spending priorities. For all of these reasons, we hope the scales of policy spending developed in this paper will enable and stimulate future research efforts in the field of state politics.

REFERENCES

Adcock, Robert, and David Collier. 2001. "Measurement Validity: A Shared Standard for Qualitative and Quantitative Research." *American Political Science Review* 95: 529-546.

Barrilleaux, Charles. 1986. "A Dynamic Model of Partisan Competition in the American States." *American Journal of Political Science* 30: 822-840.

Baumgartner, Frank R., and Bryan D. Jones. 1993. *Agendas and Instability in American Politics*. Chicago: University of Chicago Press.

Berry, William D., Evan J. Ringquist, Richard C. Fording, and Russell L. Hanson. 1998. "Measuring Citizen and Government Ideology in the American States, 1960-93." *American Journal of Political Science* 42: 327-348.

Beyle, Thad. 1999. "The Governors." In *Politics in the American States* (Seventh Edition), ed. Vrginia Gray, Russell L. Hanson, and Herbert Jacob. Washington, DC: Congressional Quarterly Press.

Borg, Ingwer, and Patrick Groenen. 1997. *Modern Multidimensional Scaling: Theory and Applications*. Springer-Verlag.

Brace, Paul, and Melinda Gann Hall. 1990. "Neo-Institutionalism and Dissent in State Supreme Courts." *Journal of Politics* 52: 54-70.

Budge, Ian, and Richard I. Hofferbert. 1990. "Mandates and Policy Outputs: U.S. Party Platforms and Federal Expenditures." *American Political Science Review* 84: 111-131.

Coombs, Clyde H. 1964. *A Theory of Data*. New York: John Wiley.

Cox, Trevor F., and Michael A. A. Cox. 2000. *Multidimensional Scaling*, 2nd edition. New York: Chapman and Hall/CRC.

Davison, Mark. L. 1983. *Multidimensional Scaling*. New York: John Wiley.

Dawson, Richard E., and James A Robinson. 1963. "Inter-Party Competition, Economic Variables, and Welfare Policies in the American States." *Journal of Politics* 25: 265-289.

DiIlulio, John J., Jr., and Richard P. Nathan, eds. 1994. *Making Health Reform Work: The View From the States*. Washington, DC: Brookings Institution.

Dye, Thomas. 1966. *Politics, Economics, and the Public: Policy Outcomes in the American States*. Chicago: Rand McNally.

Elazar, Daniel. 1984. *American Federalism: A View from the States* (Third Edition). New York: Harper and Row.

Elling, Richard C. 1983. "State Bureaucracies," In *Politics in the American States* (4th Edition), ed. Virginia Gray; Herbert Jacob; K. Vines. Boston: Little, Brown.

Elling, Richard C. 1999. "Administering State Programs: Performance and Politics," in *Politics in the American States* (7th Edition), ed. Virginia Gray, Russell L. Hanson, and Herbert Jacob. Washington, DC: Congressional Quarterly Press.

Erikson, Robert S., Gerald C. Wright, Jr., and John P. McIver. 1989. "Political Parties, Public Opinion, and State Policy in the United States." *American Political Science Review* 83: 729-750.

Erikson, Robert S., Gerald C. Wright, and John P. McIver. 1993. *Statehouse Democracy: Public Opinion and Policy in the American States*. Cambridge University Press.

Fiorini, Morris P. 1994. "Divided Government in the American States: A Byproduct of Legislative Professionalism." *American Political Science Review* 88: 314-316.

Fording, Richard C. 1996. "The Conditional Effect of Violence as a Political Tactic: Mass Insurgency, Welfare Generosity, and Electoral Context in the American States." *American Journal of Political Science* 41: 1-29.

Garand, James C. 1985. "Partisan Change and Shiftin Expenditure Priorities in the American States, 1945-1978." *American Politics Quarterly* 14: 355-391.

Garand, James C. 1988. "Explaining Government Growth in the U.S. States." *American Political Science Review* 82: 837-849.

Garand, James C., and Rebecca M. Hendrick. 1991. "Expenditure Tradeoffs in the American States: A Longitudinal Test, 1948-1984." *The Western Political Quarterly* 44: 915-940.

Garreau, Joel 1981. *The Nine Nations of North America*. Boston: Houghton Mifflin Company.

Goertz, Margaret E. 1996. "State Education Policy in the 1990s," In *Politics in the American States* (6th Edition), ed. Virginia Gray and Herbert Jacob. Washington, DC: Congressional Quarterly Press.

Gray, Virginia. 1973. "Innovation in the States: A Diffusion Study." *American Political Science Review* 67: 1174-1185.

Gray, Virginia. 1999. "The Socioeconomic and Political Context of States." In *Politics in the American States: A Comparative Analysis* (7th Edition), ed. Virginia Gray and Herbert Jacob. Washington, DC: Congressional Quarterly.

Hansen, Susan B. 1990. "The Politics of State Taxing and Spending." In *Politics in the American States*, ed. Virginia Gray, Herbert Jacob, and Robert B. Albritton. Glenview, IL: Scott, Foresman/Little, Brown Higher Education.

Hanson, Russell L. 1983. "The 'Content' of Welfare Polcy: The States and Aid to Families with Dependent Children." *Journal of Politics* 19: 771-785.

Hanson, Russell L. 1984. "Medicaid and the Politics of Redistribution." *American Journal of Political Science* 28: 313-339.

Hanson, Russell L. 1999. *Governing Partners: State-Local Relations in the United States*. Boulder, CO: Westview Press.

Hero, Rodney E., and Caroline J. Tolbert. 1996. "A Racial/Ethnic Diversity Interpretation of Politics and Policy in the States of the U.S." *American Journal of Political Science* 40: 851-871.

Hill, Kim Quaile, and Angela Hinton-Andersson. 1995. "Pathways of Representation: A Causal Analysis of Public Opinion-Public Policy Linkages." *American Journal of Political Science* 39: 924-935.

Hill, Kim Quaile, and Jan E. Leighley. 1993. "Party Ideology, Organization and Competitiveness as Mobilizing Forces in Gubernatorial Elections." *American Journal of Political Science*

Hill, Kim Quaile, Jan E. Leighley, and Angela Hinton-Andersson. 1995. "Lower-Class Mobilization and Policy Linkage in the U.S. States." *American Journal of Political Science* 39: 75-86.

Hofferbert, Richard I. 1966. "The Relation Between Public Policy and Some Structural and Environmental Variables in the American States." *American Political Science Review* 60: 73-83.

Hofferbert, Richard I. 1974. *The Study of Public Policy*. New York: The Bobbs-Merrill Company, Inc.

Holbrook, Thomas M., and Emily Van Dunk. 1993. "Electoral Competition in the American States." *American Political Science Review* 87: 955-962.

Hovey, Harold A. 1996, 1997, 1999, 2002-4. *State Fact Finder: Rankings Across America.* Washington, DC: Congressional Quarterly, Inc.

Jacoby, William. G. 1991. *Data Theory and Dimensional Analysis*. Newbury Park, CA: Sage Publications.

Jacoby, William G. 1997. *Statistical Graphics for Univariate and Bivariate Data*. Beverly Hills, CA: Sage Publications.

Jacoby, William G., and Saundra K. Schneider. 2001. "Variability in State Policy Priorities: An Empirical Analysis." *Journal of Politics* 63: 544-568.

Jenkins-Smith, Hank C., and Paul A. Sabatier. 1993. "The Study of Public Policy Processes." In *Policy Change and Learning: An Advocacy Coalition Approach*. ed. Paul A. Sabatier and Hank Jenkins-Smith. Boulder, CO: Westview.

Kaplan, Abraham. 1964. *The Conduct of Inuiry: Methodology for Behavioral Science*. San Francisco: Chandler Publishing.

Kearns, Paula S. 1993. "Determinants of State Budget Periodicity: An Empirical Analysis." *Public Budgeting and Finance* (Spring): 40-58.

Keiser, Lael. R, Vicky Wilkins, Kenneth J. Meier, and Catherine A. Holland. 2002. "Lipstick and Logarithms: Gender, Institutional Context, and Representative Bureaucracy." *American Political Science Review* 96: 553-564.

King, Gary, Robert O. Keohane, and Sidney Verba. 1994. *Designing Social Inquiry: Scientific Inference in Qualitative Research*. Princeton, NJ: Princeton University Press.

Kingdon, John W. 1984. *Agendas, Alternatives, and Public Policies.* Boston: Little, Brown, and Company.

Klingman, David, and William W. Lammers. 1984. "The 'General Policy Liberalism' Factor in American State Politics." *American Journal of Political Science* 28: 598-610.

Kuhn, Thomas S. 1977. *The Essential Tension: Selected Studies in Scientific Tradition and Change*. Chicago: University of Chicago Press.

Lascher, Edward L., Jr., Michael G. Hagen, and Steven A. Rochlin. 1996. "Gun Behind the Door? Ballot Initiatives, State Policies and Public Opinion." *The Journal of Politics* 58: 760-775.

Leichter, Howard M. 1992. "Rationing Health Care: Oregon Comes Out of the Closet." In *Health Policy Reform in America: Innovations from the States,* ed. Howard M. Leichter. NY: M. E. Sharpe.

Lieske, Joel. 1993. "Regional Subcultures of the United States." *Journal of Politics* 55: 888-913.

Nathan, Richard P. 1996. "The Role of the States in American Federalism." In *The State of the States*, ed. Carl E. Van Horn. Washington, DC: Congressional Quarterly.

Nathan, Richard P.; Fred C. Doolittle; and Associates. 1987. *Reagan and the States*. Princeton: Princeton University Press.

Neubauer, Deane. 1992. "Hawaii: The Health State." In *Health Policy Reform in America: Innovations from the States*, ed. Howard M. Leichter. Armonk, NY: M.E. Sharpe, Inc.

Peterson, Paul E. 1996. *The Price of Federalism*. Washington, DC: Brookings Institution.

Peterson, Paul E. and Mark Rom. 1990. *Welfare Magnets: A New Case for a National Standard*. Washington, D. C.: Brookings.

Plotnick, Robert D. and Richard F. Winters. 1985. "A Politico-Economic Theory of Income Redistribution." *American Political Science Review* 79: 458-473.

Plotnick, Robert D. and Richard F. Winters. 1990. "Party, Political Liberalism, and Redistribution: An Application to the American States." *American Politics Quarterly* 18: 430-458.

Poole, Keith J. 1984. "Least Squares, Metric, Unidimensional Unfolding." *Psychometrika* 49: 311-323.

Raimondo, Henry J. 1996. "State Budgeting: Problems, Choices, and Money." In *The State of The States* (3rd Edition), ed. Carl E. Van Horn. Washington, DC: Congressional Quarterly Press.

Ringquist, Evan J., and James C. Garand. 1999. "Policy Change in the American States," In *American State and Local Politics: Directions for the 21st Century*, ed. Ronald E. Weber and Paul Brace. New York: Chatham House.

Savas, E.S. 1982. *Privatizing the Public Sector*. Chatham, NJ: Chatham House Publishers, Inc.

Sabatier, Paul, and Hank Jenkins-Smith. 1993. *Policy Change and Learning: An Advocacy Coalition Approach*. Boulder, CO: Westview Press.

Sharkansky, Ira, and Richard I. Hofferbert. 1969. "Dimensions of State Politics, Economics, and Public Policy." *American Political Science Review* 63: 867-879.

Squire, Peverill. 1992. "Legislative Professionalizaiton and Membership Diversity in State Legislatures." *Legislative Studies quarterly* 17: 69-79.

Squire, Peverill. 1993. "Professionalization and Public Opinion of State Legislatives." *Journal of Politics* 55: 479-491.

Stone, Deborah. 1997. *Policy Paradox: The Art of Political Decision Making*. New York: W.W. Norton and Co.

Thompson, Joel A. 1987. "Agency Requests, Gubernatorial Support, and Budget Success in State Legislatures Revisited." *Journal of Politics* 49: 756-779.

U.S. Department of Commerce. 1982- 2000. *State Government Finances.* Washington, DC: U.S. Government Printing Office.

Van Schuur, Wijbrandt H., and Henk L. Kiers. 1994. "Why Factor Analysis is Often the Incorrect Model for Analyzing Bipolar Concepts, and What Model to Use Instead." *Applied Psychological Measurement* 18: 97-110.

Walker, Jack L. 1969. "The Diffusion of Innovations Among the American States." *American Political Science Review* 63: 880-99.

Weisberg, Herbert F. 1974. "Dimensionland: An Excursion into Spaces." *American Journal of Political Science* 18: 743-776.

Wildavsky, Aaron. 1964. *The Politics of the Budgetary Process*. Boston: Little, Brown.

Wildavsky, Aaron, and Naomi Caiden. 1997. *The New Politics of The Budgetary Process*. (3rd Edition), New York: Longman.

Williams, Bruce A., and Albert R. Matheny. 1984. "Testing Theories of Social Regulation: Hazardous Waste Regulation in the American States." *Journal of Politics* 46: 428-458.

Winters, Richard. 1999. "The Politics of Taxing and Spending," In *Politics in the American* States (7th Edition), ed. Virginia Gray; Russell L. Hanson; Herbert Jacob. Washington, DC: Congressional Quarterly Press.

Wolf, Charles, Jr. 1988. *Markets or Governments*. Cambridge, MA: The MIT Press.

Wright, Gerald C., Robert S. Erikson, and John P. McIver. 1987. "Public Opinion and Policy Liberalism in the American States." *American Journal of Political Science* 31: 980-1007.

Zeller, Richard A., and Edward G. Carmines. 1980. *Measurement in the Social Sciences*. New York: Cambridge University Press.

Table 1A: Hypothetical Data on Eleven States' Expenditures across Three Policy Areas.

	Policies		
	A	B	C
s_1	10	5	0
s_2	9	6	1
s_3	8	7	2
s_4	7	8	3
s_5	6	9	4
s_6	5	10	5
s_7	4	9	6
s_8	3	8	7
s_9	2	7	8
s_{10}	1	6	9
s_{11}	0	5	10

Table 1B: Correlation Matrix for Hypothetical State Expenditures on Three Policy Areas.

	A	B	C
A	1.00	0.00	-1.00
B	0.00	1.00	0.00
C	-1.00	0.00	1.00

Data Source: Hypothetical data created by the authors.

Table 2: Factor Pattern Coefficients (or "Factor Loadings"), Communalities, and Eigenvalues from Factor Analysis of Hypothetical State Expenditure Data.

	Factors		
	Factor 1	Factor 2	Communalities
A	1.00	0.00	1.00
B	0.00	1.00	1.00
C	-1.00	0.00	1.00
Eigenvalues	2.00	1.00	3.00

Table 3: Interpoint Distances Obtained from the Spatial Proximity Model of Hypothetical State Expenditures.

	Policy Points:		
State Points:	A	B	C
s_1	0	5	10
s_2	1	4	9
s_3	2	3	8
s_4	3	2	7
s_5	4	1	6
s_6	5	0	6
s_7	6	1	5
s_8	7	2	4
s_9	8	3	3
s_{10}	9	4	2
s_{11}	10	5	1

Figure 1: Factor Space Obtained from Factor Analysis of Hypothetical State Expenditure Data.

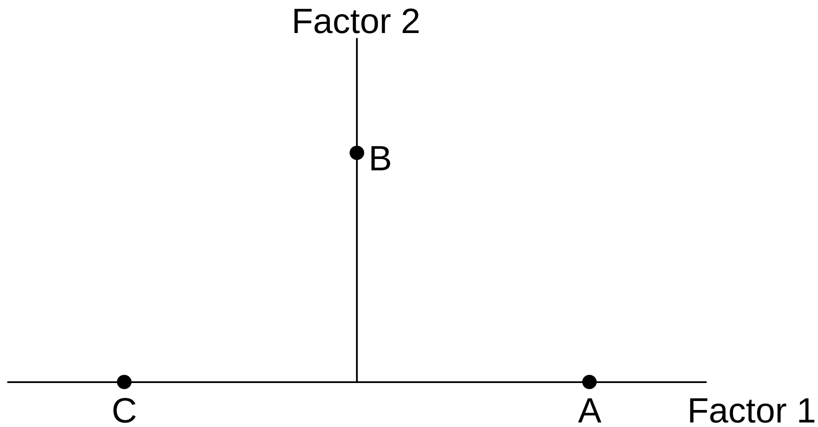


Figure 2: Spatial Proximity Model of Hypothetical State Expenditure Data.

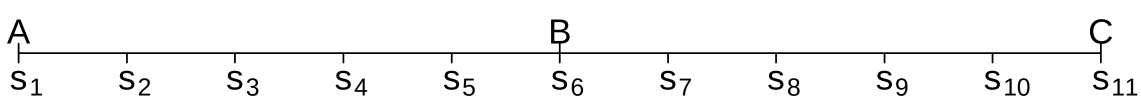
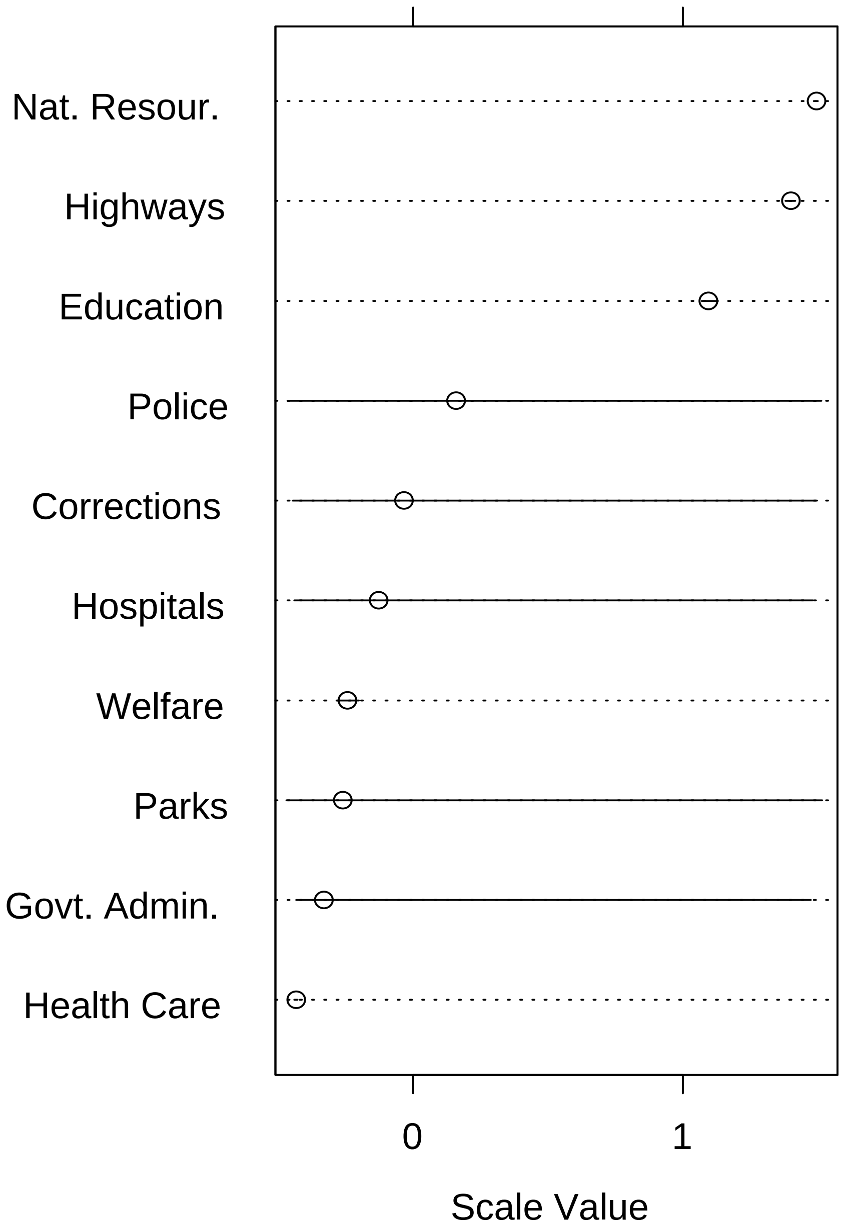
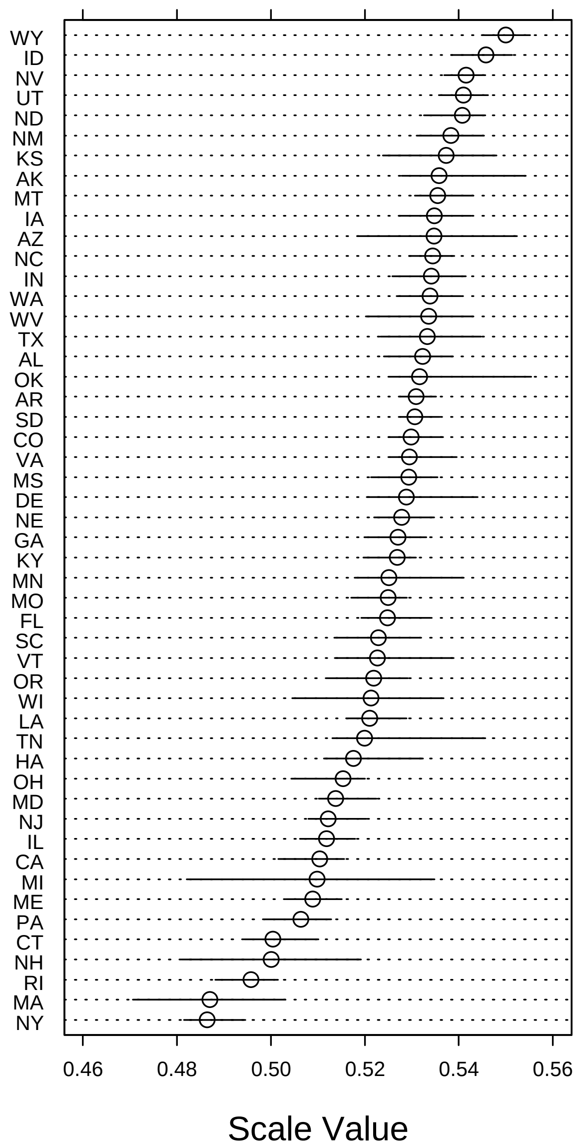


Figure 3: Dot plot showing the mean score for each policy. Means are calculated from the yearly policy scores for the nineteen-year time span (1982-2000). Error bars extend to the maximum and minum scale scores for each policy across that time period.



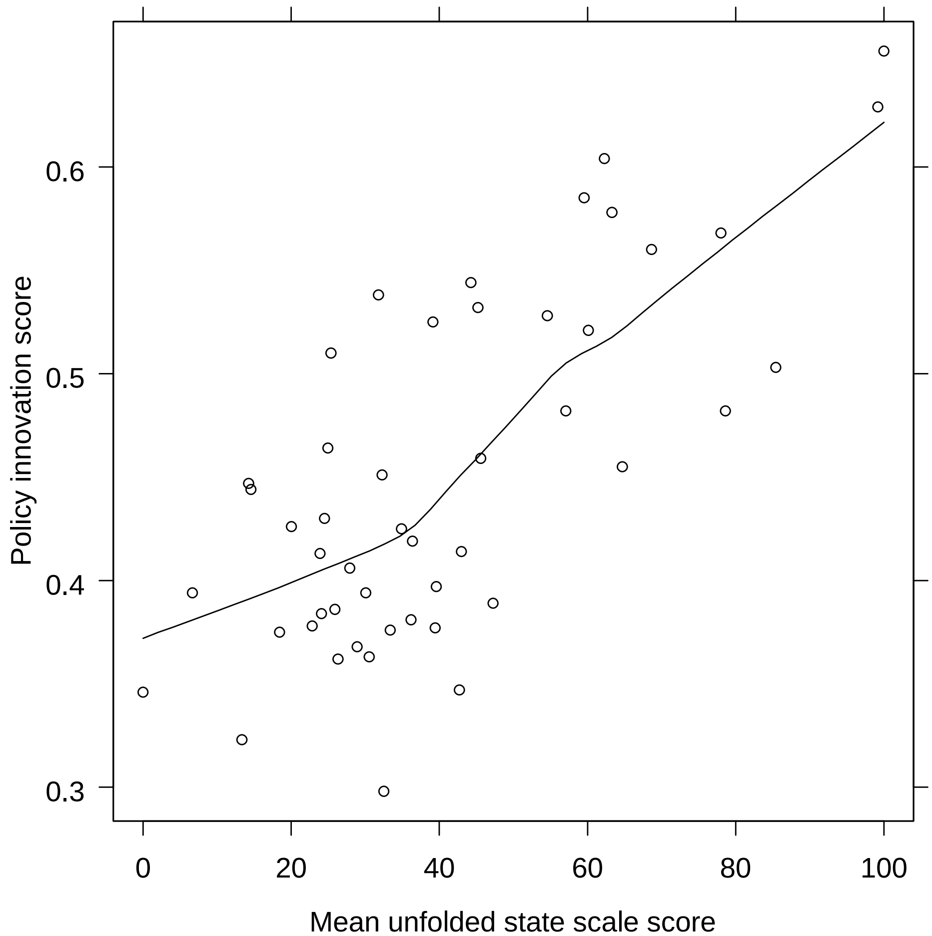
Source: Output from unfolding analysis of state spending data, 1982-2000.

Figure 4: Dot plot showing the mean score for each state. Means are calculated from the yearly state scores for the nineteen-year time span (1982-2000). Error bars extend to the maximum and minum scale scores for each state across that time period.



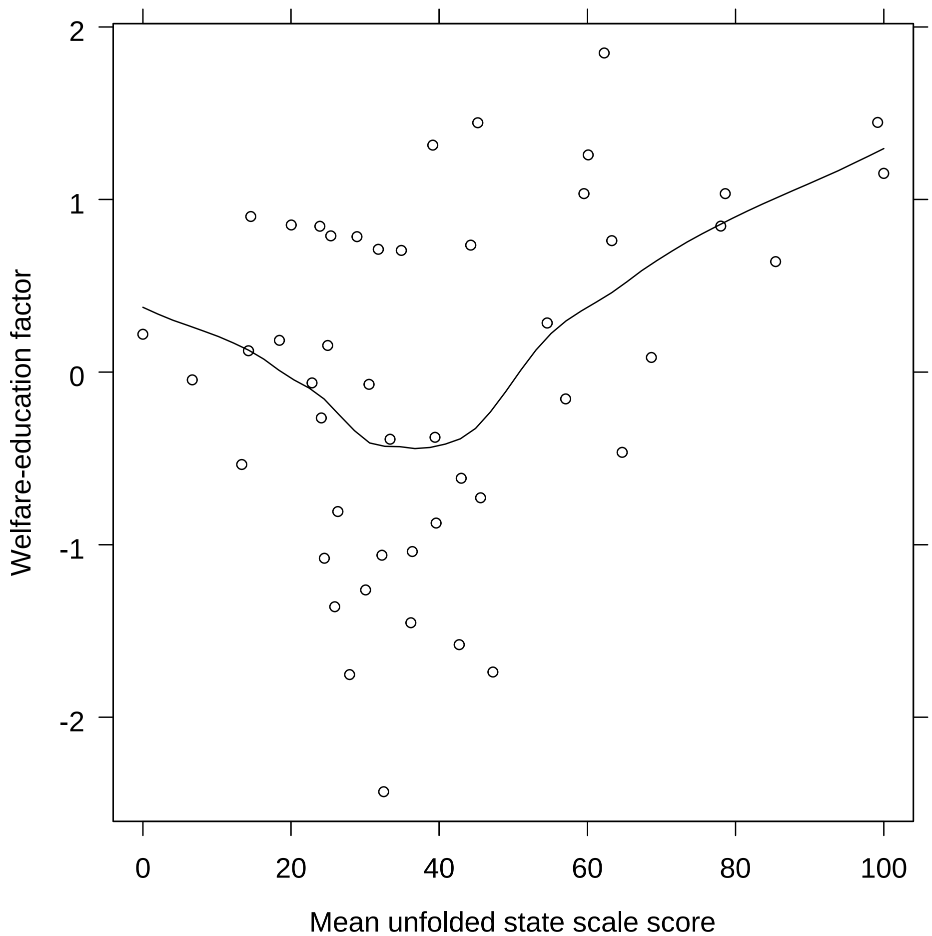
Source: Output from unfolding analysis of state spending data, 1982-2000.

Figure 5: Scatterplot of mean unfolded state scale scores versus Walker's index of State Policy Innovation.



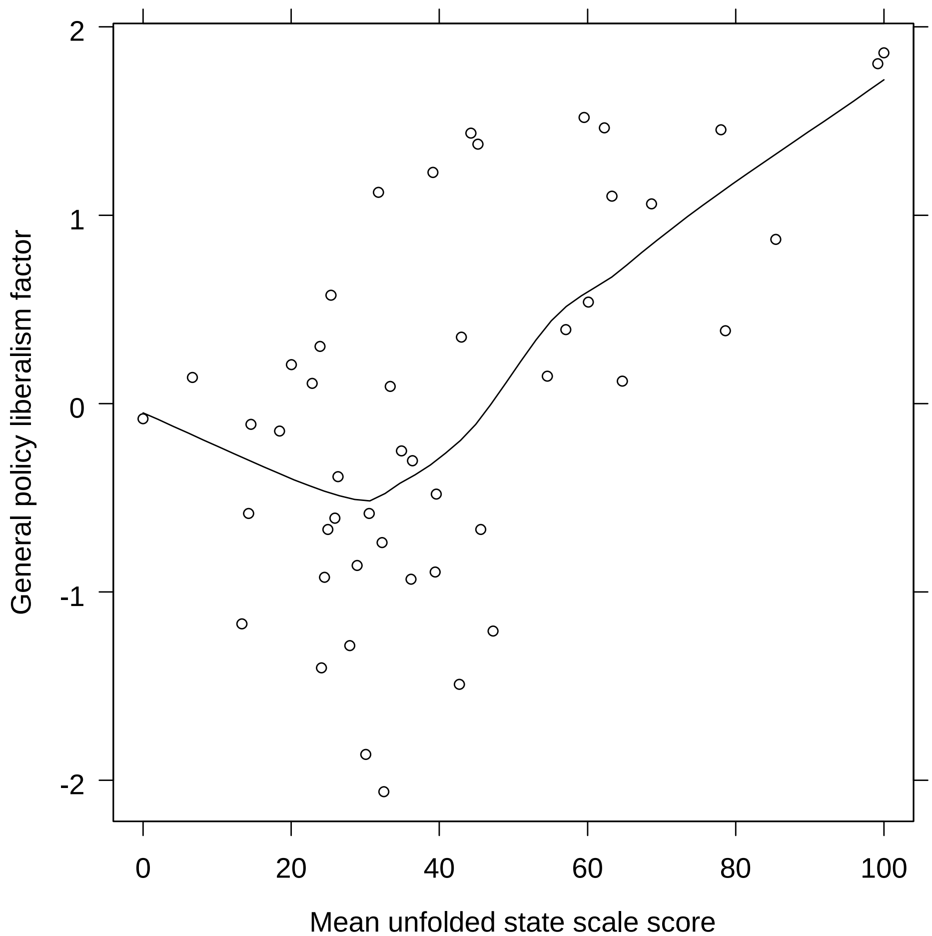
Source: Mean state scale scores are from the unfolding analysis of the 1982-2000 spending data; mean values are calculated for each state across the 19-year time span of the dataset. The policy innovation scores are obtained from Walker (1969).

Figure 6: Scatterplot of mean unfolded state scale scores versus Sharkansky and Hofferbert's welfare-education factor.



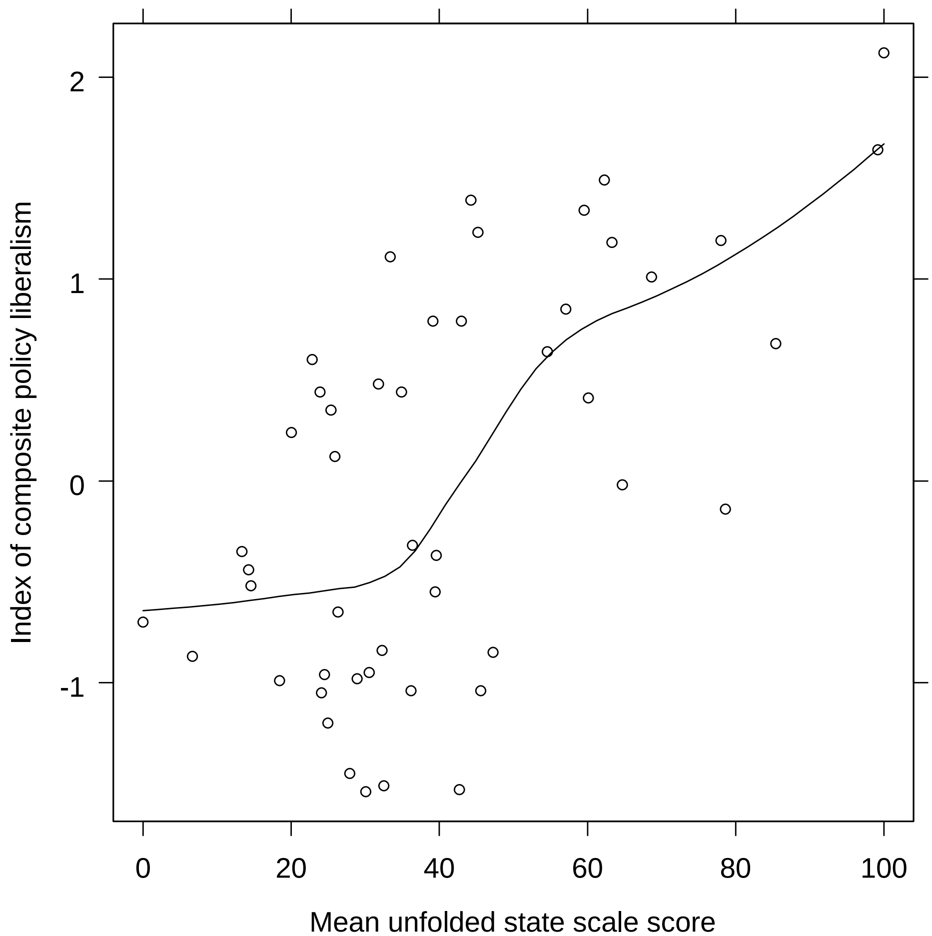
Source: Mean state scale scores are from the unfolding analysis of the 1982-2000 spending data; mean values are calculated for each state across the 19-year time span of the dataset. The scores for the welfare-education factor are obtained from Sharkansky and Hofferbert (1969).

Figure 7: Scatterplot of mean unfolded state scale scores versus Klingman and Lammers' general policy liberalism factor.



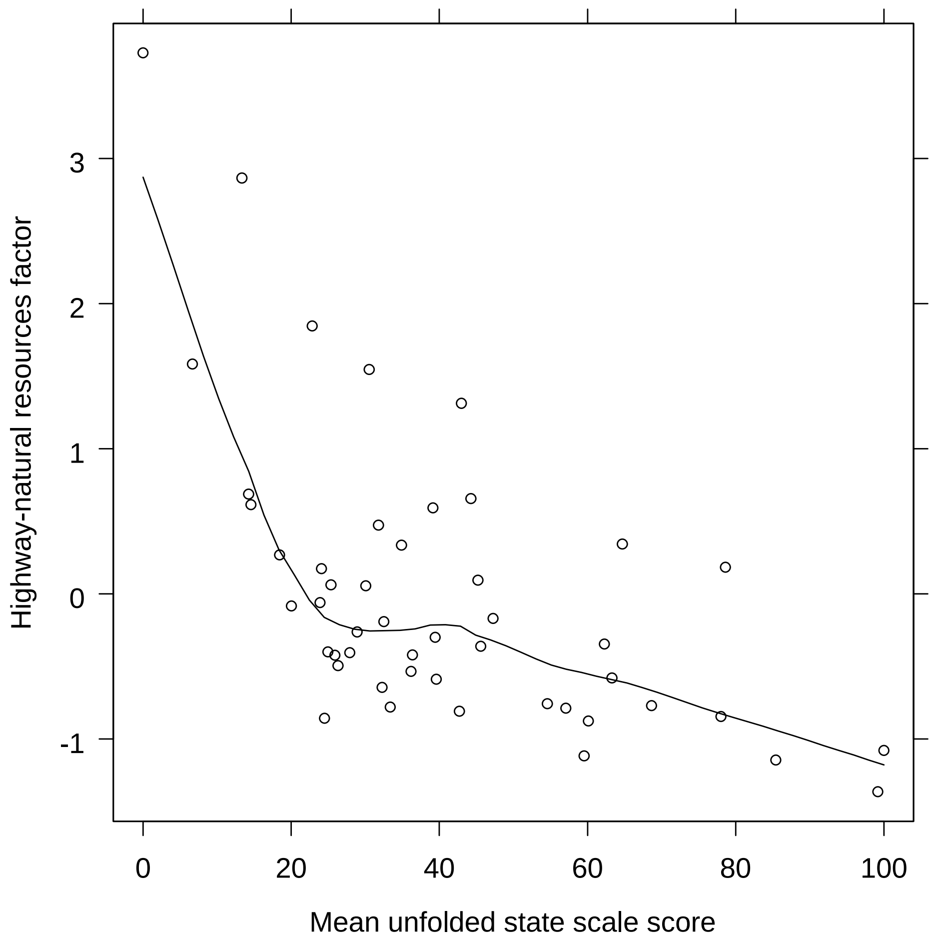
Source: Mean state scale scores are from the unfolding analysis of the 1982-2000 spending data; mean values are calculated for each state across the 19-year time span of the dataset. The general policy liberalism factor scores are obtained from Klingman and Lammers (1984).

Figure 8: Scatterplot of mean unfolded state scale scores versus Wright, Erikson, and McIver's index of composite policy liberalism.



Source: Mean state scale scores are from the unfolding analysis of the 1982-2000 spending data; mean values are calculated for each state across the 19-year time span of the dataset. The scores for the composite policy liberalism index are obtained from Wright, Erikson, and McIver (1987).

Figure 9: Scatterplot of mean unfolded state scale scores versus Sharkansky and Hofferbert's highway-natural resources factor.



Source: Mean state scale scores are from the unfolding analysis of the 1982-2000 spending data; mean values are calculated for each state across the 19-year time span of the dataset. The scores for the highway-natural resources factor are obtained from Sharkansky and Hofferbert (1969).