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Space Is More than Geography: Using Spatial Econometrics in the Study of Political Economy

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Although spatial econometrics is being used more frequently in political science, most applications are still based on geographic notions of distance. Here we argue that it is often more fruitful to consider political economy notions of distance, such as relative trade or common dyad membership. We also argue that the spatially autoregressive model usually (but not always) should be preferred to the spatially lagged error model. Finally, we consider the role of spatial econometrics in analyzing time-series–cross-section data, and show that a plausible (and testable) assumption allows for the simple introduction of space (however defined) into such analyses. We present examples of spatial analyses involving trade and democracy.

The goal of comparative research is invariably to test hypotheses about certain relationships between unit attributes and variation in outcomes of interests. However, as Galton (1889) pointed out over 100 years ago, inferences from comparisons across units assuming that observations are independent can yield misleading conclusions if the outcome of interest varies because of diffusion among units rather than functional relationships between the attributes compared. Although diffusion processes may well underlie many of the phenomena studied by political scientists, most political economy research still relies on statistical models that assume that the individual obser-

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vations are independent of one another. Spatial statistical models provide ways to test and accommodate various forms of dependence among observations.

Spatial econometric models have begun to make inroads into the study of political science, and, in particular, the study of international relations. This is evidenced, for example, by the various articles in the special issue of *Political Analysis* (10:3), as well as Gleditsch (2002a), Gleditsch and Ward (2000), and Cho (2003). Spatial econometrics has its roots in the study of geography, so naturally these applications have typically used geographic notions of distance in their spatial model specification. However, there is no inherent reason for why spatial distance should need to be limited to geographic or Euclidean distance.

In this paper, we introduce some common spatial statistical models that can be used to estimate specified forms of dependence among observations in political science research. We first show how the basic framework can be used with alternative conceptions of space other than geographical distance, using the relative importance of geographic neighbors and trading partners in analyses of the distribution of democracy as an example. We then show how spatial statistical models can be used to model dependence between dyadic observations, where the same units enter into many related dyads. Finally, we extend our discussion to time-series-cross-section (TSCS). Although it is difficult to estimate TSCS models with simultaneous spatial dependence, assuming that spatial influences operate with a temporal lag provides a practical alternative that can greatly facilitate estimation.

The Spatial Econometric Model

In this section, we lay out the basic spatial econometric model. For simplicity, we assume that y is a continuous variable.[1] Although much of our interest is in TSCS data, where units (nations or dyads) are observed annually over a long time period, we begin with a simple cross-sectional setup to avoid adding the complications of time. As the standard model is well described elsewhere (Anselin 1988), our overview will be relatively brief and will omit many of the technical details, particularly those related to the important issue of computation.[2]

As is done in all spatial econometric works, we assume that the structure of dependence between observations is known by the researcher and *not estimated*. This structure of dependence is given by what is known as the "connectivity matrix," which specifies the degree of interdependence between any two observations. The assumption that these connectivities are known a priori is both a strong assumption and critical for the methods of spatial econometrics to work. Of course, it is no stronger than the typical implicit assumption that all connectivities are zero, that is, all observations are spatially independent. As we shall see, political science can give us insight into the nature of the connectivities.

We denote the connectivity matrix by **W**, where a typical element, w_{ij}, has a value greater than 0 if the observations i and j are connected. By convention, units are not considered to be connected to themselves, so any diagonal entry $w_{ij} = 0$. In our discussion, we will assume that we are dealing with situations where no observation is an isolate without any ties to other observations (i.e., we rule out that any row is made up only of zeros, though of course there may be situations where such an assumption is unwarranted). The connectivity matrix is usually (row) standardized

[1] If y is discrete, the spatial setup is much more difficult and we do not pursue it here. See Ward and Gleditsch (2002) for one approach to this problem.

[2] Pace and Barry (1997) provide an excellent treatment of technical estimation issues. Bivand (2002) has implemented some of the spatial models discussed in this paper for R. All models in this article were estimated using LeSage's *Spatial Econometrics* MATLAB toolbox, available at http://www.spatial-econometrics.com/. Readers interested in estimating spatial models are directed to that most helpful site.

so that each row of **W**, denoted by $\mathbf{w}_i$, sums to unity. As a consequence, it is not critical to worry about the units to measure connectivity, since **W** is invariant to affine transformations.[3]

In a geographic connectivity matrix, the notion of observations being "nearby" one another is determined purely by physical distance. Geographically oriented spatial econometricians use one of two connectivity measures: either a binary measure of contiguity—whether units are closer than a certain specified threshold or a continuous measure of distance between two units, which could be based on distances between some reference point such as the capital city or the minimum distance between the two closest points on the countries' outer boundaries. However, although "nearby" is usually taken to mean geographical closeness, there is no reason why we cannot use any notion of nearness that makes theoretical sense, so long as this is specified by the analyst and so long as it does not violate any of the assumptions about the connectivity matrix stated above. In the following sections, we will return to this issue and show how spatial methods, with suitably defined non-geographic notions of "distance," can be used in several applications of interest to political economy scholars.

We start with the standard linear regression model and show how spatial dependence will give rise to violations of the classical regression assumptions. Let y_i represent some dependent variable of interest (for unit i, often referred to as "the current country"), and, as usual, we assume it is a linear function of covariates, i, and some unmeasured variables, "the error," ε_i, so that

$$y_i = X_i\beta + \varepsilon_i. \tag{1}$$

Linearity here is purely for ease of notation, and any nonlinear extensions available in typical econometric models are also available in the spatial framework.

The most critical assumption, other than that the specification of the model is correct, is that the covariates are independent of the error process. We also begin with that assumption, but then weaken the assumption that the error process (and hence the $y_i|x_i$) is independent across observations. The basic spatial insight is that "errors" ε_i (best thought of as omitted or unmeasured variables) in the current unit, i, are related to the "errors" ε_j in other units.

Spatially Lagged Errors

Letting $\mathbf{w}_i$ be the ith row of **W**, that is, the vector for how "close" the other units are to the current unit, and letting ε be the vector of all errors, we get the "spatially lagged error" model (or what Anselin 1988 calls the "spatial error" model):

$$y_i = \mathbf{x}_i\beta + \varepsilon_i + \lambda\mathbf{w}_i\varepsilon. \tag{2}$$

If $\lambda = 0$, this reduces to the standard non-spatial linear regression model. λ is the only spatial parameter in this setup that is actually estimated.

If $\lambda \neq 0$, OLS is still unbiased and consistent, but the reported standard errors will be wrong and the estimated coefficients $\hat{\beta}$ will be inefficient. This can be fixed by typical GLS reasoning (that is, transforming the model to one that can be suitably estimated by OLS, with the transformation estimated from examining the residuals of an initial OLS estimation), although complications require a full maximum likelihood estimation.

The spatially lagged error model corresponds to the model in time-series analysis, where the errors show some temporal correlation process. The analogy to the

[3] Normalizing over rows implies that the net effect of connected observations is the same for all observations and that each individual neighbor has a relative weight proportional to one over the total number of connected observations. In our discussion here we will assume that this is a reasonable assumption, although one could imagine settings where this convention is not appropriate (for examples and further discussion, see Cornes and Sandler 1996; Gleditsch and Ward 2001).

time-series serially correlated error model is useful. This analogy tells us that the only way that observations are interdependent is through unmeasured variables that are correlated, in this case across space.

The spatially lagged error model is odd (at least in many applications), in that space matters in the "error process" but not in the substantive portion of the model. Moreover, if we add a new variable to the model, so that we move it from the "error" to the substantive portion of the model, the spatially lagged error model assumes that this variable no longer has a spatial impact on nearby observations. This assumption seems to us hard to defend in many applications, although we believe that this model may be appropriate for interconnectedness among observations in certain situations.

To see why we consider the spatially lagged error model odd, at least for political economy models, let y be some economic output, say growth. Growth in one country probably depends on growth in nearby countries (where we discuss the meaning of "nearby" below). In the spatially lagged error model, the only way that nearby countries have an impact is through the interrelated error terms; the error for some country is related to all the errors for all the other nearby countries. But remember that the "errors" are just the variables that we either chose not to measure, or could not measure. In particular, they are errors from the perspective of the analyst, not the perspective of policy makers in the country. Thus, if Germany grew more quickly because of some variable not included in the specification, that growth would affect all other countries. But if Germany grew more quickly because it had a left government, and if that variable were included in the specification, then this extra German growth would have no impact on the growth in other countries. As the growth of Germany's trading partners depends on overall German growth, and not just the portion we as analysts treat as the "error" term, we find that for most political economy applications (and probably most applications more generally) the spatially lagged error model seems less appropriate. This does not mean that it is never appropriate, or that one should not think about what is the appropriate model, but that the spatially lagged error model is not the one that would come to mind first. This said, the choice of specification is, of course, based upon both theory and data analysis, not presumptions. Analysts should be aware of the spatially lagged error model and use it when theory and data suggest it is appropriate.

Spatial Autoregressive Model

The spatially lagged error model is similar to the time-series serially correlated errors model. The spatial autoregressive model (also known as the "spatial lag" or "spatially lagged" y model) corresponds to the time-series lagged dependent variable model. In this model, the dependent variable is affected by the values of the dependent variable in nearby units, with "nearby" suitably defined. It differs from the spatially lagged error model, in that both the error term and the covariates in nearby units impact the current unit.[4] Thus, for example, let the dependent variable be the level of democracy in a country. It is likely that this is partly a function of democracy in nearby countries, rather than just being related to common unmeasured variables in nearby countries.

Using the same notation as above, and letting $\mathbf{y}$ be the vector of values for y, the spatial lag model has the form

$$y_i = \mathbf{x}_i\beta + \kappa\mathbf{w}_i\mathbf{y} + \varepsilon_i. \tag{3}$$

[4] In this model the covariates in the other countries only indirectly impact the current y_i, through their impact on the y_j for other countries, which then in turn impacts the current y_i. It is also possible to allow the covariates in other countries to directly impact the current y_i, by adding a $\mathbf{w}_i\mathbf{x}$ term to the model, where $\mathbf{x}$ refers to the values of the covariates for all countries. This is easy to do using standard methods, and causes no econometric problems. See Pace and Barry (1998) for a further discussion of this type of model.

Unlike the spatially lagged error model, OLS is biased and inconsistent for the spatial autoregressive model.[5] The problem lies in that the expected value of the product of the spatial lag term and the error term is non-zero.[6] This spatial autoregressive model is difficult to estimate, but it can be done by complicated maximum likelihood.[7]

The traditional spatial autoregressive model presumes that there is only one form of dependence, which can be represented in a single connectivity matrix **W**. As above, we are primarily interested in the potential for using the model with weighting vectors that are more politically inspired than the distance or proximity weights used by geographers. However, in many cases, there may be several possible networks or forms of dependence. It is possible to generalize the spatial autoregressive model to two distinct connectivity matrices, $\mathbf{W}^A$ and $\mathbf{W}^B$, and estimate separate parameters, κ_1 and κ_2, for the relative impact of each, by

$$y_i = \mathbf{x}_i\beta + \kappa_1\mathbf{w}_i^A\mathbf{y} + \kappa_2\mathbf{w}_i^B\mathbf{y} + \varepsilon_i. \tag{4}$$

Lacombe (2004), for example, uses such a model to estimate parameters distinguishing within-state unit and between-state unit effects of welfare programs on female labor force participation.

The expanded spatial autoregressive model is even more complicated to estimate than the standard spatial autoregressive model, but the same ML estimator can be generalized to this case, provided the two matrices are sufficiently different, and do not contain entirely overlapping information. (If the matrices are too similar, problems arise, which resemble those caused by multicollinearity in the OLS case. Thus, researchers must take great care in interpreting results from estimates of this type of model.)

Beyond Euclid: Non-Geographic Notions of Space

Although most applications of spatial statistics in the social sciences have used geographic distance, there is nothing in the basic framework which requires that the connectivity matrix **W** must be based on geographic distance per se.

In political science, we usually have interesting networks or linkages defined by political or social phenomena. For example, one might envision that observations are influenced not by geographically proximate units, but rather by historically shared ties (such as language or colonial history) or high levels of interactions. Deutsch and Isard (1961) make this point in an early paper that precedes the spatial econometric models discussed in this paper. Sociologists sometimes speak of social distance or Blau-space where distances between individuals are based on coordinates that are not geographical locations. In a *small world* network, two physically distant people may be "close," in that they share a common acquaintance (Watts and Strogatz 1998).

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[5] When choosing between spatial lag and spatial error models, a researcher can also rely on diagnostic tools in addition to theoretical expectations. Moran's I statistic can be used to gauge the level of spatial dependence in the residuals of an OLS regression and thus provide some justification for using more rigorous spatial econometric methods (see, e.g., Tiefelsdorf 2000 for details). In addition, Lagrange multiplier tests can be used to test for the spatial dependence in the residuals of the spatial lag and spatial error models as an indicator of which model might be more appropriate. Finally, the log-likelihood values of each model can be compared as an additional indicator of appropriateness.

[6] As OLS omits the $\kappa\mathbf{w}_i\mathbf{y}$, this becomes part of the error term. By construction this is related to the y's in the other units, and by construction these are related to y_i so that the composite error is correlated with y_i unless $\kappa = 0$.

[7] Although we use maximum likelihood throughout, there are, of course, other, simpler, ways to estimate spatial models. As our interest is not in computations, and we find LeSage's MATLAB toolbox quite adequate, we do not pursue the computationally simpler approaches and their relative advantages under particular circumstances here. We refer interested readers to Franzese and Hayes (2004), who discuss a variety of alternative estimation approaches and political science applications.

Although researchers have often suggested that dependence may be because of distances that are not necessarily geographical, we have found very few actual examples of connectivity matrices based upon things other than Euclidean distance. Dow et al. (1984) consider dependence from geographical distance as well as language similarity in an application to the diffusion of gambling. They estimate separate models for each matrix, and the relative influence of one type of "space" when the other is taken into account is not examined empirically. Conley (1999) uses a measure of the transportation costs for physical capital between countries in a study of economic growth. In a study of environmental degradation, Lofdahl (2002) considers a measure of trade with other states relative to the size of GDP to estimate the environmental impacts of globalization or economic openness. Simmons and Elkins (2004) model the diffusion of economic liberalization as a function partially of the liberalization of one's neighbors, where one's neighborhood is defined by either trade or group membership, not geography. Lin, Wu, and Lee (2005) use occupation as a way to identify connectivity between individuals in a study of national identity formation in Taiwan. Despite the prominence of the concept of social space and the clear analogies between graph theory and spatial statistical models, the existing literature has paid very little attention to the potential for applications of spatial statistics to social distances. Anselin's monograph, for example, does not contain a single example of non-geographical distance metrics.

In this paper we use two non-geographic measures of connectivity—trade and common dyadic membership—in various spatial analyses. In the next section we start by an analysis of variation in democracy among countries around the world. We focus our attention on the spatial autoregressive model here, as this model seems more useful to us in this particular application. However, the same alternative measures of space could, in principle, be used with the spatially lagged error model, and we consider one such application in the subsequent section.

The Requisites of Democracy

Following Lipset's (1960) social requisites hypothesis, an extensive literature has examined how social and economic attributes influence the likelihood that countries will be democratic. However, there are many reasons to suspect that the level of democracy in one country could be influenced by the level of democracy in other states.[8] Previous analyses have considered diffusion in the context of relations between countries that are geographic neighbors. However, there is no particular reason why connections between states must be limited to geographic distance, and much casual evidence suggests that the nearest or most relevant actors are not necessarily the geographic neighbors. Moreover, we have no theory which specifies a priori that one particular distance measure is correct. So here we estimate a model with two measures of distance, and allow the data to suggest the relative importance of the two. Our measure of democracy is taken from the Polity IV data (we use a modified version, including estimates for countries not included in the original Polity data based on the Freedom House data, see http://weber.ucsd.edu/~kgledits/Polity.html). We use the full 21-point institutionalized democracy scale suggested by Jaggers and Gurr (1995).

Defining Connectivity and Space

We use two plausible definitions of connectivity between states. Clearly, diffusion between countries may be likely to occur between nearby countries in a geograph-

[8] See Gleditsch (2002a) for a more extended discussion. In his book *Polyarchy*, Dahl (1971) included the international context as one of the many potential influences on democracy, but this received little attention in subsequent work.

ical sense. This is the basis for our first connectivity criterion, using the geographical distance between states. We use the minimum distance data from Gleditsch and Ward (2001) to define countries as connected if they are within 500 km of one another. This yields a binary connectivity matrix where each entry w_{ij} is 1 if state i and state j are within 500 km from each other. Each neighboring country is given equal weight in the row for country i. We normalize the matrix so that each row sums to 1.

Our second specification of connectivity is based on the volume of trade flows, taken from the Expanded GDP and Trade data (version 4.1) described in Gleditsch (2002b). A country is considered connected to all other countries with which it has some trade. However, countries tend to be more dependent or influenced by their major trading partners, where the bilateral trade flows are large relative to a country's total trade. As in the previous case, we normalize the matrix so that each row sums to 1. The trade connectivity matrix differs from the previous distance matrix in two notable ways. First, whereas the distance matrix assigns equal weight to any geographical neighbor, the trade matrix consists of weights where the importance of another state j to state i is given by the volume of the dyadic trade flow between i and j as a proportion of country i's total trade. This weighs larger trading partners much more heavily than smaller trading partners. Moreover, in the distance matrix, any neighbor of i must always have i as a non-trivial neighbor. In the trade matrix, however, it will often be the case that one country, say El Salvador, has another country, say the United States, as its major trading partner, yet in turn is a relatively small and trivial trading partner to the other country.[9]

Clearly, the bases for each of the specifications of connectivity matrices are quite different, and the spatial lag measures for democracy based on geography and trade look quite different from one another. Although trading patterns are also geographically clustered and the two final spatial lag vectors are positively correlated with one another (0.616), the matrices based on the two definitions of connectivity are not so similar as to be indistinguishable from one another. Whereas the spatial lag of democracy defined over distance has a bimodal density function, much like the density of the democracy variable itself, the spatial lag of democracy defined over the trade flow matrix has a single peak, with a mean much higher than the median (or even mean) of the democracy variable. One interesting feature of the trade matrix is that some more-open developing countries have the bulk of their trade with large, wealthier countries, which more often tend to be democratic. As a result, these developing countries that have greater openness and trade will tend to have a higher "spatial lag" or average democracy score among its trading partners. This suggests that trade may identify a very different set of pull factors than geographical proximity or influence from neighbors.

Cross-Sectional Analyses

To explore the importance of spatial linkages between observations in the distribution, we start by a cross-sectional analysis of data for the year 1998. We work with a very simple social requisites model, which explains democracy by one variable, the (natural) log of GDP per capita (in constant 1996 U.S. dollars). The results are shown in Table 1. As can be seen, the OLS results for Model 1 suggest a strong positive relationship between the log of GDP per capita and the level of democracy.

However, as previously discussed, the OLS coefficient estimate of the log of GDP per capita may well be biased if values on democracy cluster spatially beyond what can be accounted for by differences in GDP per capita. The maximum-likelihood estimates of a spatially autoregressive model with a lagged term defined by

[9] This attests to the fact that the appropriate spatial weighting matrix for many research purposes will be asymmetric. Thus, methods that symmetrically decompose a covariance structure may often be inappropriate.

TABLE 1. Democracy and Social Requisites, 1998

Variable	*OLS (1)*	*Spatial Autoregressive Estimates* (2)	(3)	(4)
Constant	– 19.71 (3.66)	– 12.96 (3.35)	– 19.39 (3.39)	– 13.24 (3.11)
Ln(GDPPC)	2.66 (0.42)	1.72 (0.41)	2.22 (0.41)	1.53 (0.37)
κ_1 (distance)		0.48 (0.09)		0.89 (0.19)
κ_2 (trade)			0.51 (0.14)	0.59 (0.43)
N	170	170	170	170

Standard errors in parentheses.

geographic distances are reported as Model 2 in Table 1. The first thing to note is that the results for Model 2 in Table 1 show clear evidence of spatial clustering. The estimate of κ indicates positive spatial clustering in democracy levels across neighboring countries, and the clustering is statistically significant. Moreover, these results also indicate that the coefficient estimate and standard error of the OLS model assuming independent observations may display substantial upward bias. More specifically, we find that the coefficient estimate for the natural log of GDP per capita is reduced to less than two-thirds of its original size once we take into account the spatial clustering in democracy levels among neighboring states.

Comparing coefficients from the spatial autoregressive model to the simple non-spatial OLS model is a bit more complicated, as the spatial autoregressive model involves feedback between countries. This implies that a one unit change in GDP has an impact on democracy in the current country, which then feeds through to democracy in all the other countries (through the spatial lag), and these then feed back to the current country (again through the spatial lag), and so forth, until some equilibrium is reached (as the effects in the second and subsequent round of adjustments get smaller and smaller). It should be noted that this issue does not arise for the spatially lagged error model, as changes in the covariates do not feed through to other units (indeed, this is why we regard this model as generally less compelling).

To be more precise, consider the thought experiment of the effect of a unit change in some component of $\mathbf{x}_i$ in equation (3). After going through the loops described in the preceding paragraph, and assuming that the relevant matrix is non-singular so that a new equilibrium y exists, it must be the case (letting $\mathbf{y}$ be the vector of the values of the dependent variable for all units and $\mathbf{X}$ the matrix of all independent variables for all units) that

$$E(\mathbf{y}) = [I - \kappa\mathbf{W}]^{-1}\mathbf{X}\beta. \quad (5)$$

This shows that the effect of a unit change in a single independent variable is just the β for that independent variable times the row of $[I - \kappa\mathbf{W}]^{-1}$ corresponding to the current unit. Note that as κ goes to zero, this effect converges to the OLS estimate of the relevant β. The impact of a one unit change in an independent variable in a country depends on its connections with other countries in the system, and will vary from country to country. In the case of the connectivity matrix for geographical distance, we find that the effect of a unit increase in the log of GDP per capita ranges from a 1.75 to a 2.04 point increase in the level of democracy, with an average effect of a 1.80 point increase.

The results for Model 2 with the trade connectivities matrix in Table 1 look substantially different from the geographical connectivity matrix. The estimated κ indicates significant clustering, much the same as "neighbors" defined by geographical distance, or that countries tend to see a push toward the average level of democracy among their trading partners. Stated differently, the results suggest that countries that trade more with democracies are more likely to be democratic, over and beyond what one would expect based on their wealth or income. However, the coefficient estimate for the natural log of GDP per capita changes much less relative to the OLS coefficient estimate than was the case for the geographical connectivity specifications. This implies that the clustering of democracies with respect to trading partners does not affect our estimate of the effect of GDP per capita to the same extent as the clustering with respect to geographic proximity. Computing the implied equilibrium effect taking into account feedback in the manner previously described, we find that a one unit change in the natural log of GDP per capita on average leads to a 2.24 point increase in the level of democracy, with effects for individual countries in the sample ranging from 2.22 to 2.52.

So far we have assumed a single spatial dimension in each regression. To see the relative contribution of each definition of "space" once the other is taken into account, we now turn to cross-sectional analyses where we estimate different parameters for each of the different "spatial" metrics. The results from a spatial autoregressive model with *both* distance and trade connectivities (as in equation (4)) are reported as Model 3 in Table 1. The two matrices $\mathbf{W}^A$ and $\mathbf{W}^B$ are here jointly row-normalized, so that the rows for the two matrixes $\mathbf{w}_i^A + \mathbf{w}_i^B$ sum to 1 for each unit i.[10]

The first thing to note is that the estimated κ coefficients are all positive, suggesting that a country's level of democracy is positively associated with the extent of democracy among its geographic neighbors and trading partners. However, whereas both geographical clustering and clustering over trading partners seem to similarly matter when estimated separately, the estimated impact of spatial clustering over trade, κ_2, is smaller than the size of the coefficient for clustering over geographic neighbors, κ_1, and has a relatively large standard error.[11] This suggests that much of the clustering in democracy found over trade partners when trade connectivity was considered alone can be accounted for by geography. This is perhaps not so surprising, given that the gravity model suggests that the volume of trade flows generally declines with greater distances. However, the coefficient estimate for the impact of trade remains large. This suggests that trading relations contain information independent of geographical distance, and that democratic trade partners can pull countries toward democracy. The estimated *direct* (before feedback) effect of income is almost cut in half once these two forms of spatial dependence are taken into account. When we calculate the new equilibrium given the model, we find that the effect of a one unit change in the log of GDP per capita ranges from a 1.56 to a 2.02 point increase in the level of democracy, with an average effect of 1.63. Thus, it is important to take both spatial dependencies into account, and by using multiple forms of spatial dependencies we can make interesting inferences about the relative importance of various types of spatial dependencies.

Our next application is rather different, showing that spatial methods can solve some technical problems related to interdependent dyads. This is one of the few cases where we feel that the spatially lagged error model is appropriate.

[10] The feasible range for the spatial parameter in the autoregressive model is limited by the determinant $|\mathbf{I} - \kappa_1\mathbf{W^A} - \kappa_2\mathbf{W^B}|$. For a model with a single matrix, the range of possible values for κ is determined by the eigenvalues ω of the $\mathbf{W}$ matrix (Ord 1975). The maximum value of κ is $1/\max(\omega)$. If the matrix is row standardized, the maximum eigenvalue will be 1. This is more complicated for a model with two matrices, since the feasible range depends on the parameters κ_1 and κ_2, the matrices $\mathbf{W}^A$ and $\mathbf{W}^B$, as well as the relationship between $\mathbf{W}^A$ and $\mathbf{W}^B$. The key condition on the combination of the parameters κ_1 and κ_2 and the matrices $\mathbf{W}^A$ and $\mathbf{W}^B$ that must hold in a well-behaved model is that the inverse of the pre-multiplier $(\mathbf{I} - \kappa_1\mathbf{W^A} - \kappa_2\mathbf{W^B})^{-1}$ does not contain negative elements. The interpretation of the parameters κ obviously varies with decisions about normalizing the matrices $\mathbf{W}$. Thus, we should focus on the implied equilibrium effects rather than the κ parameters themselves.

[11] Adjusting for the rescaling of the matrices, κ_1 for Model 3 in Table 1 is similar to the κ for distance in Model 1, while κ_2 for Model 3 is considerably smaller than the κ for trade in Model 2.

Dyadic Dependence

Much analysis in international relations or international political economy is based on the dyad-year design. Most of the attention to the problem of interdependence among dyads has centered on whether the successive annual observations on the same dyad are independent (Beck and Katz 1996). However, TSCS analysts have also worried about whether observations on different units at the same time point are independent (Beck and Katz 1995). Here we consider one type of interdependence that arises in dyadic data: two dyads that contain a common member are unlikely to be independent. Perhaps even more seriously, data sets often contain the directed dyads *AB* and *BA*; these two dyads are particularly unlikely to be independent.[12] We use some spatial econometrics to help with this issue. But rather than use a geographic notion of closeness, we posit that two directed dyads are close if they share a common member, and are especially close if they are the reverse of each other.

Although we argued above that in general the spatial autoregressive model is usually theoretically more plausible than the spatially lagged error model, this is a case where the spatially lagged error model is appropriate, as the argument is that the error terms in certain dyads, not their y's, are linked. In principle, we could estimate a standard spatially lagged error model with a weighting vector that considers another dyad "near" a given dyad *AB* if they share a common member (i.e., either *A* or *B*). This has the disadvantage, however, of not distinguishing between the dyads that include either *A* or *B* (usually, this will be a large number) and the reverse dyad *BA*, composed of the same two members, but looking at the reverse flow from *B* to *A*, which is likely to be particularly influential. Thus, it is critical to consider spatial models with two distinct connectivity matrices, with the particular weight on each to be estimated.

One possibility would be to assign the weight for the reverse dyad some value v and estimate the relative weight for the reverse dyad relative to other connected dyads. In a previous paper, we estimated the value of the weight v for the reverse dyad by a search based on overall model fit (Beck and Gleditsch 2003). Another alternative that we pursue here to determine the importance of reverse dyads relative to other common member dyads (not including *BA*) is to estimate a spatially lagged error model with two matrices, where the first $\mathbf{W}^A$ includes only the reverse dyads (e.g., *BA* in the case of dyad *AB*) and the second matrix $\mathbf{W}^B$ includes connectivities for all other common member dyads. As the two matrices here are disjoint so that no non-zero element in $\mathbf{W}^A$ will be non-zero in $\mathbf{W}^B$ and vice versa, we use an approach suggested by Case (1991:959), where the two matrices are nested in a combined matrix W, with the relative weight of each as a parameter α to be estimated. More specifically, for the combined $\mathbf{W} = \alpha\mathbf{W}^A + (1-\alpha)\mathbf{W}^B$ and the estimated λ for a spatial error model based on $\mathbf{W}$, the coefficient for $\mathbf{W}^A$ is given by $\alpha\lambda$ and the coefficient for $\mathbf{W}^B$ is $(1-\alpha)\lambda$.

Example: The Politics of Dyadic Trade

Because y must be continuous, we chose a data set dealing with the political determinants of trade (viewed as exports directed from *A* to *B*). We estimate a standard political economy model of trade flows, similar to the one common in the IPE literature.[13] The non-political determinants of trade are taken to be as in a standard gravity model, where exports are regressed on the GDP and population of both

[12] The only research on this that we know of is by Mansfield and Bronson (1997), who adjoin to each model two dummy variables, one to represent each state in the dyad. As discussed in greater detail in Beck and Katz (2001), these fixed effects are not ideal in IR data.

[13] It is very similar to the basic model of Morrow, Siverson, and Tabaras (1999), except they only look at major powers.

exporter and importer and the distance between the two (all values are logged).[14] As for the political variables, we look at whether the dyad is in a Militarized Interstate Dispute (MID), the similarity of their alliance portfolios (S), and the lower of the Polity democracy scores of the two states in the dyad (DEM). To avoid the added complication of time, we have here limited ourselves to a cross-section, using only data from 1998.[15] We include all independent states in the international systems, using data from Gleditsch (2002b); other data sources are standard.

Although one can analyze very large models using sparse matrix routines, the number of non-zero entries in a connectivity matrix for dyads with common members increases very rapidly in the number of observations N. For a given N, there will be $(N-1)$ directed dyadic flows from a particular state A to the other members of the system. B likewise enters into $(N-1)$ directed dyads from B to other states. Moreover, there will be two dyadic flows from each of the remaining $(N-2)$ states in the system to A and B. Hence, it follows that for a given dyad AB there will be $2(N-1)+2(N-2)-1=4N-7$ connected directed dyads that include either A or B (not counting AB as connected to itself). For a cross-section of $N=180$, for example, we would then get a connectivity matrix with $4(180)-7=713$ entries for each row i, which in turn implies a matrix with almost 23 million non-zero weights for the $180(180-1)=32{,}220$ directed dyads.

To avoid excessive computational demands, we analyze two smaller regional subsamples. We consider two empirical examples that we believe will illustrate common situations in applied work: a European sample including only "high-quality" observations that we are relatively confident in, and an African sample including many estimates of more questionable nature. Whereas most of the European data are "observed" or reported in standard sources, an inspection of the African data reveals that many of the dyadic trade flows for the African states are based on imputations. As some of the imputations are based on assuming that flows are similar to the reverse flows or that there is no trade between countries (see Gleditsch (2002b) for a discussion of the problem of missing data in the IMF directions of trade data and possible imputation methods), they may tend to exaggerate the similarity between exports from A to B and the exports from B to A. Dropping the most contentious estimates, however, leaves very few remaining observations for African dyads. Although we believe that such strategies for addressing problems of missing data are likely to be better than simply applying listwise deletion and analyzing the remaining sample as if the observations where missing at random, many imputation techniques are known to generate serial correlation. Imputation methods based on the similarity of reverse dyads can exacerbate the problem of serially correlated errors. However, the spatially lagged error model provides a relatively simple way to address this potential problem.[16]

The OLS and spatially lagged error model results are displayed in Tables 2 and 3. In addition to the estimate λ, we report the implied terms of interests $\alpha\lambda$, indicating the estimated impact for the reverse dyad (i.e., the influence of dyad BA on dyad AB), and $(1-\alpha)\lambda$, denoting the impact of all the other common member dyads.[17]

As can be seen from Tables 2 and 3, the coefficient estimates for λ are positive and significant in both the samples. The implied $\alpha\lambda$ and $(1-\alpha)\lambda$ indicate that there is considerable similarity in the trade flows of a dyad AB and its associated common

[14] All values were logged because of the nature of the gravity model of trade used by Morrow, Siverson, and Tabaras (1999), and we use this coding here so as to be as consistent as possible with Morrow et al. This leads to nonstandard coding for dummy variables and such. However, since our interest is only on the changes in coefficients and standard errors, we need not go into this here.

[15] The method extends in a straightforward manner to TSCS data, but that introduces other issues discussed in the next section. These other issues overwhelm the discussion of dyadic dependence we wish to focus on here.

[16] See LeSage and Pace (2004) for a further discussion of missing data and imputation in the spatial context.

[17] By search, we found that for Europe $\alpha=0.32$ maximized the log-likelihood, while for Africa $\alpha=0.42$ provided the best fit to the data.

TABLE 2. Directed Export Flows, Europe, 1998

Variable	*OLS*	*Spatially Lagged Error Estimates*
Constant	– 32.70 (0.67)	– 33.68 (1.32)
Ln democracy	0.38 (0.06)	0.43 (0.12)
Ln population *A*	0.86 (0.02)	0.89 (0.03)
Ln population *B*	0.75 (0.02)	0.77 (0.03)
Ln GDP *A*	1.54 (0.04)	1.56 (0.07)
Ln GDP *B*	1.01 (0.04)	1.03 (0.07)
Ln *S*	0.33 (0.05)	0.35 (0.06)
Ln distance	– 0.34 (0.01)	– 0.34 (0.02)
Ln MID	– 1.94 (0.27)	– 1.50 (0.37)
λ		0.97 (0.01)
$\alpha\lambda$		0.31
$(1-\alpha)\,\lambda$		0.66
N	1,500	1,500

Standard errors in parentheses.

member dyads, and that this is not fully accounted for by the other covariates in the model. Moreover, the estimates from the spatially lagged error model differ notably from the OLS results which assume that the observations are independent of one another. As noted in the previous section, unlike the case for the autoregressive model with a spatially lagged dependent variable, the coefficients of the OLS and spatially lagged error models are directly comparable. In particular, we find quite large differences in the estimates for the political variables. The coefficient estimate for the democracy coefficient in the European sample increases by about 15% once we take into account the spatially lagged error structure. Likewise, the estimate for the impact of MIDs in the spatially lagged error model is reduced by about 25% from its original size in the OLS results. This is consistent with MIDs reducing not only bilateral trade flows but trade with other parties in general, so that countries in MIDs will have generally lower trade with other dyads, not just their antagonist. Clearly, many inferences about how much political factors influence trade flows seem to depend considerably on whether we are willing to assume that all observations are independent of one another, at least in the European context. Our results suggests that this assumption seems rather suspect in the analysis of trade flows.

TABLE 3. Directed Export Flows, Africa, 1998

Variable	*OLS*	*Spatially Lagged Error Estimates*
Constant	– 7.41 (0.33)	– 7.47 (1.34)
Ln democracy	– 0.04 (0.04)	0.01 (0.07)
Ln population *A*	0.26 (0.01)	0.26 (0.02)
Ln population *B*	0.23 (0.01)	0.23 (0.02)
LN GDP *A*	0.38 (0.02)	0.38 (0.04)
Ln GDP *B*	0.31 (0.02)	0.31 (0.04)
Ln similarity	3.41 (0.40)	3.43 (0.61)
Ln distance	– 0.17 (0.01)	– 0.17 (0.01)
Ln MID	– 0.71 (0.18)	– 0.42 (0.23)
λ		0.99 (0.01)
$\alpha\lambda$		0.42
$(1-\alpha)\lambda$		0.57
N	2,550	2,550

Standard errors in parentheses.

In the case of Africa, the coefficient estimates show generally smaller differences between the OLS estimates assuming independent observations and the spatially lagged error model. However, we note that the coefficient estimate for MIDs is reduced to less than 60% of its original size in the spatially lagged error model. Likewise, the proportional impact of the reverse dyad $\alpha\lambda$ relative to other common member dyads $(1 - \alpha)\lambda$ is much higher in the African sample than the European sample.

We also note that although the estimated standard error of the regression is smaller for the spatially lagged error model than the OLS estimate, the standard error estimates for the coefficient estimates are generally much larger for the spatially lagged error model, in some cases over twice the size of the OLS standard errors. In particular, in the African sample where the coefficient estimates do not differ so much, the more realistic spatially lagged error model SEs are generally more than twice the size of the OLS SEs. The large difference in the SEs likely reflects how imputations based on presuming that reverse dyads are similar are likely to induce spatially correlated errors. The spatial statistical model, however, suggests a simple way to deal with this problem in applied settings.

Of course, this does not address the question of dynamics. In a TSCS model we would expect the spatial association to matter less, once the autoregressive component in the dependent variable is taken into account. We turn to this issue in the next section.

TSCS Models

The spatial autoregressive model can be generalized for TSCS data as

$$y_{i,t} = \mathbf{x}_{i,t}\beta + \kappa\mathbf{w}_i\mathbf{y}_{i,t} + \varepsilon_{i,t}, \tag{6}$$

where observations are indexed by i (unit, usually country) and t (time, usually calendar year). For simplicity we assume that the weighting matrix is time invariant, though it is easy enough to allow for this matrix to change from year to year so long as it is known ex ante. There is also a similar obvious generalization for our less preferred spatially lagged error model.

Spatial econometricians have primarily analyzed single cross-sections. While there is recent, still unpublished, work by Kelejian and his collaborators (Kapoor, Kelejian, and Prucha, forthcoming), this is for panel, not TSCS data.[18] There is also recent work by Franzese and Hayes (2004), though their interests are orthogonal to ours.

Before beginning our analysis, it should be noted that the spatially lagged error model leads to a much more parsimonious parameterization of the contemporaneous covariance matrix of the errors, and hence deals with at least one critical flaw in the Kmenta–Parks (Parks 1967; Kmenta 1986) method as discussed in Beck and Katz (1995). The basic problem with the Kmenta–Parks method is that it allows for contemporaneous errors to be correlated with an arbitrary error structure; spatial econometricians would have specified that with a connectivity matrix. Thus, spatial econometricians would have done GLS with only one extra parameter, which works well; Kmenta–Parks, by not specifying the connectivity matrix, requires the estimation of an inordinate number of parameters. Although most TSCS analysts no longer use Kmenta–Parks, those who are considering this method should clearly prefer the spatially lagged error model. We do not pursue this further here.

[18] We will not go into the differences between these two types of data here, referring the reader to Beck (2001), other than to note that the Kelejian et al. papers deal primarily with how to combine spatial methods with random effects; random effects models are of little interest to students of political economy.

As TSCS models normally show temporal dynamics, we can add a temporal lag of y to the model, yielding

$$y_{i,t} = \mathbf{x}_{i,t}\beta + \phi y_{i,t-1} + \kappa \mathbf{w}_i \mathbf{y}_{i,t} + \varepsilon_{i,t}. \tag{7}$$

Without the spatial term $\kappa \mathbf{w}_i \mathbf{y}_{i,t}$, this equation would be easy to estimate, provided the error process shows no temporal correlations, so that the lagged y is independent of the error process. Equation (7) is often reasonable in practice, although of course it *must* be tested via a Lagrange multiplier test (Beck and Katz 1996), to make sure that the errors are temporally independent. However, the presence of the lagged dependent variable in equation (7) makes the Jacobian of the transformation in the ML estimator for the spatial autoregressive model very complex, and, so far as we know, no one has come up with a satisfactory estimator for this model.

TSCS data, however, allow an alternative specification of the spatial autoregressive model, which is simple to estimate. Of course we choose specifications that are theoretically sound, not because they are easy to estimate, but if this specification is theoretically plausible, then the ease of estimation should not be sneered at.[19] Suppose that we continue to maintain that $y_{i,t}$ is related to the neighboring y's, but we believe that this impact occurs with a one-period lag. This is often at least as plausible as spatial lags having an instantaneous effect, though of course this plausibility varies by what is being modeled and the theory available to the researcher. For example, for political economy models, we would need to decide whether we expect it to be more likely that the growth of neighboring countries immediately affects growth or that it affects growth with a temporal lag.[20] The latter case yields the model

$$y_{i,t} = \mathbf{x}_{i,t}\beta + \phi y_{i,t-1} + \kappa \mathbf{w}_i \mathbf{y}_{i,t-1} + \varepsilon_{i,t}. \tag{8}$$

This is identical to equation (7), save for the use of the lag $y_{i,t-1}$ in the term $\kappa \mathbf{w}_i \mathbf{y}_{i,t-1}$.[21] If one is willing to assume that spatial effects occur with a temporal lag and the errors are temporally independent, this model is easy to estimate via OLS.[22]

TSCS Analysis of Major Power Trade

We return to a model of trade similar to that analyzed in the previous section. Here, however, we work with only the dyads made up of the seven major powers (as in Morrow, Siverson, and Tabaras 1999) for the period 1907–90. We believe that the dependence between dyadic trade flows can be modeled with a 1-year time lag rather than instantaneously to be defensible on substantive grounds. Adjustment is likely to occur based on observed flows, or recorded past flows, rather than anticipated current flows. As in our previous trade examples, the dependent variable is the natural log exports of one country to another (in constant dollars). We follow

[19] Ease of estimation, that is being able to do OLS, allows the analyst to model many other features of the data. Committing to a complicated spatial model makes it almost impossible to solve many other problems, problems which may be as, or more, important. Thus, ease of estimation is not simply to be preferred by lazy analysts.

[20] For annual data, this lag would have to be yearly, so we only need compare instantaneous neighbor effects and those that take a year to set in. For data measured quarterly or monthly we have more choices, but such data are rare in the study of political economy. We stress that there are clearly situations where spatial effects are likely almost instantaneous, such as in financial markets (interest rate changes in other countries literally have an instantaneous effect). For trade we are comfortable with the 1-year spatial lag. We cannot simply hope that the right model is easy to estimate, but rather must use substantive knowledge to produce the right specification.

[21] As in the purely cross-sectional model, the estimated β's do not give the appropriate partial derivatives, and, as in any time-series analysis, there are both short- and long-run effects. The computation of the long-run derivatives is identical to equation (5) with an additional ϕ subtracted off of each row.

[22] Note that, as with the non-spatial TSCS lagged dependent variable model, the assumption of temporally independent errors can be tested with a Lagrange multiplier test of the OLS residuals, so researchers can do more than just assume that the lagged dependent variable causes the remaining errors to be independent.

Table 4. Directed Export Flows, Major Powers, 1907–90

Variable	*(1)*	*(2)*
Constant	− 0.25 (0.10)	0.17 (0.11)
Ln GNP *A*	0.03 (0.01)	0.02 (0.01)
Ln GNP *B*	0.04 (0.01)	0.03 (0.01)
Ln population *A*	0.02 (0.02)	0.04 (0.02)
Ln population *B*	0.02 (0.02)	0.03 (0.02)
Ln distance	− 0.03 (0.01)	− 0.04 (0.01)
Ln tau b	0.13 (0.06)	0.11 (0.06)
Ln democracy	0.13 (0.03)	0.14 (0.03)
Ln MID	− 0.20 (0.04)	− 0.20 (0.04)
Ln multipolar	− 0.30 (0.05)	− 0.28 (0.05)
Ln bipolar	− 0.06 (0.05)	− 0.04 (0.05)
Ln y_{t-1}	0.92 (0.01)	0.91 (0.01)
$\mathbf{W}(\ln y_{t-1})$	—	0.02 (0.01)
N	2,565	2,565

Standard errors in parentheses.

Morrow et al. more closely in this model.[23] The democracy measure is a binary indicator of whether both members of each dyad are democracies, as indicated by whether the states score 6 or greater on the Polity institutionalized democracy scale. We also use the tau-b measure of alliance portfolio similarity. Finally, we include two dummy variables indicating if the states in each dyad are members of an alliance during bipolarity or multipolarity. As before, we take the natural log of each variable for the gravity model specification.

Model 1 in Table 4 shows the OLS results for a specification assuming that all 42 dyads are independent of each other. Model 2 adds the temporal lag of the spatial lag where common member dyads, including the reverse dyads, are weighted equally as neighbors for simplicity. For both models, Lagrange multiplier tests indicate that there is a small, but statistically significant, amount of residual serial correlation of the errors over time. This is not uncommon given the large sample sizes for TSCS data. There is no easy answer here as to how to proceed; we are pretty sure there is some serial correlation, but we are also pretty sure there is only a small amount of serial correlation (and the seriousness of the problem varies with the amount of serial correlation). For the purposes of this paper, we choose to continue with OLS, being aware that OLS is not perfect here (but noting that the issues involved are orthogonal to our interests here, and that no estimation strategy is ideal here).

These results suggest that although there is spatial dependence among the observations, the magnitude of the spatial association appears relatively modest once the previous influences have been taken into account by a lagged dependent variable. While the coefficient estimates for Model 2 in Table 4 are different from the estimates for Model 1, these differences are small and nowhere near the differences we saw in the cross-sectional case.

We conjecture that for TSCS data with a lagged dependent variable, the spatial effects will often matter less. The reason for this is that the lagged dependent variable already contains any prior spatial effects, and hence the spatial lag provides much less independent information in the TSCS model with a lagged dependent variable than it does in the cross-sectional context. We stress that the work is being

[23] Whereas Morrow, Siverson, and Tabaras (1999:655, fn. 13) apply a transformation to the first observation after a missing period in each of the individual dyad time series, we are not persuaded that this was a good way to proceed and have simply omitted the first observation after a missing series. These differences in how we treat missing periods imply that our results are not fully comparable with Morrow et al.

done by the lagged dependent variable; spatial lags may have a strong impact on TSCS models that do not include the lagged dependent variable in the specification.

But even in our example, it is still worthwhile to include the spatial lag (the estimates with the spatial lag included must be superior to those which assume that there is no spatial effect, and if the spatial lag is insignificant, one can always then go back to the simpler model). If our substantive problem makes it plausible to assume that spatial effects also occur with a temporal lag, and if tests indicate that the remaining errors appear serially independent (or otherwise small enough to ignore), then it is easy enough to include the spatial lag in any model.[24]

This idea is not unknown to students of political economy, though they have usually not been explicit in their use of spatial econometrics. To take but two prominent examples, both Garrett (1998) and Iversen (1999) model economic outcomes and policies in the OECD nations (using TSCS data) as partly determined by economic performance in the other OECD nations. But Iversen (1999:65) used only the simple OECD average of the dependent variable as a covariate, without any discussion of either the spatial or temporal lag structure. His use of simple averages implies that all connectivities are identical, and it is unclear whether the dependent variable for a country itself was included in the OECD average. Garrett also proceeded intuitively, using the trade weighted average of the growth of GDP in the OECD countries in all his regressions (both for growth and for other economic outcomes, such as inflation and unemployment). Note that this is different from the spatial approach, which used the spatial lag of the dependent variable in any regression. So while the approaches of prominent political economists make intuitive sense, their analyses would benefit from more formal use of the spatial econometrics literature.

Conclusions

Spatial econometric techniques are now starting to be used by political scientists. Because of the geographic heritage of these models, their primary application has been to incorporate physical notions of space (distance) into political models, and, particularly, to argue that geographically nearby units are linked together (or, less usefully, that their error terms are linked together). While this approach is highly promising, we think it can be made much more fruitful if we allow for interconnectivities that go beyond geography. In the end, our message is theoretical, not technical. In international relations and comparative political economy we would expect units to be affected by what takes place in other units. We would expect the connectivity of units to be a function of political and social, as well as geographic, variables. While the heritage of spatial econometrics is geographic, there is no reason to limit spatial econometric models to geographic modes of thinking.

With a richer view of what may constitute the interconnections between units, and the ability to test which of two (or perhaps more) interconnections are more important, the spatial autoregressive model should become an important tool in the kit of the political economist (whether in comparative politics or international relations). We do not think of nations as isolates, and there is no reason that our models should treat nations in isolation either, or study interactions in a nonsystematic manner.

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[24] We conjecture that spatial econometricians have not studied our proposed method because it is both econometrically trivial and because it does not lead to enormous changes in estimated coefficients.

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