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On the spatial correlation of international conflict initiation and other binary and dyadic dependent variables☆

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ABSTRACT

We examine spatially correlated interregional flows measured as binary choice outcomes. Since the dependent variable is not only binary and dyadic, but also spatially correlated, we propose a spatial origin–destination probit model and a Bayesian estimation methodology that avoids inconsistent maximum likelihood estimates. We apply the model to militarized interstate dispute initiations, observations of which are clearly binary and dyadic and which may be spatially correlated due to their geographic distribution. Using a cross-section of 26 European countries drawn from the period leading up to WWII, we find empirical evidence for target-based spatial correlation and sizable network effects resulting from the correlation. In particular, we find that the effect of national military capability of the potential aggressor, which is a significant determinant of conflict in either case, is overstated in a benchmark model that ignores spatial correlation. This effect is further differentiated by the geographic location of a country.

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1. Introduction

Spatial autocorrelation introduces computational challenges to mathematical modeling and has been widely studied by statisticians, economists, political scientists, geographers, and others. As is well-known, ignoring substantial spatial correlation may generate inefficient or even inconsistent parameter estimates. Spatial autocorrelation may be more prominent in data collected in a dyadic setting, in which a single observation consists of a pair of individuals, such as international conflict, international trade, or migration flows. Nonetheless, dyadic data and specifically directed dyadic data, where each observation contains a distinct origin and destination, present additional challenges, because correlation between two observations involves spatial correlation between up to four individuals. In addition, many dyadic series, such as conflict initiations, are also binary. That is, an observation records whether or not the event, transaction, or flow occurred, adding a third challenge to effective modeling.

Spatially correlated binary observations have been studied by McMillen (1992), Dubin (1995), and LeSage (2000), among others, while spatially correlated directed dyadic observations have been studied more recently by Fischer et al. (2006), LeSage et al. (2007), and LeSage and Pace (2008, 2009). The latter authors develop a spatial origin–destination (spatial OD) approach to modeling directional flows that involves three different types of spatial correlation. Their modeling strategy allows for correlations in (a) neighboring origins with a common destination, (b) neighboring destinations with a common origin, and (c) neighboring origins and neighboring destinations.

The methodological contribution of this paper addresses modeling dependent variables with statistical characteristics in the intersection of these three nonstandard yet realistic assumptions: binary, dyadic, and spatially correlated data. We take an approach that extends the class of origin–destination (OD) models of LeSage and Pace (2008, 2009) by allowing for a binary and directed dyadic dependent variable. We show that a *spatial OD probit model*, highlighting all three features, may be estimated using a Bayesian method related to that discussed by LeSage and Pace (2009). Further, we derive the marginal effects from changing a country-specific regressor in the model. This task is complicated not only in the usual way by the nonlinearity of the probit

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link function and the spatial correlation, but also by the OD structure of the data, as pointed out by Thomas-Agnan and LeSage (2013).

We apply our methodology to a cross-section of binary dyadic observations on militarized interstate disputes (MIDs). Due to its devastating destructiveness to human lives and socio-economic development, interstate war has been a very active research topic for political scientists and economists. The former group tends to focus more on the causal factors of war, while the latter may be more interested in examining the relationships between war and economic fundamentals (e.g., Blomberg and Hess, 2002; Hess and Orphanides, 2001; Koubi, 2005).

We examine initiation of MIDs in a cross-section of 26 European countries during the period leading up to WWII. By modeling multiple sources of spatial correlation across directed dyads, the spatial OD probit model reveals how conflict initiations may be correlated. We find empirical evidence to support target-based (destination-based) spatial correlation, and we find the most statistically meaningful determinants of conflict to be geographical distance and national capabilities of the potential initiator. There are substantial network effects in the latter, the omission of which overstates its marginal importance. In particular, a military buildup in one country may *decrease* the probability of conflict between two others. An unexpected finding suggests that military buildups in countries at the edge of the map (the U.K., e.g.) have very different implications from buildups in countries in the center (Germany, e.g.). Specifically, such buildups have less of an impact on conflict with the immediate neighbors of the former countries than on conflict with neighbors of the latter.

Sample selection focuses on a particular historical period and geographical location with a relatively large number of conflict initiations as a percentage of the sample. However, our findings are suggestive for any spatially correlated cross-section of conflict-prone units. We note, however, that more general conflict models might allow only local spillovers, in the sense of LeSage and Pace (2013). Our model does not preclude the possibility that the military buildup of one country (Germany, e.g.) could increase the probability of conflict in the *whole* region, with the largest increases for conflicts with immediate neighbors.

The rest of this study is organized as follows. In Section 2, we motivate spatial OD modeling and outline the technical difficulties in applying the spatial OD model to binary, dyadic dependent variables. A Bayesian approach to the spatial OD probit model is presented in Section 3, and in Section 4, we discuss additional issues of empirical interest in estimating a spatial OD probit model: self-directed dyads and marginal effects. In Section 5, we apply the model to conflict initiation among European countries leading up to WWII. We conclude with Section 6.

We rely on the following notation throughout the paper. The *vec* operator converts a matrix into a column vector by stacking its columns into a single vector. $\otimes$ denotes the Kronecker product, and ι_n and ι_N denote n by 1 and N by 1 unit vectors, where n records the number of sampled countries and $N = n^2$. $|\mathbf{A}|$ refers to the determinant of a square matrix $\mathbf{A}$.

2. Modeling spatially correlated origin–destination flows

To motivate the spatial OD probit model, we borrow heavily from the structural and notational framework of LeSage and Pace (2008, 2009). Since OD flows are directional, one pair of regions will yield two observations distinguished by reversing the origin and destination. Therefore, if n regions are considered under a spatial OD model, the number of observations becomes $n^2 = N$. We use an n by n square matrix $\mathbf{Y}^*$ to denote interregional flows from each of the n origin regions to each of the n destination regions, with each column recording a specific origin's outflows to each of the n potential destination regions and each row corresponding to the inflows toward a given destination from each of the n potential origins. (We use the superscript *, because we will consider these to be latent flows subsequently.)

Specifically, the OD flow matrix is organized as follows:

$$\begin{pmatrix} o_1\rightarrow d_1 & o_2\rightarrow d_1 & \cdots & o_n\rightarrow d_1 \\ o_1\rightarrow d_2 & o_2\rightarrow d_2 & \cdots & o_n\rightarrow d_2 \\ \vdots & \vdots & \ddots & \vdots \\ o_1\rightarrow d_n & o_2\rightarrow d_n & \cdots & o_n\rightarrow d_n \end{pmatrix}.$$

To reflect an origin-centric ordering of OD flows (LeSage and Pace, 2008, p. 944), the matrix $\mathbf{Y}^*$ is then vectorized into an N by 1 matrix y^*, such that $y^* = vec(\mathbf{Y}^*)$.

In a typical spatial interaction model, where each observation is a single region, explanatory variables that represent K region-specific characteristics for each of the n regions are represented by an n by K matrix $\mathbf{Z}$. In keeping with the origin-centric arrangement of y^*, $\mathbf{Z}$ is stacked n times in a spatial OD model to form an N by K matrix $\mathbf{X_d} = \iota_n \otimes \mathbf{Z}$, which tallies destination characteristics. Similarly, $\mathbf{X_o} = \mathbf{Z} \otimes \iota_n$ produces an N by K matrix that contains origin characteristics. Representing by $\mathbf{G}$ an n by n OD distance matrix similar to the flow matrix above, $g = vec(\mathbf{G})$ is an N by 1 vector recording the distances from origins to destinations with an origin-centric ordering.

LeSage and Pace (2008) extend the spatial autoregressive model by introducing spatial lags defined by three N by N row-standardized spatial weight matrices, $\mathbf{W}_d$, $\mathbf{W}_o$, and $\mathbf{W}_w$. $\mathbf{W}_d = \mathbf{I}_n \otimes \mathbf{W}$ embodies the notion that factors causing flows from an origin to a destination may bring about similar flows to nearby destinations. Accordingly, the spatial lag $\mathbf{W}_d y^*$ attempts to pick up this type of destination-based dependence by the use of average flows from one origin to the neighbors of a given destination. Similarly, $\mathbf{W}_o = \mathbf{W} \otimes \mathbf{I}_n$ reflects origin-based dependence and the spatial lag $\mathbf{W}_o y^*$ measures an average of flows into one destination from the neighbors of a given origin.

Third, LeSage and Pace (2008) apply the "successive spatial filter" $(\mathbf{I}_N - \rho_d \mathbf{W}_d)(\mathbf{I}_N - \rho_o \mathbf{W}_o)$ to control for *both* origin-based and destination-based dependence (origin-to-destination dependence). The cross-product introduces a third type of spatial correlation modeled by the spatial weight matrix $\mathbf{W}_w = \mathbf{W} \otimes \mathbf{W}$. Since $\mathbf{W}_w$ represents a second-order connectivity between the neighborhood of an origin and the neighborhood of a destination, the spatial lag $\mathbf{W}_w y^*$ indicates an average of flows from the neighborhood of an origin to the neighborhood of a destination. Strictly speaking, $\rho_w = -\rho_d \rho_o$, but LeSage and Pace (2008) find compelling evidence to lift the restriction in their application.

Consider a model given by

$$y^* = \rho_d \mathbf{W}_d y^* + \rho_o \mathbf{W}_o y^* + \rho_w \mathbf{W}_w y^* + \alpha \iota_N + \mathbf{X_d} \beta_d + \mathbf{X_o} \beta_o + \gamma g + \varepsilon \quad (1)$$

where α is an intercept, β_d and β_o are K by 1 coefficient vectors, γ is a scalar coefficient, and $\varepsilon \sim N(0, \sigma^2 \mathbf{I}_N)$. This model features dyadic and spatially correlated y^*, and is exactly the spatial OD regression model proposed by LeSage and Pace (2008) for an *observable* continuous dependent variable y^*.

The spatial OD model in Eq. (1) implies the reduced-form equation

$$y^* = \mathbf{A}^{-1} \mathbf{X} \beta + \mathbf{A}^{-1} \varepsilon \quad (2)$$

where $\mathbf{X} = (\iota_N, \mathbf{X_d}, \mathbf{X_o}, g)$, $\beta = (\alpha, \beta_d', \beta_o', \gamma)'$ and $\mathbf{A} = (\mathbf{I}_N - \rho_d \mathbf{W}_d - \rho_o \mathbf{W}_o - \rho_w \mathbf{W}_w)$.[1]

[1] A sufficient condition for existence of the inverse is that $|\rho_d + \rho_o + \rho_w| < 1$.

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