Spatial Effects in Dyadic Data

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Abstract Political units often spatially depend in their policy choices on other units. This also holds in dyadic settings where, as in much of international relations research, analysis focuses on the interaction or relation between a pair or dyad of two political units. Yet, with few exceptions, social scientists have analyzed contagion in monadic datasets only, consisting of individual political units. This article categorizes all possible forms of spatial effect modeling in both undirected and directed dyadic data, where it is possible to distinguish the source and the target of interaction (for example, exporter/importer, aggressor/victim, and so on). This approach enables scholars to formulate and test novel mechanisms of contagion, thus ideally paving the way for studies analyzing spatial dependence between dyads of political units. To illustrate the modeling flexibility gained from an understanding of the full set of specification options for spatial effects in dyadic data, we examine the diffusion of bilateral investment treaties between developed and developing countries, building and extending on Elkins, Guzman, and Simmons's 2006 study. However, we come to different conclusions about the channels through which bilateral investment treaties diffuse. Rather than a capital-importing country being influenced by the total number of BITs signed by other capital importers, as modeled in their original article, we find that a capital-importing country is more likely to sign a BIT with a capital exporter only if other competing capital importers have signed BITs with this very same capital exporter. Similarly, other capital exporters' BITs with a specific capital importer influence an exporter's incentive to agree on a BIT with the very same capital importer.

Policy choices of one political unit are often not independent of policies implemented in other units, in which case they are said to depend spatially on each other. Recently, social scientists have become very interested in analyzing processes of "policy contagion," "policy diffusion," and "policy spillover" across jurisdictions.[1] The vast majority of these studies have used a monadic data-

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1. We use the terms contagion, diffusion, and spillover interchangeably even if they often represent somewhat different modes of spatial dependence.

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set.[2] In contrast, with few exceptions diffusion analysis remains nonexistent in studies adopting a dyadic framework, that is, a setting where, as in much of international relations research, the unit of analysis is the pair or dyad of two political units representing an interaction or a relation between the two units such as the conclusion of a bilateral treaty or the initiation of violent conflict between two countries.[3] This is surprising because spatial dependence exists whenever the marginal utility of one unit of analysis depends on the choices of other units of analysis. What one unit does in relation to other units, with which it forms a dyad, will often influence and be influenced by the relations of other dyads, such that spatial dependence is likely to exist in many dyadic settings. For example, the conclusion of bilateral treaties by some countries often affects the expected payoffs of other countries from entering into similar treaties themselves.

One potential reason for the lack of studies analyzing spatial dependence in a dyadic framework is that political scientists are not aware of the many specification options for modeling such dependence in dyadic data. Recognizing the various ways in which spatial effects in dyadic data can be modeled will enable scholars to formulate and test different and novel diffusion channels, thus facilitating and hopefully spurring a whole new generation of studies analyzing spatial dependence between dyads of political units at all levels of the political system—from the global and international right down to the local.

This research note makes two contributions. First, our analysis enriches the thriving literature applying dyadic data and calls on researchers to take spatial dependence in such data seriously. Spatial dependence often seems to be theoretically warranted but is practically always ignored. For example, the conclusion of bilateral and multilateral trade, investment, alliance, and other agreements among some dyads most likely influences the incentives for other dyads to conclude similar agreements. The conclusion of such agreements often generates externalities, increases competition, induces cooperation, or leads to coercion, learning, emulation, or other effects by which the policy choices of other dyads are affected. Yet, to our knowledge only three studies analyze spatial dependence in the diffusion of bilateral investment treaties (BITs), preferential trade agreements, and bilateral alliance formation, respectively.[4] Another good example is the democratic peace literature. King argues that "dyadic observations in international conflict data have *complex dependence structures*. . . . [I]n dyadic data, observation 1 may be U.S.-Iraq; observation 2, U.S.-Iran; and observation 3, Iraq-Iran. The dependence among these separate observations is complicated, central to our theories and the inter-

2. See, for example, Cho 2003; Murdoch and Sandler 2004; Simmons and Elkins 2004; Jahn 2006; Franzese and Hays 2006; Gleditsch and Ward 2006; Salehyan and Gleditsch 2006; Swank 2006; and Brooks 2007.

3. The rare examples of studies analyzing spatial dependence in dyadic data include Porojan 2001; Manger 2006; Gartzke and Gleditsch 2006; and Elkins, Guzman, and Simmons 2006.

4. See Elkins, Guzman, and Simmons 2006; Manger 2006; and Gartzke and Gleditsch 2006, respectively.

national system, critical for our methodological analyses, and ignored by most previous researchers."[5] We agree with this judgment. Spatial dependence in international conflict is typically ignored,[6] leading to biased estimates of the observed dyadic and unit-specific explanatory variables. However, contrary to King we do not believe that Bayesian hierarchical or random effects models provide the methodologically optimal solution if researchers are indeed interested in spatial effects. Rather, the spatial dependence should be modeled directly by the inclusion of spatial effects in dyadic data analyses. If theory suggests the existence of spatial dependence, then modeling spatial patterns as nuisance—as in the "spatial error" model or King's hierarchical model—will be inferior to directly testing for spatial dependence by fitting a spatial effect model, because none of the different possible "nuisance models" allows for a direct test of the spatial hypotheses derived from the theory.[7]

Second, the few studies that actually do analyze spatial dependence in dyadic data do so in a limited way, focusing solely on aggregate forms of contagion. A good example is Elkins, Guzman, and Simmons's study of the diffusion of bilateral investment treaties (BITs).[8] The authors consider what we define further below as aggregate target contagion from capital-importing countries only, where the decision of a capital importer to sign a BIT with a capital exporter depends on the weighted sum of BITs signed by all other capital importers, regardless of the potential capital exporter with which these existing contracts have been signed. Yet, there is nothing in the theory of BIT diffusion that necessarily suggests such an aggregate form of contagion being unconditional on the specific dyad under observation. From a theoretical perspective, it seems at least as plausible to argue that a capital importer's BIT with a specific capital exporter depends on the BITs signed by other capital importers with that very same capital exporter—but not with any other capital exporting country.

This research note discusses all possible forms of channels through which policies may diffuse in dyadic data. We start by briefly discussing spatial dependence in monadic settings before categorizing the different and complex ways of modeling spatial effects in dyadic data. We will show that in undirected dyadic data, dyads can spatially depend only on the policy choices of other dyads, which is similar to the monadic setting in which units can depend only on the policy choices of other units. In directed dyadic data, there is more flexibility. Here we have of course the same possibility of *dyad contagion* as in undirected data. However, given that in directed data one can distinguish the source from the target of the interaction, researchers can additionally model four more forms of contagion. Two of these model contagion as emanating from the aggregate policy choices of other

5. King 2001, 498 (emphasis in original).
6. We are not aware of any dyadic conflict study that models spatial dependence.
7. Beck, Gleditsch, and Beardsley 2006.
8. Elkins, Guzman, and Simmons 2006.

sources and other targets, which leads to *aggregate source contagion* and *aggregate target contagion*, respectively. If, however, contagion does not come from the aggregate policy choices of other sources or other targets, but only from their policy choices with respect to a specific third party, then we get the two remaining modeling options of *specific source contagion* and *specific target contagion*, respectively. In other words, the probability that source i interacts with target j increases if (but only if) i already interacts with other targets m similar to j or if j already interacts with other sources k similar to i.

Together, there are thus five forms of contagion for directed dyadic data, which can be combined with various specifications of the weighting matrix. The spatial analysis of dyadic data therefore offers multiple options to researchers and makes the choice of the correct model a difficult task—a task in which theory needs to inform the specification of the spatial effects in the empirical model.[9]

In order to demonstrate the full potential of modeling spatial dependence in dyadic data, we extend the analysis of Elkins and colleagues on the diffusion of BITs by modeling and testing all possible forms of spatial lags. To our knowledge, their study was the first published article to include spatial lags in a directed dyadic sample and it is also commendable for clearly specifying and justifying their modeling approach. Our analysis provides additional insights into the study of BIT diffusion. While we find that Elkins and colleagues were right in arguing that competition among capital-importing target countries drives BIT spillovers, our results suggest that a capital importer's decision to sign a BIT with a capital exporter depends only on similar importers' BITs with the very same capital exporter rather than on the similar importers' total number of BITs with any capital exporter. In other words, we find that dyad-specific target contagion matters rather than aggregate target contagion. In addition, we provide evidence that the diffusion process also works through competition among capital-exporting source countries: when other capital exporters have signed a BIT with a specific capital importer, a capital exporting nation is more likely to also seek a BIT with the very same capital importer. Hence, here again, diffusion is driven by dyad-specific source contagion. Thus, we reproduce Elkins and colleagues' finding that the agreement of BITs between two countries spatially depends on the choices of other countries, but we come to different conclusions with respect to the channels through which BITs diffuse.

Spatial Dependence in Dyadic Data: A Categorization

Spatial effects between two jurisdictions occur whenever the marginal utility of one unit depends on the policy choices of at least one other unit.[10] There is no

9. See also Plümper and Neumayer forthcoming.
10. Franzese and Hays 2008, 3.

shortage of theories predicting processes of policy diffusion and spillover across units.[11] All of these theories can also be applied to dyadic frameworks. Moreover, these theories are in principle compatible with all of the types of contagion we will categorize in the sense that, depending on the context and the exact formulation of these theories, each theory can require one or more of these types of contagion.

Dyadic data allows the modeling of far more complex forms of spatial dependence than monadic data. To see why this is the case, we start with a brief exposition of spatial effects in monadic data, then discuss spatial dependence in dyadic data in more detail.

Spatial Dependence in Monadic Data

Besides spatial error models, which are rarely useful for political science research,[12] two main ways of modeling spatial dependence exist. By far the most popular one, and the one we focus on in this study, is the spatial lag model, which regresses the dependent variable on the spatially lagged dependent variable. However, everything we say equally applies to spatial-x models, which regress the dependent variable on the weighted values of one or more independent explanatory variables (other than the dependent variable), and to spatial error models, which seek to identify spatial dependence in the error term.

In its simplest purely cross-sectional form without control variables, spatial lag models in a monadic dataset can be formulated as:

$$y_i = \rho \sum_k w_{ik} y_k + \varepsilon_i. \tag{1}$$

The spatial lag $\sum_k w_{ik} y_k$ consists of two elements, namely what in the following we refer to as the "spatial y" and the spatial weighting matrix w_{ik}.[13] The spatial y is the contemporaneous or temporally lagged value of the dependent variable in all units k. This is multiplied with an $N \cdot N$ block-diagonal spatial weighting matrix, which measures the relative connectivity between N number of units i and N number of units k in the off-diagonal cells of the matrix (the diagonal of the matrix has values of zero because there $i = k$ and units cannot spatially depend on themselves). The spatial autoregression parameter ρ gives the impact of the spatial lag

11. Elkins and Simmons 2005; Simmons, Dobbin, and Garrett 2006; and Franzese and Hays 2008, 2, among others, distinguish between coercion (that is, what Levi-Faur 2005 calls top-down approaches to diffusion), externalities (Simmons and Elkins 2004; and Franzese and Hays 2006), competition (Hallerberg and Basinger 1998; and Basinger and Hallerberg 2004), cooperation (Genschel and Plümper 1997), learning (Mooney 2001; and Meseguer 2005), and emulation (Weyland 2005).

12. Beck, Gleditsch, and Beardsley 2006.

13. We would call y_k the spatially lagged dependent variable, which we regard as the more appropriate term, if Anselin (2003, 159) and others did not use this term for the entire spatial lag $\sum_k w_{ik} y_k$.

on the dependent variable. We will discuss the issue of specifying the weighting matrix in more detail below.

Of course, in reality, researchers usually do not estimate the basic model displayed in equation (1), but they add control variables, use a cross-sectional time-series dataset, control for temporal dynamics,[14] control for common trends and common shocks with period dummies, and sometimes account for unobserved spatial heterogeneity (or spatial clustering) with unit fixed effects. To keep the exposition simple, in what follows we will ignore everything that distracts from the modeling of spatial dependence itself and therefore employ the most basic cross-sectional setting, always keeping in mind that such a model can and should often be extended to include a time dimension, dynamic modeling, control variables, and so on.[15]

In monadic data, the specification of spatial lags gives researchers some flexibility with respect to the variable that measures connectivity among units, but these spatial lags leave researchers little choice on the specification of the weighting matrix or on the specification of the spatial y.[16] Dyadic data allows more flexible and different specifications of both the weighting matrix and the spatial y. Dyadic data comes in two forms—undirected and directed—and we discuss the different options for spatial lags available in both settings in turn after a brief introduction to the differences between monadic and dyadic data.

Dyadic Data

Dyadic data consists of observations in which two individual units form a pair (the dyad). There exist directed and undirected dyadic data. In directed dyadic data, the interaction between two dyad members ij initiates with i and is directed toward j. There is a source and a target, an origin and a destination, a sender and a recipient, a giver and a taker, an aggressor and a victim, or some similar directed relationship. For example, in international trade one can distinguish between exporters and importers. In foreign investment one can distinguish between home and host countries. In international migration or remittance flows, one can distinguish sending and recipient countries. In interstate violent conflict, there exist aggressor and victim states, and so on.

In undirected dyadic data, it is either unclear from the data which of the two dyad members initiated the interaction or this question is theoretically unimportant. There-

14. See Beck and Katz 1996; and Plümper, Troeger, and Manow 2005.

15. We will similarly neglect all issues of estimation of spatial lag models, which is complicated by the fact that with interdependent units of analysis, spatial dependence models typically suffer from endogeneity (see Anselin 1988; Ward and Gleditsch 2002; and Franzese and Hays 2006, 2007, and 2008). There are also important specification choices that researchers need to consider, which we discuss in a separate article (Plümper and Neumayer forthcoming).

16. If the weighting variable used is directed, then researchers can specify w_{ki} instead of w_{ik}. See section on "Choice of Weighting Matrices" for more details.

fore, while one can still distinguish *i* from *j*, one either cannot distinguish between *ij* and *ji* or one does not want to make such a distinction. Consequently, the variable of interest is identical for dyads *ij* and *ji* and researchers typically keep only one or the other in their dataset to avoid "double counting."[17] Theory can typically determine the choice between undirected and directed dyadic data. Take the conclusion of a contract as an example. If the contract is voluntarily entered or if it is of no further interest who was the initiator of the contract, then an undirected dyadic dataset suffices. If, however, researchers have an interest in who initiated the contract or if contract agreement has not been reached voluntarily or if the contract means different things to the two contract partners, then this could, and in fact should, be analyzed with a directed dyadic dataset.

Bilateral investment treaties (BITs) provide a good example of a case in which contracts mean different things to the two contracting partners. These treaties grant foreign investors certain rights by limiting the policy autonomy of the government of the country hosting the investment, whereas few, if any, costs are imposed by the treaty on either the foreign investor or its home government.[18] BITs are, at least putatively, entered voluntarily, and it is not always clear who initiated the treaty.[19] Nevertheless, even though in principle BITs are symmetric in that both governments face the same restrictions, in reality the vast majority of BITs have been concluded between countries with radically different net foreign investment positions. For the predominantly capital-exporting country, the BIT mainly provides rights to its investors with few actual restrictions on its policy autonomy, whereas the predominantly capital-importing country experiences the full restrictions on its policy autonomy (which can still pay off due to the economic benefits of increased inward FDI). Because of the asymmetry of the treaty's effect, it makes sense to analyze the conclusion of BITs in a country dyad dataset that is directed from the capital-exporting to the capital-importing country, as Elkins and colleagues do. The decision to treat a dyadic relationship as directed or undirected thus requires theoretical justification.

Modeling Spatial Dependence in Undirected Dyads

The modeling of spatial dependence in undirected data strongly resembles that of monadic data. The only difference is that instead of contagion stemming from other units, it comes from other dyads. Hence, to model spatial dependence in undirected dyadic data researchers make the dependent variable in a dyad between *i* and *j* a function of the weighted sum of the dependent variable of all other dyads:

17. Undirected dyadic data are commonly used in the international conflict literature (see Russett, Oneal, and Davis 1998; and Gartzke, Li, and Boehmer 2001).

18. See Guzman 1998; and Neumayer and Spess 2005.

19. Elkins, Guzman, and Simmons 2006 argue that capital-importing developing countries are the major initiators of BITs, whereas Neumayer 2006 argues that BITs predominantly initiate from capital-exporting developed countries.

$$y_{ij} = \rho \sum_{km \neq ij} \omega_{pq} y_{km} + \varepsilon_{ij}, \tag{2a}$$

which due to the undirectedness of the dyadic dataset is equivalent to

$$y_{ji} = \rho \sum_{mk \neq ji} \omega_{pq} y_{mk} + \varepsilon_{ji}. \tag{2b}$$

We have denoted the connectivity or weighting matrix as ω_{pq}. Later we will discuss six different specifications of the weighting matrix, such that $\omega_{pq} \in \{w_{ik}, w_{ki}, w_{jm}, w_{mj}, w_{(ij)(km)}, w_{(km)(ij)}\}$, but these are not exhaustive since combinations of these links can also be theoretically warranted. We leave a detailed explanation and discussion of the weighting matrix until then.

Equations (2a) and (2b) are appropriate if, for example, one thinks that the decision of whether country i and country j enter into a voluntary treaty depends on the weighted sum of existing treaties in all other dyads, where the weight is given by ω_{pq}. This form of contagion we call *undirected dyad contagion*.[20] It is the modeling strategy adopted in Manger's analysis of the diffusion of preferential trade agreements and in Gleditsch and Gartzke's analysis of the effect of alliance ties on international conflict.[21]

Modeling Spatial Dependence in Directed Dyads

Both monadic and undirected dyadic data offer only one option each for modeling contagion. In contrast, there are five options for modeling spatial dependence if we analyze directed dyadic data. The reason is that in directed dyads two actors i and j have an asymmetric interaction and one can distinguish dyads ij, where unit i is the source and unit j is the target, from dyads ji where these roles are reversed. This means contagion can come from other dyads, as in undirected dyadic data, but contagion can also come from other sources or from other targets. Moreover, where contagion stems from other sources or other targets, it can be their aggregate policy choices that matter or their choices with respect to only the specific dyad under consideration.

Starting with the option that directly resembles the modeling of spatial dependence in undirected dyadic data, dyad ij can be modeled to be more likely to sign a BIT if other dyads between capital-exporting and capital-importing countries

20. Undirected dyad contagion can be further restricted such that all dyads containing either unit i or unit j are excluded from having a contagious effect. Such exclusive undirected dyad contagion would be represented by $y_{ij} = \rho \sum_{k \neq i, m \neq j} \omega_{pq} y_{km} + \varepsilon_{ij}$.

21. See Manger 2006; and Gartzke and Gleditsch 2006.

have already agreed on such a treaty. This form of spatial dependence we call *directed dyad contagion*.[22] Hence:

$$y_{ij} = \rho \sum_{km \neq ij} \omega_{pq} y_{km} + \varepsilon_{ij}. \tag{3}$$

Equation (3) describes a situation in which the probability of two countries i and j signing a BIT depends on the weighted sum of all other BITs existing between capital-exporting countries k and capital-importing countries m.

In directed dyad contagion, the aggregate policy choices of other, similar dyads matter. In the remaining four forms of contagion in directed dyadic data, one can, first, assume that the aggregate policy choices of other sources and other targets matter. In addition, one can also assume that only a subset of the sources (targets) influence the dyad under observation, namely those sources (targets), which are linked to the target (source) of the dyad under observation. If the policy choice of the directed dyad ij spatially depends on the aggregate actions of other sources k $(\neq i)$, that is on their relationship with all other targets m, not just the specific target j, then we get what we name *aggregate source contagion*:

$$y_{ij} = \rho \sum_{k \neq i} \sum_{m} \omega_{pq} y_{km} + \varepsilon_{ij} \tag{4}$$

Alternatively, one can make the policy choice of dyad ij depend on the aggregate actions of other targets m, that is, on their policy choices with all other sources k, not just the specific source i. This leads to *aggregate target contagion*:

$$y_{ij} = \rho \sum_{k} \sum_{m \neq j} \omega_{pq} y_{km} + \varepsilon_{ij} \tag{5}$$

Equation (5) is appropriate if the BIT decision of dyad ij spatially depends on the aggregate or total number of BITs that other capital importers m $(\neq j)$ have concluded with any capital-exporting country k.

Additionally, instead of policy choices depending on the aggregate choices of other sources or targets, they may well depend on the choices of other sources or targets in relation to the specific dyad under consideration. With

$$y_{ij} = \rho \sum_{k \neq i} \omega_{pq} y_{kj} + \varepsilon_{ij} \tag{6}$$

22. As in the undirected case, directed dyad contagion can similarly be further restricted such that all dyads containing either source i or target j are excluded from having a contagious effect. Such exclusive directed dyad contagion would be represented by $y_{ij} = \rho \sum_{k \neq i, m \neq j} \omega_{pq} y_{km} + \varepsilon_{ij}$.

the probability of, say, two countries i and j signing a BIT depends on the weighted sum of BITs signed by other capital-exporting countries k with the very same capital-importing country j. This we name *specific source contagion*. In comparison to the aggregate source contagion represented by equation (4), equation (6) describes a situation in which other sources k affect i's interaction with j only if countries k have signed a BIT with the very same target country j. In other words, Canada's interest in signing BITs with capital importers remains largely unaffected by the total number of BITs the United States, Germany, France, and others have signed. However, if the United States, Germany, France, and others sign a BIT with—say Chile—the incentive for Canada to also sign a BIT with Chile increases.

Lastly, in equation (7) country j's incentive to sign a BIT with country i depends on the weighted sum of BITs signed by other capital importing countries m with the very same capital-exporting country i:

$$y_{ij} = \rho \sum_{m \neq j} \omega_{pq} y_{im} + \varepsilon_{ij}, \tag{7}$$

This type of spatial dependence we call *specific target contagion*. Compared to the aggregate target contagion described by equation (5), equation (7) describes a situation in which other targets m affect j's interaction with i only if countries m have signed a BIT with the very same source country i. In other words, Chile's interest in signing BITs with capital exporters remains largely unaffected by the total number of BITs Argentina and Brazil have signed. However, if Argentina and Brazil sign a BIT with—say the United States—the incentive for Chile to also sign a BIT with the United States increases.

The Choice of Weighting Matrices

The specification of spatial effects requires two choices. First, the researcher needs to specify the spatial y, as discussed above. Second, one also needs to specify the type of weighting matrix used to model the connectivity between units or dyads that form the spatial dependence.[23]

In monadic data analysis, the weighting matrix provides a link between unit i and units k. For each observation y_i, the corresponding element of the spatial lag gives a weighted sum of the y_k observations, with weights always given by the relative connectivity between i and k. Hence, the spatial effect is a weighted function of the dependent variable in all other units k. The connectivity can be directed as with, say, exports. This leads to two possible link functions, namely, $\omega_{pq} = w_{ik}$, which would measure exports from i to k; and $\omega_{pq} = w_{ki}$, which would measure

23. We do not discuss the issue of row-standardization here. It is an important issue (see Plümper and Neumayer forthcoming)—but equally important for monadic and dyadic data.

exports from k to i. If the connectivity is undirected as with, for example, contiguity or geographical distance, then there is only one link function since $w_{ik} = w_{ki}$.

Compared to monadic data, the choice of weighting matrix becomes more complicated in dyadic data. Starting with undirected dyadic data, we distinguish basic from more complex link functions. As for the basic ones, the effect of the spatial y may be weighted by a link function measuring connectivity between either unit i or unit j on the one hand and other units, called $k(\neq i)$ or $m(\neq j)$, on the other hand. Formally, the weighting matrix ω_{pq} can thus take the following four different forms: $\omega_{pq} = w_{ik}$, $\omega_{pq} = w_{ki}$, $\omega_{pq} = w_{jm}$, or $\omega_{pq} = w_{mj}$. Note that there are four (rather than two) basic link functions because even if the spatial y is undirected, the variable of connectivity can of course be directed. If connectivity is undirected, however, then there are only two basic link functions: $\omega_{pq} = w_{ik} = w_{ki}$ and $\omega_{pq} = w_{jm} = w_{mj}$. More complex functions link dyads rather than units with each other. These will be discussed shortly for directed data. Finally, one can create further link functions by combining any of these link functions with each other in any way.

In directed dyadic data, it is useful again to distinguish basic link functions, that is, those that link either sources or targets with each other, from more complex link functions that link dyads with each other. As for basic link functions, in aggregate and specific source contagion the link function can represent connectivity between the source unit i and other source units k ($\omega_{pq} = w_{ik}$ or $\omega_{pq} = w_{ki}$).[24] Whereas in aggregate and specific target contagion it can measure connectivity between the target unit j and other target units m ($\omega_{pq} = w_{jm}$ or $\omega_{pq} = w_{mj}$).[25] In directed dyad contagion, any of the four basic link functions just presented can be used.

Link functions that represent connectivity between dyads are more complex and are bound to be employed far less commonly than the more basic link functions.[26] For aggregate and specific source contagion, the link function can represent connectivity between the dyad ij and dyads kj, that is, connectivity between the dyad consisting of source unit i and target unit j on the one hand and dyads made up of other source units k and the same target unit j on the other hand. This leads to either $\omega_{pq} = w_{(ij)(kj)}$ or $\omega_{pq} = w_{(kj)(ij)}$. For aggregate and specific target contagion, the link function can measure connectivity between the dyad ij and dyads im, that is, connectivity between the dyad consisting of source unit i and target unit j on the one hand and dyads comprised of the same source unit i and other target units

24. Strictly speaking, other link functions are possible (for example, the weighting matrix could measure connectivity between i and m), but these two are the most plausible ones. A similar point applies, *mutatis mutandis*, to the weighting matrices listed for aggregate and specific target contagion.

25. As before, these collapse to one each if connectivity is undirected.

26. The reason is that in order to create these complex link functions one needs a dataset that links dyads with dyads, that is, a so-called 4-adic dataset with dimension $(N_i \cdot N_j)(N_i \cdot N_j)T$, where N_i is the number of sources, N_j the number of targets and T the number of time periods. For many applications, this would lead to a dataset too big to be handled by a personal computer. In contrast, the Stata ado-files provided by the authors can create spatial lags employing the more basic link functions from a simple dyadic dataset of dimension $(N_i \cdot N_j)$ T as they parse through a virtual 4-adic dataset.

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TABLE 1. *Spatial lag specification in monadic and dyadic data*

Type of contagion	*(Partial) model*	*Basic link functions*	*More complex link functions*
Monadic data			
Unit contagion	$y_i = \rho \sum_{k} \omega_{pq} y_k + \cdots + \varepsilon_i$	$\omega_{pq} = \begin{cases} w_{ik} \\ w_{ki} \end{cases}$	
Undirected dyads			
Undirected dyad contagion	$y_{ij} = \rho \sum_{km \neq ij} \omega_{pq} y_{km} + \varepsilon_{ij}$ $\Leftrightarrow$ $y_{ji} = \rho \sum_{mk \neq ji} \omega_{pq} y_{mk} + \varepsilon_{ji}$	$\omega_{pq} = \begin{cases} w_{ik} \\ w_{ki} \\ w_{jm} \\ w_{mj} \end{cases}$	$\omega_{pq} = \begin{cases} w_{(ij)(km)} \\ w_{(km)(ij)} \\ \text{any of the functions for directed data} \\ \text{or function of any combination thereof} \end{cases}$
Directed dyads			
Directed dyad contagion	$y_{ij} = \rho \sum_{km \neq ij} \omega_{pq} y_{km} + \varepsilon_{ij}$	$\omega_{pq} = \begin{cases} w_{ik} \\ w_{ki} \\ w_{jm} \\ w_{mj} \end{cases}$	$\omega_{pq} = \begin{cases} w_{(ij)(km)} \\ w_{(km)(ij)} \\ \text{any of the functions for directed data} \\ \text{or function of any combination thereof} \end{cases}$
Aggregate source contagion	$y_{ij} = \rho \sum_{k \neq i} \sum_{m} \omega_{pq} y_{km} + \varepsilon_{ij}$	$\omega_{pq} = \begin{cases} w_{ik} \\ w_{ki} \end{cases}$	$\omega_{pq} = \begin{cases} w_{(ij)(kj)} \\ w_{(kj)(ij)} \end{cases}$
Aggregate target contagion	$y_{ij} = \rho \sum_{k} \sum_{m \neq j} \omega_{pq} y_{km} + \varepsilon_{ij}$	$\omega_{pq} = \begin{cases} w_{jm} \\ w_{mj} \end{cases}$	$\omega_{pq} = \begin{cases} w_{(ij)(im)} \\ w_{(im)(ij)} \end{cases}$
Specific source contagion	$y_{ij} = \rho \sum_{k \neq i} \omega_{pq} y_{kj} + \varepsilon_{ij}$	$\omega_{pq} = \begin{cases} w_{ik} \\ w_{ki} \end{cases}$	$\omega_{pq} = \begin{cases} w_{(ij)(kj)} \\ w_{(kj)(ij)} \end{cases}$
Specific target contagion	$y_{ij} = \rho \sum_{m \neq j} \omega_{pg} y_{im} + \varepsilon_{ij}$	$\omega_{pq} = \begin{cases} w_{jm} \\ w_{mj} \end{cases}$	$\omega_{pq} = \begin{cases} w_{(ij)(im)} \\ w_{(im)(ij)} \end{cases}$

m on the other hand, which would lead to either $\omega_{pq} = w_{(ij)(im)}$ or $\omega_{pq} = w_{(im)(ij)}$. For both undirected and directed dyad contagion, any of these complex link functions can be employed.[27] Additionally, the link function can measure connectivity between dyad ij and dyads km, that is, either $\omega_{pq} = w_{(ij)(km)}$ or $\omega_{pq} = w_{(km)(ij)}$.

As with undirected data, further link functions can be created by combining in any way any of the basic or complex link functions with each other. The two simplest ways of combining connectivities are linear addition and multiplication. Other functional forms may be theoretically warranted in certain cases.

Summary

We have categorized all possible forms of spatial dependence along the distinction between monadic data, undirected dyadic data, and directed dyadic data. Table 1 summarizes all the available specification options for spatial lags.

Clearly, not only does the proper specification of the spatial y become more flexible when researchers move from monadic to undirected dyadic data and from there to directed dyadic data[28]—researchers also gain degrees of freedom in the specification of the weighting matrices. The increased flexibility means that the analysis of spatial effects in dyadic data sets requires much more theoretical reasoning than in monadic data. Researchers need to consider what type of contagion their theoretical model demands and also justify the specification of the weighting matrix.

Application: Spatial Dependence in a Directed Country Dyad Sample of BIT Diffusion

In order to demonstrate how the different forms of spatial dependence can lead to different insights on the process of policy diffusion, we build on and extend Elkins and colleagues' analysis of the diffusion of BITs over the period 1970 to 2000 using a Cox proportional hazard model.[29] They argue that competition among potential host countries, typically developing countries, for FDI causes the diffusion of BITs.[30] We restrict our analysis to dyads in which source countries i are Western developed countries and countries j (targets) are developing countries, giving us a

27. For undirected dyad contagion, simply read this paragraph with the words "source" and "target" deleted. For example, $\omega_{pq} = w_{(ij)(kj)}$ links dyad ij to dyads kj, that is, link the dyad of unit i with j to dyads consisting of units other than i with unit j.

28. In addition, one can of course combine all the possible spatial lags of directed dyadic data into one estimating equation.

29. Their analysis covers the period 1960 to 2000, but data for the 1960s often seem to be extrapolated backward, which we do not follow.

30. In their directed dyadic country sample, the richer country of a dyad is always the origin country i and the poorer country is the destination country j and dyads between high-income countries are excluded.

directed dyad sample of dimension $N_i \cdot N_j \cdot T$ in which sources never become targets and vice versa.[31]

Elkins and colleagues propose three different measures of competition for the weighting matrix: export-market, export-product, and infrastructure competition. For our application we use export-product competition, which we regard as theoretically most plausible.[32] The weighting matrix thus measures the extent to which countries export a similar basket of goods.[33]

Elkins and colleagues analyze a variant of *aggregate target contagion* by estimating a variant of equation (5), namely

$$y_{ijt} = \rho \sum_{k} \sum_{m \neq j} w_{jmt-1} y^{*}_{kmt-1} + \varepsilon_{ijt}. \tag{8}$$

where y^* is the sum total of BITs in force in each host country in year $t-1$.[34] Note that by using y^* rather than y in the spatial dependence variable, this is not strictly speaking a spatial lag model. Spatial dependence derives from the sum total of existing BITs in other developing countries m in year $t-1$, with connectivity represented by a row-standardized matrix that measures connectivity between j and m, that is, by export-product competition among developing countries. In other words, a developing country j is more likely to sign a BIT with a developed country i at time t if other developing countries m with a similar basket of export-products have a larger sum total of BITs in place with developed countries k in the period $t-1$.

To this, we add all the other possible forms of spatial dependence, which are all consistent with common micro-foundations seeking to explain the spread of BITs. We do so in order to show what happens to the results of Elkins and colleagues, but also because these other forms can be theoretically justified. To start, we will analyze *aggregate source contagion* by estimating a variant of equation (4), namely

$$y_{ijt} = \rho \sum_{k \neq i} \sum_{m} w_{ikt-1} y^{*}_{kmt-1} + \varepsilon_{ijt}. \tag{9}$$

The only difference to Elkins and colleagues is that competition among developed countries causes the spread of BITs rather than competition among develop-

31. Western developed countries are defined as Canada, the United States, Western European countries, Japan, Australia, and New Zealand. These countries typically do not conclude BITs with each other and FDI flows almost exclusively from developed to developing countries over the period to 2000.

32. Results are similar for using one of the other two weighting matrices (results available on request).

33. Measured on a scale from -1 to 1 (from total dissimilarity to total similarity). Like Elkins, Guzman, and Simmons (2006), to make it strictly nonnegative we add 1 to this measure so it runs from 0 to 2.

34. Control variables are suppressed from the formal exposition for simplicity.

ing countries. This specification can be motivated if one follows the argument that developed countries are usually the driving force behind the conclusion of BITs.[35]

Both forms of spatial dependence so far assumed that the aggregate behavior of competing developing or developed countries matters for other dyads' decisions to conclude BITs. However, it may well be that countries look more specifically at the question with whom their competitors have signed a BIT, not just how many BITs have been signed by competitors no matter with whom. With

$$y_{ijt} = \rho \sum_{m \neq j} w_{jmt-1} y_{imt-1} + \varepsilon_{ijt}, \tag{10}$$

a developing country j more likely accepts a BIT with a developed country i if other export-product competing developing countries m have previously concluded a BIT with the same developed country i (*specific target contagion*). Whereas with

$$y_{ijt} = \rho \sum_{k \neq i} w_{ikt-1} y_{kjt-1} + \varepsilon_{ijt}, \tag{11}$$

a developed country i more likely concludes a BIT with developing country j if other export-product competing developed countries k have previously concluded a BIT with that same developing country m (*specific source contagion*).

Finally, it is conceivable as well that both countries of a dyadic pair ij are influenced by the behavior of other competing developed and other competing developing countries with respect to each other. This leads us to model *directed dyad contagion* in the form of

$$y_{ijt} = \rho \sum_{km \neq ij} w_{ikt-1} w_{jmt-1} y_{kmt-1} + \varepsilon_{ijt}, \tag{12}$$

where country i is more likely to sign a BIT with country j if other developed countries k with whom country i competes have previously signed a BIT with other developing countries m with whom country j competes.[36]

Table 2 presents the estimation results. We include most of the control variables of Elkins and colleagues[37] using the same sources of data, leaving out variables with poor data availability, variables that had no effect in their analysis as well as

35. Neumayer 2006.

36. We have chosen a multiplicative functional form connecting the weighting matrix of export-product competition among developed countries (w_{ik}) with that of developing countries (w_{jm}). By doing so we implicitly assume that both competitions are simultaneously important for the spatial lag. A linear additive form would have assumed that competition among, say, developing countries can substitute for the lack of competition among developed countries. The results in Table 2 are hardly affected if one chooses this alternative functional form.

37. Elkins, Guzman, and Simmons 2006.

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TABLE 2. *Spatial dependence in the diffusion of bilateral investment treaties*

	Model 1 Aggregate target contagion	*Model 2 Aggregate source contagion*	*Model 3 Specific target contagion*	*Model 4 Specific source contagion*	*Model 5 Directed dyad contagion*	*Model 6 Multiple forms of contagion*	*Model 7 Multiple forms of contagion*	*Model 8 Specific forms of contagion*
$\sum_{k}\sum_{m\neq j} w_{jmt-1}\, y^{*}_{kmt-1}$	0.011 (3.77)***					0.005 (1.24)		
$\sum_{k\neq i}\sum_{m} w_{ikt-1}\, y^{*}_{kmt-1}$		0.004 (1.44)					−0.001 (0.33)	
$\sum_{m\neq j} w_{jmt-1}\, y_{imt-1}$			0.060 (18.92)***			0.061 (18.72)***	0.062 (19.12)***	0.062 (19.24)***
$\sum_{k\neq i} w_{ikt-1}\, y_{kjt-1}$				0.032 (13.55)***		0.033 (13.84)***	0.033 (13.89)***	0.033 (13.87)***
$\sum_{km\neq ij} w_{ikt-1}\, w_{jmt-1}\, y_{kmt-1}$					0.005 (1.31)	−0.004 (0.96)	−0.000 (0.09)	
EXTRACTIVE INDUSTRIES/EXPORTS (HOST)	−0.002 (1.18)	−0.002 (1.24)	−0.003 (1.63)	−0.002 (0.94)	−0.002 (1.23)	−0.002 (1.31)	−0.002 (1.32)	−0.002 (1.32)
COMMON LAW (HOST)	−0.336 (3.13)***	−0.349 (3.25)***	−0.398 (3.70)***	−0.257 (2.37)**	−0.352 (3.26)***	−0.306 (2.82)***	−0.310 (2.85)***	−0.310 (2.85)***
IMF CREDIT DUMMY (HOST)	0.413 (3.63)***	0.426 (3.76)***	0.375 (3.32)***	0.197 (1.72)*	0.429 (3.79)***	0.132 (1.15)	0.137 (1.19)	0.135 (1.17)
LN GDP (HOST)	0.224 (4.34)***	0.227 (4.44)***	0.195 (3.80)***	0.132 (2.49)**	0.224 (4.37)***	0.094 (1.75)*	0.093 (1.74)*	0.093 (1.73)*

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PER CAPITA INCOME (HOST)	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(1.21)	(1.02)	(0.87)	(1.28)	(0.93)	(1.20)	(1.09)	(1.12)
GDP GROWTH (HOST)	0.045	0.043	0.043	0.020	0.043	0.021	0.020	0.021
	(4.43)***	(4.28)***	(4.28)***	(1.98)**	(4.27)***	(2.01)**	(2.00)**	(2.02)**
FDI INFLOW (HOST)	0.019	0.026	0.026	0.030	0.027	0.027	0.029	0.028
	(1.20)	(1.66)*	(1.72)*	(1.97)**	(1.75)*	(1.73)*	(1.84)*	(1.79)*
CAPITAL ACCOUNT (% OF GDP) (HOST)	1.259	1.229	1.006	0.825	1.217	0.635	0.612	0.620
	(2.28)**	(2.24)**	(1.83)*	(1.56)	(2.23)**	(1.18)	(1.14)	(1.16)
LEVEL OF DEMOCRACY (HOST)	0.011	0.010	0.006	0.007	0.009	0.006	0.005	0.005
	(1.39)	(1.28)	(0.81)	(0.95)	(1.17)	(0.78)	(0.65)	(0.68)
DIPLOMATIC REPRESENTATION (HOST)	0.008	0.007	0.010	0.007	0.007	0.012	0.011	0.011
	(2.75)***	(2.40)**	(3.52)***	(2.40)**	(2.34)**	(3.76)***	(3.59)***	(3.71)***
BILATERAL TRADE TO GDP OF HOST	3.288	3.071	2.518	3.028	2.978	2.227	2.138	2.180
	(2.16)**	(1.99)**	(1.48)	(1.95)*	(1.93)*	(1.28)	(1.23)	(1.26)
COLONIAL TIES	1.055	1.057	0.562	1.069	1.054	0.620	0.618	0.617
	(4.43)***	(4.42)***	(2.29)**	(4.49)***	(4.41)***	(2.54)**	(2.53)**	(2.52)**
COMMON LANGUAGE	−0.113	−0.109	0.017	−0.088	−0.098	0.068	0.067	0.067
	(0.60)	(0.58)	(0.09)	(0.47)	(0.52)	(0.36)	(0.35)	(0.35)
AIC | *BIC*	7299 | 7419	7311 | 7431	7018 | 7138	7154 | 7274	7312 | 7432	6854 | 6999	6855 | 7001	6852 | 6980
$-ll$	3635.5	3641.7	3494.9	3563.0	3641.9	3405.0	3410.7	3410.8

Notes: BITs = 555. Dyads = 2411. N = 38395. Z-statistics in brackets. *significant at 10% level; **significant at 5% level; ***significant at 1% level.

variables that do not vary across dyads (the flexible baseline hazard captures their effect). To be consistent with their analysis we do not instrument for the spatial lags or apply spatial maximum likelihood even though this may be warranted given serial correlation in the data, in which case the use of spatial lags temporally lagged by one time period cannot fully solve the endogeneity problem. Importantly, we normalize the spatial effect variables to fall into the interval from 0 to 100 by dividing each lag by its maximum and multiplying by 100. We do this because before normalization the spatial effect variables are in different units, given that we follow Elkins and colleagues' use of y^*, the sum total of BITs in force, rather than y for aggregate target and source contagion. Normalization allows us to directly compare the relative importance of all the spatial effect variables with each other without needing to compute conditional effects.

Models 1 to 5 in Table 2 estimate the effect of each spatial lag separately. In column (1), the spatial lag models aggregate target contagion. The lag coefficient is positive and statistically significant, corroborating the finding of Elkins and colleagues that the aggregate past behavior of other developing countries with similar export-product structures matters for the conclusion of a BIT between a developed and a developing country. In column (2), the spatial lag models source contagion instead. The lag coefficient is statistically insignificant, suggesting that the aggregate past behavior of other export-competing developed countries does not matter for the agreement on BITs.

In column (3), we move away from aggregate behavior and the spatial lag models specific target contagion. The lag coefficient is positive and highly significant, suggesting that a developing country is more likely to sign a BIT with a specific developed country if other developing countries with similar export-product structures have an existing BIT with the same developed country. Column (4) reports a model of specific source contagion. The coefficient of this spatial lag is again positive and statistically significant. This result qualifies the finding of column (2). The aggregate BIT behavior of other competing developed countries as such does not matter, but if other competing developed countries have signed a BIT with a specific developing country, then this makes it more likely that a developed country will also sign a BIT with this specific developing country j. In column (5), we test directed dyad contagion, which does not have an effect statistically different from zero. Accordingly, we find no evidence that a developing country is more likely to sign a BIT with a developed country if other developing countries with an export-product structure similar to the developing country have previously signed BITs with other developed countries that have an export-product structure similar to the developed country.

So far, we have included the spatial lag variables separately. However, these spatial lags could be correlated with each other. A harder test of the various diffusion channels thus requires their joint inclusion in one model. Unfortunately, the aggregate source and target contagion spatial lags are so highly correlated with each other that their simultaneous inclusion leads to severe multicollinearity problems, whereas the correlations among the other spatial lag variables remain moderate. We therefore present two sets of regressions, one including all spatial lags but the aggregate source contagion one—column (6)—and the other including all spatial lags but the aggregate target contagion one—column (7). Strikingly, with the dyadic contagion spatial lags included, aggregate target contagion no longer matters. Instead, we find evidence that the diffusion of BITs works exclusively through specific source and target contagion. Column (8) reports the results from a model which includes only these two significant forms of contagion.

One can also compare the goodness of fit of the estimated models with each other. Note that each of Models 1 to 5, which estimate separate and isolated forms of contagion, are nested in either Model 6 or 7. Both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) suggest that Models 6 and 7 fit the data better than the restricted Models 1 to 5. This suggests that the models with multiple forms of contagion perform better than all models with individual forms of contagion. However, Model 8, which includes only specific source and target contagion has the lowest AIC and BIC of all the models. Since Model 8 is itself nested in both Models 6 and 7, this suggests that aggregate source and target contagion do not improve the model fit relative to a model that contains only dyad-specific forms of source and target contagion. From this perspective, Model 8 is clearly superior to all other models.

The normalization of spatial lag variables allows us to assess their relative substantive importance. We find that the effect of the specific target contagion spatial lag is about twice as large as the effect of the specific source contagion lag, suggesting the former is the substantively more important diffusion channel. In conclusion, we find that Elkins and colleagues were right in arguing that competition among developing countries exerts an important influence on the diffusion of BITs. However, policies do not diffuse via competition among capital importers at the aggregate level, but via their competition at the dyad-specific level. In addition, Elkins and colleagues neglected competition among developed countries for signing BITs with specific developing countries, which also has a statistically significant, but substantively less important effect compared to competition among developing countries.

Our findings are consistent with several theories of policy diffusion. It seems, however, that theories of policy learning and bargaining theories of policy concessions explain the specific forms of BIT diffusion better than theories of economic competition. If theories of competition were valid, one should find evidence for the aggregate form of diffusion that Elkins and colleagues have modeled. If other competing capital importers and exporters agree on BITs, then this should affect the allocation of investment flows across countries since BITs reduce the risk of foreign investment, thereby inducing a capital importer or exporter to react by similarly seeking to conclude more BITs. Yet, the superiority of specific forms of contagion in our empirical analysis suggests that other governments learn from a BIT that the two signatory countries are indeed willing to sign BITs with other partners as well. A capital importer that accepts a BIT with one capital-exporting country is less likely to resist another capital exporter's suggestion to also agree on a BIT. The same applies for a capital exporter: having signed a BIT with one capital importer signals willingness to conclude a BIT with another capital importer as well. In addition, our results inform the debate over whether BITs mainly serve as a commitment or signaling device.[38] If capital importers sign BITs to signal to any potential investor an investment-friendly domestic climate, then aggregate target contagion should matter: if one's competitors have concluded more BITs then one needs to conclude more BITs to send a firm signal to potential investors. That aggregate target contagion does not seem to matter suggests that BITs mainly serve as a commitment device to protect investment from the specific capital exporter with whom a BIT has been concluded.

Conclusion

Spatial analyses can be fruitfully extended to dyadic relations between countries or other political units. In particular, we have shown that the menu of choice increases by moving from monadic to undirected dyadic data and increases further still when analyzing directed dyadic data. We have illustrated the modeling possibilities in directed dyadic data by extending Elkins and colleagues' analysis of the diffusion of BITs. Elkins and colleagues correctly argued that competition among capital importers determines the spread of BITs, but we conclude that the diffusion of BITs is more specific, with a capital importer's decision to sign a BIT with a capital exporter depending only on whether other competing capital importers have signed a BIT with this very same capital exporter and not just with any capital exporter. In addition, we found evidence for similar dyad-specific source contagion working via competition among capital exporters.

In our application, all types of contagion have theoretical plausibility and were therefore tested. In general, however, researchers should not mine the data for potential evidence of all types of contagion but test only those types of contagion specified by their theory. Aggregate source and/or target contagion will often be a plausible diffusion channel, but the specific channels can be equally, if not more appropriate. To give but three examples. In the bipolar world of the Cold War period one might theorize that alliances diffused primarily via directed dyad contagion: if the Soviet Union allied with, say, India this increased the likelihood that the United States would ally with neighboring Pakistan. With economic sanctions, one might consider specific source contagion as most appropriate: as some states impose sanctions on a specific target, the likelihood increases that other states will follow suit. With preferential bilateral trade agreements between developed and developing countries, one might theorize that diffusion works mainly via specific target and specific source contagion. If, say, Chile has managed to conclude such

38. See Neumayer and Spess 2005.

an agreement with the United States, other developing countries such as Peru, Colombia, and Panama will want to conclude a similar treaty with the United States, while other developed countries such as Canada, the European Union, and Japan seek a similar treaty with Chile. A better understanding of the full set of options of specifying spatial effects in dyadic data will allow formulating and testing novel hypotheses predicting dependence of a dyad of two political units on the policy choices of other sources, other targets, or other dyads.

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