

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, the focus of the analysis is the pair or dyad of two political units. Yet, with few exceptions, social scientists have analyzed contagion only in monadic datasets, consisting of individual political units. This article categorizes all possible forms of modeling spatial lags in both undirected and directed dyadic data. This 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. We illustrate the modeling flexibility gained from an understanding of the full set of specification options for spatial effects in dyadic data by an application to the diffusion of bilateral investment treaties between developed and developing countries, building and extending on Elkins, Guzman and Simmons. (2006. *Competing for Capital: The Diffusion of Bilateral Investment Treaties, 1960-2000*. *International Organization* 60 (4):811-846). We come to different conclusions about the channels through which bilateral investment treaties diffuse. We find that rather than a capital importing country being influenced by the total number of BITs signed by other capital importers, as modeled in the original article, a capital importing country is only more likely to sign a BIT with a capital exporter 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.

1. Introduction

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 spill-over’ across jurisdictions.¹ The vast majority of these studies have used a monadic dataset.² In contrast, with few exceptions diffusion analysis remains inexistent in studies adopting a dyadic framework, i.e. a setting where the unit of analysis is the pair or dyad of two political units, which has particularly gained importance in international relations research and which has become increasingly popular over the last decade or so.³ This is surprising because spatial dependence exists in a many dyadic settings. What one unit does in relation to other units, with which it forms a dyad, will often influence as well as be influenced by the relations of other dyads.

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

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

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, Brooks 2007.

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

political units at all levels of the political system – from the global and international right down to the local.

This paper 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 generate externalities, increase competition, induce cooperation, or lead 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 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 international 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 intra-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

⁴ Elkins et al. 2006, Manger 2006 and Gleditsch and Gartzke 2006, respectively.

⁵ King 2001, 498 (emphasis in original).

⁶ We are not aware of any dyadic conflict study that models spatial dependence.

solution if researchers are indeed interested in spatial effects. Rather, the spatial dependence should be modeled directly by the inclusion of spatial lags 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 lag model, because none of the different possible ‘nuisance models’ allows to directly test the spatial hypotheses derived from the theory.⁷

Second, the few studies that actually do analyze spatial dependence in dyadic data have done so in a limited way, focusing solely on aggregate forms of contagion. A good example is Elkins et al.’s study of the diffusion of bilateral investment treaties (BITs).⁸ The authors only consider aggregate target contagion from capital-importing countries, 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 which 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

⁷ Beck et al. 2006.

⁸ Elkins et al. 2006.

spatial effects in dyadic data. We will show that in undirected dyadic data, dyads can only spatially depend on the policy choices of other dyads, which is similar to the monadic setting in which units can only depend 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 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 lags 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 et al. 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 com-

⁹ See also Plümper and Neumayer 2009.

mendable for clearly specifying and justifying their modeling approach. Our analysis provides additional insights into the study of BIT diffusion. While we find that Elkins et al. 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 only depends 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 et al.'s 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.

2. 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 shortage of theories predicting processes of policy diffusion and spill-over across units.¹¹ All of

¹⁰ Franzese and Hays 2008, 3.

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

these theories can also be applied to dyadic frameworks. Moreover, these theories are in principle compatible with all of the types of contagion categorized below 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.

We will show that 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 we discuss in detail spatial dependence in dyadic data.

2.1. 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 here 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 model, 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:

$$y_i = \rho \sum_k w_{ik} y_k + \varepsilon_i \quad . \quad (1)$$

¹² Beck et al. 2006.

The spatial lag $\sum_k w_{ik} y_k$ consists of two elements, namely what in the following we will 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 as there $i = k$ and units cannot spatially depend on themselves). The spatial autoregression parameter ρ gives the impact of the spatial lag on the dependent variable. We will discuss the issue of specifying the weighting matrix in more detail below in section 2.5.

Of course, in reality, researchers usually do not estimate the basic model displayed in (1a) or (1b), but add control variables, use a cross-sectional time-series data set, 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 modelling 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 modelling, control variables etc.¹⁵

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

$$\sum_k w_{ik} y_k .$$

¹⁴ Beck and Katz 1995; Plümper et al. 2005.

¹⁵ We will similarly neglect all issues of estimation of spatial lag models, which is complicated by the fact that with inter-dependent units of analysis, spatial dependence models typically suffer

In monadic data, the specification of spatial lags gives researchers some flexibility with respect to the variable that measures connectivity among units, but they 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.

2.2. 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 inter-state 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-

from endogeneity (see Anselin 1988; Ward and Gleditsch 2002; Franzese and Hays 2006, 2007, 2008). There are also important specification choices that researchers need to consider, which we discuss in a separate article (Plümper and Neumayer 2009).

¹⁶ If the weighting variable used is directed, then researchers can specify w_{ki} instead of w_{ik} . See section 2.5 for more details.

fore, whilst one can still distinguish i from j , one either cannot distinguish between ij and ji or 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. To illustrate, 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

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

¹⁸ Guzman 1998; Neumayer and Spess 2005.

¹⁹ Elkins et al. 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.

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 et al. do. The decision to treat a dyadic relationship as directed or undirected thus requires theoretical justification.

2.3. 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:

$$y_{ij} = \rho \sum_{km \neq ij} \omega_{pq} y_{km} + \varepsilon_{ij} \quad , \quad (3a)$$

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

$$y_{ji} = \rho \sum_{mk \neq ji} \omega_{pq} y_{mk} + \varepsilon_{ji} \quad . \quad (3b)$$

We have denoted the connectivity or weighting matrix as ω_{pq} . In section 2.5 we will discuss five different specifications of the weighting matrix, such that $\omega_{pq} \in \{w_{ik}, w_{im}, w_{jk}, w_{jm}, w_{(ij)(km)}\}$, 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 to section 2.5.

Equations (3a) and (3b) 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

2.4. *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 merely 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 only their choices with respect to 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 have already

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 Gleditsch and Gartzke 2006.

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

$$y_{ij} = \rho \sum_{km \neq ij} \omega_{pq} y_{km} + \varepsilon_{ij} \quad . \quad (4)$$

Equation (4) 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*:

$$y_{ij} = \rho \sum_{k \neq i} \sum_m \omega_{pq} y_{km} + \varepsilon_{ij} \quad (5)$$

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

$$y_{ij} = \rho \sum_k \sum_{m \neq j} \omega_{pq} y_{km} + \varepsilon_{ij} \quad (6)$$

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 $y_{ij} = \rho \sum_{k \neq i, m \neq j} \omega_{pq} y_{km} + \varepsilon_{ij}$.

Equation (6) 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

$$y_{ij} = \rho \sum_{k \neq i} \omega_{pq} y_{kj} + \varepsilon_{ij} \quad (7)$$

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 (5), equation (7) describes a situation in which other sources k only affect i 's interaction with j 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 US, Germany, France etc. have signed. However, if the US, Germany, France and others sign a BIT with – say Chile – the incentives for Canada to also sign a BIT with Chile increases.

Lastly, in equation (8) 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 :

$$y_{ij} = \rho \sum_{m \neq j} \omega_{pq} y_{im} + \varepsilon_{ij} \quad , \quad (8)$$

This type of spatial dependence we name *specific target contagion*. Compared to the aggregate target contagion described by equation (6), equation (8) describes a situation in which other targets m only affect j 's interaction with i 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 has signed. However, if Argentina and Brazil sign a BIT with – say the US – the incentives for Chile to also sign a BIT with the US increases.

2.5 *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 unit 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. 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 exports from k to i . If the connectivity is undirected as with, e.g., 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, let us 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

²³ We do not discuss the issue of row standardization here. It is an important issue (see Plümer and Neumayer 2009) – but equally important for monadic and dyadic data.

the one hand and other units, call them $k(\neq i)$ 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 below for directed data. Finally, one can create further link functions by combining any of these link functions with each other in any way. We provide two examples further below.

In directed dyadic data, it is useful again to distinguish basic link functions, i.e. 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.

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.

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 , i.e. connectivity between the dyad consisting of source unit i and target unit j on the one hand and dyads comprised 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 , i.e. 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 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 , i.e. either $\omega_{pq} = w_{(ij)(km)}$ or $\omega_{pq} = w_{(km)(ij)}$.

²⁶ The reason is that in order to create these complex link functions one needs a dataset that links dyads with dyads, i.e. 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.

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 , i.e. link the dyad of unit i with j to dyads consisting of units other than i with unit j .

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.

2.6. *Summary*

In this section, 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.

< Insert Table 1 around here >

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. In sum, 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.

3. **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 upon and extend Elkins et al.'s analysis of the diffusion of BITs over the period 1970 to 2000 using a Cox

²⁸ In addition, one can of course combine all the possible spatial lags of directed dyadic data into one estimating equation. Such a model, however, is very likely to suffer from multicollinearity.

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

Elkins et al. 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 et al. analyze a variant of *aggregate target contagion* by estimating a variant of equation (6), namely

$$y_{ijt} = \rho \sum_k \sum_{m \neq j} w_{jmt-1} y_{kmt-1}^* + \varepsilon_{ijt} \quad (9)$$

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.

³¹ Western developed countries are defined as Canada, the US, 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 upon request).

³³ Measured on a scale from -1 to 1 (from total dissimilarity to total similarity). Like Elkins et al., to make it strictly non-negative we add 1 to this measure so it runs from 0 to 2.

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 measured 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 et al., but also because these other forms can be theoretically justified. To start, we will analyze *aggregate source contagion* by estimating a variant of equation (5), namely

$$y_{ijt} = \rho \sum_{k \neq i} \sum_m w_{ikt-1} y_{kmt-1}^* + \varepsilon_{ijt} \quad . \quad (10)$$

The only difference to Elkins et al. is that now competition among developed countries causes the spread of BITs rather than competition among developing 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

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

³⁵ Neumayer 2006.

question with whom their competitors have signed a BIT, not just how many BITs have been signed by competitors no matter with whom. With

$$y_{ijt} = \rho \sum_{m \neq j} w_{jmt-1} y_{imt-1} + \varepsilon_{ijt} \quad , \quad (11)$$

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

$$y_{ijt} = \rho \sum_{k \neq i} w_{ikt-1} y_{kjt-1} + \varepsilon_{ijt} \quad , \quad (12)$$

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

$$y_{ijt} = \rho \sum_{km \neq ij} w_{ikt-1} w_{jmt-1} y_{kmt-1} + \varepsilon_{ijt} \quad , \quad (13)$$

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

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 below are hardly affected if one chooses this alternative functional form.

Table 2 presents the estimation results. We include most of the control variables of Elkins et al. (2006) using the same sources of data, leaving out variables with poor data availability, variables which had no effect in their analysis as well as 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 et al.'s (2006) 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.

< Insert Table 2 around here >

Models 1 to 5 estimate the effect of each spatial lag separately. In column 1 the spatial lag models target contagion. The lag coefficient is positive and statistically significant, corroborating the finding of Elkins et al. that the aggregate past behavior of other export competing developing countries 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 export competing developing countries 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 export-product competing developing countries have previously signed BITs with other export-product competing developed countries.

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 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 source contagion one (column 6) and the other including all spatial lags but the 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 models 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 only contains 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 et al. 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 et al. 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 et al. 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 two countries agree upon that these two countries are indeed willing to sign BITs. A capital importer which 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 (see Neumayer and Spess 2005). 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.

4. Conclusion

This research note has demonstrated that 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 et al.'s analysis of the diffusion of BITs. Elkins et al. 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

only depending on whether competing other capital importers have signed a BIT with the very same capital exporter and not 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 an agreement with the US, other developing countries such as Peru, Colombia and Panama want to conclude a similar treaty with the US, 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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Table 1. Spatial lag specification in monadic and dyadic data.

<i>type of contagion</i>	<i>(partial) model</i>	<i>Basic link functions</i>	<i>More complex link functions</i>
<i>monadic data:</i>			
unit contagion	$y_i = \rho \sum_k \omega_{pq} y_k + \dots + \varepsilon_i$	$\omega_{pq} = \begin{cases} W_{ik} \\ W_{ki} \end{cases}$	
<i>undirected dyads:</i>			
undirected dyad contagion	$y_{ij} = \rho \sum_{km \neq ij} \omega_{pq} y_{km} + \varepsilon_{ij}$ \Leftrightarrow $y_{ji} = \rho \sum_{mk \neq ji} \omega_{pq} y_{mk} + \varepsilon_{ji}$	$\omega_{pq} = \begin{cases} W_{ik} \\ W_{ki} \\ W_{jm} \\ W_{mj} \end{cases}$	$\omega_{pq} = \begin{cases} W_{(ij)(km)} \\ W_{(km)(ij)} \\ \text{any of the functions for} \\ \text{directed data or function} \\ \text{of any combination thereof} \end{cases}$
<i>directed dyads:</i>			
directed dyad contagion	$y_{ij} = \rho \sum_{km \neq ij} \omega_{pq} y_{km} + \varepsilon_{ij}$	$\omega_{pq} = \begin{cases} W_{ik} \\ W_{ki} \\ W_{jm} \\ W_{mj} \end{cases}$	$\omega_{pq} = \begin{cases} W_{(ij)(km)} \\ W_{(km)(ij)} \\ \text{any of the functions for} \\ \text{directed data or function} \\ \text{of any combination thereof} \end{cases}$
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	$y_{ij} = \rho \sum_{m \neq j} \omega_{pq} y_{im} + \varepsilon_{ij}$	$\omega_{pq} = \begin{cases} W_{jm} \\ W_{mj} \end{cases}$	$\omega_{pq} = \begin{cases} W_{(ij)(im)} \\ W_{(im)(ij)} \end{cases}$

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)*
per capita income (host)	-0.000 (1.21)	-0.000 (1.02)	-0.000 (0.87)	-0.000 (1.28)	-0.000 (0.93)	-0.000 (1.20)	-0.000 (1.09)	-0.000 (1.12)
GDP growth (host)	0.045 (4.43)***	0.043 (4.28)***	0.043 (4.28)***	0.020 (1.98)**	0.043 (4.27)***	0.021 (2.01)**	0.020 (2.00)**	0.021 (2.02)**
FDI inflow (host)	0.019 (1.20)	0.026 (1.66)*	0.026 (1.72)*	0.030 (1.97)**	0.027 (1.75)*	0.027 (1.73)*	0.029 (1.84)*	0.028 (1.79)*
capital account (% of GDP) (host)	1.259 (2.28)**	1.229 (2.24)**	1.006 (1.83)*	0.825 (1.56)	1.217 (2.23)**	0.635 (1.18)	0.612 (1.14)	0.620 (1.16)
level of democracy (host)	0.011 (1.39)	0.010 (1.28)	0.006 (0.81)	0.007 (0.95)	0.009 (1.17)	0.006 (0.78)	0.005 (0.65)	0.005 (0.68)
diplomatic representation (host)	0.008 (2.75)***	0.007 (2.40)**	0.010 (3.52)***	0.007 (2.40)**	0.007 (2.34)**	0.012 (3.76)***	0.011 (3.59)***	0.011 (3.71)***
bilateral trade to GDP of host	3.288 (2.16)**	3.071 (1.99)**	2.518 (1.48)	3.028 (1.95)*	2.978 (1.93)*	2.227 (1.28)	2.138 (1.23)	2.180 (1.26)
colonial ties	1.055 (4.43)***	1.057 (4.42)***	0.562 (2.29)**	1.069 (4.49)***	1.054 (4.41)***	0.620 (2.54)**	0.618 (2.53)**	0.617 (2.52)**
common language	-0.113 (0.60)	-0.109 (0.58)	0.017 (0.09)	-0.088 (0.47)	-0.098 (0.52)	0.068 (0.36)	0.067 (0.35)	0.067 (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

BITs: 555. Dyads: 2411. N: 38395. Z-statistics in brackets. *, **, *** significant at 10, 1 and 0.1% level, respectively.