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Conditional Spatial Policy Dependence:

Theory and Model Specification

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Abstract

When the policy choice in one jurisdiction depends on those of other jurisdictions, then policies are said to be spatially dependent. In this article, we discuss how scholars can bring theories of spatial policy dependence and empirical model specifications closer in line so that the empirical analysis actually tests the theoretical predictions. Specifically, comprehensive theories of spatial policy dependence will typically suggest that the jurisdictions receiving spatial stimuli systematically differ in their exposure to such signals as a function of the intensity of their interaction with other jurisdictions. Similarly, theories will often predict that governments also differ in their responsiveness to any given spatial stimulus as a function of the institutional, political, economic or social context in which they operate. In other words, theories typically postulate that spatial dependence is conditional on exposure and responsiveness, neither of which is accounted for in the standard empirical practice of estimating one single common coefficient for a row-standardized spatial lag variable. We show how scholars can adequately model both forms of heterogeneity with properly specified interaction effects models.

1. Introduction

Most policies are spatially dependent. The policy choice of one country, region, state or municipality depends partly on previous policy choices of other countries, regions, states or municipalities. Yet, though political scientists had discussed spatial policy dependence since at least the early 1970s from a theoretical perspective,¹ it required advances in spatial econometrics and methodological advice (Anselin 1988, 2002, Beck, Gleditsch and Beardsley 2006; Franzese and Hays 2007a, 2008) to turn the study of spatial policy dependence into one of the fastest growing fields in comparative politics and international relations. Political scientists have developed theories identifying externalities, learning, and coercion as main causal mechanisms for spatial policy dependence (Jahn, 2006, Swank, 2006, Gilardi et al. 2009). They have also recently started exploring heterogeneity in exposure and responsiveness to spatial effects (Basinger and Hallerberg 2004, Swank 2006, Shipan and Volden 2008). However, much existing empirical literature seeks to provide evidence for the mere existence of spatial policy dependence, rather than on the causal mechanisms through which policy choices become spatially dependent on previous choices of the same policy in other jurisdictions (Boehmke and Witmer 2004: 39). Similarly, almost no empirical studies explicitly test for heterogeneity among recipients of spatial effects. There thus remains a considerable gap between the predictions derived from theories of spatial policy dependence and the hypotheses de facto tested in empirical research.

¹ Early works include Cooper's *The Economics of Interdependence* (Cooper 1968), Vernon's *Sovereignty at Bay* (Vernon 1971) and Keohane and Nye's *Power and Interdependence* (Keohane and Nye 1977). See Graham, Shipan and Volden (2008) for a review of recent theoretical advances and Gilardi (2010) for a discussion of learning theories.

This article seeks to close this gap. Starting from the observation that theories of spatial policy dependence and the empirical models political scientists employ to test these theories are often not well connected, we argue that most theories of spatial policy dependence either are already inherently conditional or, if not, should be, while empirical models with few exceptions estimate an unconditional spatial effect. We show that empirical tests of spatial policy dependence require more attention to two kinds of causal heterogeneity. First, in following the common practice of row-standardizing the connectivity or weighting matrix, scholars implicitly assume that the aggregate spatial stimulus is the same for all receiving countries. In contrast, theories of spatial policy dependence usually predict that the strength of this stimulus systematically differs across receiving jurisdictions. For example, theories of spatial policy dependence which rely on learning as the principal causal mechanism often contend that the policy-makers learn more if they have more and more intensive social interactions with other policy-makers in international organizations and other venues (Sikkink 1993, Ramirez et al. 1997). Likewise, externalities tend to increase with the level of total interaction with the outside world (Garrett 1995, 2000).

Second, with few exceptions, empirical analyses assume that the strength of the spatial effects is independent of the responsiveness of the jurisdiction receiving the stimulus. In contrast, theory suggests that the responsiveness of governments to a given spatial stimulus systematically varies with the political context and economic and social circumstances. For example, Gilardi (2005: 92) states that “[T]he impact of liberalization (...) is conditional on the characteristics of the political system, notably the extent to which policy change is difficult”, while Basinger and Hallerberg (2004: 275) argue that “a country’s own political situation, combined with the institutional makeup of potential competitors, affects a country’s decisions regarding competing for capital.” Mosley and Uno (2007: 941) highlight “exploring further (...) the interaction between the internal (domestic) and external drivers” as a top priority for

research on spatial dependence in labor rights. These theories thus predict that political systems and other domestic factors exert an influence on the spatial effect itself.

This paper contributes to the rapidly growing literature on the analysis of spatial policy dependence by offering theoretical and model specification advice.² As Graham, Shipan and Volden (2008: 31) have put it, while “scholars have found sparks of insights about the conditional nature of policy diffusion”, they have “yet to illuminate a systematic path forward.” By identifying two causes for conditional spatial policy dependence – exposure and responsiveness – and by developing empirical models for testing these theories, we try to push the literature forward in the direction in which Graham et al. (2008: 30) locate the “future of policy diffusion” research. Like these authors, we contend that comprehensive theories of spatial policy dependence must go beyond explaining why policies are spatially dependent. Instead, they must identify the causal mechanisms of spatial policy dependence, they have to consider whether and how the strength of the aggregate spatial stimulus varies across receiving jurisdictions, and they have to explain why governments of different jurisdictions respond differently to any given spatial stimulus.

² Spatial policy dependence, as we use the term, is conceptually close, but not identical to policy diffusion and interdependence. Interdependence is the most general term, describing a situation in which policy choices or outcomes in one country affect the same or other policies or outcomes in other countries. Diffusion is the most restrictive term, referring to situations in which policy choices in one jurisdiction affect the choice of the same policies in other jurisdictions in the same direction. In contrast, spatial policy dependence describes situations in which the choice of a specific policy in one jurisdiction influences the choice of the same policy in other countries, but not necessarily in the same direction. Distinguishing these terms is more than an exercise in semantics, it has repercussions on empirical model specification for analyzing these processes. Interdependence that is not also spatial policy dependence cannot be adequately modeled by what is known as a spatial lag model, in which the dependent variable is regressed on the weighted values of the dependent variables in other units of observation. Instead, it needs to be modeled by what is known as a spatial-x model (Plümper and Neumayer 2010a).

We also contribute to the methodological state-of-the-art in spatial econometric model specification. We show that the standard specification suggested by methodologists and used by applied researchers does not fit comprehensive theories of spatial policy dependence. This holds especially for the conditionalities that theorists claim to exist but researchers implicitly assume away by row-standardizing the spatial lag variable and by failing to explicitly model the influence of contextual factors on governments' responsiveness to spatial policy influences. We demonstrate how researchers can stick to the common practice of row-standardizing the weighting matrix and yet capture differences in exposure to the spatial stimulus experienced by jurisdictions as well as differences in the responsiveness of jurisdictions to any given spatial stimulus. Both types of conditional spatial policy dependence are best modeled as interaction effects, even if the underlying reason for heterogeneity is different.

2. The Logic of Spatial Policy Dependence and the Case for Conditionality

Theories of spatial policy dependence typically predict that whilst many policies are spatially dependent, this dependence is unlikely to be uniform across jurisdictions. This section advances this generally accepted theoretical idea by arguing that spatial policy dependence is conditioned by two factors: exposure to the influence of other jurisdictions and responsiveness to any given spatial stimulus. We develop our argument referring to three genuine causal mechanisms for spatial policy dependence: externalities, which are conceptually indistinguishable from competition; learning, which is typically indistinguishable from emulation (Meseguer 2005); and coercion.³ In what follows, we discuss these three main

³ Causal mechanisms of spatial policy dependence are of course not mutually exclusive. Instead, they can reinforce each other, rendering it empirically difficult to empirically disentangle their effects. Note also that others have identified as few as two (Boehmke and

causal mechanisms of spatial policy dependence, providing arguments for the existence of heterogeneity in exposure and responsiveness in each one of them.

2.1. *Exposure and Responsiveness to Externalities*

Externalities describe a situation in which the policy choices of other jurisdictions k create a cost (negative externality) or benefit (positive externality) to jurisdiction i . If the strength of the externality is sufficiently strong, jurisdiction i may wish to offset or magnify by also changing its policy. Externalities can be distinguished according to whether they are direct or indirect, with indirect externalities that exert an influence via third parties often called competition. Theories of direct externalities require some form of cross-border movement between the sender of the spatial stimulus and its receiver, for example, the cross-border exchange of capital, goods, services, persons, or pollutants, which carries the externality from the sender to the receiver. Yet, externalities do not need to be direct. Assume, for example, that two countries have industries which produce and export similar products, but these two countries do not trade with each other. This constellation does not prevent externalities because both countries could compete on third markets with each other.

Whether direct or indirect, theories of externalities will also make straightforward predictions on exposure: jurisdictions that, *in total*, exchange more goods and services (relative to their size), more capital, more people, more pollutants than others are more exposed to externalities than these other jurisdictions, which have less of such exchange. Thus, for example, if direct externalities are carried over to other countries by, say, trade, then two countries which have the same set of major trading partners will experience different exposure to externalities

Witmer 2004: 40) and as many as six (Simmons and Elkins 2004; Dobbin et al. 2007) causal mechanisms.

if one country is very open toward trade in terms of either a larger volume of trade or a higher level of trade openness (trade relative to economic size), while the other one is more closed. In fact, it is very difficult to conceive of an externality-based theory of spatial policy dependence that would not also predict that exposure varies across jurisdictions.

Likewise, governments' responsiveness to externalities caused by other jurisdictions is very likely to vary even if jurisdictions have similar levels of exposure. Fundamentally, our argument is that the very same institutional, political, economic and social conditions which drive differences in policies across jurisdictions should also drive differences in the responsiveness to a spatial stimulus from the outside. First, a government's response depends on whether externalities affect actors that exert an influence on the survival of the government. Constitutional rules exert a large influence on governments' responsiveness by determining the pivotal actor on which the support for and eventually the survival of the government depends (Bueno de Mesquita et al. 1999, Persson and Tabellini 2003, Plümper and Martin 2003), by defining the limits of political autonomy, and by delimiting the opposition's influence on policy choices. The most obvious constitutional influence results from the importance of elections on the survival of the government. If elections do not exist or if they have no influence on government survival and externalities do not affect the ruling elite, the autocratic governments' responsiveness to policies in other countries remains limited. In democracies, externalities are likely to affect voters and interest groups, but responsiveness may still depend on a government's accountability, the political strength of the government, political institutions that may reduce the political autonomy of the government, on partisan preferences, the existence and position of veto players, the influence of lobby groups and so on (Golder 2005, Boix 1999; Grossman and Helpman 2001; Cao and Prakash 2009). For example, left-leaning governments may be less responsive to the spatial stimulus induced by international tax competition as they are, all other things equal, averse to lower corporate tax rates, which

might well have to be accompanied by either lower public spending or higher labor tax rates. As another example, more unitary governments may find it easier to respond to international tax competition than more fractionalized governments, in which many players with diverging interests and positions can exert an influence on government policy (Laver and Shepsle 1990). In societies, in which the social norm of fairness and equality is more deeply entrenched than others, governments might find it more difficult to respond to spatial stimuli pushing in the direction of more free-market policies.

2.2. *Exposure and Responsiveness to Learning*

Learning theories of spatial dependence presuppose that governments do not know the optimal policy. Governments can observe the effect of policies in other jurisdictions and profit from their good or bad experiences (Bennett 1991: 221; Dolowitz and Marsh 1996). As a consequence, learning can lead to policy diffusion if jurisdictions learn from positive examples and under certain circumstances learning will lead to convergence, but it can also create divergence if policies diffuse first among a minority of jurisdictions that previously held a different policy implemented by the majority of jurisdictions. Divergence may also result if jurisdictions learn from negative examples (Zimring and Hawkins 1986: 38-45, Epstein and Kobylka 1992).⁴

Most proponents of learning theories assume that learning depends on direct interaction and communication between policy-makers, policy advisers⁵ or other relevant stakeholders with influence on policies (Rogers 1995: ch. 1). For many scholars, learning is a mere function of

⁴ Interestingly, the social sciences have no term for the spatial process in which a policy change in one jurisdiction provides an incentive for others to shift policies in the opposite direction. We thus prefer the more general term spatial policy dependence, which can account for both policy diffusion and the opposite effect, call it policy repulsion (for lack of a better term).

⁵ See, inter alia, Haas (1992), Dobbin et al. (2007), King (2005) and Weishaupt (2010).

interaction and communication rather than a deliberative process consisting of collecting and evaluating information and making inferences from other jurisdictions' experiences to their own (Gilardi 2010, Boehmke 2009, Meseguer 2005). Learning as a side-effect of interaction and communication, call it diffuse learning, tempted researchers to use joint membership in committees and international organizations as a proxy for the degree to which actors learn from each other or perhaps emulate each other's behavior (Haas 1992, Kemmerling 2010, Needergard 2009, Jahn 2006).

Even for such diffuse learning or for mere emulation, it is likely that the learning process depends on exposure in the form of the density of interactions with important senders. Therefore, diffuse learning becomes more likely as the frequency and the intensity of contacts increase. Whatever contact scholars have in mind – be it diplomatic relations, joint membership in international organizations, informal fora for negotiations and discussions, or the same set of interest groups – different governments will have different levels of exposure to learning environments depending on the extent to which they have contact with policy makers from other jurisdictions (Hafner-Burton et al. 2008).

The case for heterogeneous exposure to learning becomes even clearer when we consider intentional learning. This form of deliberate learning occurs when government representatives seek to solve a problem, i.e. improve the outcomes in a certain area by trying to find a suitable policy reform (Baturu and Gray 2009, Lee and Strang 2006). In these situations, governments actively seek to identify similar jurisdictions with a different policy that achieved better (or worse) results. The extent to which governments can learn from the policy outcomes in other jurisdictions depends on the frequency and the intensity of direct interactions with these other jurisdictions as learning presupposes that policy makers understand which policy choices led to the better or worse outcomes from those who had enacted them.

Whether diffuse or intentional learning is considered, governments also differ in their responsiveness to outside learning stimuli in the form of differences in the capacity to learn from others as well as in the constraints they face for changing policies in the direction of what has been learned. Heterogeneity in capacity to learn may be modeled by the level of human capital and the quality of the administrative infrastructure at the disposal of policy-makers wishing to learn. Heterogeneity in the constraints imposed on governmental leeway to change policies will often resemble the manifold reasons for heterogeneous responsiveness we have listed above for externalities as the causal mechanism of spatial policy dependence. Thus, for example, jurisdictions in which fundamental policy changes require constitutional change or super-majorities will find changing policies toward other jurisdictions' role model examples more difficult. Jurisdictions with fractionalized governments may respond less to learning, not least because different parts of the governing coalition may take home different, and sometimes contradictory, lessons from the learning experience. Responsiveness to learning can also be a function of the state of the economy and the stability of the political system. Crises can increase the willingness of governments to take risks and engage in policy experiments (Drazen and Grilli 1993; Rodrik 1996). If a government believes it will lose the next election unless an economic miracle happens, it becomes more willing to try policies, which were seemingly successful elsewhere, even if their voters and influential lobby groups dislike them.

Variation in the degree to which political actors learn from the policy experience in other jurisdictions can also result from processes, for which the line between heterogeneity in exposure and heterogeneity in responsiveness is blurred. The extent to which new information changes the behavior of political actors depends on their priors and the extent to which political actors allow themselves to be exposed to new information that contradicts these priors. Even the most compelling evidence is typically met with reservation by those who hold views

that largely deviate from this new evidence (Gilardi 2010). Under many circumstances, the probability of policy changes given new information thus depends on the distance between the actor's established beliefs and the new information received. In these cases, spatial dependence becomes inherently conditional because – depending on their prior beliefs and the nature of the new information – policy-makers and governments have different propensities to learn from and to respond to new information and evidence. Their response will systematically vary with the degree to which new evidence supports their prior beliefs and policy intentions. What makes this hard to categorize as either heterogeneity in exposure or in responsiveness is that governments who do not wish to respond to inconvenient new information will select to expose themselves less to venues in which such information is disseminated. For example, countries have the option to choose the policy of empty chairs and stay away from international conferences, in which case they choose not to be exposed to potentially new information. Alternatively, governments can attend the conference, but refuse to update their priors despite potential new information.⁶

2.3. *Exposure and Responsiveness to Coercion*

Coercion causes spatial policy dependence if and only if other actors directly or indirectly (via other actors) exert pressure on a government to change a policy to bring it in line with their own policy.⁷ Coercion can be exercised “by governments, international organizations,

⁶ The avoidance of learning is difficult if not impossible for individuals. However, governments can send delegates to conferences and then ignore any new information they might bring home.

⁷ It is important to clearly distinguish the motive for coercion from its means. Governments do not coerce other governments simply because they can, but because they have an ideological, political, economic, social, or cultural incentive to do so. Since coercion is not only costly to

and nongovernmental actors through physical force, the manipulation of economic costs and benefits, and even the monopolization of information or expertise.” (Dobbin et al. 2007: 454)⁸

The probability of using coercive means will vary across potential senders, while the probability of “giving in” will vary across receivers. Even if senders are willing and in principle able to coerce, they may not be fully successful across the range of receivers of coercion. One reason is that receivers differ in the extent they are exposed to the actual pressure from co-ercer, which is a function of receiver’s power to withstand coercive attempts. Another reason for differences in the probability of succumbing to coercion stems from differences in responsiveness to pressure of any given strength. Governments are more likely to react to outside pressure if they find themselves in a serious economic or political crisis, which renders maintaining the status quo extremely costly. The same governments that will dismiss condi-

the receiver of political pressure but also to the sender, governments may be reluctant to coerce other governments if the cost of coercion is higher than the potential gain from the other government giving in. In turn, even if governments have an incentive to coerce other governments, they may simply lack the means of doing so.

⁸ In many cases, coercion is a response to externalities. For example, in the second half of the 1980s, the US exerted pressure on Japan’s monetary and fiscal policies because the US government did not want to adjust its own monetary and fiscal policies in a way that reduces the effect of Japan’s policies on the US labor market (McKinnon and Ohno 1997). A special case of coercive spatial policy dependence emanates from conditional membership in international organizations. Membership in the EU, for example, depends on prior implementation of the *acquis communautaire* (Mattli and Plümper 2004, Plümper and Schneider 2007). As a consequence, policies of applicant countries spatially depend on prior EU decisions and indirectly on policies other EU members have already in place.

tions on their fiscal and monetary policies imposed by the International Monetary Fund (IMF) or the Euro-zone countries as unwarranted interference in their sovereign decision-making when economic times are good, will readily accept such conditions if they find themselves in deep economic crisis.

3. Exposure and Responsiveness in Empirical Research on Spatial Policy Dependence

Before the rise of spatial econometric methods in comparative politics, empirical analyses modeled spatial policy dependence as a function of a jurisdiction's total interaction with others in the form of total trade openness (e.g., Garrett 1995; Rodrik 1997), the presence or absence of capital controls (e.g., Garrett 1995; Quinn 1997), the number of international meetings attended (Haas and Schmitter 1964) and so on. Such specifications failed to take into account that spatial policy dependence presupposes different policies in different countries and that policy makers react to these different foreign policies or changes in these policies. For example, foreign pressure on effective capital tax rates does not only depend on capital mobility, but also on the effective capital tax rates in other countries. If all countries employed the same tax policies, the absence of capital controls would not lead to tax competition.

While the move to spatial econometric models meant explicitly taking differences in policies across jurisdictions into account, a fundamental insight of these earlier studies was lost along the way, namely that a jurisdiction's total level of interaction with the outside world matters as well – as argued above, it determines heterogeneity in exposure to the spatial stimulus. This insight was lost because methodologists advise applied scholars to row-standardize the connectivity matrix, a habit regarded as 'commonly' (Franzese and Hays 2006: 174, 2008: 29), 'generally' (Darmofal 2006: 8), 'typically' (Anselin 2002: 257) or 'usually' (Beck et al.

2006: 28) followed.⁹ Row-standardization – for each row of the matrix each cell is divided by its row sum, resulting in a new row-standardized weighting matrix in which the weights in each row now must add up to one – takes out all level effects from the weighting matrix. The row-standardized connectivity or weighting matrix merely measures the relative importance of other jurisdictions k to the jurisdiction i under observation and the resulting spatial lag variable represents a weighted *average* of policies in other jurisdictions k . Consider, for example, the simple case of contiguity between countries. If scholars row-standardize, countries receive the same spatial stimulus regardless of whether they have one neighbor such as Portugal or nine neighbors such as Germany if the average value of the dependent variable in the countries around Germany is the same as the value of the dependent variable in Spain – Portugal’s only neighbor. In other words, with row-standardization, exposure varies only if the average value of the dependent variable in the connected countries varies, without row-standardization, exposure also varies in the number of connections.¹⁰

Row-standardization has never been theoretically justified. It has always simply been a habit imposed by econometric convenience. Because row-standardization ensures that the spatial lag will have “the same potential metric or units” as the dependent variable itself (Ward and Gleditsch 2008: 80), it allows an easy interpretation of the coefficient size of the spatial lag

⁹ Whether this advice has actually been followed is hard to say. A survey of studies employing spatial effects in political science research revealed that few scholars explicitly state that they row-standardize their weighting matrix (Plümper and Neumayer 2010a), rendering it difficult to assess whether they actually row-standardize and fail to say so or do something else.

¹⁰ With a non-binary connectivity variable, exposure also varies with the level of connectivity, not just the number of connections.

variable and an easy comparison with the coefficient of the temporal lag (Franzese and Hays 2008: 55).

If row-standardization is a matter of convenience rather than necessity, why not simply abandon it? In Plümper and Neumayer (2010a) we have in fact argued that scholars should consider using weighting matrices that are not row-standardized to allow for differences in the exposure to the spatial stimulus unless theory clearly predicts that the spatial stimulus is equal across jurisdictions. Yet, in the next section we will show that this turns out to be a special case of an interaction effect model, in which the row-standardized spatial lag variable is interacted with the variable capturing differences in exposure, thus representing a superior modeling strategy. Yet, we know of only one existing study that explicitly accounts for heterogeneity in exposure in this way. Basinger and Hallerberg (2004) show that countries with higher domestic capital controls are less exposed to the spatial effect from competitor countries' changes in tax rates than countries with lower or no capital controls, while Wasserfallen (2011) demonstrates that cantons with a more favorable geo-strategic location are less exposed to tax competition among Swiss cantons.

What about heterogeneity in responsiveness to a given spatial stimulus, the other form of conditional spatial policy dependence? To our knowledge, Basinger and Hallerberg (2004) were the first to argue for spatial policy dependence being conditional on domestic political factors and to explicitly test for such conditionality in international tax competition. They find that a country's responsiveness to changes in competitors' tax rates is systematically higher where the ideological distance among domestic veto players decreases and where the domestic government moves further right along the political spectrum. Only a handful or so of other studies specify spatial policy dependence as conditional on responsiveness – see Swank (2006) and Wasserfallen (2011) on tax policies, Shipan and Volden (2008) on anti-smoking policies, Martin (2009a, 2009b) on tobacco taxation and smoke free air legislation,

Cao and Prakash (2009) on environmental pollution, Perkins and Neumayer (2010, 2011a) on corporate voluntary standards and carbon dioxide efficiency, and Aklın and Urpelainen (2010) on the establishing of environmental ministries. This represents a tiny minority of the 800 or so articles on spatial policy dependence that Graham, Shipan and Volden (2008) have identified in the top fifty political science journals. If our argument is right, then many more future studies should explicitly test for both types of conditional spatial policy dependence. In the remainder of this article, we therefore discuss model specifications that allow researchers to appropriately test theories of conditional spatial policy dependence.

4. Testing Theories of Spatial Policy Dependence

We have argued that while many policy choices depend on previous choices of the same policy in other jurisdictions, spatial policy dependence is unlikely to be unconditional. We have developed two arguments suggesting conditional spatial policy dependence. First, the extent of spatial exposure is likely to differ across jurisdictions. The “openness” of countries, states, districts, and communities varies with respect to their economic integration, the mobility of their people, the extent of contact with central senders, the capacity of their governments to look elsewhere for innovative policy solutions or to learn from the mistakes other governments made in the past. Jurisdictions that are more exposed to external stimuli are therefore *ceteris paribus* likely to respond more to policies in other jurisdictions. Yet, everything is not equal. The political responsiveness to any given spatial stimulus also varies. Political regime type, electoral system, veto players and other constitutional and institutional factors as well as economic and social conditions are likely to shape a government’s responsiveness to policy choices and policy experiences of governments in other jurisdictions. For both reasons spatial policy stimuli are unlikely to unconditionally influence policy choices.

In this section, we develop model specifications which allow appropriate tests for theories of conditional spatial policy dependence. We will show that not row-standardizing the spatial lag variable is in fact a special case of a more general interaction model, in which the row-standardized spatial lag variable is interacted with the row sum of weights used in the creation of the spatial lag. We thus show it is possible to estimate spatial econometric models in a way that allows the convenience of spatial lags created with row-standardized weighting matrices without imposing the implausible assumption of uniform exposure to the spatial stimulus by interacting the row-standardized spatial lag variable with a measure of absolute or relative exposure. Similarly, heterogeneity in responsiveness can also be accounted for via an interaction effect.

All empirical tests of theories of spatial policy dependence have to address four important questions. We start with two questions researchers must answer even in the case of unconditional spatial dependence, before moving to conditional dependence.

4.1. Unconditional Spatial Policy Dependence

The first question to ask is whether a specific policy of a jurisdiction depends on the same policy in other jurisdictions? A positive answer to this question is the pre-condition for the existence of spatial policy dependence. Simply because jurisdictions adopt the same policies or change their policies in the same direction does not constitute spatial dependence since they may either all be driven by some third factor or make joint policy decisions. Referring to the jurisdiction of interest as i (receiver) and all other jurisdictions as k (sender), spatial policy dependence is defined as

$$y_i = f(y_k) \tag{1}$$

with $i \neq k$, where y denotes the policy of interest. We restrict the discussion to cases in which i and k come from the same population N , but it is possible that receivers are different from the senders of spatial stimuli.

Secondly, do policies of the other countries exert the same influence on the policy choice of the country of interest or do the policies in some countries exert a stronger influence on the country of interest than others and if so why and how? In almost all relevant empirical applications, some senders will be more important than others, such that one needs an $N \times N$ connectivity or weighting matrix, which links jurisdictions i with k and gives differential weight to jurisdictions k according to their importance as a sender of the spatial stimulus for i . These connectivity elements are strictly non-negative and take a value of zero if the observations i and k are unconnected. If one wishes to model positive and negative spatial dependence at the same time – for example, positive learning from some states’ success and negative learning from other states’ failure or positive externalities from some countries’ military expenditures and negative externalities from other countries’ expenditures – then this should not be modeled by positive weights for the former and negative weights for the latter. Instead, two separate spatial lag variables should be constructed, one with positive weights for countries from which positive spatial dependence emanates and another one with positive weights for countries from which negative spatial dependence is received. This more general model specification avoids artificially restricting the strength of positive and negative spatial dependence to be the same. Accordingly, spatial policy dependence in which outside jurisdictions exert differential influence on the policy choice of the jurisdiction i under observation is modeled as a function of both the value of the dependent variable in other units of observation and a weighting matrix w_{ik} that links jurisdictions i to k :

$$y_i = f(w_{ik}, y_k) \quad . \quad (2)$$

4.2. *Heterogeneity in Exposure to the Spatial Stimulus*

The third question to ask is whether exposure to the spatial stimulus of all jurisdictions is thought to be identical or variable across the population and if so how? If the strength of spatial stimulus is identical across all i , we can row-standardize the connectivity weights. Moving to a scalar notation, a row-standardized spatial lag variable in monadic cross-sectional time-series or panel data is specified as follows:¹¹

$$y_{it} = \rho \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] + \beta X_{it} + \varepsilon_{it} \quad , \quad (3)$$

where X_{it} is a vector of explanatory (control) variables, which could include the temporally lagged dependent variable as well as period and unit fixed effects, and ε_{it} is an identically and independently distributed (i.i.d.) error process.¹²

Yet, row-standardization assumes that the strength of the spatial stimulus is equal for all i and we have argued in the previous section that this is not necessarily a plausible theoretical assumption. In Plümper and Neumayer (2010a) we suggested that not to row-standardize spatial lag variables often provides a better fit between theory and model specification.¹³ Not row-standardized models are specified as follows:

¹¹ See Neumayer and Plümper (2010a) for spatial effects in a dyadic setting.

¹² Sometimes the spatial lag is also temporally lagged.

¹³ This is the empirical model specification adopted in Neumayer and Plümper (2010b) and Perkins and Neumayer (2011a, 2011b), explicitly justified on the grounds of heterogeneity in exposure.

$$y_{it} = \rho \sum_k w_{ikt} y_{kt} + \beta X_{it} + \varepsilon_{it} \quad , \quad (4)$$

Instead of representing the weighted *average* of the value of the dependent variable in other jurisdictions, a not row-standardized spatial lag variable represents the weighted *sum* of the value of the dependent variable. However, such models are a special case of a more general model with a row-standardized spatial lag variable interacted with the sum of weights:

$$y_{it} = \rho_1 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] + \rho_2 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot \sum_k w_{ikt} + \rho_3 \sum_k w_{ikt} + \beta X_{it} + \varepsilon_{it} \quad , \quad (5)$$

The first term on the right-hand side of the equation represents the row-standardized spatial lag variable, the second term is the interaction between it and the row sum of weights, while the third term is the row sum of weights – for example, total absolute trade or, depending on theory, total trade openness, i.e. trade divided by GDP, in case of trade as the connectivity variable. The specification of the not row-standardized spatial lag variable of equation (4) is nothing else but specification (5) and simultaneously constraining the coefficients ρ_1 and ρ_3

both to zero since $\sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot \sum_k w_{ikt} = \sum_k w_{ikt} y_{kt}$. Simply including a spatial lag variable

that is not row-standardized in one's estimation model can still be justified if one has reason to believe that ρ_1 and ρ_3 should be zero, i.e. if one believes that contingent on the presence of the not row-standardized spatial lag in the estimation model there is no independent effect of the row-standardized spatial lag and that there is no independent effect of the row sum of weights on the dependent variable. However, in general it will be better to free the coefficients ρ_1 and ρ_3 and to estimate model (5) rather than not to row-standardize the spatial lag variable. In many spatial lag applications the weighting matrix is time-invariant. If scholars estimate equation (5) in a fixed effects model, ρ_3 cannot be estimated since $\sum_k w_{ikt}$

is perfectly co-linear with the unit effects. Yet, the estimation of ρ_1 and ρ_2 remains unbiased.

Standard textbooks on interaction effects provide guidance on how to interpret and plot the interaction effects – see Brambor et al. (2004), Braumoeller (2004), and Franzese and Kam (2007). If no evidence for heterogeneity in exposure to the spatial stimulus is found,¹⁴ then scholars may as well estimate the more parsimonious model (3) with a row-standardized spatial lag variable only, i.e. without the interaction effect. Note that even then, one may wish to keep $\sum_k w_{ikt}$ in the estimation model if there is reason to expect that the variable that constitutes the row-sums of the weighting matrix linking jurisdictions i and k has an independent effect on the dependent variable. For example, if the weights w_{ikt} represent bilateral trade of country i with foreign countries k (either in absolute terms or relative to country i 's GDP), then one may wish to include $\sum_k w_{ikt}$ in the estimation model if one believes that country i 's total trade openness with all other countries k has an independent effect on the dependent variable.

In many settings specification (5) will be appropriate for testing for heterogeneity in exposure to the spatial stimulus. However, the conditioning variable used for testing for heterogeneity in exposure to the spatial stimulus need not be the same variable used in the weighting matrix. For example, one may use distance as the weighting matrix in lieu of bilateral FDI stock positions, for which often data are not available, on the basis of a gravity-type model of bilateral FDI stocks, but use the total FDI openness of country i , for which data is often available, as the conditioning variable. If so, then the specification is different from (5), namely:

¹⁴ This can be tricky to establish in non-linear models – see, for example, Ai and Norton (2003) and Franzese and Kam (2007).

$$y_{it} = \rho_1 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] + \rho_2 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot z_{it}^1 + \phi z_{it}^1 + \beta X_{it} + \varepsilon_{it} \quad , \quad (6)$$

where z_{it}^1 is the conditioning variable – total FDI openness in the example above.

Specifications (5) and (6) already point clearly in the direction that testing for heterogeneity in exposure to the spatial stimulus is nothing else but testing for conditional spatial policy dependence. However, there are two conceptually separate reasons for such conditionality – one arising from heterogeneity in exposure to the spatial stimulus, the other coming from heterogeneity in responsiveness to any given stimulus, to which we turn now.

4.3. *Heterogeneity in Responsiveness*

Finally, the fourth and last question to be addressed is whether the responsiveness to spatial stimuli is thought to systematically differ among jurisdictions i and if so how? Governments often respond differently to identical stimuli given their institutional, political, economic or social setting. This is again best modeled as an interaction effect between the spatial lag variable and the conditioning context variable, which leads to the following specification:

$$y_{it} = \rho_1 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] + \rho_2 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot z_{it}^2 + \phi z_{it}^2 + \beta X_{it} + \varepsilon_{it} \quad , \quad (7)$$

Specification (7) is essentially the same as (6), with the exception that z_{it}^1 has been replaced by z_{it}^2 to clarify that these are different conditioning variables: while z_{it}^1 conditioned for heterogeneity in exposure to the spatial stimulus, z_{it}^2 conditions for heterogeneity in the responsiveness of jurisdictions. For example, z_{it}^2 could measure political constraints imposed by the existence and location of veto players or could measure the partisan location of the government.

If there is both heterogeneity in exposure to the spatial stimulus and heterogeneity in the responsiveness to any given stimulus, then researchers need to employ two interaction effects. There are two options then. Either one specifies, following Braumoeller (2004), a full double interaction effects model, in which all possible interactions between the constituent terms of both interaction effects are also included in the model, unless theory strongly suggests that certain constituent components can safely be assumed to be equal to zero (Franzese and Kam 2007). This leads to:

$$\begin{aligned}
y_{it} = & \rho_1 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] + \rho_2 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot \sum_k w_{ikt} + \rho_3 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot z_{it}^2 \\
& + \rho_4 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot \sum_k w_{ikt} \cdot z_{it}^2 + \phi^1 \sum_k w_{ikt} + \phi^2 z_{it}^2 + \phi^3 \sum_k w_{ikt} \cdot z_{it}^2 + \beta X_{it} + \varepsilon_{it}, \quad (8)
\end{aligned}$$

or

$$\begin{aligned}
y_{it} = & \rho_1 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] + \rho_2 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot z_{it}^1 + \rho_3 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot z_{it}^2 \\
& + \rho_4 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot z_{it}^1 \cdot z_{it}^2 + \phi^1 z_{it}^1 + \phi^2 z_{it}^2 + \phi^3 z_{it}^1 \cdot z_{it}^2 + \beta X_{it} + \varepsilon_{it}, \quad (9)
\end{aligned}$$

depending on whether heterogeneity in exposure to the spatial stimulus is modeled according to (5) or (6). Alternatively, one can follow Franzese (1999, 2003) and Plümper and Neumayer (2010b) and first estimate the joint effect of the row-standardized spatial lag variable and the conditioning variable that accounts for heterogeneity in exposure to the spatial stimulus (i.e. either the row sum of weights or another variable), compute the vector of this joint effect and then interact this vector with the institutional, political, economic or social conditioning vari-

able that accounts for heterogeneity in responsiveness. Formally, define \hat{V}_{it} as the vector of the following joint effect:

$$\hat{V}_{it} = \rho_1 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] + \rho_2 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot \sum_k w_{ikt} + \rho_3 \sum_k w_{ikt}, \quad (10)$$

Or, alternatively, if another variable is used in lieu of the row sum of weights, as:

$$\hat{V}_{it} = \rho_1 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] + \rho_2 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot z_{it}^1 + \phi z_{it}^1, \quad (11)$$

then the full model is specified as follows:¹⁵

$$y_{it} = \varphi_1 \hat{V}_{it} + \varphi_2 \hat{V}_{it} \cdot z_{it}^2 + \phi z_{it}^2 + \beta X_{it} + \varepsilon_{it} \quad (12)$$

Specification (12) is justified if one believes that it is the entire spatial effect, including the part which accounts for heterogeneity in exposure to the spatial stimulus, that is conditioned by some institutional, political, economic or social variable accounting for heterogeneity in responsiveness. If one is unwilling to make this assumption, then one needs to estimate either model (8) or (9).

Table 1 provides an overview of our model specification advice for cases in which scholars wish to model heterogeneity in exposure only, heterogeneity in responsiveness only, or both types of heterogeneity together.

¹⁵ Upon publication, we provide Stata example code that allows scholars to easily apply this specification choice.

5. An Application Example: Diffusion of Double Taxation Treaties

In order to show how failing to take into account heterogeneity in exposure and responsiveness can lead to wrong inferences with respect to spatial policy dependence, we look at the diffusion of double taxation treaties (DTTs) as an application example. DTTs are costly to capital-importing countries because such treaties typically favor residence over source taxation and they are costly even to capital exporters as they create a loss of national sovereignty. Concluding DTTs also creates benefits, however, in terms of additional FDI between the country pair or at least preventing FDI diversion toward other dyads with DTTs in place.

Barthel and Neumayer (2012) study in detail how country pair dyads spatially depend in their decision on whether to conclude a DTT between themselves on the prior DTT behavior of other dyads. Specifically, they argue that, among other factors, countries will look toward whether other countries with whom they compete in export markets have previously concluded DTTs. They analyze DTT diffusion over the period 1969 to 2005 in a Cox proportional hazard model. Since DTTs represent a so-called undirected variable (it is typically impossible to determine who initiated the DTT), they model what Neumayer and Plümper (2010) have termed undirected dyad contagion. They find that a spatial lag variable, in which the sum of measures of export market similarity between country i and country k on the one hand and country j and country m on the other hand represents the weighting variable between the dyad ij under observation and other dyads km , does not have a statistically significant effect on the time it takes for the dyad ij to conclude a DTT. This result is replicated in model 1 of table 1 and it seemingly suggests the absence of spatial policy dependence in DTT conclusions via export market similarity as the diffusion mechanism.

Model 2 of table 2 demonstrates that this would in fact be a wrong inference to make. Model 1 fails to take into account that dyads will strongly differ in their exposure to a spatial stimulus from other dyads inducing them to conclude a DTT. Model 2 takes one possible determinant of such heterogeneity in exposure into account: the maximum number of DTTs (DTT_{max}) that either of the two countries i or j has previously concluded. The reason is that if one of the dyad members has already a large DTT network in place, they will have covered already the most attractive countries with whom to conclude a DTT, rendering this country much less likely to conclude yet another DTT and the dyad is thus far less exposed to the spatial stimulus from other dyads. This is exactly what the results for model 2 suggest. There is a positive spatial stimulus on the dyad ij to conclude a DTT if other export market competing countries have previously concluded DTTs. However, this spatial stimulus decreases as DTT_{max} increases and it becomes zero if one of the dyad members has already approximately 90 DTTs in place.

In addition to heterogeneity in exposure, heterogeneity in political responsiveness is also likely to condition spatial policy dependence in DTT diffusion. Recall that DTTs generate national sovereignty losses. It is therefore plausible that governments, which are led by nationalist parties, for whom the preservation of national sovereignty is a major policy objective, are less likely to respond to the spatial policy stimulus coming from competing dyads. To test this hypothesis, we follow the modeling strategy of equation (10) above and compute the joint effect of the spatial lag variable, the DTT_{max} variable and their interaction. In model 3, we include this vector as an explanatory variable in lieu of its constituent variables. By definition, this vector must have a coefficient of exactly one. More importantly, in model 4 we then interact this vector with a dummy variable that is set to one if at least one of the country pair's governments' chief executive is from a nationalist party, using information from the Database of Political Institutions (Beck et al. 2001). Consistent

with our expectation, nationalist governments are less likely to respond to the spatial policy stimulus from other countries, where heterogeneity in exposure of dyads to the spatial policy stimulus is already taken into account. In sum, this application example demonstrates how failure to take into account heterogeneity in exposure and responsiveness can lead to wrong inferences with respect to spatial policy dependence.

6. Conclusion

Spatial policy dependence is easily confused with the clustering of policies or the temporal coincidence of changes in policy choices. Striving for greater clarity in theoretical accounts of spatial policy dependence with particular attention paid to the causal mechanisms underlying such dependence will help convincing others that policies in one jurisdiction truly causally depend on policies in other jurisdictions. Comprehensively specified theories are also likely to postulate heterogeneity in the exposure of jurisdictions to the spatial stimulus received from other jurisdictions as well as heterogeneity in the responsiveness to any given stimulus. We have provided general theoretical arguments, which suggest spatial policy dependence is often conditioned by differences in exposure as a consequence of differences in the intensity of interactions among jurisdictions with the outside world. Similarly, we have demonstrated how theory typically predicts differences in responsiveness to any stimulus as a consequence of the institutional, political, economic or social context in which jurisdictions operate. Current standard empirical model specification practice does not match such comprehensive theories of spatial policy dependence: by estimating one single common coefficient for a row-standardized spatial lag they implicitly assume uniformity in both exposure and responsiveness.

Appropriate tests of theoretical predictions require a good ‘fit’ between theory and model specification. We have therefore advised on how models can be specified to take into account

both types of conditional spatial policy dependence. Heterogeneity in exposure could in principle be accounted for by not row-standardizing the spatial lag variable, as suggested in Plümper and Neumayer (2010a). However, such a model specification is a special case of a more general model, in which the spatial lag is row-standardized, as typically recommended by methodologists, but is also interacted with another variable that accounts for the extent of exposure. Such a variable will typically be the row-sums of the connectivity matrix (e.g. the row-sums of bilateral trade dependencies summing to total trade dependence for each unit of observation) employed in the creation of the row-standardized spatial lag variable; but it could also be another variable capturing levels of exposure. Heterogeneity in responsiveness is also best modeled as an interaction effect between the spatial lag variable and a variable capturing the factor that drives differences in responsiveness to any given spatial stimulus. Both types of conditionality are thus best modeled as interaction effects, even if the underlying reason for conditionality is different.

Model specification becomes more complex if both types of conditionality simultaneously exist. This requires either a model with double interaction effects, which must therefore also include all possible interactions among all constituent terms of both individual interactions, or a model that interacts the variable capturing differences in responsiveness with a vector consisting of the joint effect of the interaction of the row-standardized spatial lag variable with the conditioning variable that accounts for heterogeneity in exposure. The latter approach is justified if one is willing to assume that it is the entire spatial effect (incorporating heterogeneity in exposure) that is conditioned by institutional, political, economic or social variables. This assumption is not very restrictive, hence we believe applied researchers will wish to resort to this model specification, the results of which are more easily interpreted than the rather complex double interaction effect models.

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Table 1. Overview of modeling specification advice.

Heterogeneity in exposure only (row sum of weights as exposure variable):

$$y_{it} = \rho_1 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] + \rho_2 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot \sum_k w_{ikt} + \rho_3 \sum_k w_{ikt} + \beta X_{it} + \varepsilon_{it} \quad , \quad (5)$$

Heterogeneity in exposure only (a third variable other than the row sum of weights as exposure variable):

$$y_{it} = \rho_1 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] + \rho_2 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot z_{it}^1 + \phi z_{it}^1 + \beta X_{it} + \varepsilon_{it} \quad , \quad (6)$$

Heterogeneity in responsiveness only:

$$y_{it} = \rho_1 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] + \rho_2 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot z_{it}^2 + \phi z_{it}^2 + \beta X_{it} + \varepsilon_{it} \quad , \quad (7)$$

Heterogeneity in both exposure and responsiveness (row sum of weights as exposure variable):

$$\begin{aligned}
y_{it} = & \rho_1 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] + \rho_2 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot \sum_k w_{ikt} + \rho_3 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot z_{it}^2 \\
& + \rho_4 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot \sum_k w_{ikt} \cdot z_{it}^2 + \phi^1 \sum_k w_{ikt} + \phi^2 z_{it}^2 + \phi^3 \sum_k w_{ikt} \cdot z_{it}^2 + \beta X_{it} + \varepsilon_{it}, \quad (8)
\end{aligned}$$

or

$$\hat{V}_{it} = \rho_1 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] + \rho_2 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot \sum_k w_{ikt} + \rho_3 \sum_k w_{ikt}, \quad (10)$$

$$y_{it} = \phi_1 \hat{V}_{it} + \phi_2 \hat{V}_{it} \cdot z_{it}^2 + \phi z_{it}^2 + \beta X_{it} + \varepsilon_{it} \quad (12)$$

Heterogeneity in both exposure and responsiveness (a third variable other than the row sum of weights as exposure variable):

$$\begin{aligned}
y_{it} = & \rho_1 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] + \rho_2 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot z_{it}^1 + \rho_3 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot z_{it}^2 \\
& + \rho_4 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot z_{it}^1 \cdot z_{it}^2 + \phi^1 z_{it}^1 + \phi^2 z_{it}^2 + \phi^3 z_{it}^1 \cdot z_{it}^2 + \beta X_{it} + \varepsilon_{it}, \tag{9}
\end{aligned}$$

or

$$\hat{V}_{it} = \rho_1 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] + \rho_2 \sum_k \left[\frac{w_{ikt}}{\sum_k w_{ikt}} y_{kt} \right] \cdot z_{it}^1 + \phi z_{it}^1, \tag{11}$$

$$y_{it} = \phi_1 \hat{V}_{it} + \phi_2 \hat{V}_{it} \cdot z_{it}^2 + \phi z_{it}^2 + \beta X_{it} + \varepsilon_{it} \tag{12}$$

Table 2: Conditional Spatial Policy Dependence in DTT Diffusion.

<i>Model</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>
Row-standardized spatial lag (SL)	6.212 (5.560)	20.48*** (5.837)		
Row-standardized SL*DTT_max		-0.227*** (0.0285)		
Max. number of DTTs (t-1)	-0.0381*** (0.00384)	-0.0125** (0.00513)		
Vector from grey-shaded variables			1.000*** (0.0748)	1.043*** (0.0767)
Vector * Nationalist dummy				-0.164** (0.0791)
Nationalist dummy				-0.104 (0.0895)
Product of populations (ln)	0.126*** (0.0271)	0.128*** (0.0268)	0.128*** (0.0260)	0.112*** (0.0271)
Product of GDPs per capita (ln)	0.0696*** (0.0268)	0.0709*** (0.0269)	0.0709*** (0.0265)	0.0667** (0.0279)
Bilateral trade (ln, t-1)	0.128*** (0.0164)	0.124*** (0.0163)	0.124*** (0.0162)	0.118*** (0.0168)
Product of openness to trade	6.66e-05*** (6.22e-06)	6.29e-05*** (6.03e-06)	6.29e-05*** (6.05e-06)	6.28e-05*** (6.25e-06)
Bilateral Investment Treaty dummy	1.437*** (0.0789)	1.408*** (0.0746)	1.408*** (0.0752)	1.418*** (0.0770)
Regional Trade Agreement dummy	-0.103 (0.0984)	-0.157 (0.0995)	-0.157 (0.0995)	-0.0896 (0.0974)
Offshore Financial Centre dummy	-0.413*** (0.113)	-0.322*** (0.106)	-0.322*** (0.110)	-0.409*** (0.117)
Diplomatic representation	0.998*** (0.0941)	1.041*** (0.0951)	1.041*** (0.0950)	1.096*** (0.0998)
Distance (ln)	-0.358*** (0.0455)	-0.349*** (0.0461)	-0.349*** (0.0454)	-0.343*** (0.0480)
Product of political constraints	0.612*** (0.151)	0.581*** (0.145)	0.581*** (0.144)	0.513*** (0.148)
Min. years of independence	-0.00656*** (0.00187)	-0.00604*** (0.00184)	-0.00604*** (0.00182)	-0.00587*** (0.00189)
Cum. number of DTTs country 1 (t-1)	0.0461*** (0.00397)	0.0462*** (0.00369)	0.0462*** (0.00306)	0.0476*** (0.00292)
Cum. number of DTTs country 2 (t-1)	0.0439*** (0.00384)	0.0438*** (0.00359)	0.0438*** (0.00294)	0.0462*** (0.00282)
Observations	249,357	249,357	249,357	213,907

Notes: Cox proportional hazard estimator. Standard errors clustered on country dyads in parentheses; OECD grouping dummy variables included (not shown); Breslow approximation for tied events; * statistically significant at .1, ** .05, or *** .01 level.