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Model Specification in the Analysis of Spatial Dependence

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Model Specification in the Analysis of Spatial Dependence

Abstract

The recent surge in studies analyzing spatial dependence in political science has gone hand in hand with increased attention paid to the choice of estimation technique. In comparison, specification choice has been relatively neglected, even though it leads to equally, if not more, serious inference problems. In this article we analyze four specification issues. We argue that to avoid biased estimates of the spatial effects, researchers need to consider carefully how to model temporal dynamics, common trends and common shocks, as well as how to account for spatial clustering and unobserved spatial heterogeneity. The remaining two specification issues relate to the weighting matrix employed for the creation of spatial effects: whether it should be row-standardized and what functional form to choose for this matrix. We demonstrate the importance of these specification issues by replicating Hays's (2003, 2009) model of spatial dependence in international capital tax rate competition. Seemingly small changes to model specification have major impacts on the spatial effect estimates. We recommend that spatial analysts develop their theories of spatial dependencies further to provide more guidance on the specification of the estimation model. In the absence of sufficiently developed theories, the robustness of results to specification changes needs to be demonstrated.

1. Introduction

Political units often spatially depend on each other in their policy choices. For example, capital tax rates in one country are typically affected by tax policies in other countries. Patterns of spatial dependence have been studied in areas as diverse as social policies (Franzese and Hays 2006, Brooks 2007, Cho 2003, Bailey and Rom 2004; Jahn 2006), monetary policies (Simmons and Elkins 2004; Plümper and Troeger 2008), tax and fiscal policies (Basinger and Hallerberg 2004; Hays 2003, 2009; Swank 2006, Plümper et al. 2009), trade and investment policies (Mansfield and Reinhardt 2003; Elkins, Guzman and Simmons 2006), military spending and armed conflict (Shin and Ward 1999; Salehyan and Gleditsch 2006), democratization (Gleditsch and Ward 2006), diffusion of environmental technologies and standards (Perkins and Neumayer 2008, 2009), and many others.

A search through the top 50 (in terms of total cites) political science journals in the Social Sciences Citation Index revealed very few studies published in the 1990s that included spatial effects, but almost 50 articles already published in this decade. This surging interest in analyzing spatial dependence in the political sciences was fuelled by two developments: the swift increase in global market integration, technological changes and cross-border communication on the one hand, and the rapid improvement in both computing power and spatial estimation techniques on the other hand (Anselin 1988, Beck et al. 2006; Franzese and Hays 2007a, 2009; Ward and Gleditsch 2008). While the first development raised the interest in spatial dependencies, the latter, which culminated in the development of instrumental variable and spatial maximum likelihood estimators, facilitated their actual estimation.

Contrary to the aforementioned work, this paper is not concerned with estimation techniques in spatial econometrics. Instead, it provides a complementary discussion of specification issues.[1] As it is well understood, misspecification increases the probability of wrong inferences at least as much as does the choice of a biased or inefficient estimator. Specifically, we analyze in detail the importance of four specification issues in spatial econometrics. First, failure to model temporal dynamics and to control for common shocks and common trends in cross-sectional time-series or panel data is likely to bias the estimated coefficient of the spatial effect variable, with the bias often being upward. Second, failure to model appropriately spatial patterns in the dependent variable also biases the spatial effect estimation. The remaining two issues relate directly to the connectivity or weighting matrix. Different, but equally justifiable specifications of the weighting matrix can easily lead to starkly differing results. This threatens the validity and reliability of inference. In particular, we show that row-standardization of the weighting matrix changes the relative influence of other units on the spatial effect, thereby altering the estimation results. Despite being regarded as usual practice by spatial econometricians, it is not always appropriate, requires theoretical justification and should therefore not be applied without further thought as a general default rule. Furthermore, changes to the functional form of the weighting matrix, whether row-standardized or not, can dramatically change the estimated results of the spatial effect. This is of great importance because existing theories of spatial dependence typically do not derive a functional form for the weighting matrix. This is amplified by the fact that one cannot simply interpret estimation results on the spatial effect as evidence for the correct specification of the weighting matrix.

Are these specification problems in spatial analyses worse than in other types of econometric analysis? On the one hand, the answer can only be 'no'. Misspecification may lead to estimation results that largely differ from the true effects and this is no different in

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1 To be sure, the existing literature discusses some of the issues covered here, but not all of them and not in great detail. There are also more issues of specification choice of course, which we cannot discuss here for reasons of space (see, for example, Darmofal 2006).

spatial econometrics than it is in any other econometric subfield. However, we suggest that these problems are more common in spatial econometrics, because 'getting the specification right' is more difficult for at least three reasons: first, theories predicting spatial effects usually provide little guidance on the functional form of weighting matrices. Second, spatial effects are notoriously difficult to distinguish from common shocks, common trends as well as spatial clustering and unobserved spatial heterogeneity. And third, applied researchers still have little understanding of the specification issues in spatial econometrics and are thus less likely to avoid or solve them. In sum, the specification problems in spatial econometrics are not different from specification problems in other areas as such, but they tend to be more pertinent and more difficult to solve.

We use one of Hays's (2003, 2009) models of tax competition for replication purposes. We have chosen his work not because his models are flawed (they are not), but because they represent the state of the art of empirical research into spatial dependence in political science. We demonstrate that model specification has a very large effect on the estimation results for the spatial effect. Whilst we show this for the specific results reported in Hays (2003, 2009), we contend that the specification issues we discuss are relevant to all studies of spatial dependence and that the identified problems occur with positive probability in all of them.

Researchers can model temporal dynamics and can easily control for common trends and shocks as well as for spatial clustering and unobserved spatial heterogeneity. However, the remedies typically recommended come with problems of their own. There is, similarly, no easy solution to the problem of specifying the weighting matrix. This opens spatial analysts to the charge that they can produce results that fit their hypotheses by making one or more seemingly arbitrary specification decisions. We offer two potential solutions to this problem. Ideally, scholars formulate their theories more comprehensively providing sufficient detail on the spatial effect modeling. Theory should always be able to decide on whether to row-standardize the weighting matrix and while one will rarely be able to specify the exact functional form of the matrix, one can often exclude certain functional forms. In the absence of sufficiently specified theories, the second-best solution is to show in robustness tests how the results on the spatial effect change if different functional forms of the weighting matrix are used.

2. Modeling Spatial Effects: a Very Brief Overview

There are three ways of modeling spatial effects, namely as spatial lag, spatial-x and spatial error models. Spatial lag models regress the dependent variable on the spatially lagged dependent variable, that is, on the (weighted) values of the very same dependent variable in all other units. Using a scalar notation, in a monadic cross-sectional time-series or panel dataset, the spatial lag is formally modeled as follows:[2]

$$y_{it} = \rho \sum_k w_{ikt} y_{kt} + \beta X_{it} + \varepsilon_{it} \qquad , \qquad (1)$$

where $i = 1,2,..,N$, $t = 1,2,..,T$, $k = 1,2,..N$. Notation is standard so that y_{it} is the value of the dependent variable in unit *i* at time *t*, estimated with a spatially lagged dependent variable $\left(\sum_k w_{ikt} y_{kt}\right)$, X_{it} is a vector of unit specific variables influencing y_{it} and ε_{it} is an identically and independently distributed (i.i.d.) error process. To these, researchers may want to add the temporally lagged dependent variable as well as period and unit fixed effects if necessary.

The spatial autoregression parameter ρ gives the impact of the spatial lag on y_{it}. The spatial lag consists of the product of two elements. The first element is an $N \cdot N \cdot T$ block-diagonal spatial weighting matrix, which measures the relative connectivity between *N* number of units *i* and *N* number of units *k* in *T* number of time periods in the off-diagonal cells of the matrix (the diagonal of the matrix has values of zero as there *i* = *k* and units cannot

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2 The analysis of spatial dependence is more flexible but also more complicated in dyadic data – see Neumayer and Plümper (2010) for an analysis of all the possible forms of modeling spatial dependence in such datasets.

spatially depend on themselves of course). The second element we call the "spatial *y*".[3] It is an $N \cdot T$ matrix of the contemporaneous value of the dependent variable, where *N* is the number of units *k* and *T* the number of time periods.[4]

Spatial-x models regress the dependent variable on the (weighted) values of one or more independent explanatory variables (other than the dependent variable) in all other units:

$$y_{it} = \alpha + \rho \sum_k w_{ikt} x_{kt} + \beta X_{it} + \varepsilon_{it} \quad . \tag{2}$$

Spatial error models seek to identify spatial dependence in the error term, which is assumed to consist of two parts: one is an independent and identically distributed spatially uncorrelated component ε_{it}, the other is a spatial component $\rho \sum_k w_{ikt} u_{kt}$. The model to be estimated is thus:

$$y_{it} = \alpha + \beta X_{it} + \varepsilon_{it} + \rho \sum_k w_{ikt} u_{kt} \quad . \tag{3}$$

Political scientists have focused much of their attention on the choice of estimation technique for these three models, paying less attention to specification issues.[5] Here we will instead focus entirely on specification issues, disregarding entirely the choice of estimator. The choice between these models is of course also a specification issue. However, it is an issue which has been extensively addressed by Beck, Gleditsch and Beardsley (2006), so we refer readers to their exhaustive discussion. Here, we concentrate on spatial lag models, which are

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3 We would call this 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.

4 The spatial *y* may also be temporally lagged which can be advantageous for estimation purposes – see Beck et al. (2006) for details.

5 Based on Monte Carlo analyses, Franzese and Hays (2007a) have demonstrated that Spatial-OLS, Spatial-2SLS and Spatial-ML provide flexible approaches to estimating different types of spatial dependencies. For example, using OLS as an estimator of spatial dependence (spatial-OLS) works well if researchers either analyze spatial-x models or spatial lag models with sender-receiver relations in which senders cannot also be receivers. Using a maximum likelihood estimator (spatial-ML) instead usually changes results only marginally. If, however, in a spatial lag model the sender can also be a receiver, researchers need to solve the endogeneity problem, which can be done by using instruments for the spatially dependent variable (spatial-2SLS) or by maximizing the joint likelihood of all the data (spatial-ML).

the most popular in political science, but everything we say applies similarly to spatial-x and spatial error models.

3. Temporal Dynamics, Common Trends, and Common Shocks

Most spatial lag models in political science use cross-sectional time-series or panel data, which have well known advantages over cross-sectional designs. Amongst other things, they allow accounting for temporal dynamics, common trends, and common shocks. At the same time, however, failure to control for these complications in the data generating process has even more severe consequences in spatial than in standard panel data analysis. Such failure will typically lead to upward biased spatial effects and may thus cause wrong inferences.[6] Even though this problem is widely discussed in the theoretical literature in spatial econometrics (e.g., Beck et al. 2006; Franzese and Hays 2006), only a minority of analyses control for common trends by adding the lagged dependent variable to the list of regressors (e.g., Hays 2003, Franzese and Hays 2006, Swank 2006) or additionally account for common shocks by further adding period dummies (e.g. Bailey and Rom 2004; Madariaga and Poncet 2007; Franzese and Hays 2006; Hays 2009).

To demonstrate the effect of failing to model temporal dynamics and control for common shocks and common trends, we analyze the case of capital taxation in OECD countries. Theories of tax competition contend that when capital is fully or partially mobile, independent jurisdictions compete to some extent for a common tax base (Wildasin 1989; Plümper et al 2007). The lower the effective tax rate in one jurisdiction relative to those of other jurisdictions, the larger the share of the mobile tax base it will attract. Thus, low capital taxation leads to an inflow of capital, which at least in the short run increases the tax base of

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[6] Downward bias is possible in rare cases. For example, downward bias is possible in international tax competition if countries with similar initial levels respond differently to common shocks. Governments have more than one tax instrument to generate revenues. A common shock in tax revenues may thus lead to higher labor taxation in some countries, an increase in VAT in others and rising capital tax rates in a third group of countries. If these responses are negatively correlated to the initial pattern of capital taxes, then not controlling for common shocks may downward bias the estimate of the spatial lag.

the capital importing jurisdiction so that tax revenue may increase even though the tax rate becomes smaller.

Yet, the success of one jurisdiction in attracting mobile capital leads to a decline in the tax revenue for the other jurisdictions. If policy-makers in these jurisdictions want to avoid budget deficits, they either need to increase taxes on immobile factors, cut spending, or competitively reduce their own capital taxes to attract an inflow of capital. Early models of tax competition focus on the latter option and unequivocally predicted a 'race to the bottom', that is, in equilibrium, tax rates on mobile tax bases approach zero.[7]

However, empirical analyses do not find much support for the race-to-the-bottom hypothesis (Hays 2003, 2009; Basinger and Hallerberg 2004). Indeed, 'taxes on mobile capital continue to be the rule rather than the exception' (Plümper et al 2009). Effective capital tax rates remain positive and converge to a mean tax rate rather than approaching zero (Hays 2009). Hays's theory of capital tax rate competition explains this by arguing that the ability of governments to actively engage in such competition is constrained by the domestic political incentive structure governments face and by capital being imperfectly mobile.[8]

Common wisdom has it that the average effective capital tax rate in OECD countries has declined over time, at least since the abolition of capital controls in the early 1980s. However, as figure 1 shows, while a common trend clearly exists between 1966 and 2000, it is upward rather than downward.[9] Whether common shocks also exist is not clear from this figure, but

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7 See inter alia Wildasin (1989), Zodrow and Mieszkowski (1986), and Frey (1990).

8 At least three other theories have been put forward to explain the apparent puzzle of tax rates failing to converge to the low-rate equilibrium predicted by early models. First, Rodrik (1997), Garrett (1998) and Swank and Steinmo (2002) argue that shifting tax revenues to immobile factors, especially to labor, is costly. Second, Basinger and Hallerberg (2004) explain persistently high capital tax rates by the existence of veto-players which prevent some governments from lowering tax rates. Third, Plümper et al. (2007) show that empirical observations are in line with a model in which capital mobility is limited and governments are constrained by voter preferences for low budget deficits and tax fairness.

9 The upper and lower bands denote the average tax rate plus and minus one standard deviation, respectively.

one should keep in mind that OECD countries were affected by two oil price hikes during this period.

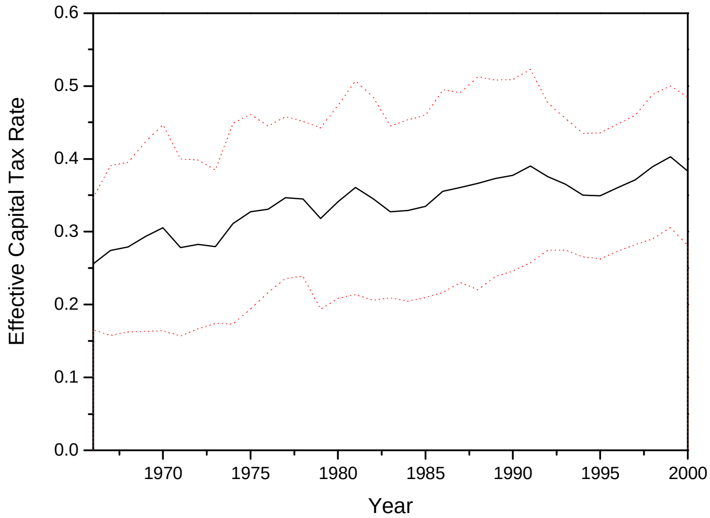

Figure 1: Common Trend in the Average Effective Capital Tax Rate of OECD Countries (Data Source: Hays 2009).

If they are not fully explained or controlled, common trends and common shocks bias the estimation of spatial lags because when one country has relatively high (low) effective tax rates, the majority of the other countries and thus the weighted mean of the other countries also has relatively high (low) effective capital tax rates even in the absence of spatially dependent tax policies. In other words, failure to control for common trends and shocks can make one believe that spatial dependence exists, even if there might not be any such dependence. To demonstrate this, we replicate and extend the analysis of Hays (2009), which builds upon Hays (2003).[10] He analyzes effective capital tax rates in an unbalanced panel of 20 OECD countries over the time period 1966 to 2000. His main variables of interest are capital mobility interacted with various measures of political economy that are of no further

10 Recognizing that a failure to include period dummies may bias the spatial lag coefficient, Hays (2009) includes period dummies, which were missing from Hays (2003).

interest here. In addition to a temporal lag as well as country and period fixed effects, a spatial lag enters the estimations with row-standardized contiguity as the weighting matrix (see section 5 for a discussion of row-standardization).

Table 1: Replication of Hays (2008) and S-OLS Estimation of the Model

dependent variable: effective capital tax rate	model 1 replication S-ML	model 2 S-OLS with robust s.e.
temporal lag (LDV)	0.772	0.771
	(0.025) ***	(0.034) ***
spatial lag	0.040	0.047
	(0.010) ***	(0.026) *
capital mobility	0.088	0.088
	(0.038) *	(0.035) *
union density	0.037	0.037
	(0.059)	(0.053)
left government	-0.018	-0.018
	(0.019)	(0.025)
european union	6.670	6.613
	(2.723) *	(3.214)
capital mobility interacted with		
capital endowment	-0.004	-0.004
	(0.001) ***	(0.001) ***
consensus democracy	0.016	0.017
	(0.010)	(0.016)
union density	-0.000	-0.000
	(0.000)	(0.001)
left government	0.000	0.000
	(0.000)	(0.000)
european union	-0.074	-0.074
	(0.030) *	(0.035) *
unit fixed effects	yes	yes
period fixed effects	yes	yes
W row-standardized	yes	yes
weight	contiguity	contiguity
R^2	0.921	0.935
Nobs	581	581

Note: results reported in Hays (forthcoming) are not exactly replicable due to minor changes in the data structure. * statistically significant at .1 level ** at .01 level *** at .001 level

Model 1 reported in the first column of table 1 replicates column 2 of table 2 in Hays (2009), using, like Hays, a maximum likelihood (ML) estimator. In the next column we estimate the same model with ordinary least squares (OLS) instead. The coefficient size of the spatial lag variable in model 2 is slightly higher than under ML estimation, but substantively identical.

The standard errors are higher in OLS estimations, indicating the greater efficiency of ML estimators.

There is evidence for positive spatial dependence: higher tax rates in contiguous countries raise the domestic tax rate and vice versa for lower tax rates. For comparison we stick to the ML estimations in what follows. The short-term spatial effect of the ML estimations is 0.04, whereas the asymptotic long-term spatial effect – computed according to Plümper, Troeger and Manow (2005: 336) – is

$$\left.\frac{\partial y_{it}}{\partial \sum_k w_{ikt} y_{kt}}\right|_{\beta X_{it},\, t \to T} = \sum_{t=1}^{T} \left(\rho \sum_k w_{ikt} y_{kt} \right) \beta_0^{T-t} \quad , \tag{4}$$

Where β_0 is the coefficient of the lagged dependent variable, T is the number of periods with t denoting a single period and $t \to T$ meaning that period t approaches T. In our case, the asymptotic long-term spatial effect is approximately 0.18.

Table 2 presents the estimation results of three models, which deal differently with temporal dynamics, common trends and common shocks. Deviating from Hays's specification, we first exclude the lagged dependent variable from the estimations (model 3), then the period fixed effects (model 4), and then both the lagged dependent variable and the period fixed effects (model 5). Note that the period fixed effects control for common shocks and partly capture common trends (Plümper et al. 2005), while the lagged dependent variable solely but effectively captures common trends and accounts for temporal dynamics.

Table 2: Different Treatments for Common Trends and Common Shocks.

	model 3 ldv excluded	model 4 period fe excluded	model 5 ldv and period fe excluded
temporal lag		0.776 (0.023) ***	
spatial lag	0.124 (0.016) ***	0.078 (0.012) ***	0.257 (0.039) ***
unit fixed effects	yes	yes	yes
period fixed effects	yes	no	no
W row-standardized	yes	yes	yes
weight	contiguity	contiguity	contiguity
N	581	581	581

Note: all models include the full battery of control variables reported in table 1.

In model 3, the degree of spatial dependence is 0.124, which is slightly but statistically significantly lower than the long-term spatial effect of model 1, which was 0.18. In model 4, the coefficient size of the spatial lag almost doubles while the standard error increases only slightly compared to model 1. The asymptotic long-term effect of the spatial lag is now approximately 0.35. Clearly, failure to control sufficiently for common shocks and common trends tends to inflate the spatial effect. In model 5 both period dummies and the temporal lag are left out. The spatial effect is approximately 0.26.

The reported differences in the size of the spatial effect thus demonstrate the importance of accounting for temporal dynamics and controlling for common shocks and common trends, especially when the data is so obviously trended as it is for capital taxation. Importantly, for capital taxation, we are on safe grounds arguing that the common trend is not primarily caused by spatial dependence, because according to all theories, tax competition should not lead to the common increase in capital taxation, which can be observed in the data, but to a decrease instead. If, however, the common trend is partly due to spatial dependence, then inclusion of the temporally lagged dependent variable can downward bias the coefficient of the spatial lag if the lagged dependent variable does not correctly specify the temporal dynamics. Moreover, the inclusion of period fixed effects will in general induce a small-sample Hurwicz-Nickell downward bias of the spatial lag coefficient (Franzese and Hays 2007b: 67).

4. Spatial Clustering, Unobserved Spatial Heterogeneity and Unit Fixed Effects

Spatial patterns in the distribution of the dependent variable do not need to be caused by contagion. The odds are that contiguous or geographically close political units are more similar than more distant units. Observable as well as unobservable phenomena such as cultures and customs, preferences and perceptions, constitutions and institutions, and so on are very often spatially clustered, which leads to spatial patterns in the dependent variable even in the absence of spatial dependence. Such spatial patterns can also emerge along non-geographic ordering principles. For example, cultural similarity can impose similar constraints on policy-makers from very distant countries and the absence of capital controls suggest a certain type of banking regulation even though regulatory agencies may not compete with or learn from each other. If these determinants of spatial patterns in the dependent variable are observed (i.e. the regressors show spatial patterns), we refer to them as spatial clustering and we denote unobserved spatial patterns as unobserved spatial heterogeneity (spatial patterns in errors).

Distinguishing such spatial clustering and unobserved spatial heterogeneity from spatial dependence is a problem commonly known as Galton's (1889) problem.[11] If they are not adequately modeled, then a spatial analysis will spuriously suggest spatial dependence. In other words, the challenge is to identify the true spatial effect. Identification rests on the assumption that all the spatial pattern of the dependent variable that has nothing to do with spatial dependence itself is fully explained by the independent variables other than the spatial lag. This is a strong assumption, which will not often hold, so that the estimated coefficients for the spatial effects are likely to be biased.

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[11] Franzese and Hays (2008) discuss the source and nature of this problem in some detail.

A popular method for mitigating the problem created by the unobserved spatial heterogeneity is the inclusion of unit fixed effects. Such models take out all of the between variation in the data and are estimated based on the within variation of the data in each observational unit only. This reduces bias because any spatial clustering or unobserved spatial heterogeneity in policy *levels* are fully captured by the fixed effects. However, spatial clustering or unobserved spatial heterogeneity in policy *changes* may still bias the estimates of the spatial lag even if researchers simultaneously control for common shocks. Moreover, the inclusion of unit fixed effects reduces the efficiency of the estimate of the spatially clustered independent variables, such that their point estimates become less reliable.

Thus, this seemingly easy fix to the problem of spatial clustering and unobserved spatial heterogeneity does not necessarily provide an adequate solution. In addition, the inclusion of unit fixed effects reduces mis-specification bias; in small samples it also introduces another bias into the estimations known as Nickell-Hurwicz bias (Franzese and Hays 2007b). More importantly perhaps, unit fixed effects estimation also changes the tested hypothesis. To see why this is the case, let us briefly consider the within transformation of the data in the unit fixed effects model formally. Starting from equation (1), the within transformation generates as the new estimating equation

$$y_{it} - \overline{y}_i = \alpha + \rho\left(\sum_k w_{ikt} y_{kt} - \overline{\sum_k w_{ik} y_k}\right) + \ldots + \varepsilon_{it} - \overline{\varepsilon}_i \quad . \tag{5}$$

where

$$\overline{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}, \quad \overline{\sum_k w_{ik} y_k} = \frac{1}{T}\sum_{t=1}^{T}\sum_k w_{ikt} y_{kt} \tag{6}$$

and likewise for all control variables and the stochastic error.

This within-transformation effectively eliminates the level effects of all observed variables, including the dependent variable, the spatial lag and all control variables. By regressing deviations of the dependent variable from its unit mean on deviations of all regressors from their unit means, hypotheses on level effects become virtually untestable. Similar problems occur if researchers estimate differences-in-differences models, which in addition often suffer from failure to model adequately heterogeneous lag structures (Plümper et al. 2005).[12]

In many cases, the advantages of using unit fixed effects will outweigh the disadvantages. In particular, if the between variation of the transformed variables is small relative to the within variation, the loss in efficiency remains unimportant relative to the decline in omitted variable bias and the decline in problematic spatial clustering and unobserved spatial heterogeneity. In other cases, however, the specification of a unit fixed effects model is either too costly in terms of efficiency loss (when the within variation is small relative to the between variation) or not appropriate (when the theory suggests level effects).

Researchers should therefore first clearly specify their theory and justify whether they expect level effects or effects in changes. In international tax competition, for example, both explanations seem possible. Theory would predict level effects if one were to argue that tax competition is a function of existing differences in effective tax rates and competition is triggered at a point in time by institutional changes such as the abolition of capital controls, which exposes countries to the effect of international tax rate differences. In contrast, theory will predict dynamic effects if one were to argue that tax competition is triggered by tax reforms in one or more countries. In this latter case, it is not so much the existing differences in tax levels, which lead to competitive adjustment processes, but the changes in tax rates. Model 6 of table 3 presents the effects on the estimation results of excluding unit fixed

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[12] Note that differencing requires a correctly specified temporal lag structure. Fixed effects models are far less vulnerable to misspecification of the lag structure because they do not estimate in differences but in deviations from the unit means.

effects, which were so far included. The spatial lag coefficient is no longer statistically significant and indeed even changes its coefficient sign relative to model 1, which is reported again in table 3 for ease of comparison.

Table 3: Excluding Unit Fixed Effects.

	model 1 (repeated)	model 6 no fixed effects
temporal lag	0.772	0.945
	(0.025) ***	(0.014) ***
spatial lag	0.040	-0.018
	(0.010) ***	(0.011)
unit fixed effects	yes	no
period fixed effects	yes	yes
W row-standardized	yes	yes
weight	contiguity	contiguity
N	581	581

Note: all models include the full battery of control variables reported in table 1.

5. Row-Standardization of the Weighting Matrix

The specification of the weighting matrix also represents a delicate issue. In this section, we deal with whether the weighting matrix should be "row-standardized". In the next section, we discuss the influence of functional form choice for the weighting matrix. Row-standardization means that 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. This makes the spatial lag a weighted *average* of the lagged dependent variable in other units. In contrast, if the weighting matrix is not row-standardized, then the spatial lag is a weighted *sum* of the lagged dependent variable in other units.

Our survey of studies employing spatial effects in political science research revealed that few scholars actually row-standardize their weighting matrix (or if they do, they fail to say so). In contrast, spatial econometricians typically treat row-standardization as something that is 'commonly' (Franzese and Hays 2006: 174; Franzese and Hays 2008: 29), 'generally' (Darmofal 2006: 8), 'typically' (Anselin 2002: 257) or 'usually' (Beck et al. 2006: 28) done.

This seems to suggest that row-standardization is both unproblematic and need not be justified.

Neither is warranted. Row-standardization is not unproblematic since, apart from one special case discussed below, it changes the relative weight that observations of all the other units exert in the creation of spatial lags. Thus, it needs to be well justified. Some spatial econometricians are aware of this (e.g., Franzese and Hays 2008: 68; Ward and Gleditsch 2008: 80), but often mention the potential problems of row-standardization merely in passing.

Why would one want to row-standardize at all? One reason given by, for example, Ward and Gleditsch (2008: 80) is that 'this specific normalization has the advantage that the spatial lag will have the same potential metric or units' as the dependent variable itself. This can be advantageous if one wants to compare the coefficient size of the spatial lag with that of the temporal lag. Row-standardization allows an easy check on the stationarity requirement: the sum of the coefficient of the temporal lag and the coefficient of the row-standardized spatial lag must be less than one (Franzese and Hays 2008: 55). It also allows interpreting the estimated coefficient size of the spatial lag as the approximate strength of interdependence (Franzese and Hays 2008: 35). However, it is only for one specific type of weighting matrix that row-standardization changes nothing else but the metric or unit of the spatial lag. This specific type is a weighting matrix with unitary weights, which contains values of one in all of the off-diagonal cells. This is identical to not using any weighting at all. For such a weighting matrix row-standardization obviously makes no substantive change.

These 'unweighted' or 'identically weighted' spatial lags can make sense in special cases, but are in general unappealing from a theoretical point of view since it is often unlikely that the strength of the spatial interdependence effect should be the same independent of the degree with which the 'infected' unit *i* and the units *k* from which the spatial effect emanates are connected to each other. For all other matrices row-standardization not only changes the metric or unit of the spatial lag, but also the relative weight given to the observations of the *k* units.[13]

An example helps illustrate this point. Take a weighting matrix that measures contiguity. It has cell entries of one for observations that are contiguous, and zero otherwise. If country *i* has two contiguous countries whereas country *j* has six contiguous countries, then both of *i*'s neighbors and all six of *j*'s neighbors exert the same influence each on the spatial lag variable. After row-standardization, however, the two neighbors of *i* now exert an influence on the spatial lag that is three times larger than the influence of the six neighbors of *j*. Row-standardization has changed the relative substantive weight of units from which the contagion originates. Without row-standardization all contiguous countries exert the same influence no matter how many contiguous countries there are. After row-standardization contiguous countries exert an influence that becomes proportionally smaller the larger the number of contiguous countries. Either can be consistent with a specific theory of spatial dependence, but of course not the same theory. In other words, a row-standardized weighting matrix and a weighting matrix that has not been row-standardized relate to substantively different theories of spatial dependence.

To illustrate the effect of row-standardization in our replication exercise and for easy comparison, column 1 of table 4 reports again results from model 1, i.e. the results of the model with period dummies and a temporal lag and row-standardized contiguity as the weighting matrix for the spatial lag. Model 7, reported in the second column of table 4, is identical in its specification with one important exception: this time contiguity is not row-standardized in the weighting matrix.

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13 If, however, each of the row sums of the weighting matrix happens to be the same, which is generally not the case, then row-standardization makes no substantive change even for non-uniform weighting matrices.

Table 4: Weighting Matrix Not Row-Standardized.

	model 1 (repeated)	model 7 not row-standardized
temporal lag	0.772	0.762
	(0.025) ***	(0.025) ***
spatial lag	0.040	0.019
	(0.010) ***	(0.002) ***
unit fixed effects	yes	yes
period fixed effects	yes	yes
W row-standardized	yes	no
weight	contiguity	contiguity
N	581	581

Note: all models include the full battery of control variables reported in table 1.

With the weighting matrix not row-standardized in model 7, the degree of spatial dependence can no longer be derived directly from the estimated coefficient of the spatial lag, but needs to be computed. With an average number of neighboring countries of 3.1, the short-term effects of the row-standardized and the not row-standardized model are significantly different from each other (0.04 in the row-standardized case versus 0.06 in the not row-standardized case) as are the asymptotic long-term effects (0.18 versus 0.24). At the same time, the not row-standardized estimate shows a much higher level of significance. Changing the relative weight of observation from which spatial dependence emanates has thus the potential to impact inference.

The change in relative weights following from row-standardization is not restricted to a binary weighting matrix that only contains values of one or zero. It equally applies to cardinal weighting matrices. If the weights relate to, for example, stocks of foreign direct investment (FDI), then row-standardization implies that only differences in relative shares of FDI matter instead of differences in a country's absolute foreign investment exposure.

Our argument is not that one cannot justify a diminishing influence of contiguous units as the number of these units increases or that one cannot justify measuring connectivity by FDI stock shares instead of absolute FDI stock exposure. Depending on the context, one clearly can. Rather, our point is that row-standardization is not substantively neutral. It changes the relative substantive weight of units from which the spatial dependence originates and therefore needs careful theoretical justification. In other words, row-standardization is not just a question of convenience for making the coefficient sizes of the spatial and temporal lags easily comparable and should not be applied thoughtlessly as a default rule.

6. The Functional Form of the Weighting Matrix

By far the most popular variables for measuring connectivity in existing spatial econometric work are contiguity and geographical distance (Beck et al. 2006). Apart from the question of row-standardization, it is clear how contiguity is to be specified, namely as a binary matrix with values of one for contiguous units and zero otherwise. However, with non-dichotomous measures such as geographical distance there is no obviously "correct" functional form for specifying connectivity (Anselin 2002: 259). In many cases, estimation results depend on the assumed functional form, which gives researchers substantial leeway in choosing a form that produces results favourable to their hypothesis.

To illustrate the problem, we use geographical distance as the measure of connectivity, but our argument applies equally to other substantive weights such as trade or investment links. Assume a theory which predicts that the spatial dependence from more proximate units should be stronger than the dependence from more distant units. This would be in line with what is known as the first "law" of geography: 'Everything is related to everything else, but near things are more related than distant things.' (Tobler 1970: 236). However, assume further that the theory does not specify the degree with which the spatial dependence decreases as distance increases. This would leave researchers with an infinite number of possibilities for specifying a functional form for the weighting matrix. For example, one could specify proximity as $1/d^n$, where d is distance and n is some positive number greater than zero, as $1/(\ln d)^n$ or as $1-d/d_{\max}$, where d_{max} is maximum observable distance, and so on. Furthermore, one can divide the continuum of distance into several discrete bands, e.g., from 0 to 500 miles, 501 to 1000 miles, etc. By changing the weight one attaches to each band, one changes the relative importance that units falling into one of these bands exert on the spatial lag. One popular choice is to set the weight for one or more of these bands to one and the other ones to zero (Gleditsch and Ward 2000; Murdoch and Sandler 2004). This creates a dichotomous weighting matrix out of the continuous variable distance in which units within a certain distance, say within 1000 miles, all exert the same influence, while units further away do not count at all.

To demonstrate the enormous influence that choosing the functional form of the weighting matrix can exert, we now use geographical distance instead of contiguity for the weighting matrix in our replication example.[14] Both contiguity and distance are compatible with many theories of international tax competition. In fact, if one were to ignore that countries can be geographically close to each other without necessarily being contiguous, then contiguity would merely be an extreme form of distance in which spatial dependence derives only from geographically close countries defined as contiguous countries whereas distant (non-contiguous) countries do not count at all. Using a continuous measure of distance relaxes this strict dichotomy. More proximate countries still matter more than more distant countries. Just how much more depends on the functional form used in the weighting matrix.

In model 8, reported in the first column of table 5, we use $1/d = d^{-1}$ in the weighting matrix, where d is distance in kilometers between countries. In model 9, reported in the second column of table 5, we use $1/\ln d = (\ln d)^{-1}$ for the weighting matrix instead. We do not row-standardize either of these two matrices, but the results are qualitatively the same if we do.

14 Data come from Mayer and Zignago (2006). The variable measures distance in kilometers between the principal cities of countries weighted by population size, which thus takes into account the uneven spread of population across a country.

Table 5: Different Functional Forms of the Weighting Matrix.

	model 8 1/(distance)	model 9 1/ln(distance)
temporal lag	0.730	0.808
	(0.034) ***	(0.031) ***
spatial lag	3.392	-0.181
	(1.606) *	(0.050) ***
unit fixed effects	yes	yes
period fixed effects	yes	yes
W row-standardized	no	no
weight	d^{-1}	$(\ln d)^{-1}$
Nobs	581	581

Note: all models include the full battery of control variables reported in table 1.

The coefficient of the spatial lag is positive and statistically significant in model 8, with an asymptotic long-term degree of spatial dependence of approximately 0.38. Strikingly, the coefficient of the spatial lag becomes negative and statistically significant in model 9. Thus, a seemingly small change in the functional form chosen for the weighting matrix exerts a large influence on the estimated spatial lag, entirely reversing inferences. Model 8 would suggest that higher taxes in other countries, particularly more proximate ones, *raise* the domestic tax rate. In contrast, model 9 suggests that higher taxes in other countries, again particularly so in more proximate ones, *reduce* the domestic tax rate.

Apparently, the difference in results is driven by the fact that in model 8 the weight given to more distant countries decreases much faster than in model 9. In the particular data sample that we analyze more proximate countries tend to have a positive impact on domestic tax rates, whereas more distant countries tend to have a relatively stronger negative impact. With $1/d$ as the functional form for the weighting matrix the positive effect dominates, whereas the negative effect dominates with $1/(\ln d)$ as the functional form, which gives more distant countries a relatively higher weight.[15]

[15] Not surprisingly then, the spatial lag with 1/d as the weighting variable has a non-monotonic effect in the estimations: the coefficient of the linear spatial lag term is positive and statistically significant, whereas the coefficient of its squared term is negative and significant (results not shown).

Not all datasets are equally sensitive to functional form specification of the weighting matrix and it may not always be possible to find functional forms that lead to once positive once negative estimated coefficients for the spatial lag variable. However, all datasets are to some extent sensitive. Just how much so is almost impossible to tell for those other than the ones choosing the functional form.

The problem posed by the choice of functional form is amplified by the fact that the correct operationalization and functional form of connectivity must be known (based on theoretical reasoning) by the researcher and the validity of these assumptions cannot be easily tested. As Beck et al. (2006: 28) state: 'As is done in all spatial econometric works, we assume that the structure of dependence between observations is known by the researcher and not estimated. (…) The assumption that these connectivities are known a priori is both a strong assumption and critical for the methods of spatial econometrics to work.' To demonstrate this, the first column of table 6 repeats model 8, in which $1/d$ was the functional form for the weighting matrix. We now reverse distance by subtracting distance from the sum of the minimum and the maximum of distance. The resulting variable – let us call it p for proximity – is one that has the same range (same minimum and maximum) as the distance variable, but is perfectly negatively correlated with it. The minimum (maximum) of distance is the maximum (minimum) of proximity and the standard deviation of both variables is the same, whereas the mean differs of course. In model 10, reported in column 2, we use $1/p$ as the functional form. Strikingly, the spatial lag is still positive in model 10 and not far from statistical significance either.[16] Since neither of the weighting matrices in table 6 are row-standardized the degree of spatial dependence needs to be computed and cannot simply be inferred from the coefficient sizes. The asymptotic long-term spatial effect is 0.38 in model 8 and 0.05 in model 10.

16 The coefficient from the spatial-OLS estimation of model 10 is in fact significant.

Table 6: Reversing the Weighting Matrix Variable.

	model 8 repeated 1/(distance)	model 10 1/(distance reversed)
temporal lag	0.730	0.775
	(0.034) ***	(0.025) ***
spatial lag	3.392	1.354
	(1.606) *	(0.998)
unit fixed effects	yes	yes
period fixed effects	yes	yes
W row-standardized	no	no
weight	d^{-1}	p^{-1}
Nobs	581	581

Note: all models include the full battery of control variables reported in table 1.

This result may seem counterintuitive. After all, distance and reversed distance (or proximity) are perfectly negatively correlated with each other. If these were not weighting matrices, but simply explanatory variables entering the estimation model on their own, then their coefficients would be the same, but with opposite signs. However, because they are multiplied with the spatial y this becomes far less likely. Even if the two weights are perfectly negatively correlated with each other, the spatial lags never are. It follows that these two spatial lags can both lead to a statistically significant coefficient with the same sign for the spatial lag.

It would therefore be illegitimate to interpret the spatial lag coefficient as telling us anything on the validity of the weighting matrix. For example, a statistically significant positive spatial lag coefficient with $1/d$ as the weighting matrix does not provide evidence that spatial dependence is correctly modeled as decreasing with the inverse of geographical distance. If we are correct in our belief that $1/d$ is the right specification of the weighting matrix, then a positive and significant coefficient of the spatial lag provides evidence that other countries' policy choices affect domestic policy choices and the more so the closer these countries are to the home country. But our belief in the weighting matrix specification cannot be tested this directly.

Since theory must ultimately determine the weighting matrix, no simple or unproblematic empirical test exists which would allow researchers to determine the "correct" functional form of the weighting matrix. For this reason there is no straightforward econometric solution to the apparent arbitrariness in the choice of functional form. We recommend one of two solutions. The first and ideal one is if researchers provide a better specification of the underlying theory. Some theories will suggest that spatial dependence diminishes very rapidly as distance increases, whereas others would suggest that such dependence diminishes only slowly. Some theories will suggest that spatial dependence diminishes at an increasing, others at a decreasing rate. Admittedly, even with better specified theories some arbitrariness will remain. Still an infinite number of functional forms can specify, say, rapidly decreasing spatial dependence that decreases at an increasing rate. However, more specified theories lead to less arbitariness than less specified ones.[17]

Robustness tests provide the second-best solution. If scholars can show that their results uphold using several functional forms for the weighting matrix and the results are sufficiently similar, then one can be more confident in the existence of a true spatial effect. At the very least, we would suggest testing the robustness of results to such simple modifications of the weighting matrix as doing a Box-Cox transformation[18] or taking the natural log of the

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[17] An alternative option developed in network analysis that recently caught the attention of spatial econometricians (Franzese et al. 2008) is the 'parameterization' of the weighting matrix. In order to be able to 'parameterize' the weighting matrix, an assumption on the distribution of the effect strengths is needed. Scholars usually assume a normal distribution – an assumption that we believe is usually highly problematic. Moreover, the odds are that this technique simply overfits the data, as it is simply an optimization procedure. Hence, more extensive Monte Carlo analyses are needed before applied researchers should use this technique.

[18] In many cases, a Box-Cox (or Power) transformation ensures that the distribution of the transformed variable y approaches $y \sim N(\mathbf{X}\beta, \sigma^2 \mathbf{I}_n)$, i.e. the Normal distribution. Transformation of positive integers is usually done by

connectivity variable as well as using its squared value. Converting a continuous connectivity variable into several discrete bands and reporting results for each band separately may also be worthwhile. What is the best way to show robustness depends on the problem at hand. The important message is that demonstrating robustness is necessary in the absence of a theory that provides sufficient guidance on the functional form.

7. Conclusion

Model specification matters, and even more so in the analysis of spatial dependence. In this article, we have demonstrated that seemingly small changes to the specification of one of Hays's (2003, 2009) models of tax competition lead to a surprisingly large variety of results that are partly contradictory. Our replication exercise raises four important issues that spatial analysts need to address.

First, failure to model temporal dynamics and control for common trends and common shocks will lead to bias in the spatial effect estimates. Second, the same applies if one fails to model adequately spatial clustering and unobserved spatial heterogeneity. Of course, common shocks, common trends and unobserved heterogeneity are widely discussed in non-spatial panel data analysis. However, if anything, they are more likely to be present and at the same time more difficult to solve in spatial panel data analysis.

Third, the question of row-standardization must be decided on theoretical grounds and should not be employed as a general default rule. Row-standardization changes the relative

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$$y(\lambda)=\begin{cases}\dfrac{y^{\lambda}-1}{\lambda} & , if\ \lambda\neq 0\\ \log(y) & , if\ \lambda=0\end{cases}\ .$$

(More complicated variants are available). Scholars often use the Box-Cox transformation to ensure a normal distribution of variables in the linear models. Note, however, that linear models only assume that errors are normally distributed.

weight of observations from which spatial dependence emanates in all weighting matrices but the unitary one, which is in general an unappealing matrix. For the vast majority of weighting matrices of interest therefore row-standardization will influence the results and may impact inference.

Finally, we have shown that estimation results can crucially hinge on the functional form of the weighting matrix, unless the matrix consists of a binary variable such as contiguity. For continuous variables measuring connectivity, researchers need to be concerned not only about whether to row-standardize, but also about choosing the right functional form. As we have demonstrated, small changes to the functional form can lead to very different results. Spatial analysts are thus vulnerable to the charge that their results were obtained by choosing a specific functional form and disregarding others that led to different results.

There are no simple econometric fixes for any of these four problems. Franzese and Hays (2007b, 2008) recommend using temporal and unit fixed effects as a conservative estimation strategy, i.e. one that is less likely to find spurious evidence for spatial dependence in the absence of true dependence.[19] We have sympathy for such a view: failure to control for common trends and common shocks is likely to lead to bias of the spatial lag coefficient, which is often an upward bias. However, controlling for these dynamics by adding period dummies and either the temporally lagged dependent variable as suggested by Beck and Katz (1995), or Prais-Winsten transformation as advocated by Plümper et al. (2005), or by a distributed lag model as preferred by Adolph et al. (2005) may easily lead to the opposite problem. If the trend is partly explained by the spatial lag, then these control mechanisms are likely to lead to downward bias in the estimated coefficient of the spatial lag since it is all too easy for the period dummies (and, if applicable, the temporal lag) to fully capture the trend (Plümper at al. 2005). Which bias is more problematic will depend on the context. We

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19 They also suggest that spatial-ML is a more conservative estimator than either spatial-OLS or spatial-2SLS.

recommend that researchers carefully consider different options for modeling temporal dynamics and controlling for common trends and common shocks and that they show how robust the results are to different dynamic modeling options.

Similarly, controlling for spatial clustering and unobserved spatial heterogeneity by including unit fixed effects (or eliminating levels by another technique) is neither a sufficient solution nor one that is always appropriate. If there is spatial clustering or unobserved spatial heterogeneity in policy *changes* that has nothing to do with spatial dependence itself, then this still needs to be carefully modeled by control variables and, if this is not possible, estimation bias persists. Even when unit fixed effects sufficiently eliminate irrelevant spatial clustering and unobserved heterogeneity, the resulting estimations can be so inefficient as to be useless. In addition, if the theory predicts level effects then unit fixed effects estimation is inappropriate. We recommend that researchers compare the unit fixed effects model to alternative specifications, e.g., the model without unit fixed effects, the inclusion of group dummies (rather than unit dummies), estimation with a differenced dependent variable, or the fixed effects vector decomposition model, which only de-means variables that have sufficient within variation (Plümper and Troeger 2007). Clearly, researchers not only need to develop more fully their theory, they also need to understand and communicate what their chosen estimation procedure and the empirical model specification do to the data (King 1990: 11).

We also do not see a straightforward econometric solution to the problem of specification of the weighting matrix. In its absence, we believe it is generally justified to expect researchers to derive from theory predictions on whether to row-standardize the weighting matrix. We are more skeptical whether theories of spatial dependencies will ever be able to convincingly predict a functional form for the weighting matrix. Even then, we believe that researchers can develop their theories further, specifying that certain types of functional forms are more plausible, while others should be excluded. For example, in many cases it would seem possible to justify theoretically whether the first and second derivatives of the functional form are positive or negative. For example, a theoretical model should not only be able to tell us that spatial dependence decreases with geographical distance, but also whether it decreases slowly or rapidly and at an increasing or decreasing rate as other units are located further away. In the absence of a theoretically fully specified functional form of the weighting matrix only robustness tests can help. At the least, applied researchers should show whether the spatial effect is robust if they use a linear, a logged and a squared function of the weighting matrix. This may be a good idea in any case even if one is fairly confident that one has specified the functional form on firm theoretical grounds.

The more developed the underlying theory of spatial dependence, the less arbitrary the specification of the empirical model. Of course, it is trivially the case that, all other things equal, a more comprehensively specified theory is better than a less comprehensively specified one. However, this seems to be even more important for the analysis of spatial dependencies than in most other fields of research. The peculiar effects of the weighting matrix on the estimation results and the fact that researchers cannot test but have to assume its correctness, make more theoretical guidance an essential element of the research process.

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