Spatial Interdependence in Comparative and International Political Economy

Robert J. Franzese, Jr. (franzese@umich.edu)*
Associate Professor of Political Science, University of Michigan, Ann Arbor

Jude C. Hays (jchays@uiuc.edu)*
Assistant Professor of Political Science, University of Illinois, Urbana-Champaign

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ABSTRACT: Interdependence is ubiquitous, and often central, across political economy. In comparative political economy, for example, globalization and rising capital mobility imply tax competition that suggests the fiscal policies of one country must depend crucially upon those of other countries with which it competes for capital. In international political economy, to give another example, security concerns and the global structure of military alliances are likely to make trade flows interdependent across country dyads. We explain how any situation that involves externalities from one unit's actions on others' implies interdependence and show how to model such interdependent processes empirically. We discuss how to estimate properly specified interdependence models with spatial lags by maximum likelihood and how to interpret and present the resulting estimated spatio-temporal effects, response paths, and long-run steady-states, with their associated standard errors. We illustrate with replications of two noteworthy earlier studies from comparative and international political economy.

KEYWORDS: Political Economy, Globalization, Interdependence, Strategic Interactions, Spatial Econometrics, Taxation, Trade.

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I. Introduction

Empirical analyses of spatial interdependence in the social sciences have until recently remained largely confined to specialized areas of applied economics (e.g., urban/regional, environmental, and real-estate economics) and sociology (i.e., network analysis). However, social-scientific interest in and applications of spatial modeling have burgeoned lately—including in political economy—due partly to advances in theory that imply interdependence and in methodology for addressing it, partly to global developments that have enhanced interconnectivity substantively, and partly to advances in technology for obtaining and working with spatial data.

This rising attention is an extremely welcome development as many phenomena that political economists study entail substantively important spatial interdependence: see Eising (2002), Franzese & Mosher (2002), Brune et al. (2004), Simmons & Elkins (2004), Brooks (2005), Elkins et al. (2006), and Simmons et al. (2006) regarding economic liberalizations; and Genschel (2002), Swank (2002), Swank & Steinmo (2002), Hays (2003), Basinger & Hallerberg (2004), Knill (2005), Jahn (2006), Swank (2006), and Franzese & Hays (2003, 2006b, 2007ab, 2008a) regarding globalization, tax competition, and convergence. The literature on security externalities and the relationship between trade and conflict is also notable in this respect (see, for example, Polachek 1980, Gowa and Mansfield 1993, Morrow et al. 1998, Keshk et al. 2004).

Empirical work in political economy, meanwhile, has come to recognize that time-series-cross-section (TSCS) data usually correlate across space as well as over time, which is commendable; however, whereas researchers usually model temporal dependence directly—again: commendable—they tend to view spatial interdependence solely as a nuisance to be "corrected" (by FGLS) or to which standard-error estimates should be made "robust" (by PCSE), which is less laudable. That is, current practice relies almost exclusively on non-spatial or, at most, "nuisance-spatial" empirical models. This paper discusses the strong theoretical/substantive argument for explicitly spatially and spatio-temporally dynamic models, the empirical specification and estimation of such models, and the evaluation (i.e., testing), interpretation, and presentation of spatially and spatio-temporally dynamic effect-estimates.

II. A General Theoretical Model of Spatial Interdependence

To elucidate formally and generally the ubiquity and operation of interdependence, we follow Brueckner (2003) to show that strategic interdependence arises whenever the actions of some unit(s) affect the marginal utility of alternative actions for some other unit(s). Consider two units (i,j) that derive utilities, (U^i,U^j), from their alternative actions or policies, (p_i,p_j).[1] Due to externalities, i's utility depends on j's policy, p_j, as well as its own, p_i. For example, imagine two countries with populations homogenous with respect to, say, their economic and environmental preferences. Due to environmental externalities (e.g., those stemming from pollution) and economic ones (e.g., those arising from the costs of environmental regulations), domestic welfare (i.e., net political-economic benefits/utilities to policymakers) in each country will depend on both countries' actions:

$$U^i \equiv U^i(p_i,p_j) \;\; ; \;\; U^j \equiv U^j(p_j,p_i) \tag{1}$$

When the government of country i chooses p_i to maximize its own social welfare, its optimal choice depends on country j's policy, p_j, and *vice versa*. For example, as j strengthens (weakens) its anti-pollution policies, environmental spillovers decrease (increase) the need for effective anti-pollution policies in i. We can express such strategic interdependence between i and j with two best-response functions, giving i's optimal policies, p_i^*, as a function of j's chosen policies, p_j, and *vice versa*:[2]

[1] Technically, these will typically be indirect utilities derived over policies from direct utilities over, say, consumption and leisure. Standard notation for indirect and direct utilities are W and U, respectively, but W figures prominently in the standard notation of spatial econometrics, so we accept the abuse of notational standards here to preserve them there.

[2] Explicitly, we obtain country i's optimum policy by maximizing with respect to p_i, taking p_j as given (fixed); i.e., setting the first derivative of the welfare function with respect to p_i equal to zero and solving for the resulting p_i^* as a

$$p_i^* \equiv \text{Argmax}_{p_i}\ U^i(p_i, p_j) \equiv R^i(p_j) \quad ; \quad p_j^* \equiv \text{Argmax}_{p_j}\ U^j(p_j, p_i) \equiv R^j(p_i) \qquad (2)$$

The slopes of these best-response functions indicate whether actions by *j* induce *i* to move in the same direction, in which case we call the actions of *i* and *j strategic complements*, or in the opposite direction, in which case they are *strategic substitutes*. For example, anti-pollution policies are strategic substitutes in terms of their environmental effects as described above. The slopes of these best-response functions depend on the following ratios of second cross-partial derivatives:

$$\frac{\partial p_i^*}{\partial p_j} = -U^i_{p_i p_j} \Big/ U^i_{p_i p_i} \quad ; \quad \frac{\partial p_j^*}{\partial p_i} = -U^j_{p_j p_i} \Big/ U^j_{p_j p_j} \qquad (3)$$

If governments maximize their utility, the second-order condition implies negative denominators in (3), so the slopes will depend directly on the signs of the second cross-partial derivatives (i.e., the numerators). If policies are strategic substitutes ($U^{i,j}_{p_i p_j} < 0$), reaction functions slope downward, as suggested regarding the environmental benefits of anti-pollution regulation. If policies are strategic complements ($U^{i,j}_{p_i p_j} > 0$), reaction functions slope upward. Regarding the *economic* costs of anti-pollution regulation, for example, increased (reduced) regulation in *j* may lower (raise) the costs of regulation in competitors *i*, and so induce *i* to tighten (loosen) its regulations too. Tax competition, as commonly understood, would also arise from such strategic complementarity. Tariff and NTB "wars" driven by security externalities should follow a similar logic.[3] If the second cross-partial derivative is zero, strategic interdependence does not materialize and best-responses are flat.

III. Empirical-Methodological Challenges of Spatial Interdependence

A. The Spatio-Temporal-Lag Model

Most empirical studies of political economy where interdependence arises analyze panel or time-series-cross-section (TSCS) data (i.e., observations on units over time). To estimate effects and draw sound causal inferences in such contexts, analysts should specify both temporal and spatial

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function of p_j (and then verifying that the second derivative is negative).

[3] In short, the security externalities argument is that consumers (or importers more generally) fail to internalize the security consequences of their market transactions. Individual consumers in country A buy products from producers in country B, which generates taxable income and potentially alters the balance of military power. Consumers will buy more products than is socially optimal from producers in adversarial countries, and, therefore, governments have an incentive to implement policy measures that lower the volume of imports. This action, in turn, creates incentives for adversarial governments to follow suit.

interdependence in their models.[4] As Section II demonstrated theoretically, failure to model spatial interdependence in any strategic context, and probably in many non-strategic contexts also, is a serious misspecification risking great omitted-variable bias. The easiest and most straightforward way to incorporate this interdependence is with a spatio-temporal lag model, which we can write in matrix notation as:[5]

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \phi\mathbf{M}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{4}$$

where $\mathbf{y}$, the dependent variable, is an $NT\times1$ vector of cross sections stacked by periods (i.e., the N units' first-period observations, then their second-period ones, and so on to the N period-T ones).[6] ρ is the spatial autoregressive coefficient, and $\mathbf{W}$ is an $NT\times NT$ block-diagonal spatial-weighting matrix. In detail, this $\mathbf{W}$ matrix is the Kronecker product of a $T\times T$ identity matrix and an $N\times N$ weights matrix $\left(\mathbf{I}_T \otimes \mathbf{W}_N\right)$, with the elements w_{ij} of $\mathbf{W}_N$ reflecting the relative connectivity from unit j to i as previously described. $\mathbf{W}\mathbf{y}$ is the *spatial lag*; i.e., for each observation y_{it}, $\mathbf{W}\mathbf{y}$ gives a weighted sum of the y_{jt}, with weights w_{ij}. Notice how $\mathbf{W}\mathbf{y}$ thus directly and straightforwardly reflects the dependence of each unit *i*'s outcome on unit *j*'s, following the theoretical models and arguments reviewed above. The parameter ϕ is the temporal autoregressive coefficient, and $\mathbf{M}$ is an $NT\times NT$ matrix with ones on the minor diagonal, i.e., at coordinates $(N+1,1)$, $(N+2,2)$, …, $(NT, NT\text{-}N)$, and zeros elsewhere. Thus, $\mathbf{M}\mathbf{y}$ is just a (first-order) temporal lag. The matrix $\mathbf{X}$ contains NT observations on k independent variables, and $\boldsymbol{\beta}$ is a $k\times1$ vector of

[4] Methodologically, two approaches to spatial analysis can be discerned: spatial statistics and spatial econometrics. The distinction, according to Anselin (2002, 2006), lies on the one side in (1) the relative emphasis in spatial econometrics to theoretical models of interdependence processes, (2) wherein space may often have broad meaning, well beyond geography and geometry to encompass all manner of social, economic, or political connection that induces effects from outcomes in some units on outcomes in others (Brueckner 2003; Beck et al. 2006). (3) The spatial-lag regression model plays a starring role in that tradition (Hordijk 1974; Paelinck & Klaassen 1979; Anselin 1980, 1988, 1992; LeSage 1999). In this approach to model specification and estimation, (4) Wald tests of the unrestricted spatial-lag model (top-down) are the main tools and strategy for gauging the importance of spatial interdependence. On the other side, (1) spatial-error models, analysis of spatial-correlation patterns, spatial kriging, and spatial smoothing, e.g., characterize the (2) more-exclusively data-driven spatial-statistics approach, and the (3) typically narrower conception of space in solely geographic/geometric terms in its longer tradition (reaching crucial methodological milestones in Whittle 1954; Cliff & Ord 1973, 1981; Besag 1974; Ord 1975; Ripley 1981; Haining 1990; Cressie 1993). (2) Data problems such as measurement error tend to drive spatial analysis in this approach, with spatial correlation often viewed as a *nuisance*. In this approach to model specification and estimation, (4) Lagrange multiplier tests of the restricted non-spatial lag model (bottom-up) are the main tools and strategy.

[5] We discuss here only the spatial-lag model for linear-continuous dependent-variables. Spatial interdependence raises considerably greater challenges for estimation, evaluation, and interpretation of qualitative- and limited-dependent-variable models. Franzese & Hays (2007d, 2008b) introduce the spatial probit model for binary-outcome models.

[6] Nonrectangular and/or missing data are manageable, but we assume full-rectangularity for expository simplicity.

coefficients on them. Finally, $\boldsymbol{\varepsilon}$ is an $NT \times 1$ vector of stochastic components, assumed to be independent and identically distributed.[7]

There are four common estimators for such models: non-spatial least-squares (i.e., regression omitting the spatial component, as in most extant research: OLS), spatial OLS (i.e., OLS estimation of models like (4), which is common in diffusion studies and is becoming so in globalization/tax-competition ones: S-OLS), instrumental variables (e.g., spatial 2SLS or S-2SLS), and spatial maximum-likelihood (S-ML). Analytically, we can show that the first two strategies produce biased and inconsistent estimates, the first because of omitted-variable bias and the second because the spatial lag is endogenous and so induces simultaneity bias.

If researchers omit the spatial lag that would properly reflect the true interdependence of their data, their OLS coefficient estimates will suffer omitted-variable biases,[8] the formula for which is well-known to be $\mathbf{F\beta}$ where $\mathbf{F}$ is the matrix of coefficients obtained by regressing the omitted on the included variables and $\boldsymbol{\beta}$ is the vector of (true) coefficients on the omitted variables. In this case:

$$\text{plim}\ \hat{\beta}_{\text{OLS}} = \beta + \rho \times \frac{\text{cov}(\mathbf{Wy}, \mathbf{x})}{\text{var}(\mathbf{x})} \qquad (5).$$

$\hat{\rho}_{\text{OLS}} \equiv 0$, of course, which is biased by $-\rho$. Thus, insofar as the spatial lag covaries with the non-spatial regressors, which is highly likely if domestic conditions correlate spatially and is certain for common exogenous-external shocks, OLS will overestimate domestic, exogenous-external, or context-conditional effects while ignoring spatial interdependence.

On the other hand, including spatial lags in models for OLS estimation entails an endogeneity and so will suffer simultaneity bias. S-OLS estimates are inconsistent because the spatial lag, $\mathbf{Wy}$, covaries with the residual, $\boldsymbol{\varepsilon}$. The reason is simple; the spatial lag, being a weighted average of outcomes in other units, puts the left-hand side of some observations on the right-hand side of others: textbook simultaneity. Even more simply *via* example: Germany causes France, but France also causes Germany. To see the implications of this endogeneity, first rewrite (4) as:

$$\mathbf{y} = \mathbf{Q}\boldsymbol{\delta} + \boldsymbol{\varepsilon}, \text{ where } \mathbf{Q} = [\mathbf{Wy} \quad \mathbf{x}] \text{ and } \boldsymbol{\delta} = [\rho \quad \beta]' \qquad (6).$$

The asymptotic simultaneity bias for the S-OLS estimator is then given by

[7] Alternative distributions of $\boldsymbol{\varepsilon}$ are possible but add complication without illumination.

[8] Likewise, maximum-likelihood estimates of limited- or qualitative-dependent-variable models, like logit or probit, which exclude relevant spatial lags will suffer analogous omitted-variable biases, although $\mathbf{F\beta}$ would not describe those.

$$\text{plim } \hat{\boldsymbol{\delta}}_{\text{S-OLS}} = \boldsymbol{\delta} + \text{plim } \left[\left(\tfrac{\mathbf{Q}'\mathbf{Q}}{n}\right)^{-1} \left(\tfrac{\mathbf{Q}'\boldsymbol{\varepsilon}}{n}\right) \right] \qquad (7).$$

In the case where $\mathbf{x}$ is exogenous, we can rewrite the biases expressed in (16) as

$$\text{plim } \hat{\boldsymbol{\delta}}_{\text{S-OLS}} = \begin{bmatrix} \rho \\ \beta \end{bmatrix} + \frac{1}{|\boldsymbol{\Psi}|} \begin{bmatrix} \text{cov}\left(\mathbf{Wy}, \boldsymbol{\varepsilon}\right) \times \text{var}(\mathbf{x}) \\ -\text{cov}\left(\mathbf{Wy}, \boldsymbol{\varepsilon}\right) \times \text{cov}(\mathbf{Wy}, \mathbf{x}) \end{bmatrix} \text{ where } \boldsymbol{\Psi} = \text{plim}\left(\frac{\mathbf{Q}'\mathbf{Q}}{n}\right) \qquad (8).$$

So, e.g., in the likely common case of positive interdependence and positive covariance of spatial-lag and exogenous regressors, *S-OLS* would generally over-estimate interdependence strength, $\hat{\rho}$, and correspondingly underestimate domestic, exogenous-external, and/or context-conditional effects, $\hat{\beta}$.

In sum, empirical analyses that ignore substantively appreciable interdependence will also thereby tend to overestimate the importance of non-spatial factors; in fact, the effect of factors that most correlate spatially will be most over-estimated. On the other hand, simply controlling spatial-lag processes (or considering them qualitatively) will introduce simultaneity biases, usually in the opposite direction, exaggerating interdependence effects and understating domestic/unit-level, exogeneous-external, and context-conditional impacts. Again, those factors that correlate most with the interdependence pattern will have the most severe induced deflation biases. Using these intuitions another way, note that these conclusions hold as a matter of degree as well; insofar as the non-spatial components of the model are inadequately specified and measured relative to the interdependence aspects, the latter will be privileged and the former disadvantaged (and *vice versa*). Thus, careful, accurate, and powerful specification of **W** is of crucial empirical, theoretical, and substantive importance to those interested in interdependence, obviously, but also to those for whom domestic/unit-level, contextual/exogenous-external, or context-conditional factors are of primary interest.[9] Conversely, careful, accurate, and powerful specification of the domestic/unit-level, contextual/exogenous-external, and context-conditional non-spatial components is of equally crucial importance to those interested in gauging the importance of interdependence. One implication is that both comparative political economists, who may be relatively uninterested directly in the interdependence of the domestic political economies they are comparing, and international political economists, who may be relatively uninterested directly in the domestic political economies of the

[9] Strategies to parameterize **W** and estimate models in which an *unobserved* pattern of interconnections between units *affects* their choices or outcomes are of great interest but as yet mostly remain for future work. (The italicized words differentiate this challenge from that of network analysis, in which the estimation of the *observed* network, as opposed to its effects on units' choices or outcomes, is the *direct object* of the study.)

nations whose interdependence is their more-central concern, must strive to model the other's core interest as well as they do their own in order to draw valid inferences about their core concerns.

B. *Effective Estimation of the Spatio-Temporal-Lag Model*

The omitted-variable biases of OLS are almost always worse and often far, far worse than S-OLS' simultaneity biases. In fact, for milder interdependence strengths ($\rho \times \Sigma_j w_{ij}$ less than about 0.3), S-OLS may perform adequately. However, S-OLS' simultaneity biases become more sizable as interdependence grows stronger, and employing some consistent estimator, such as S-2SLS or S-ML, is definitely advised in such instances. The choice of which consistent estimator is decidedly secondary, but S-ML seems close to weakly dominant across all four estimation strategies (2006a, 2007c, 2008ab). Accordingly, we introduce only it here.[10]

The conditional likelihood function for the spatio-temporal-lag model, which assumes the first observation in each unit to be non-stochastic, is a straightforward extension of the standard spatial-lag likelihood function, which, in turn, adds only one mathematically and conceptually small complication (albeit a computationally intense one) to the likelihood function for the standard linear-normal model (OLS). To see this, start by rewriting the spatial-lag model with the stochastic component on the left:

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \Rightarrow \boldsymbol{\varepsilon} = \left(\mathbf{I} - \rho\mathbf{W}\right)\mathbf{y} - \mathbf{X}\boldsymbol{\beta} \equiv \mathbf{A}\mathbf{y} - \mathbf{X}\boldsymbol{\beta} \quad (9).$$

Assuming *i.i.d.* normality, the likelihood function for $\boldsymbol{\varepsilon}$ is then just the typical linear-normal one:

$$L(\boldsymbol{\varepsilon}) = \left(\frac{1}{\sigma^2 2\pi}\right)^{\frac{NT}{2}} \exp\left(-\frac{\boldsymbol{\varepsilon}'\boldsymbol{\varepsilon}}{2\sigma^2}\right) \quad (10),$$

which, in this case, will produce a likelihood in terms of $\mathbf{y}$ as follows:

$$L(\mathbf{y}) = |\,\mathbf{A}\,| \left(\frac{1}{\sigma^2 2\pi}\right)^{\frac{NT}{2}} \exp\left(-\frac{1}{2\sigma^2}\left(\mathbf{A}\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\right)'\left(\mathbf{A}\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\right)\right) \quad (11).$$

This still resembles the typical linear-normal likelihood, except that the transformation from $\boldsymbol{\varepsilon}$ to

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[10] The instrumental-variables (IV), two-stage-least-squares (2SLS), generalized-method-of-moments (GMM) family of estimators relies on the spatial structure of the data to instrument for the endogenous spatial lag. On the assumption that what we call *cross-spatial endogeneity*, **y**'s in some units cause **x**'s in others, does not exist, instruments comprised of **WX** are ideal by construction. Cross-spatial endogeneity may seem highly unlikely in many contexts, perhaps, until one realizes that combinations of vertical connections from $\mathbf{y}_i$ to $\mathbf{y}_j$ and horizontal ones from $\mathbf{y}_j$ to $\mathbf{x}_j$ (the usual sort of endogeneity) combine to give the offending diagonal ones from $\mathbf{y}_i$ to $\mathbf{x}_j$. As usual, there are no magic instruments in empirical analysis.

$\mathbf{y}$ is not by the usual factor, 1, but by $|\mathbf{A}|=|\mathbf{I}-\rho\mathbf{W}|$.[11] Written in ($N\times 1$) vector notation, the spatio-temporal-model conditional-likelihood is mostly conveniently separable into parts, as seen here:

$$\text{Log} f_{\mathbf{y}_t,\mathbf{y}_{t-1},\ldots,\mathbf{y}_2|\mathbf{y}_1} = -\frac{1}{2}N(T-1)\log\left(2\pi\sigma^2\right)+(T-1)\log\left|\mathbf{I}-\rho\mathbf{W}\right|-\frac{1}{2\sigma^2}\sum_{t=2}^{T}\boldsymbol{\varepsilon}_t'\boldsymbol{\varepsilon}_t \quad (12),$$

where $\boldsymbol{\varepsilon}_t=\mathbf{y}_t-\rho\mathbf{W}_N\mathbf{y}_t-\phi\mathbf{I}_N\mathbf{y}_{t-1}-\mathbf{X}_t\boldsymbol{\beta}$.

We note that the unconditional (exact) likelihood function, which retains the first time-period observations as non-predetermined, is more complicated (Elhorst 2001, 2003, 2005):[12]

$$\begin{aligned}\text{Log} f_{\mathbf{y}_t,\ldots,\mathbf{y}_1} &= -\frac{1}{2}NT\log\left(2\pi\sigma^2\right)+\frac{1}{2}\sum_{i=1}^{N}\log\left(\left(1-\rho\omega_i\right)^2-\phi^2\right)+(T-1)\sum_{i=1}^{N}\log\left(1-\rho\omega_i\right) \\ &-\frac{1}{2\sigma^2}\sum_{t=2}^{T}\varepsilon_t'\varepsilon_t-\frac{1}{2\sigma^2}\varepsilon_1'\left(\left(\mathbf{B}_N-\mathbf{A}_N\right)'\right)^{-1}\left(\mathbf{B}_N'\mathbf{B}_N-\mathbf{B}_N'\mathbf{A}_N\mathbf{B}_N^{-1}\left(\mathbf{B}_N'\mathbf{A}_N\mathbf{B}_N^{-1}\right)'\right)^{-1}\left(\mathbf{B}_N-\mathbf{A}_N\right)^{-1}\varepsilon_1\end{aligned} \quad (13),$$

where $\boldsymbol{\varepsilon}_1=\mathbf{y}_1-\rho\mathbf{W}_N\mathbf{y}_1-\phi\mathbf{I}_N\mathbf{y}_1-\mathbf{X}_1\boldsymbol{\beta}$, $\mathbf{A}_N=\mathbf{I}_N-\rho\mathbf{W}_N$, and $\mathbf{B}_N=\phi\mathbf{I}_N$. When T is small, the first observation contributes greatly to the overall likelihood, and scholars should use the unconditional likelihood to estimate the model. In other cases, the more compact conditional likelihood is acceptable for estimation purposes.

One easy way to ameliorate or even eliminate the simultaneity problem with S-OLS is to lag temporally the spatial lag (Beck et al. 2006; see Swank 2006 for an application). To the extent that time-lagging renders the spatial lag pre-determined—that is, to the extent spatial interdependence does not incur instantaneously, where *instantaneous* here means *within an observation period, given the model*—the S-OLS bias disappears. In other words, provided that the spatial-interdependence process does not operate within an observational period but only with a time lag, and also that spatial and temporal dynamics are sufficiently modeled to prevent that problem arising via measurement/specification error, OLS with a temporally lagged spatial-lag on the RHS is a simple and effective estimation strategy without simultaneity bias. However, even in this best-case scenario, *OLS with time-lagged spatial-lags only provides unbiased estimates if the first observation is non-stochastic* (i.e., if initial conditions are fixed across repeated samples). Elhorst (2001:128) derived

[11] This difference does complicate estimation somewhat. Two strategies that simplify the problem are using an eigenvalue approximation for the determinant (Ord 1975) and maximizing a concentrated likelihood function (Anselin 1988).

[12] Note that the same condition that complicates ML estimation of the spatio-temporal lag model, namely the first set of observations is stochastic, also invalidates the use of OLS to estimate a model with a temporally lagged spatial lag under those conditions. Hence, asymptotically, this consideration offers no econometric reason to prefer S-OLS over S-ML estimation of spatio-temporal-lag models or the converse.

the likelihood for the spatio-temporal lag model with time-lagged spatial-lag and showed it to retain the offending Jacobian. On the other hand, testing for either or both of remaining temporal or spatial correlation in residuals given the time-lagged spatio-temporal-lag model is possible and highly advisable.[13]

We explained above that model specifications that omit spatial lags assuming zero interdependence by construction. If and insofar as interdependence does operate, this induces omitted-variable biases that inflate the estimated effects of non-spatial model-components (Franzese & Hays 2004, 2006a, 2007c, 2008ab). Note, e.g., that this means that most extant globalization studies, having neglected spatial lags, likely overestimated the effects of domestic and exogenous-external factors while effectively preventing globalization-induced interdependence from manifesting empirically. Conversely, standard regression estimates of models that include spatial lags suffer simultaneity biases. Such models have grown more common recently among researchers interested in interdependence and have been the norm in studies of policy-diffusion. Simultaneity biases notwithstanding, inclusion of spatial lags in simple regression models vastly improves on non-spatial estimation strategies. Still, previous studies that simply inserted spatial lags in least-squares or logit/probit regressions will have tended toward inflated interdependence-strength estimates at the expense of domestic/unit-level, exogenous-external, and context-conditional factors. The spatial-ML approach just described effectively redresses these simultaneity issues.

Before proceeding to interpretation and presentation of estimated spatial effects and dynamics, and their certainty estimates, one important estimation issue remains: stationarity. Spatio-temporally dynamic models raise more complicated stationarity issues than do the solely time-dynamic models that are more familiar. Nonetheless, the conditions and issues arising in the former are reminiscent of those arising in the latter. Defining $\mathbf{B}=\phi\mathbf{I}$, $\mathbf{A}=\mathbf{I}-\rho\mathbf{W}$, and ω as a characteristic root (i.e., eigenvalue) of $\mathbf{W}$, the spatio-temporal process is covariance stationary if

$$\left|\mathbf{B}\mathbf{A}^{-1}\right|<1 \qquad (14),$$

or, equivalently, if

$$\begin{cases} |\phi|<1-\rho\omega_{\max}, & \text{if } \rho\geq 0 \\ |\phi|<1-\rho\omega_{\min}, & \text{if } \rho<0 \end{cases} \qquad (15).$$

[13] Standard Lagrange-multiplier tests for remaining temporal correlation in regression residuals remain valid; tests for remaining contemporaneous spatial-interdependence are more complex. (Franzese & Hays 2004, 2008b introduce some of the latter.)

For example, in the case of positive time-dependence and positive, uniform spatial dependence ($\rho > 0$ and $w_{ij} = 1/(N-1)\ \forall\ i \neq j$), stationarity requires that $\phi + \rho < 1$. In fact, the maximum characteristic root, and so the upper bound on $\phi + \rho$ is +1 for any row-standardized **W**.

C. Calculating and Presenting Spatio-Temporal Effects

Calculation, interpretation, and presentation of effects in empirical models with spatio-temporal interdependence, as in any model beyond the strictly linear-additive (in variables and parameters, explicitly or implicitly),[14] involve more than simply considering coefficient estimates. *Coefficients* do *not* generally equate to *effects* beyond that simplest strictly linear-additive case. In models with spatio-temporal dynamics, as in those with solely temporal dynamics, coefficients on explanatory variables give only the pre-dynamic impetuses to the outcome from changes in those variables. That is, the coefficients represent only the (often inherently unobservable) pre-interdependence impetus to outcomes from each right-hand-side variable. This section discusses the calculation of spatio-temporal multipliers, which allow expression of the effects of counterfactual shocks of various kinds to some unit(s) on itself (themselves) and other units over time, accounting the full spatio-temporal dynamics. These multipliers also allow expression of the long-run, steady-state, equilibrium[15] impact of permanent shocks. In this section, we also apply the delta-method to derive analytically the asymptotic approximate standard errors for these response-path and long-run effect estimates.[16]

One calculates the cumulative, steady-state spatio-temporal effects most conveniently working with the spatio-temporal-lag model in (Nx1) vector form:

$$\mathbf{y}_t = \rho\mathbf{W}\mathbf{y}_t + \phi\mathbf{y}_{t-1} + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \qquad (16).$$

To find the long-run, steady-state, equilibrium (cumulative) level of $\mathbf{y}$, simply set $\mathbf{y}_{t-1}$ equal to $\mathbf{y}_t$ in (16) and solve. This gives the steady-state effect, assuming stationarity and that exogenous RHS

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[14] For example, the familiar (a) linear-interaction models are explicitly nonlinear in variables although linear-additive in parameters; (b) logit/probit class of models are explicitly nonlinear in both variables and parameters; and (c) temporally dynamic models of all sorts are implicitly nonlinear in parameters and sometimes in variables too (via the presence of terms like $\rho\beta X_{t-s}$ implicitly in the right-hand-side lag terms). Spatial-lag models are likewise implicitly nonlinear-additive. In any of these cases, i.e., in all models beyond those with only and strictly linear-additively separable right-hand-side terms, like the introductory textbook linear-regression model, *coefficients* and *effects* are very different things.

[15] We use the terms *long-run*, *steady-state*, and *equilibrium* effects interchangeably. More precisely, the steady-state of a dynamic process is the equilibrium that obtains in the long-run after all dynamics have unfolded following a hypothetical shock. For stationary processes, the long-run steady-state equilibrium following a transitory shock is always zero (i.e., full return to the state before the hypothetical), so we usually consider a hypothetical *permanent* shock.

[16] For fuller discussion of spatial multipliers, see Anselin (2003).

terms, $\mathbf{X}$ and $\boldsymbol{\varepsilon}$, remain permanently fixed to their hypothetical/counterfactual levels:

$$\begin{aligned}\mathbf{y}_t &= \rho\mathbf{W}\mathbf{y}_t + \phi\mathbf{y}_t + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \\ &= \left(\rho\mathbf{W} + \phi\mathbf{I}\right)\mathbf{y}_t + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \\ &= \left[\mathbf{I}_{\mathrm{N}} - \rho\mathbf{W} - \phi\mathbf{I}_{\mathrm{N}}\right]^{-1}\left(\mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right) \\ &= \begin{bmatrix} 1-\phi & -\rho w_{1,2} & \cdots & \cdots & -\rho w_{1,\mathrm{N}} \\ -\rho w_{2,1} & 1-\phi & & & \vdots \\ \vdots & & \ddots & & \vdots \\ \vdots & & & 1-\phi & -\rho w_{(\mathrm{N}-1),\mathrm{N}} \\ -\rho w_{\mathrm{N},1} & \cdots & \cdots & -\rho w_{\mathrm{N},(\mathrm{N}-1)} & 1-\phi \end{bmatrix}^{-1}\left(\mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right) \\ &\equiv \mathbf{S}\times\left(\mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right)\end{aligned} \qquad (17).$$

Decomposing $\boldsymbol{\varepsilon}_t = \boldsymbol{\eta} + \boldsymbol{\gamma}_t$ with $\boldsymbol{\eta}$ fixed and $\boldsymbol{\gamma}_t$ stochastic is conceptually useful for considering the responses across units to counterfactual shocks to the outcome(s) in some unit(s). For instance, long-run-steady-state responses to counterfactual permanent shocks are best understood as permanent changes in $\boldsymbol{\eta}$. The researcher simply fills the $N\times 1$ vector $\boldsymbol{\eta}$ with the desired counterfactual-shock values in the desired units; then $\mathbf{S}\boldsymbol{\eta}$ gives the long-run-steady-state responses to those shocks across the entire vector of units, the one(s) receiving the shock and any or all others.

To offer standard-error estimates for the estimated steady-states, one could use the delta method. I.e., give a first-order Taylor-series linear-approximation to nonlinear (17) around the estimated parameter-values and determine the asymptotic variance of that linear approximation.[17] To find the key elements needed for this, begin by denoting the i^{th} column of $\mathbf{S}$ as $\mathbf{s}_i$ and its estimate as $\hat{\mathbf{s}}_i$. The steady-state spatio-temporal equilibrium effects of a one-unit increase in the i^{th} element of $\boldsymbol{\eta}$ are $\mathbf{s}_i$, so the asymptotic approximate variance-covariance matrix of these estimates by the delta-method are

$$\widehat{\mathbf{V}(\hat{\mathbf{s}}_i)} = \left[\frac{\partial\hat{\mathbf{s}}_i}{\partial\hat{\boldsymbol{\theta}}}\right]\widehat{\mathbf{V}\left(\hat{\boldsymbol{\theta}}\right)}\left[\frac{\partial\hat{\mathbf{s}}_i}{\partial\hat{\boldsymbol{\theta}}}\right]' \qquad (18),$$

where $\hat{\boldsymbol{\theta}} \equiv \begin{bmatrix}\hat{\rho} & \hat{\phi}\end{bmatrix}'$, $\left[\frac{\partial\hat{\mathbf{s}}_i}{\partial\hat{\boldsymbol{\theta}}}\right] \equiv \left[\frac{\partial\hat{\mathbf{s}}_i}{\partial\hat{\rho}} \quad \frac{\partial\hat{\mathbf{s}}_i}{\partial\hat{\phi}}\right]$, and the vectors $\left[\frac{\partial\hat{\mathbf{s}}_i}{\partial\hat{\rho}}\right]$ and $\left[\frac{\partial\hat{\mathbf{s}}_i}{\partial\hat{\phi}}\right]$ are the i^{th} columns of $\hat{\mathbf{S}}\mathbf{W}\hat{\mathbf{S}}$ and $\hat{\mathbf{S}}\hat{\mathbf{S}}$ respectively.

Similarly, the steady-state spatio-temporal effects of a one-unit increase in explanatory variable k

[17] Greater accuracy may be obtained by applying higher-order linear-approximations.

in country i are $\mathbf{s}_i\beta_k$, with delta-method standard-errors for those effects of

$$\widehat{\mathbf{V}\left(\hat{\mathbf{s}}_i\hat{\beta}_k\right)} = \left[\frac{\partial \hat{\mathbf{s}}_i\hat{\beta}_k}{\partial \hat{\boldsymbol{\theta}}}\right]\widehat{\mathbf{V}\left(\hat{\boldsymbol{\theta}}\right)}\left[\frac{\partial \hat{\mathbf{s}}_i\hat{\beta}_k}{\partial \hat{\boldsymbol{\theta}}}\right]' \quad (19),$$

where $\hat{\boldsymbol{\theta}} \equiv \begin{bmatrix} \hat{\rho} & \hat{\phi} & \hat{\beta}_k \end{bmatrix}'$, $\left[\frac{\partial \hat{\mathbf{s}}_i\hat{\beta}_k}{\partial \hat{\boldsymbol{\theta}}}\right] \equiv \begin{bmatrix} \frac{\partial \hat{\mathbf{s}}_i\hat{\beta}_k}{\partial \hat{\rho}} & \frac{\partial \hat{\mathbf{s}}_i\hat{\beta}_k}{\partial \hat{\phi}} & \hat{\mathbf{s}}_i \end{bmatrix}$, and the vectors $\left[\frac{\partial \hat{\mathbf{s}}_i\hat{\beta}_k}{\partial \hat{\rho}}\right]$ and $\left[\frac{\partial \hat{\mathbf{s}}_i\hat{\beta}_k}{\partial \hat{\phi}}\right]$ are the i^{th} columns of $\hat{\beta}_k\hat{\mathbf{S}}\mathbf{W}\hat{\mathbf{S}}$ and $\hat{\beta}_k\hat{\mathbf{S}}\hat{\mathbf{S}}$ respectively.

The spatio-temporal response path of the $N\times1$ vector of unit outcomes, $\mathbf{y}_t$, to the exogenous RHS terms, $\mathbf{X}$ and $\boldsymbol{\varepsilon}$, could also emerge by rearranging (16) to isolate $\mathbf{y}_t$ on the LHS:

$$\begin{aligned} \mathbf{y}_t &= \left[\mathbf{I}_N - \rho\mathbf{W}_N\right]^{-1}\left\{\phi\mathbf{y}_{t-1} + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right\} \\ &= \mathbf{S}\left\{\phi\mathbf{y}_{t-1} + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right\} \end{aligned} \quad (20).$$

This formula gives the response-paths of all unit(s) $\{i\}$ to counterfactual one-unit shocks to $\mathbf{X}$ or $\boldsymbol{\varepsilon}$ (i.e., in $\boldsymbol{\eta}$) in any unit(s) $\{j\}$, including a shock in $\{i\}$ itself/themselves, just by setting $\left(\mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right)$ to the value reflecting that hypothetical in row(s) $\{j\}$. This formulation is especially useful for plotting estimated response paths in a spreadsheet, for instance. To calculate marginal spatio-temporal effects (non-cumulative) or plot the over-time path of responses to a permanent change in an explanatory variable (cumulative), and their standard errors, working with the entire NT x NT matrix may be easier. Simply redefine $\mathbf{S}$ in the (17) as $\mathbf{S} \equiv \left[\mathbf{I}_{\text{NT}} - \rho\mathbf{W} - \phi\mathbf{M}\right]^{-1}$ and follow the steps just outlined.

IV. Illustrations from Comparative and International Political Economy

A. Internal vs. External Determinants of Fiscal Policy: A Reanalysis of Swank & Steinmo

This section presents the results of a reanalysis of the tax regressions in Swank & Steinmo (2002), but expressly accounting the potential for strategic policy interdependence across countries. Swank & Steinmo (2002) stress domestic factors—particularly budgetary dynamics, public-sector indebtedness, and macroeconomic performance—and also some external factors—namely capital-account and trade openness—in this well-known empirical study of tax-policy reform in OECD countries. However, all of the models assume independent national responses to these political-economic variables, whether internal or external; i.e., spatial lags are omitted and so interdependence suppressed.

Some of their findings are counterintuitive: for example, that increased capital mobility and trade exposure lower marginal *statutory* but not *effective* capital tax rates and that greater capital mobility does lower effective tax rates on *labor*. They argue that governments combine statutory rate-cuts with the elimination of specific investment incentives, leaving effective tax burdens unaffected. To explain why greater capital mobility does tend to lower effective labor-tax rates instead, they suggest that labor taxes may raise the nonwage costs of employment, cutting into profits. We suspect these counter-intuitive findings arise from failure to consider interdependence directly. Swank & Steinmo do recognize that their data correlate spatially in that they report panel corrected standard errors (PCSE), as has become standard advised practice for TSCS data, but this default PCSE strategy treats such correlation as "nuisance" rather than as evidence for the importance of further external factors *or* interdependence processes in determining tax policy. Swank & Steinmo (2002:650) suggest their results: "are consistent with the argument that while internationalization has influenced the shift in the content of tax policy, the combined effect of statutory tax rate cuts and base-broadening reductions in investment incentives has left the effective tax burden on capital largely unchanged." The "spatial nuisance" approach abets such conclusions because it relegates any spatial dependence actually in the data to the sole role of adjusting standard-error estimates. Spatial dependence is thereby, in a cliché, "out of sight, and out of mind."

Recently, Swank (2006) greatly advanced this agenda, focusing squarely on several potentially important sources of spatial interdependence in tax policy: competition for foreign direct investment, policy learning, and social emulation. He estimates spatio-temporal lag models with several different kinds of spatial weights matrices. The first gives equal weights to (i.e., averages) all $j \neq i$ countries in the sample. The second weights countries j by the strength of their competition with i for capital, which is measured by total dyadic trade flows, FDI flows, and the correlation between their direct-investment portfolios. The third matrix gives positive weights to countries in the same *family* of nations and no weight to countries outside of the *family*.[18] Swank finds that tax policies do not respond to these variables, but rather to a fourth spatial-lag wherein US capital-tax policy influenced

[18] Citing Castles (1993, 1998), Swank states *families* are "culturally and politically similar groups of nations. In the democratic capitalist world, these families include the English-speaking countries that are linked by language and common legal and political traditions, the Nordic countries who share culture, legal traditions, and centuries of interdependent political development, and the continental European nations that are united by religion and other cultural attributes as well as shared political history" (p. 860).

capital-tax policy in other countries, with this *dependence* effect[19] being conditional on a country's domestic politics, production regime, and economic integration with the US.

This new research represents a great advancement in this literature, although some further refinements occur to us, particularly with respect to the spatial lags. First, Swank does not consider geographic proximity, which others have found to play an important role in competition for FDI through third-country effects. Second, Swank uses a temporally lagged spatial lag, which may be appropriate econometrically given his choice of the S-OLS estimator (Beck et al. 2006) but does raise concerns discussed above. That is, if interdependence incurs within an observational period, which strikes us as very likely in the capital-tax-competition context and in annual data, simultaneity is not avoided (due to the misspecification of the spatio-temporal dynamics) and interdependence strength will likely be underestimated (as the time-lagged spatial-lag effectively misses all within-period action). As noted above, models with contemporaneous interdependence can be estimated by instrumental-variables or maximum-likelihood strategies. Implementing the latter and using a binary-contiguity spatial-lag (described below), we find strong evidence of contemporaneous (i.e., within-year) spatial interdependence in capital-tax policy based on geographic proximity. Following this demonstration, presentation of these estimated spatio-temporal effects and related certainty estimates is illustrated.

We focus on the capital- and labor-tax-rate results reported in Swank & Steinmo's Table 2 (Appendix, pp. 653-4).[20] Their sample covers 13 countries over the period 1981-1995 giving a total of 195 observations. We add a spatial lag to the right-hand-side of their first-order temporal lag model, making our specification equivalent to equation (4) above. We calculated our spatial lag, $\mathbf{Wy}$, using a standardized *binary contiguity-weights matrix* which begins by coding w_{ij}=1 for countries i and j that share a border and w_{ij}=0 for countries that do not border. As exceptions, we code France, Belgium, and the Netherlands as contiguous with Britain. Then, we *row-standardize* (as commonly done in spatial-econometrics) the resulting matrix by dividing each cell in a row by that row's sum. This gives $\mathbf{Wy}$ as the unweighted average of $\mathbf{y}$ in "neighboring" (so-defined) countries.

We chose to use a binary contiguity-weights matrix because a number of recent papers have concluded that geographic location is important for determining which countries compete for capital

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[19] We say *dependence* rather than *interdependence* to underscore the mono-directionality of this spatial-lag structure.

[20] These regressions include fixed unit and period effects, which, in our reanalysis, prove necessary to meet the stationarity requirements discussed above.

(Blonigen et al. 2004, Guerin 2006, Abreu & Melendez 2006). The main reason is that multinational enterprises (MNEs) use host countries as "export platforms" to nearby markets. A good example of this is Ireland where are large percentage of the foreign direct investment is used to produce goods that are then exported to the European continent. The implication is that Ireland and Britain compete not only for each other's capital but also for the capital of third countries. American MNEs may see Ireland and Britain as substitutable production bases for export to the nearby Benelux, French, and German markets. Portugal and Spain may compete in the same way. Canada attracts FDI from firms intending to service the American market, and therefore, because of its proximity to the States, competes with the US for foreign capital from third countries in a way that Germany, for example, does not. Note that this competition differs from the kind Swank has in mind, which is almost exclusively bilateral in nature. This kind of FDI also makes a contemporaneous spatial lag more appropriate than a temporally lagged spatial lag. If two countries are competing for FDI from a third, they will be aware of any planned policy changes by their competitor and try to match the timing of reform. Countries that are slow to change will lose capital.

Table 1 presents the original results along with the estimates from our reanalysis. We include two sets of estimates for each tax rate, one for a model that includes both fixed unit and period (i.e., country and year) effects and one for a model that includes fixed unit effects only. In short, we come to different conclusions about the importance of international factors for capital taxes. In each model, the coefficient estimate on the spatial lag is statistically significant. When a spatial lag is included on the right hand-side of their regression model we see this conclusion about the effects of international, external factors is likely incorrect. Changes in effective capital tax rates in one country have statistically significant consequences for effective capital tax rates in other countries. Moreover, some of the coefficients on the domestic variables that were statistically significant are not significant in the spatio-temporal lag model—most notably, the elderly population and Christian Democratic government variables. In both instances the size of the coefficient estimate shrinks, suggesting that these domestic variables are clustered spatially.

<u>Table 1</u>: Reanalysis of Swank & Steinmo (2002, Appendix Table 2)

	Effective Tax Rate on Capital			*Effective Tax Rate on Labor*		
	Swank & Steinmo	*Reanalysis (1)*	*Reanalysis (2)*	*Swank & Steinmo*	*Reanalysis (3)*	*Reanalysis (4)*
Temporal Lag	0.809**	0.808** (0.05)	0.864** (0.048)	0.671**	0.66** (0.054)	0.711** (0.054)
Spatial Lag		0.104* (0.054)	0.126** (0.054)		0.017 (0.058)	0.05 (0.055)
Liberalization	1.146	1.235* (0.725)	0.629 (0.702)	-.261**	-0.255** (0.102)	-0.168* (0.091)
Trade	-0.018	0.009 (0.064)	0.005 (0.061)	-0.009	0.001 (0.023)	-0.001 (0.023)
Structural Unemployment	-1.147**	-1.218** (0.306)	-1.033** (0.283)	-0.359**	-0.38** (0.189)	-0.148 (0.189)
Public Sector Debt	0.089**	0.099** (0.036)	0.046 (0.032)	0.053**	0.056** (0.014)	0.038** (0.013)
Elderly Population	1.264**	1.011 (0.615)	-0.08 (0.481)	-0.018	0.03 (0.23)	0.171 (0.184)
Growth	0.230*	0.242 (0.151)	0.307** (0.147)	-0.008	-0.009 (0.051)	0.009 (0.051)
% Change in Profits	0.127**	0.136** (0.055)	0.174** (0.054)			
Domestic Investment	0.066	0.045 (0.055)	0.059 (0.049)			
Inflation				0.115**	0.115** (0.05)	0.063 (0.043)
Unemployment				0.280**	0.296** (0.084)	0.144* (0.079)
Left Government	0.018**	0.018* (0.01)	0.012 (0.01)	0.008**	0.008** (0.004)	0.007* (0.004)
Christian Democratic Government	0.041**	0.035 (0.028)	0.01 (0.026)	0.001	0.002 (0.011)	0.009 (0.01)
Fixed Effects:	**Ctry, Yr**	**Ctry, Yr[1]**	**Ctry**	**Ctry, Yr**	**Ctry, Yr[1]**	**Ctry**
R^2	**.928**	**.922**	**.914**	**.989**	**.989**	**.988**

NOTES: Parentheses contain standard errors. **, * = significant at 5%, 10% levels, respectively. [1]=Biannual period effects.

The labor-tax-rate estimates provide a stark contrast. In neither case does the coefficient on the spatial lag achieve statistical significance at conventional levels. Not surprisingly, our estimates, particularly for the model that includes both fixed unit and period effects, are almost identical to Swank & Steinmo's. There is no evidence of strategic policy interdependence when it comes to labor taxes so the original estimates were unbiased. This result is consistent with our argument about globalization as the source of strategic policy interdependence. The international mobility of capital means that capital tax policy changes have externalities that spill across national borders, and these spillovers, in turn, cause the spatial interdependence we observe in capital tax rates. Since workers are not as mobile as capital, we would expect to find far less evidence of strategic policy interdependence in labor taxes.[21]

Table 2 gives estimates of the spatial effects of counterfactual shocks to structural unemployment for a subset of European countries. The cells report estimated effects of unit increases in column-country structural-unemployment on row-country capital-tax-rates. The first number is the estimated first-period effect (direct effect plus spatial feedback), calculated using (20). For example, the immediate spatial effect (i.e., post-spatial but pre-temporal dynamics) of a unit increase in German structural employment on all thirteen countries is $\mathbf{s}_6\beta_5$, where $\mathbf{s}_6$ is the sixth column of $\mathbf{S}$ (Germany's column in the spatial-multiplier) as defined in (20) and β_5 is the fifth row of the column-vector $\boldsymbol{\beta}$ (structural unemployment is $\mathbf{x}_5$). The second number is the standard error of this estimate, from (19) with i=6, k=5; and the last number is the estimated LRSS effect of a permanent unit-increase, from (17). For instance, we estimate a unit *permanent* increase in German structural unemployment produces a LRSS 7%-reduction in Germany's capital-tax rate, which, along the way, induces France to lower its LRSS capital-tax rate by almost 1.4%.

Table 2: Short-Run and Steady-State Spatial Effects from a Shock to Structural Unemployment

	BEL	FRA	GER	ITA	NTH	GBR
BEL	-1.22**	-0.034*	-0.034*	-0.001	-0.034*	-0.034*
	0.307	0.021	0.02	0.001	0.021	0.02
	-7.403	-1.672	-1.51	-0.227	-1.549	-1.51
FRA	-0.034*	-1.224**	-0.033*	-0.032*	-0.003	-0.033*
	0.021	0.307	0.019	0.018	0.003	0.019
	-1.672	-7.643	-1.395	-1.036	-0.731	-1.395
GER	-0.045*	-0.044*	-1.222**	-0.001	-0.044*	-0.004
	0.027	0.026	0.306	0.001	0.026	0.004
	-2.013	-1.859	-7.187	-0.252	-1.723	-0.836
ITA	-0.004	-0.127*	-0.003	-1.221**	0	-0.003
	0.004	0.073	0.004	0.306	0.001	0.004
	-0.907	-4.144	-0.756	-6.912	-0.396	-0.756
NTH	-0.045*	-0.004	-0.044*	0	-1.222**	-0.044*
	0.028	0.005	0.026	0	0.307	0.026
	-2.066	-0.974	-1.723	-0.132	-7.253	-1.723
GBR	-0.045*	-0.044*	-0.004	-0.001	-0.044*	-1.222**
	0.027	0.026	0.004	0.001	0.026	0.306
	-2.013	-1.859	-0.836	-0.252	-1.723	-7.187

NOTES: The cell entries report the effect of a one-unit increase in the column country's level of structural unemployment on the row country's capital-tax rate. The first number reported in each cell is the estimated short-run effect (direct effect plus spatial feedback). The second number is that estimate's standard error. The final number is the estimated long-run steady-steady effect. Australia and Japan are excluded because they have no *neighbors* in the sample. **Significant at the5% Level; *Significant at the 10% Level.

For those of us interested in globalization, spatial interdependence across observational units is

[21] That strategic policy-interdependence does not manifest in labor tax-rates provides no direct evidence about how any capital-tax-revenue losses associated with heightened global competition for capital are being met with labor or other tax increases, spending cuts, deficits, or some combination. It shows only that domestic labor-tax responses to these and other developments are not significantly dependent on "neighbor's" labor tax-rates.

more than a mere statistical nuisance; it is the very substance of our study. Research that ignores this interdependence will be biased toward finding internal-domestic and exogenous-external factors are more important than international-interdependence in determining political, economic, and policy outcomes. Thus, the empirical deck will be stacked against globalization-related hypotheses. Swank & Steinmo's capital-tax-rate estimates are a clear example.

B. Interstate Conflict and Trade: A Reanalysis of Beck, Gleditsch and Beardsley

In this section, we reanalyze the Beck, Gleditsch, and Beardsley (henceforth BG&B) model of directed export flows among major powers using a contemporaneous spatial lag and the conditional ML estimator. Their $\mathbf{W}$ weights common member dyads equally as neighbors.[22] Our purpose is not to criticize BG&B's analysis but rather to build on what they recommend by illustrating how to calculate and present some of the spatio-temporal effects implied by their model. We wholeheartedly agree with BG&B that theory should drive our spatio-temporal specification choices (with intellectual openness to theories being informed and refined by empirical results), and we find little in their empirical results and conclusions with which to disagree. Indeed, we choose this article for our re-analysis precisely because it represents the state of the art in our view. However, BG&B, citing the relative difficulty in implementing S-ML estimator for panel and TSCS data and the theretofore-apparent lack of an unambiguously superior estimator in such data,[23] estimate their spatio-temporal models exclusively by S-OLS with time-lagged spatial-lags. As we have shown above, though, the conditional S-ML estimator is relatively straightforward to specify. And, with relatively large T (as in BG&B's case), analysts should not hesitate to use conditional S-ML when theory suggests that initial spatial-effects are likely to incur quickly (i.e., within period, as in BG&B's case, in our opinion) or when they harbor suspicions that temporal or spatial-dynamic

[22] More specifically, cells in $\mathbf{W}$ that correspond to common member dyads (e.g., US-Germany and US-Russia) are given a 1 initially, and then the matrix is row standardized. Ideally, we would like to estimate a model with two spatial weights matrices, one for common member dyads that include allies (Country A—Ally 1 and Country A—Ally 2) and one for common member dyads that include adversaries (Country A—Adversary 1 and Country A—Adversary 2). This would provide a better test of the security externalities argument since theoretically we expect political conflict to initiate a very different set of spatio-temporal dynamics in exports among allies and adversaries, concentrating trade among the former and reducing it among the latter. However, because of the computational difficulties that come with calculating likelihoods with more than one spatial weights matrix and our desire to maintain comparability with the Beck et al. study, we save this for later research.

[23] Indeed, an unambiguously superior estimator for all data conditions and spatial-dependence processes has not quite emerged yet, and may be unlikely to emerge, although S-ML has increasingly established itself as the leading candidate in our experiments to date.

misspecification might induce contemporaneous interdependence (as in BG&B's case, by their own assessment[24]). Accordingly, we reformulate BG&B's empirical model to a contemporaneous rather than a time-lagged spatial-lag and re-estimate by conditional S-ML before proceeding to illustrate the calculation and presentation of spatio-temporal dynamic and steady-state effects.

There are seven major powers during the period BG&B examine, and their unit of analysis is the directed dyad, giving 42 total directed-dyads ($N\times(N\text{-}1)$). We are comfortable with conditioning on the first set of observations because the average number of observations for each dyad is 61 years. The first set of observations represents less than 2% of the full dataset and therefore contributes relatively little to the overall value of the likelihood function.

Our results are reported in Table 3. We present three new sets of estimates. The first set (Reanalysis (1)) is most directly comparable to the estimates in Beck et al. (Table 4 (2006:41)). The only change is that we substitute a contemporaneous spatial-lag for the temporally-lagged spatial-lag in Beck et al. We see no reason to prefer on *a priori* theoretical grounds a time-lagged spatial-lag over a contemporaneous one (if anything, the reverse strikes us as more plausible), and therefore we rely on the data to help choose our specification.[25] Not surprisingly, our results suggest the spatial effects in export flows are much larger than the Beck et al. results, our coefficient estimate for ρ being more than three times the size of theirs. With this specification, however, we have some concern about stationarity ($\hat{\phi}+\hat{\rho}=.971$), and so we allow for fixed effects, starting with dyadic fixed effects (Reanalysis (2)). A likelihood-ratio test suggests this specification is superior to the pooled, common intercept model, but unfortunately the dyadic fixed effects do not solve the stationarity problem. Therefore, in our final specification, we allow for both dyadic and period (year) fixed effects (Reanalysis (3)). Again, a likelihood-ratio test supports the new specification and the sum of our lag coefficients in now comfortably below one.

[24] BG&B note that their models fail Lagrange-multiplier tests for remaining residual (temporal) autocorrelation, with residual (temporal) autocorrelation on the order of 0.1.

[25] Likelihood and R^2 values are higher for the contemporaneous spatial-lag model, but these models are non-nested and have the same degrees of freedom, so those quantities are not directly comparable and standard statistical tests would not apply. On theoretical grounds, one might argue that, because the "spatially" connected dyads are dyads with a common member (e.g., US-Germany and US-Russia) the idea that the effects are instantaneous (i.e., occur within one year) is highly plausible. The same factors that cause the US to alter its trade with Germany would likely cause it to adjust trade with Russia more or less instantaneously and, in any event, largely within one year. Note too that with a spatio-temporal specification spatial effects are not entirely felt instantaneously but rather unfold over time given the temporal dynamics. The maximum marginal effect could even occur several years after the initial effect.

Table 3: Reanalysis of Beck et al. (2006, Table 4)
Directed Export Flows, Major Powers, 1907-1990

	Beck et al.	*Beck et al.*	*Reanalysis (1)*	*Reanalysis (2)*	*Reanalysis (3)*
LN GDP *A*	0.03** (.01)	0.02** (.01)	-0.001 (.012)	0.029** (.015)	0.028* (.016)
LN GDP *B*	0.04** (.01)	0.03** (.01)	-0.001 (.012)	-0.015 (.015)	-0.003 (.016)
LN POP *A*	0.02 (.02)	0.04** (.02)	0.064** (.023)	0.012 (.06)	0.056 (.065)
LN POP *B*	0.02 (.02)	0.03 (.02)	0.056** (.023)	0.031 (.055)	0.059 (.059)
LN Distance	-0.03** (.01)	-0.04** (.01)	-0.043** (.009)	0.014 (.073)	-0.004 (.072)
LN Tau-b	0.13** (.06)	0.11 (.06)	0.05 (.058)	-0.053 (.06)	-0.063 (.06)
LN Democracy	0.13** (.03)	0.14** (.03)	0.155** (.031)	0.143** (.034)	0.089** (.037)
LN MID	-0.20** (.04)	-0.20** (.04)	-0.19** (.037)	-0.186** (.039)	-0.157** (.039)
LN Multipolar	-0.30** (.05)	-0.28** (.05)	-0.229** (.053)	-0.157** (.053)	-0.055 (.056)
LN Bipolar	-0.06 (.05)	-0.04 (.05)	-0.011 (.048)	0.054 (.053)	0.032 (.055)
Temporal Lag	0.92** (.01)	0.91** (.01)	0.901** (.007)	0.795** (.01)	0.825** (.01)
Spatial Lag		0.02** (.01)	0.07** (.012)	0.18** (.014)	.097** (.039)
Fixed Effects:	No	No	No	Dyad	Dyad, Yr
Contemporaneous Spatial Lag	No	No	Yes	Yes	Yes
Estimator	OLS	OLS	ML	ML	ML
Observations	2565	2565	2565	2565	2565
Log-Likelihood	—	—	31.57	140.71	282.68
LR Statistic				218.28**	283.94**

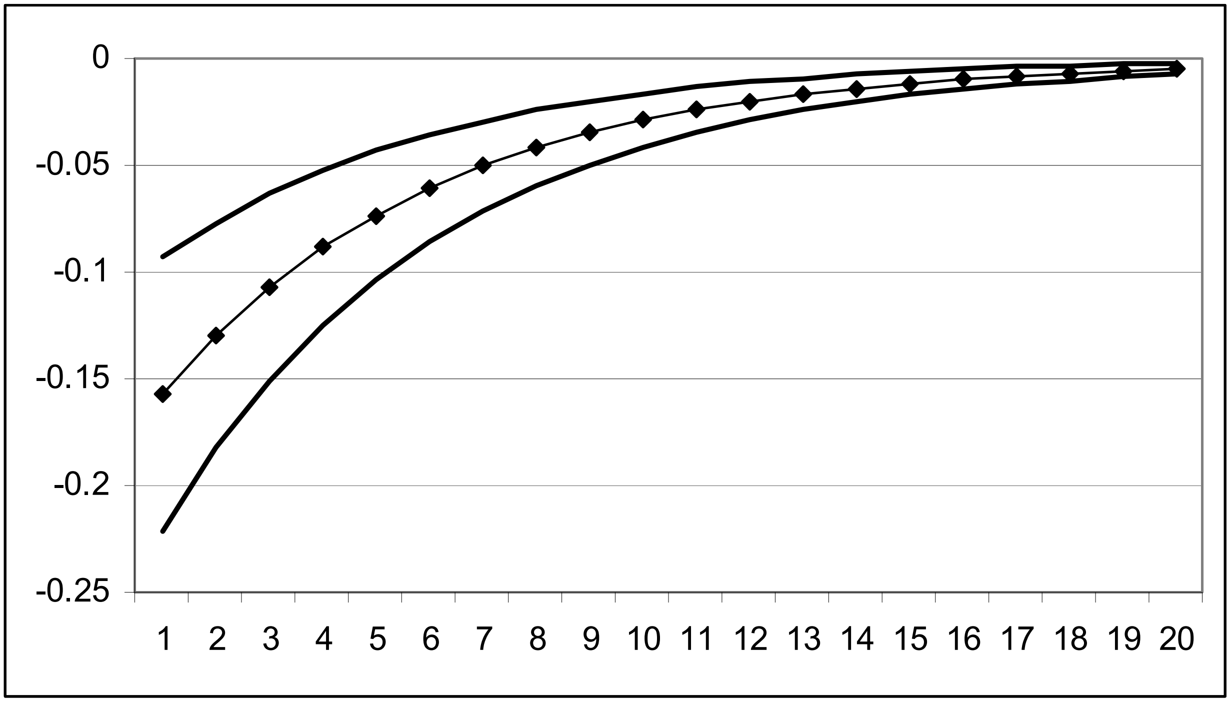
Notes: Parentheses contain standard errors. **, * = significant at 5%, 10% levels, respectively. The Likelihood Ratio (LR) Statistics evaluate the null hypotheses that the coefficients on the dyad dummies (41) and year dummies (67) are jointly zero with 5% critical values of 56.94 ($\chi^2_{d.f.=41}$) and 87.11 ($\chi^2_{d.f.=67}$) respectively.

We have no interest in rehashing here an earlier debate on the topic of whether to include or exclude fixed effects in general (cf. Greene et al. 2001 and Beck and Katz 2003). In part, this is because the inclusion of dyad and year dummies renders our estimates of spatio-temporal interdependence highly conservative, which only strengthens our demonstration of strong interdependence. To elaborate, omitted unit effects can inflate coefficient estimates for temporal lags (Judson and Owen 1999) and omitted period effects can inflate coefficient estimates for spatial lags (Franzese & Hays 2004, 2006a, 2007c, 2008ab). Including unit and period dummies is an extremely conservative way to control for these effects because the converses are also true in limited samples; that is, insofar as effects are not fixed but simply correlated across time and space, inclusion of those fixed effects will tend to deflate estimates of spatio-temporal dependence (Beck and Katz 2003). In our case, unit-root concerns add further to the standard arguments for preferring conservative to generous biases in hypothesis testing. Given the insertion of dyad and year fixed-effects, several of our estimates differ predictably from BG&B's. For example, our coefficient estimates on slowly changing variables (e.g., joint democracy, distance, alliances) are much smaller than BG&B's estimates, likely due to the dyad dummies.[26] Our coefficient estimate for the temporal lag is also noticeably smaller, and our estimate for the spatial lag is almost five times larger.

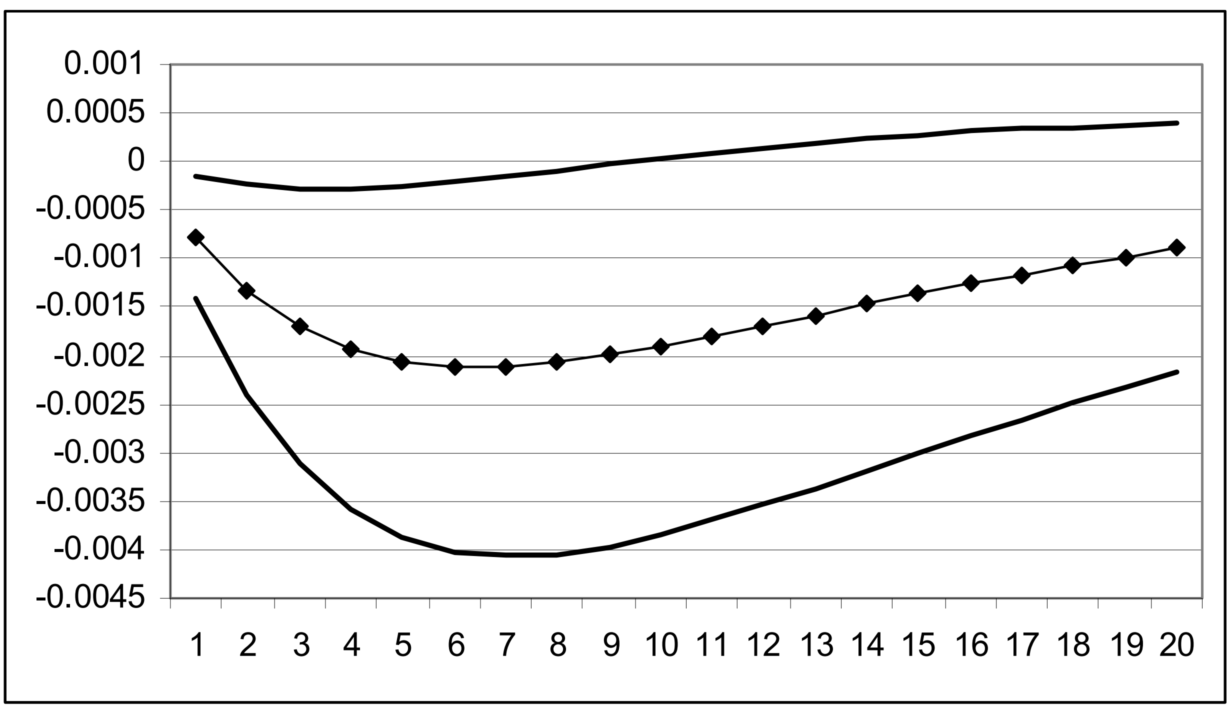
Because the sum of our coefficient estimates for the temporal and spatial lags is less than one, which suffices to show the process stationary in this case, we can calculate the spatio-temporal effects along the lines described in Section III. In Figures 1-3, we present the over-time path of the marginal (i.e., the year-by-year incremental, not the cumulative) spatio-temporal effects from a permanent one-unit increase in the MID variable. These figures show three types of estimated responses to this counterfactual: Figure 1 shows the temporal effects with spatial feedback (effect of a US-Russia MID on US exports to Russia over time; Figure 2 gives the first-order spatio-temporal effects (effect of a US-Russia MID on US exports to Germany over time; and Figure 3 shows the second-order spatio-temporal effects (effect of a US-Russia MID on German exports to Russia over time). The cumulative (20-year) type 1 response to a permanent one-unit increase in the MID variable is to decrease the log of exports by almost -.90 (approximately 90%). The two other effects are smaller in size, take longer to reach their maximum, with increments fading more slowly.

[26] Due to political division and reunification, distance, a seemingly time invariant measure, does change for the dyads including Germany.

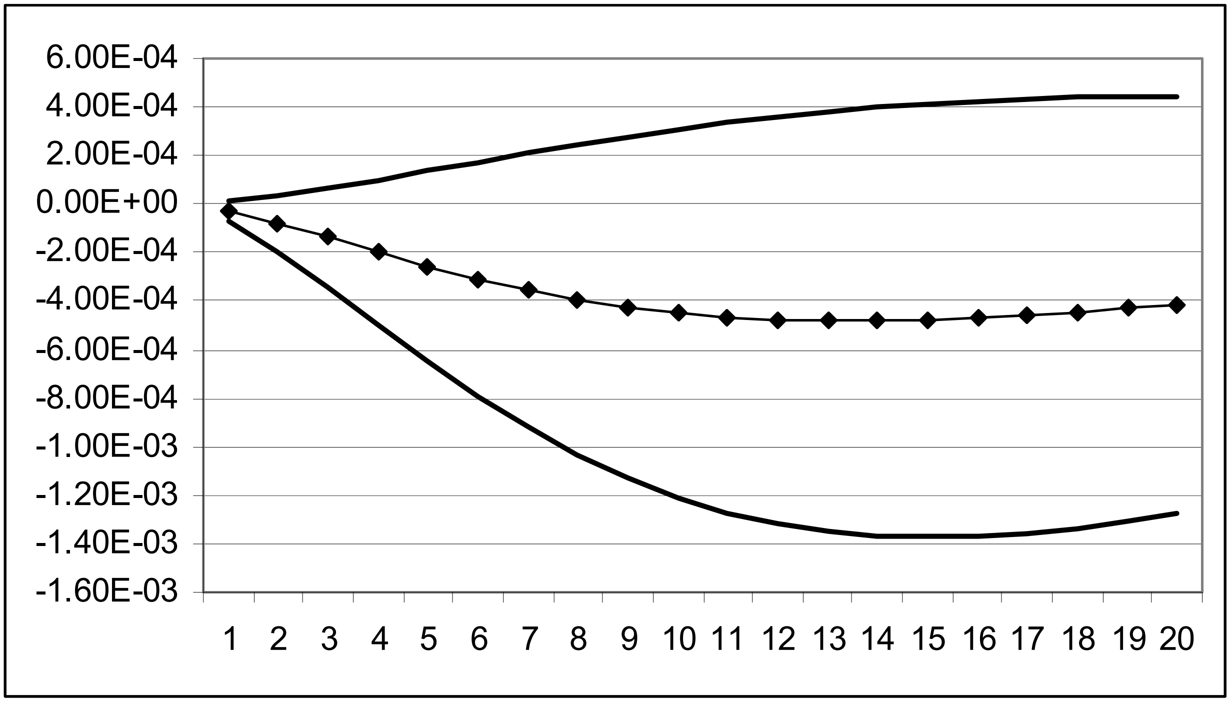
<u>Figure 1</u>: Temporal Effects with Spatial Feedback
(E.g., US Exports to Russia response to US-Russia MID)



<u>Figure 2</u>: First Order Spatio-temporal Effects
(E.g., US Exports to Germany response to US-Russia MID)



<u>Figure 3</u>: Second Order Spatio-temporal Effects
(E.g., German Exports to Russia response to US-Russia MID)



VI. Conclusion

This paper first outlined the broad substantive range across political economy in which spatial interdependence plays a potentially large role. It then showed how strategic interdependence arises whenever one unit's course of action depends on some other(s)'s, which seems to us ubiquitous across the social sciences. (In fact, that may even serve as a workable definition of *social* science!) We then described the serious empirical challenges these considerations raise, in particular perhaps for political economy, in that the crux of the difficulty is the empirical similarity of interdependence on the one hand with spatially correlated domestic/unit-level factors, common or correlated exogenous-external shocks or conditions, and context-conditionality (the interaction of the previous two) on the other. We showed how standard empirical practices—of omitting interdependence or treating it as nuisance on the one hand or of including spatial lags but failing to recognize their endogeneity on the other—tended to bias results, oppositely understating the relative explanatory power of spatial-interdependence versus non-spatial factors, respectively. Stated as simply as we can: omitting or relatively under-specifying the one tends to induce its underestimation and the other's overestimation. We discussed one way, spatial maximum-likelihood, to estimate properly models that appropriately specify spatial interdependence directly by spatial lags, and we discussed how to present the implied spatio-temporally dynamic effect-estimates along with estimated certainties for those short-run or long-run responses and response-paths. Finally, we illustrated all this via replications of Swank & Steinmo's (2002) path-setting study of globalization and taxation in developed democracies, offering an alternative or additional direction to Swank's (2006) great extension of that agenda to explore interdependence explicitly, and Beck et al.'s (2006) study of conflict and trade among major powers.

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