Empirical Modeling of Spatial Interdependence in Time-Series Cross-Sections

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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 comparative politics—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 thus the popular and scholarly perception of and attention to it, at all levels, from micro-/personal to macro-/international, and partly to advances in technology for obtaining and working with spatial data.

This is an extremely welcome development as many phenomena that comparativists study entail substantively important spatial interdependence. Indeed, the substantive range of interdependence spans comparative politics, from policy and/or institutional diffusion across national or sub-national governments (Schneider & Ingram 1988, Rose 1993, Meseguer 2004, 2005, Gilardi 2005); diffusion of coups (Li & Thompson 1975), riots (Govea & West 1981), revolutions (Brinks & Coppedge 2006), civil wars (O'Loughlin 2004, O'Loughlin & Raleigh 2007), and democracy/democratization (as mentioned in Dahl's 1971 classic, *Polyarchy*, given titular billing in Starr's 1991 "Democratic

Dominoes" and Huntington's 1991 *Third Wave*, and recently emphasized in Eastern European post-communist transitions by Beissinger 2007 and Bunce & Wolchik 2006, 2007, in Latin American transitions by Hagopian & Mainwaring 2005, and finally estimated empirically in its extent, paths, and/or patterns by O'Loughlin et al. 1998, Brinks & Coppedge 2006, and Gleditsch & Ward 2006, 2007); the strategic or network interdependence of democratic representatives' legislative behavior (Porter et al. 2005, Fowler 2006); the dependence of voting, election outcomes, or candidate qualities or strategies in some contests on those in others (Blommestein & Nijkamp 1986, Kohfeld & Sprague 2001, O'Loughlin 2002, Lin et al. 2004, Caleiro & Guerreiro 2005, Cho & Gimpel 2007, Cho & Rudolph 2007, Kayser 2007); the dependence of respondents' behaviors or opinions on aggregates of others' behaviors or opinions—e.g., those of the respondent's region, community, or social network—in so-called *contextual*, *network*, or *neighborhood effects* (Cho 2003, Lin et al. 2006). This substantive centrality of interdependence manifests perhaps especially in comparative political economy, wherein see Eising (2002), Brune et al. (2004), Simmons & Elkins (2004), Brooks (2005), Elkins et al. (2006), and Simmons et al. (2006) regarding economic liberalizations; Franzese & Hays (2006b) regarding active-labor-market policies; and Genschel (2002), Basinger & Hallerberg (2004), Knill (2005), Jahn (2006), Swank (2006), and Franzese & Hays (2006a, 2007a) regarding globalization, tax competition, and convergence.

Empirical work in political science, including in comparative politics, 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 (much of our own past work included) relies almost exclusively on non-spatial or, at most, "nuisance-spatial" empirical models. This chapter 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. The Myriad Mechanisms and a General Theoretical Model of Spatial Interdependence

In sum, spatial interdependence is quite common and often quite central across the substance of comparative politics. *Tobler's Law*[1] (1970)—*Everything is related to everything else, but near things are more related than distant things*—plus Beck et al.'s (2006) corollary—*Space is More than Geography* convey this ubiquity and importance pithily. The corollary means that the substantive content of *proximity* in Tobler's Law, and so the pathways along which interdependence between units may operate, extend well beyond basic physical distance and bordering. Elkins & Simmons (2005) and Simmons et al. (2006), e.g., define and discuss four mechanisms by which international interdependence may arise: coercion, competition, learning, and emulation. *Coercion*, which may be direct or indirect and hard (force) or soft (suasion), encompasses generally "vertical" means by which the powerful induce actions by the weaker. *Competition* refers to interdependence stemming from economic pressures that the actions of each unit place upon others in competition with it or as substitutes for or complements to it. *Learning* entails situations where actors learn, in rational-Bayesian or some other fashion, from others' actions something regarding the attractiveness of their own alternative actions.[2] *Emulation*, finally, is ritualistic (i.e., neither coerced nor responsive to competition or to learning) following or doing oppositely of others (e.g., leaders, co-ethnics, co-partisans). Although enumerated specifically for international-diffusion contexts, these categories nicely span many of the possible channels of spatial interdependence across its broader substantive domain. To these four, we add a fifth, *migration* or *pure contagion*, wherein some components of some units move directly into and become part of other units, the most obvious examples being human or microbial migration, which will generate a direct and more-mechanical interdependence in addition to those deriving from power, competitive, or idea-dissemination pathways.

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

[1] A.k.a. *Tober's 1st Law of Geography*; Waldo Tobler (1930-), geographer: http://en.wikipedia.org/wiki/Waldo_Tobler.
[2] What is learned affects actors' choices, but may be objective or subjective, true/correct or false/incorrect, and may regard the politics, economics, sociology, or any other aspect of those choices.

derive utilities, (U^i, U^j), from their alternative actions or policies, (p_i, p_j).[3] 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*:[4]

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

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:

$$\frac{\partial p_i^*}{\partial p_j} = -U^i_{p_i p_j} \Big/ U^i_{p_i p_i} \;\; ; \;\; \frac{\partial p_j^*}{\partial p_i} = -U^j_{p_j p_i} \Big/ U^j_{p_j p_j} \tag{3}$$

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

[3] 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.
[4] 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 function of p_j (and then verifying that the second derivative is negative).

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. If the second cross-partial derivative is zero, strategic interdependence does not materialize and best-responses are flat.

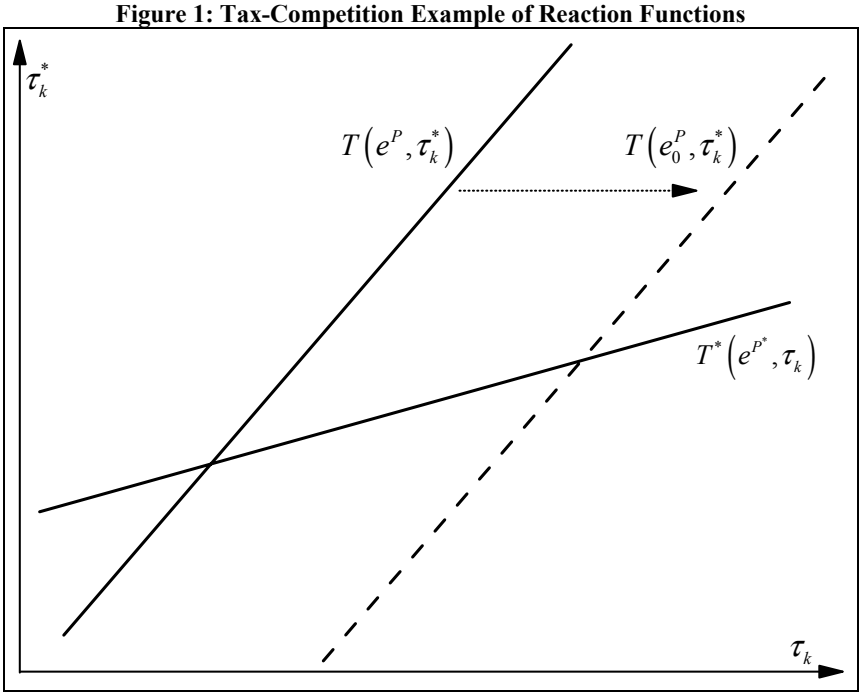
Generally speaking, then, positive externalities (*and diminishing marginal utility*) yield strategic-substitute relations, and policies will move in opposite directions while *free-rider* dynamics obtain. Franzese & Hays (2006a) find such free-riding dynamics in EU active-labor-market policies, for example. Notice, furthermore, that free-rider contexts also confer late-mover advantages and so war-of-attrition dynamics (i.e., strategic delay and inaction) are likely. Conversely, negative externalities (*and diminishing marginal utilities*) induce strategic complementarity, with policies moving in the same direction. As just noted, tax-competition likely has these features. Tax cuts in one unit have negative externalities for competitors, who are thereby spurred to cut taxes as well. Such contexts advantage early movers, so *competitive races* can unfold.[5] Other good examples here are currency-devaluation or trade-barrier competitions. Economically, earlier movers in these competitions reap disproportionate benefits, so races to move first are likely. Thus, positive and negative externalities induce strategic-complement and -substitute relations, respectively, which spur competitive-races and free-riding, respectively, with their corresponding early- and late-mover advantages, and so strategic rush to go first on the one hand and delays and inaction on the other.

Figure 1 graphs two such reaction functions, taken from a model of capital-tax competition due to Persson & Tabellini (2000), in which $\tau_k = T(e^P, \tau_k^*)$ and $\tau_k^* = T^*(e^{P*}, \tau_k)$—in words: the domestic (foreign) capital-tax rate, τ_k^* (τ_k), depends on the domestic (foreign) policymaker's labor-capital endowment, e^P (e^{P*}), and the foreign (domestic) capital tax rate, τ_k^* (τ_k). The graphed example assumes both reaction-functions slope positively, and the counterfactual illustrated is an increase in

[5] We intentionally eschew the labels *race to the bottom* and *convergence* because these competitive races need not foster convergence on any top, bottom, or mean, and could further divergence (see below and also Plümper & Schneider 2006).

the domestic policymaker's labor-capital endowment (intended to reflect a leftward shift in government). This change shifts the function *T* outward, raising the equilibrium capital-tax rate *in both countries*, demonstrating that capital taxes are strategically interdependent.

Figure 1: Tax-Competition Example of Reaction Functions



Formal tax-competition models like this one or Hays (2003) or Basinger & Hallerberg (2004) clearly imply the strategic spatial-interdependence of capital taxes, as do most alternatives. Garrett (1998), Boix (1998), Hall & Soskice (2001), Mosher & Franzese (2002), and Swank (2002), e.g., stress that various domestic political-economic contexts condition the pressures on policymakers from economic integration, but, however conditioned domestically, these pressures invariably derive at root from policies and conditions in other political economies. Nevertheless, none have directly modeled that interdependence empirically (until very recently: e.g., Basinger & Hallerberg 2004, Franzese & Hays 2006a, 2007b, Jahn 2006, Swank 2006). Not all globalization-and-welfare-state-retrenchment arguments necessarily involve tax-competition though. Iversen & Cusack (2000), for instance, argue that labor-force-structural change (*deindustrialization*) is the primary force behind welfare/tax-state retrenchment. Pierson (2001) concurs in part but also stresses *path dependence* (technically, *state* dependence: Page 2006), namely the accumulation and entrenchment (or not) of interests behind pro- and/or anti-welfare policies and institutions. Rodrik (1998) emphasized instead,

as had Cameron (1978), the added demand for welfare-state services that greater economic exposure would engender from some domestic interests. Labor-force structural-change, domestic-interest entrenchment, etc. may be related to, or even partly caused by, globalization, but at base these are domestic-factor explanations, or arguments about domestic factors modifying responses to *exogenous* external trends, and so do not inherently entail strategic interdependence. Distinguishing the effects like these of spatially correlated domestic or unit-level factors, of exogenous-external or contextual factors, and their interaction (context-conditional factors) from those of interdependence like those that tax-competition arguments suggest raises severe empirical challenges.

III. Empirical-Methodological Challenges of Spatial Interdependence

A. Generic Empirical Models of Domestic/Unit-Level, Exogenous-External/Contextual, Context-Conditional, and Interdependent Processes in Comparative Politics

We begin by distinguishing four broad approaches in comparative politics to explaining cross-unit variation and offering generic empirical models to represent each. One approach emphasizes unit-level (e.g., individual, domestic) variables and ignores contextual effects and interdependence processes. Another grants key roles to external/contextual conditions/shocks. In a third, a unit's responses to these exogenous conditions may depend on that unit's characteristics, and, *vice versa*, the effects of unit-level characteristics depend on context, but context remains exogenously external to the observed units. I.e., exogenous-external conditions affect outcomes for units, with or without domestic context-conditioning, but units' outcomes do not themselves affect other units' outcomes and so do not reverberate throughout the population. Finally, in truly interdependent processes, the outcomes in some units directly affect other units' outcomes, perhaps in addition to the possibility that multiple units are exposed to common or correlated unit-level, exogenous-external, and/or context-conditional factors. For example, a country might respond to some exogenous domestic or global political-economic shock (unit or contextual level) by cutting tax rates, and its response to exogenous-external shocks may depend on its domestic factors and *vice versa* (context-conditional), but its response may further depend on what its competitors do and, conversely, its own response may affect other countries' policymakers' choices (*interdependence*). Likewise, German and French

respondents' opinions might correlate because some individual characteristics (unit-level) correlate across countries or regions, or because some political-economic conditions correlate regionally (exogenous-external context), and opinions may respond to the common regional stimuli in manners conditioned by individual characteristics and *vice versa* (context-conditional), but opinions may also correlate regionally because the opinion of each regional resident depends on the aggregate regional opinion, i.e., on the opinions of all the other regional residents (interdependence). The last phrases of each example give the hallmark of truly interdependent processes: outcomes (i.e., explanandums, left-hand sides, or dependent variables, y_i, or components thereof, $\hat{y}_i$ or ε_i) in some units are among the explanators (right-hand sides, "independent" variables) of outcomes in others.

As the end of last section described in the globalization, tax competition, and tax/welfare-state retrenchment context, a central challenge for empirical researchers, known as *Galton's Problem* (see below), is the great difficulty distinguishing *common shocks* (i.e., correlated responses to correlated unit-level, contextual, or context-conditional factors) from *interdependence*. As elaborated below, on the one hand, ignoring or inadequately modeling interdependence processes will lead analysts to exaggerate the impact of common shocks, privileging unit-level/domestic or contextual/exogenous-external explanations. On the other, if the simultaneity inherent in interdependence is insufficiently redressed, spatial-lag models (see below) will misestimate (usually overestimate) interdependence at the expense of common shocks, especially insofar as the common shocks are inadequately modeled.

1. Unit-Level, Contextual, Context-Conditional, and Spatial Interdependence Models

Consider first a strictly unit-level model of a single outcome. In closed-polity or closed-economy comparative-polity-economy (CPE), for instance, domestic political-economic institutions (*e.g.*, electoral systems or central-bank autonomy), structures (*e.g.*, socioeconomic-cleavage or economic-industrial structures), and conditions (*e.g.*, electoral competitiveness or business cycles) are the paramount explanators of domestic outcomes. Such domestic-primacy substantive stances imply theoretical and empirical models of this form:

$$y_{it} = \boldsymbol{\beta}'\mathbf{d}_{it} + \varepsilon_{it} \tag{4}$$

where y_{it} are the outcomes to be explained (dependent variables) and $\boldsymbol{d}_{it}$ are the *domestic* conditions or the unit-level/individual factors that explain y_{it} (independent variables), each of which may vary across time and/or space. Most early empirical studies in comparative politics and CPE, whether quantitative or qualitative, took this form, later perhaps allowing the stochastic component, ε_{it}, to exhibit spatial correlation, but treating this correlation as nuisance either to be 'corrected' by Parks procedure (FGLS) or, later, to require an adjustment to standard-errors (PCSE). CPE examples include most of the early empirical literature on the political economy of fiscal and monetary policy (*e.g.*, Tufte 1978, Hibbs 1987, and successors), coordinated wage bargaining and corporatism (*e.g.*, Cameron 1984, Lange 1984, Lange & Garrett 1985, and successors), and the early central-bank-independence literature (*e.g.*, Cukierman 1992, Alesina & Summers 1993, and successors).

As economies grew more interconnected by international trade and, later, finance, and as perhaps polities' geopolitical interconnectedness rose too, controls for global political-economic conditions became both more important substantively and more common in practice. At first, however, such global conditions were assumed to impinge upon all domestic units equally and so to induce equal responses from each unit, yielding theoretical/empirical models like this:

$$y_{it} = \boldsymbol{\beta}_d' \mathbf{d}_{it} + \boldsymbol{\beta}_s' \mathbf{s}_t + \varepsilon_{it} \tag{5}$$

where $\mathbf{s}_t$ are global shocks (e.g., the oil crises), felt equally by all of the sample spatial units, each of whom respond equally (each i feels identical shocks, $\mathbf{s}_t$, and responds thereto in equal amounts, $\boldsymbol{\beta}_s$). Again, the random component, ε_{it}, may exhibit spatial correlation—i.e., spatial correlation distinct from that induced by exposure to these common shocks—but any such correlation was treated as nuisance either to be 'corrected' by Parks procedure (FGLS) or, later, to require an adjustment to standard-errors (PCSE). Examples of empirical models reflecting such stances (often implicit) are the many post-oil-crisis political-economy studies, including later rounds of the above literatures, wherein time-period dummies or controls for global economic conditions or the practice of differencing domestic from global conditions[6] began to appear: see, e.g., Alvarez et al. (1991) with

[6] Differencing the dependent variable thusly is identical to controlling for global conditions and forcing their coefficient

regard to partisanship and corporatism interactions; Alesina et al. (1997) with regard to political and/or partisan cycles; Powell & Whitten (1993) with regard to economic voting.

Finally, a modern institutional or otherwise context-conditional argument might emphasize that unit's responses to external or contextual stimuli may depend on unit-level characteristics and, *vice versa*, the effect of unit characteristics upon external or contextual conditions. As examples: (a) domestic institutions, structures, and conditions shape the degree and nature of domestic exposure to external shocks/conditions and *moderate* the domestic policy or outcome responses to these differently felt foreign stimuli; (b) individuals' education, attention, or informational levels moderate their voting or their opinion responses to contextual factors such as features of the party or electoral system under which they live. This yields characteristic theoretical and empirical models like this:[7]

$$y_{it} = \boldsymbol{\beta}'_d \mathbf{d}_{it} + \boldsymbol{\beta}'_s \mathbf{s}_t + \boldsymbol{\beta}'_{sd} \left(\mathbf{d}_{it} \otimes \mathbf{s}_t \right) + \varepsilon_{it} \tag{6}$$

where the incidence, impact, and/or effects of contextual/external shocks, $\mathbf{s}_t$, on domestic/unit-level outcomes, y_{it}, are conditioned by domestic/unit-level contextual factors, $\mathbf{d}_{it}$, and so differ across spatial units (and, *vice versa*, the effects of $\mathbf{d}_{it}$ are conditioned by $\mathbf{s}_t$). Examples here include much of modern, open-economy and -polity comparative politics and CPE, including, e.g., the contributions to (Bernhard et al. 2002) on the choice of exchange-rate regimes and other monetary institutions (notable because exchange rates are inherently interdependent phenomena). That varying domestic institutions/structures moderate the response of domestic policies and outcomes to globally common shocks, or that they shape how common shocks are felt domestically, are also central arguments in Franzese (2002) and Garrett (1998). Welfare/tax-state retrenchment examples of such an approach include the aforementioned Iversen-Cusack or Cameron-Rodrik arguments. The exogenous-external conditions in those cases might reflect technological or other progress in production, shipping, or

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to be -1. Differencing independent variables so amounts to controlling for global conditions and fixing their coefficient to minus the coefficient on the domestic independent variables.

[7] The Kronecker product, $\otimes$, means the entire $k_d x1$ vector of domestic factors, **d**, multiplies each element of the $k_s x1$ vector of exogenous-external shocks, **s**, resulting in the $(k_d k_s)x1$ vector of interactions in parentheses, each such term getting its own coefficient, β_{sd}. This is the most-general (among linear-interactive) model(s) of such context-conditional arguments.

financial processes.[8] The domestic institutional, structural, or contextual conditions might include union density, existing industrial structure, and partisan electoral-competitiveness. Once again, any spatial correlation distinct from that induced by common or correlated responses to *common shocks* would typically be left to FGLS or PCSE "corrections".[9]

Analyses that recognize the *interdependence* of outcomes across units, contrarily, must have outcomes in units *i* and *j* affecting each other, yielding this final extension of the generic model:

$$y_{it} = \rho \sum_{j \neq i} w_{ij} y_{jt} + \boldsymbol{\beta}'_d \mathbf{d}_{it} + \boldsymbol{\beta}'_s \mathbf{s}_t + \boldsymbol{\beta}'_{sd} \left(\mathbf{d}_{it} \otimes \mathbf{s}_t \right) + \varepsilon_{it} \tag{7}$$

where y_{jt} is the outcome in another ($j \neq i$) unit, which in some manner (given by ρw_{ij}) directly affects the outcome in unit *i*. Notice that w_{ij} reflects the *relative degree* of connection from *j* to *i*, and ρ reflects the overall *strength of dependence* of the outcome in *i* on the outcomes in the other ($j \neq i$) spatial units, as weighted by w_{ij}. Substantively for tax competition, for example, the w_{ij}, could gauge the sizes of, the similarity (substitutability) or complementarity of, and/or the capital and/or goods-and-services trade between *i*'s and *j*'s economies. The other right-hand-side elements reflect the non-spatial components: unit-level/domestic, contextual/exogenous-external, and context-conditional.[10]

B. Galton's Problem: Distinguishing Open-Economy CPE from C&IPE

1. The Nature of Galton's Problem

Since models like (7) subsume those like (4)-(6), some might argue that one should always begin with (7) and work downward as their data suggest/allow. However, as we summarize below (from Franzese & Hays 2004, 2006a, 2007b, 2008), obtaining *good* (unbiased, consistent, and efficient) estimates of coefficients and standard errors in such models—more generally, distinguishing open-economy CPE and comparative-politics from interdependence empirically (by any methodological

[8] The exogenous-external conditions in this and the previous model are assumed to be identical across units; more generally, they will at least tend to correlate across units.

[9] In some open-economy CPE empirical models, the controls for common shocks or other conditions abroad are actually *dependent-variable* conditions abroad—as, e.g, in Franzese's (2002) models of transfers, debt, unemployment, and inflation, and in Garrett's (1998) growth model. However, these regressors are seen as proxying exogenous-external conditions, and their inherent interdependence implications receive little to no mention. I.e., the spatial lags are treated solely as nuisances, rather having their implied spatial dynamics interpreted, which is analogous to using time-lagged dependent variables as nuisance control for serial correlation and ignoring the implied models of temporal dynamics. Furthermore, these spatial lags are usually endogenous as well, which also typically went unnoticed.

[10] One could also allow spatial error-correlation to remain and address it by FGLS and/or PCSE, but optimal strategies will be to model the interdependence and correlation in the first moment insofar as possible.

means, including qualitative methods)—is *not* straightforward. Others would suggest starting with (4) and working up as the data demand—top-down or bottom-up remains a point of contention among methodologists—but tests that can distinguish spatial interdependence from other potential sources of spatial correlation in residuals from models like (4)-(6) are lacking and/or weak (Anselin 2006, Franzese & Hays 2008), raising similarly high hurdles. The first and prime considerations in considering these alternatives and in estimating the role of the corresponding components in (7) are the relative and absolute theoretical and empirical precisions and explanatory powers of the spatial and non-spatial parts of the model, i.e., of the *interdependence* part and of the *common, correlated, or context-conditional responses to common or correlated exogenous-external factors* (henceforth: the *common-shocks*) part. To elaborate: the relative and absolute accuracy and power with which the spatial-lag weights, w_{ij}, reflect and can gain leverage upon the *interdependence* mechanisms actually operating and with which the domestic, exogenous-external, and/or context-conditional parts of the model reflect and can gain leverage upon the true *common-shocks* alternatives critically affect the empirical attempt to distinguish and evaluate their relative strength. This is simply because the two mechanisms produce similar effects (a challenge known as *Galton's Problem*[11]) so that inadequacies or omissions in specifying the one part tend, intuitively, to induce overestimates of the other part's importance. Secondarily, even if the *common-shocks* and *interdependence* mechanisms are modeled perfectly, the spatial-lag explanator(s) will be endogenous (i.e., technically, they will covary with the residuals), so estimates of ρ (or, equally, attempts to distinguish interdependence from common shocks qualitatively) will suffer simultaneity biases. Furthermore, as with the primary concerns of

[11] Galton originally raised the issue thusly: "[F]ull information should be given as to the degree in which the customs of the tribes and races which are compared together are independent. It might be that some of the tribes had derived them from a common source, so that they were duplicate copies of the same original. ...It would give a useful idea of the distribution of the several customs and of their relative prevalence in the world, if a map were so marked by shadings and colour as to present a picture of their geographical ranges" (Sir Francis Galton, *The Journal of the Anthropological Institute of Great Britain and Ireland* 18:270, as quoted in Darmofal 2007.) Further historical context is given in http://en.wikipedia.org/wiki/Galton's_problem: "In [1888], Galton was present when Sir Edward Tylor presented a paper at the Royal Anthropological Institute. Tylor had compiled information on institutions of marriage and descent for 350 cultures and examined the correlations between these institutions and measures of societal complexity. Tylor interpreted his results as indications of a general evolutionary sequence, in which institutions change focus from the maternal line to the paternal line as societies become increasingly complex. Galton disagreed, pointing out that similarity between cultures could be due to borrowing, could be due to common descent, or could be due to evolutionary development; he maintained that without controlling for borrowing and common descent one cannot make valid inferences regarding evolutionary development. Galton's critique has become the eponymous Galton's Problem (Stocking 1968: 175), as named by Raoul Naroll (1961, 1965), who proposed [some of] the first statistical solutions."

(relative) omitted-variable or misspecification bias, these simultaneity biases in estimated strength of interdependence (usually overestimation) will induce biases in the opposite direction (usually under-estimation) regarding the importance of common shocks. Thus, researchers who emphasize unit-level/domestic, exogenous-external, or context-conditional processes to the exclusion or relative neglect of interdependence mechanisms (micro-level scholars and comparativists?) will typically be biased in their empirical analyses toward results favoring the former and handicapping the latter sorts of explanations. Conversely, those who stress interdependence to the under-specification of domestic/unit-level and exogenous-contextual considerations or who fail to account sufficiently the endogeneity of spatial lags (macro-level and international-relations scholars?) will generally offer empirical analyses biased in the opposite directions, pro-interdependence and anti-common-shock.

2. The Precise Terms of Galton's Problem in the Spatio-Temporal-Lag Model

Most empirical studies of many of the subjects across the span of comparative politics where interdependence arises (reviewed in introduction), notably the policy diffusion and the globalization, tax-competition, and policy-autonomy literatures, 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 interdependence in their models.[12] 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

[12] 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 (inspired by Sir Galton's famous comments at the 1888 meetings of the Royal Anthropological Society, and 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.

is with a spatio-temporal lag model, which we can write in matrix notation as:

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \phi\mathbf{M}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{8}$$

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).[13] ρ is the previously described 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 (see note 7) of a $T\times T$ identity matrix and an $N\times N$ weights matrix $(\mathbf{I}_T \otimes \mathbf{W}_N)$, with the elements w_{ij} of $\mathbf{W}_N$ reflecting the relative connectivity from unit j to i as previously described. $\mathbf{Wy}$ is the *spatial lag*; i.e., for each observation y_{it}, $\mathbf{Wy}$ gives a weighted sum of the y_{jt}, with weights w_{ij}. Notice how $\mathbf{Wy}$ 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, $\mathbf{My}$ 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 coefficients on them. In our generic models, $\mathbf{X}$ would contain columns $\mathbf{d}$, $\mathbf{s}$, and $\mathbf{d}\otimes\mathbf{s}$; i.e., $\mathbf{X}$ is the non-spatial part of the model, reflecting domestic/unit-level, contextual/exogenous-external, and context-conditional factors, i.e., the common shocks. Finally, $\boldsymbol{\varepsilon}$ is an $NT\times1$ vector of stochastic components, assumed to be independent and identically distributed.[14]

In earlier work (Franzese & Hays 2004, 2006a, 2007b, 2008), we explored analytically and by simulation several properties of four estimators for such models: non-spatial least-squares (i.e., regression omitting the spatial component as is common in most extant research: OLS), spatial OLS (i.e., OLS estimation of models like (8), 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

[13] Nonrectangular and/or missing data are manageable, but we assume full-rectangularity for expository simplicity.
[14] Alternative distributions of $\boldsymbol{\varepsilon}$ are possible but add complication without illumination.

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.

These biases can be thought of as reflecting the terms of *Galton's Problem*. On the one hand, if researchers omit the spatial lag that would reflect the true interdependence of their data, their OLS coefficient estimates will suffer omitted-variable biases,[15] 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:

$$\text{plim}\ \hat{\beta}_{\text{OLS}} = \beta + \rho \times \frac{\text{cov}(\mathbf{Wy}, \mathbf{x})}{\text{var}(\mathbf{x})} \qquad (9).$$

$\hat{\rho}_{\text{OLS}} \equiv 0$, 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. Notice (as Sir Galton did) that the same applies to qualitative analyses that ignore interdependence of their observed phenomena.

On the other hand, including spatial lags in models for OLS estimation (or considering qualitatively the observed correlation of outcomes in some units with those in others or tracing putative diffusion processes) 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 (7) as:

$$\mathbf{y} = \mathbf{Q\delta} + \boldsymbol{\varepsilon}, \text{ where } \mathbf{Q} = \begin{bmatrix} \mathbf{Wy} & \mathbf{x} \end{bmatrix} \text{ and } \boldsymbol{\delta} = \begin{bmatrix} \rho & \beta \end{bmatrix}' \qquad (10).$$

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

$$\text{plim}\ \hat{\boldsymbol{\delta}}_{\text{S-OLS}} = \boldsymbol{\delta} + \text{plim}\left[\left(\tfrac{\mathbf{Q}'\mathbf{Q}}{n}\right)^{-1}\left(\tfrac{\mathbf{Q}'\boldsymbol{\varepsilon}}{n}\right)\right] \qquad (11).$$

[15] 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.

In the case where **x** is exogenous, we can rewrite the biases expressed in (16) as

$$\text{plim}\ \hat{\boldsymbol{\delta}}_{\text{S-OLS}} = \begin{bmatrix} \rho \\ \beta \end{bmatrix} + \frac{1}{|\boldsymbol{\Psi}|}\begin{bmatrix} \text{cov}\left(\mathbf{Wy}, \boldsymbol{\varepsilon}\right) \times \text{var}(\mathbf{x}) \\ -\text{cov}\left(\mathbf{Wy}, \boldsymbol{\varepsilon}\right) \times \text{cov}(\mathbf{Wy}, \mathbf{x}) \end{bmatrix} \text{ where } \boldsymbol{\Psi} = \text{plim}\left(\frac{\mathbf{Q}'\mathbf{Q}}{n}\right) \qquad (12).$$

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, $\hat{\beta}$.

3. Effective Estimation of the Spatio-Temporal-Lag Model: Addressing Galton's Problem

In sum, *Galton's Problem* implies that 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 correlate spatially the most will be most over-estimated. On the other hand, simply controlling (or considering qualitatively) spatial-lag processes 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.[16] 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.

We also showed in this previous work that 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

[16] Strategies to parameterize **W** and estimate such models are of great interest but as yet mostly remain for future work.

strengths ($\rho \times \Sigma_j w_{ij}$ less than about 0.3), S-OLS may perform adequately, although standard-error accuracy may be a bit of an issue, and in a manner for which PCSE will not compensate. 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. Our analyses, which considered bias, efficiency, and standard-error accuracy, indicated that the choice of which consistent estimator is decidedly secondary, but S-ML seems close to weakly dominant across all four estimation strategies.[17] Accordingly, we introduce only it here.[18]

C. Maximum-Likelihood Estimation of Spatio-Temporal Lag Models[19]

The conditional likelihood function for the spatio-temporal-lag model, which assumes the first observations 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:

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\mathbf{B} + \boldsymbol{\varepsilon} \Rightarrow \boldsymbol{\varepsilon} = \left(\mathbf{I} - \rho\mathbf{W}\right)\mathbf{y} - \mathbf{X}\mathbf{B} \equiv \mathbf{A}\mathbf{y} - \mathbf{X}\mathbf{B} \qquad (13).$$

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

$$L(\boldsymbol{\varepsilon}) = \left(\frac{1}{\sigma^2 2\pi}\right)^{\frac{NT}{2}} \exp\left(-\frac{\boldsymbol{\varepsilon}'\boldsymbol{\varepsilon}}{2\sigma^2}\right) \qquad (14),$$

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

$$L(\mathbf{y}) = |\mathbf{A}| \left(\frac{1}{\sigma^2 2\pi}\right)^{\frac{NT}{2}} \exp\left(-\frac{1}{2\sigma^2}\left(\mathbf{A}\mathbf{y} - \mathbf{X}\mathbf{B}\right)'\left(\mathbf{A}\mathbf{y} - \mathbf{X}\mathbf{B}\right)\right) \qquad (15).$$

[17] See especially Franzese & Hays (2007b, 2008) regarding S-ML estimation; they correct some misleading preliminary conclusions from the earlier work on that estimator.

[18] 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*, $\mathbf{y}$'s in some units cause $\mathbf{x}$'s in others, does not exist, instruments comprised of $\mathbf{WX}$ 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.

[19] We currently use J.P. LeSage's MatLab code to estimate our spatial models, having found existing Stata code for spatial analysis, third-party contributed .ado files, to be badly untrustworthy and/or extremely computer-time intensive. We have written Stata code, which we believe more reliable and efficient, to implement many of our suggestions. We will make this code publicly available once we have tested its reliability more thoroughly. Regarding LeSage's MatLab code, sar.m, as we have noted before, the line of code calling the standard errors from the parameter-estimate variance-covariance matrix must be corrected to reference the proper element for the $\hat{\rho}$ estimate.

This still resembles the typical linear-normal likelihood, except that the transformation from $\boldsymbol{\varepsilon}$ to $\mathbf{y}$ is not by the usual factor, 1, but by $|\mathbf{A}|=|\mathbf{I}-\rho\mathbf{W}|$.[20] Written in ($N\times 1$) vector notation, the spatio-temporal-model conditional-likelihood is mostly conveniently separable into parts, as seen here:

$$\text{Log} f_{\mathbf{y}_t,\mathbf{y}_{t-1},\ldots,\mathbf{y}_2|\mathbf{y}_1} = -\frac{1}{2}N(T-1)\log\left(2\pi\sigma^2\right)+(T-1)\log\left|\mathbf{I}-\rho\mathbf{W}\right|-\frac{1}{2\sigma^2}\sum_{t=2}^{T}\boldsymbol{\varepsilon}_t'\boldsymbol{\varepsilon}_t \qquad (16),$$

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).[21]

$$\begin{aligned}\text{Log} f_{\mathbf{y}_t,\ldots,\mathbf{y}_1} = &-\frac{1}{2}NT\log\left(2\pi\sigma^2\right)+\frac{1}{2}\sum_{i=1}^{N}\log\left(\left(1-\rho\omega_i\right)^2-\phi^2\right)+(T-1)\sum_{i=1}^{N}\log\left(1-\rho\omega_i\right)\\ &-\frac{1}{2\sigma^2}\sum_{t=2}^{T}\varepsilon_t'\varepsilon_t-\frac{1}{2\sigma^2}\varepsilon_1'\left(\left(\mathbf{B}-\mathbf{A}\right)'\right)^{-1}\left(\mathbf{B}'\mathbf{B}-\mathbf{B}'\mathbf{A}\mathbf{B}^{-1}\left(\mathbf{B}'\mathbf{A}\mathbf{B}^{-1}\right)'\right)^{-1}\left(\mathbf{B}-\mathbf{A}\right)^{-1}\varepsilon_1\end{aligned} \qquad (17)$$

where $\boldsymbol{\varepsilon}_1 = \mathbf{y}_1 - \rho\mathbf{W}_N\mathbf{y}_1 - \phi\mathbf{I}_N\mathbf{y}_1 - \mathbf{X}_1\boldsymbol{\beta}$. 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 ease or even erase 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 temporal 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 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

[20] 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). We discuss both of these procedures, and estimation more generally, elsewhere (Franzese & Hays 2004, 2006a, 2007b, 2008).

[21] 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.

strategy. 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 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. Standard Lagrange-multiplier tests for remaining temporal correlation in regression residuals remain valid. (See Franzese & Hays 2004, 2008 for an introduction to several tests for/measures of spatial correlation, some of which retain validity when applied to estimated residuals from models containing spatial and temporal lags.)

We explained above that model specifications that omit spatial lags assume zero interdependence by construction and have shown elsewhere (analytically and in simulation) that this induces omitted-variable biases that inflate the estimated effects of non-spatial model-components. 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, we also showed that standard regression estimates of models with spatial lags suffer simultaneity biases. Such models have grown more common recently among researchers interested in interdependence and have been the norm in policy-diffusion and studies of micro-behavioral interdependence. Our previous analyses have also shown such inclusion of spatial lags in simple regression models to be vast improvements over non-spatial estimation strategies. Still, these previous studies simply inserting 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. We have also shown that 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 more familiar solely time-dynamic models. Nonetheless, the conditions and issues arising in the former are reminiscent if not

identical to those arising in the latter. Defining $\mathbf{A} = \phi\mathbf{I}$, $\mathbf{B} = \mathbf{I} - \rho\mathbf{W}$, and ω as a characteristic root (i.e., eigenvalue) of $\mathbf{W}$, the spatio-temporal process is covariance stationary if

$$\left|\mathbf{A}\mathbf{B}^{-1}\right| < 1 \qquad (18),$$

or, equivalently, if

$$\begin{cases} |\phi| < 1 - \rho\omega_{\max}, & \text{if } \rho \geq 0 \\ |\phi| < 1 - \rho\omega_{\min}, & \text{if } \rho < 0 \end{cases} \qquad (19).$$

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 simply 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**.

D. 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),[22] involve more than simply considering coefficient estimates. *Coefficients* do <u>*not*</u> 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, or equilibrium[23]

[22] 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.

[23] 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.

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.[24]

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

$$\mathbf{y}_t = \rho\mathbf{W}\mathbf{y}_t + \phi\mathbf{y}_{t-1} + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \qquad (20).$$

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 (20) and solve. This gives the steady-state effect, assuming stationarity and that exogenous RHS terms, $\mathbf{X}$ and $\boldsymbol{\varepsilon}$, remain permanently fixed to their hypothetical/counterfactual levels:

$$\begin{aligned}
\mathbf{y}_t &= \rho\mathbf{W}\mathbf{y}_t + \phi\mathbf{y}_t + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \\
&= \left(\rho\mathbf{W} + \phi\mathbf{I}\right)\mathbf{y}_t + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \\
&= \left[\mathbf{I}_{\mathrm{N}} - \rho\mathbf{W} - \phi\mathbf{I}_{\mathrm{N}}\right]^{-1}\left(\mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right) \qquad (21). \\
&= \begin{bmatrix} 1-\phi & -\rho w_{1,2} & & -\rho w_{1,\mathrm{N}} \\ -\rho w_{2,1} & 1-\phi & & \\ & & & \\ & & 1-\phi & -\rho w_{(\mathrm{N}-1),\mathrm{N}} \\ -\rho w_{\mathrm{N},1} & & -\rho w_{\mathrm{N},(\mathrm{N}-1)} & 1-\phi \end{bmatrix}^{-1}\left(\mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right) \\
&\equiv \mathbf{S}\times\left(\mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right)
\end{aligned}$$

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, Franzese & Hays (2006b) report estimates of long-run-steady-state responses across the European Union to counterfactual permanent shocks to labor-market-training expenditures in each member state or in all member states. Such hypotheticals 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 (21) around the estimated

[24] For fuller discussion of spatial multipliers, see Anselin (2003) and/or Franzese & Hays (2006a, 2007b, 2008).

parameter-values and determine the asymptotic variance of that linear approximation.[25] To find the key elements needed for this, begin by denoting the ith 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 ith element of $\boldsymbol{\eta}$ are $\mathbf{s}_i$, so the asymptotic approximate variance-covariance matrix of these estimates by the delta-method are

$$\mathbf{V}\left(\hat{\mathbf{s}}_i\right) = \left[\frac{\partial \hat{\mathbf{s}}_i}{\partial \hat{\boldsymbol{\theta}}}\right] \mathbf{V}\left(\hat{\boldsymbol{\theta}}\right) \left[\frac{\partial \hat{\mathbf{s}}_i}{\partial \hat{\boldsymbol{\theta}}}\right]' \qquad (22),$$

where $\hat{\boldsymbol{\theta}} \equiv \begin{bmatrix} \hat{\rho} & \hat{\phi} \end{bmatrix}'$, $\left[\frac{\partial \hat{\mathbf{s}}_i}{\partial \hat{\boldsymbol{\theta}}}\right] \equiv \begin{bmatrix} \frac{\partial \hat{\mathbf{s}}_i}{\partial \hat{\rho}} & \frac{\partial \hat{\mathbf{s}}_i}{\partial \hat{\phi}} \end{bmatrix}$, 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 ith 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 in country i are $\mathbf{s}_i\beta_k$, with delta-method standard-errors for those effects of

$$\mathbf{V}\left(\hat{\mathbf{s}}_i\hat{\beta}_k\right) = \left[\frac{\partial \hat{\mathbf{s}}_i\hat{\beta}_k}{\partial \hat{\boldsymbol{\theta}}}\right] \mathbf{V}\left(\hat{\boldsymbol{\theta}}\right) \left[\frac{\partial \hat{\mathbf{s}}_i\hat{\beta}_k}{\partial \hat{\boldsymbol{\theta}}}\right]' \qquad (23),$$

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 ith 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 $N\times 1$ vector of unit outcomes, $\mathbf{y}_t$, to the exogenous RHS terms, $\mathbf{X}$ and $\boldsymbol{\varepsilon}$, could also emerge by rearranging (20) to isolate $\mathbf{y}_t$ on the LHS:

$$\begin{aligned} \mathbf{y}_t &= \left[\mathbf{I}_N - \rho\mathbf{W}_N\right]^{-1}\left\{\phi\mathbf{y}_{t-1} + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right\} \\ &= \mathbf{S}\left\{\phi\mathbf{y}_{t-1} + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right\} \end{aligned} \qquad (24).$$

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

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

(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 (21) as $\mathbf{S} \equiv \left[\mathbf{I}_{\mathrm{NT}} - \rho\mathbf{W} - \phi\mathbf{M}\right]^{-1}$ and follow the steps just outlined. We calculate these effects for the presentation of our empirical reanalysis below, for example.

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

This section reanalyzes 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, but why investors would fail to notice is unexplained. 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[26] in determining tax policy. Swank & Steinmo (2002:650) suggest their results: "are consistent with the argument that

[26] Recall Galton's Problem and the weakness of tests in the bottom-up strategy for distinguishing potential sources of spatial correlation; the *or* is crucial since finding PCSE's to differ from least-squares SE's may suggest interdependence or correlated domestic, exogenous-external, and/or context-conditional considerations beyond those modeled (or both).

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*.[27] Swank finds that tax policies do not respond to these variables, but rather to a fourth spatial-lag wherein US capital-tax policy influenced capital-tax policy in other countries, with this *dependence* effect[28] 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 estimator (Beck et al. 2006) but does raise concerns discussed above. That is, temporally lagged spatial lags may not suffer the endogeneity that subjects OLS estimates to simultaneity bias, but, if interdependence incurs within an observational period, which strikes us as very likely in the capital-tax-competition context and in annual data, simultaneity

[27] 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).

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

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 missing within-period action). As shown 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).[29] 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 (8) 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. Each of the thirteen countries and their geographic neighbors are listed in Table 1. 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 (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

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

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. Geographic Neighbors in the Sample

	Neighbors
Australia	*None*
Belgium	France, Germany, Netherlands, UK
Canada	US
Finland	Norway, Sweden
France	Belgium, Germany, Italy, UK
Germany	Belgium, France, Netherlands
Italy	France
Japan	*None*
Netherlands	Belgium, Germany, UK
Norway	Finland, Sweden
Sweden	Finland, Norway
United Kingdom	Belgium, France, Netherlands
United States	Canada

Table 2 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.

Table 2. 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**	0.864**	0.671**	0.66**	0.711**
		(0.05)	(0.048)		(0.054)	(0.054)
Spatial Lag		0.104*	0.126**		0.017	0.05
		(0.054)	(0.054)		(0.058)	(0.055)
Liberalization	1.146	1.235*	0.629	-.261**	-0.255**	-0.168*
		(0.725)	(0.702)		(0.102)	(0.091)
Trade	-0.018	0.009	0.005	-0.009	0.001	-0.001
		(0.064)	(0.061)		(0.023)	(0.023)
Structural Unemployment	-1.147**	-1.218**	-1.033**	-0.359**	-0.38**	-0.148
		(0.306)	(0.283)		(0.189)	(0.189)
Public Sector Debt	0.089**	0.099**	0.046	0.053**	0.056**	0.038**
		(0.036)	(0.032)		(0.014)	(0.013)
Elderly Population	1.264**	1.011	-0.08	-0.018	0.03	0.171
		(0.615)	(0.481)		(0.23)	(0.184)
Growth	0.230*	0.242	0.307**	-0.008	-0.009	0.009
		(0.151)	(0.147)		(0.051)	(0.051)
Percent Change in Profits	0.127**	0.136**	0.174**			
		(0.055)	(0.054)			
Domestic Investment	0.066	0.045	0.059			
		(0.055)	(0.049)			
Inflation				0.115**	0.115**	0.063
					(0.05)	(0.043)
Unemployment				0.280**	0.296**	0.144*
					(0.084)	(0.079)
Left Government	0.018**	0.018*	0.012	0.008**	0.008**	0.007*
		(0.01)	(0.01)		(0.004)	(0.004)
Christian Dem. Government	0.041**	0.035	0.01	0.001	0.002	0.009
		(0.028)	(0.026)		(0.011)	(0.01)
Fixed Effects:						
Country	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes[1]	No	Yes	Yes[1]	No
R^2	.928	.922	.914	.989	.989	.988

[1] Biannual period effects. Standard errors in parentheses. **Significant at the .05 level; *Significant at the .10 level.

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

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.[30]

In Table 3, we present estimates of the spatial effects from counterfactual shocks to structural unemployment in eleven of our sample countries.[31] The cells in this table 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 is the estimated short-run effect (direct effect plus spatial feedback), which is calculated using equation (24); for example, the immediate spatio-temporal effect of a one-unit increase in German structural employment is $\mathbf{s}_6\beta_5$, where $\mathbf{s}_6$ is the sixth column of $\mathbf{S}$ (Germany's column in the spatial weights matrix) as it is defined in equation (24) and β_5 is the fifth row of the column vector $\boldsymbol{\beta}$ (structural unemployment is X_5 in the regression; The second number is the standard error of this estimate (equation (23); *i=6, k=5*); and the final number is the estimated long-run steady-state effect. Using Germany as our example again, we estimate that a one-unit increase in German structural unemployment, if it persists, will lead to a 7-point reduction in Germany's capital tax rate in the long-run, which, in turn, will cause France to lower its capital tax rate by almost 1.4 percentage points. These effects are calculated using equation (21), again with *i=6, k=5*.

Table 3. Short-Run and Steady-State Spatial Effects from a Shock to Structural Unemployment

	BEL	CAN	FIN	FRA	GER	ITA	NTH	NOR	SWE	GBR	USA
	-1.222**	0	0	-0.034*	-0.034*	-0.001	-0.034*	0	0	-0.034*	0
BEL	0.307	0	0	0.021	0.02	0.001	0.021	0	0	0.02	0
	-7.403	0	0	-1.672	-1.51	-0.227	-1.549	0	0	-1.51	0
	0	-1.231**	0	0	0	0	0	0	0	0	-0.128*
CAN	0	0.309	0	0	0	0	0	0	0	0	0.074
	0	-8.994	0	0	0	0	0	0	0	0	-4.876
	0	0	-1.225**	0	0	0	0	-0.067*	-0.067*	0	0
FIN	0	0	0.307	0	0	0	0	0.04	0.04	0	0
	0	0	-7.954	0	0	0	0	-2.958	-2.958	0	0
	-0.034*	0	0	-1.224**	-0.033*	-0.032*	-0.003	0	0	-0.033*	0
FRA	0.021	0	0	0.307	0.019	0.018	0.003	0	0	0.019	0
	-1.672	0	0	-7.643	-1.395	-1.036	-0.731	0	0	-1.395	0

[30] 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.

[31] Two countries in our sample—Australia and Japan—have no *neighbors* and therefore no spatial effects to report.

	-0.045*	0	0	-0.044*	-1.222**	-0.001	-0.044*	0	0	-0.004	0
GER	0.027	0	0	0.026	0.306	0.001	0.026	0	0	0.004	0
	-2.013	0	0	-1.859	-7.187	-0.252	-1.723	0	0	-0.836	0
	-0.004	0	0	-0.127*	-0.003	-1.221**	0	0	0	-0.003	0
ITA	0.004	0	0	0.073	0.004	0.306	0.001	0	0	0.004	0
	-0.907	0	0	-4.144	-0.756	-6.912	-0.396	0	0	-0.756	0
	-0.045*	0	0	-0.004	-0.044*	0	-1.222**	0	0	-0.044*	0
NTH	0.028	0	0	0.005	0.026	0	0.307	0	0	0.026	0
	-2.066	0	0	-0.974	-1.723	-0.132	-7.253	0	0	-1.723	0
	0	0	-0.067*	0	0	0	0	-1.225**	-0.067*	0	0
NOR	0	0	0.04	0	0	0	0	0.307	0.04	0	0
	0	0	-2.958	0	0	0	0	-7.954	-2.958	0	0
	0	0	-0.067*	0	0	0	0	-0.067*	-1.225**	0	0
SWE	0	0	0.04	0	0	0	0	0.04	0.307	0	0
	0	0	-2.958	0	0	0	0	-2.958	-7.954	0	0
	-0.045*	0	0	-0.044*	-0.004	-0.001	-0.044*	0	0	-1.222**	0
GBR	0.027	0	0	0.026	0.004	0.001	0.026	0	0	0.306	0
	-2.013	0	0	-1.859	-0.836	-0.252	-1.723	0	0	-7.187	0
	0	-0.128*	0	0	0	0	0	0	0	0	-1.231**
USA	0	0.074	0	0	0	0	0	0	0	0	0.309
	0	-4.876	0	0	0	0	0	0	0	0	-8.994

Notes: The elements of the table 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 the standard error of this estimate. The final number is the estimated long-run steady-steady effect. Australia and Japan are omitted from the table because they have no "neighbors" in the sample. **Significant at the5% Level; *Significant at the 10% Level.

Figures 2-3 present temporal response paths to this counterfactual shock to German structural unemployment. Both are calculated using the ith column of $\mathbf{S} \equiv \left[\mathbf{I}_{\mathrm{NT}} - \rho\mathbf{W} - \phi\mathbf{M}\right]^{-1}$ multiplied by β_k. The spatial effects are stacked by periods. In other words, the first *N* rows of column *i* give the time-*t* spatial effects of a shock to country *i* on the other sample countries and itself. The next *N* rows give the time *t+1* effects, etc. (In the case of German structural employment, *i=6* and *k=5*.) Figure 2 gives the over-time marginal response in the German capital tax rate, including all spatial feedback effects, with standard-error bands reflecting a 90% confidence interval. The cumulative effect after 15 periods is -6.523, which is just over 90% of the long-run steady-state effect. Figure 3 plots the marginal first-order spatial effects from a one-unit increase in German structural unemployment on French capital-tax rates. An increase in German structural unemployment leads to a decrease in German capital tax rates, and this, in turn, produces a decrease in French capital tax rates. Roughly 68% of the steady state effect (-.943/-1.395) is felt in the first 15 periods after the shock.

Figure 2: Spatio-Temporal Effects on the German Capital Tax Rate from a Positive One-Unit Counterfactual Shock to Structural Unemployment in Germany (with a 90% C.I.)

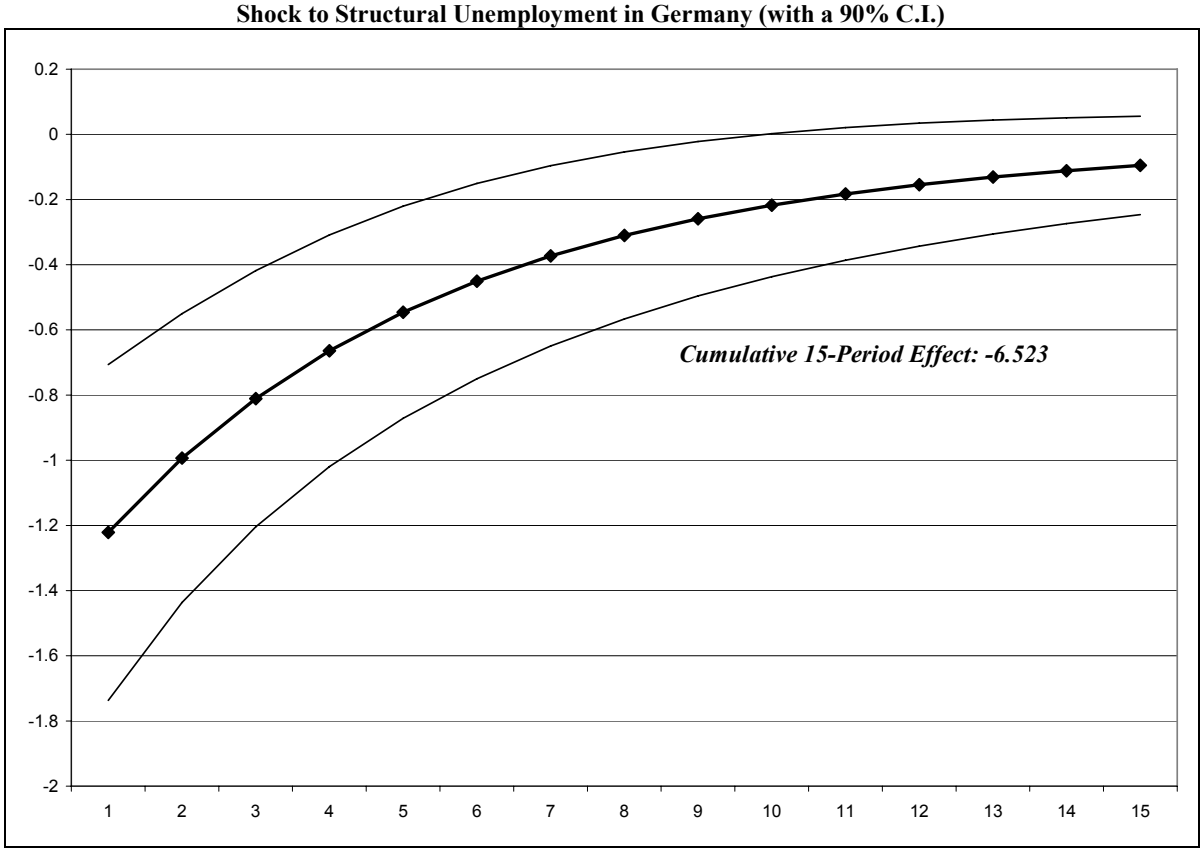
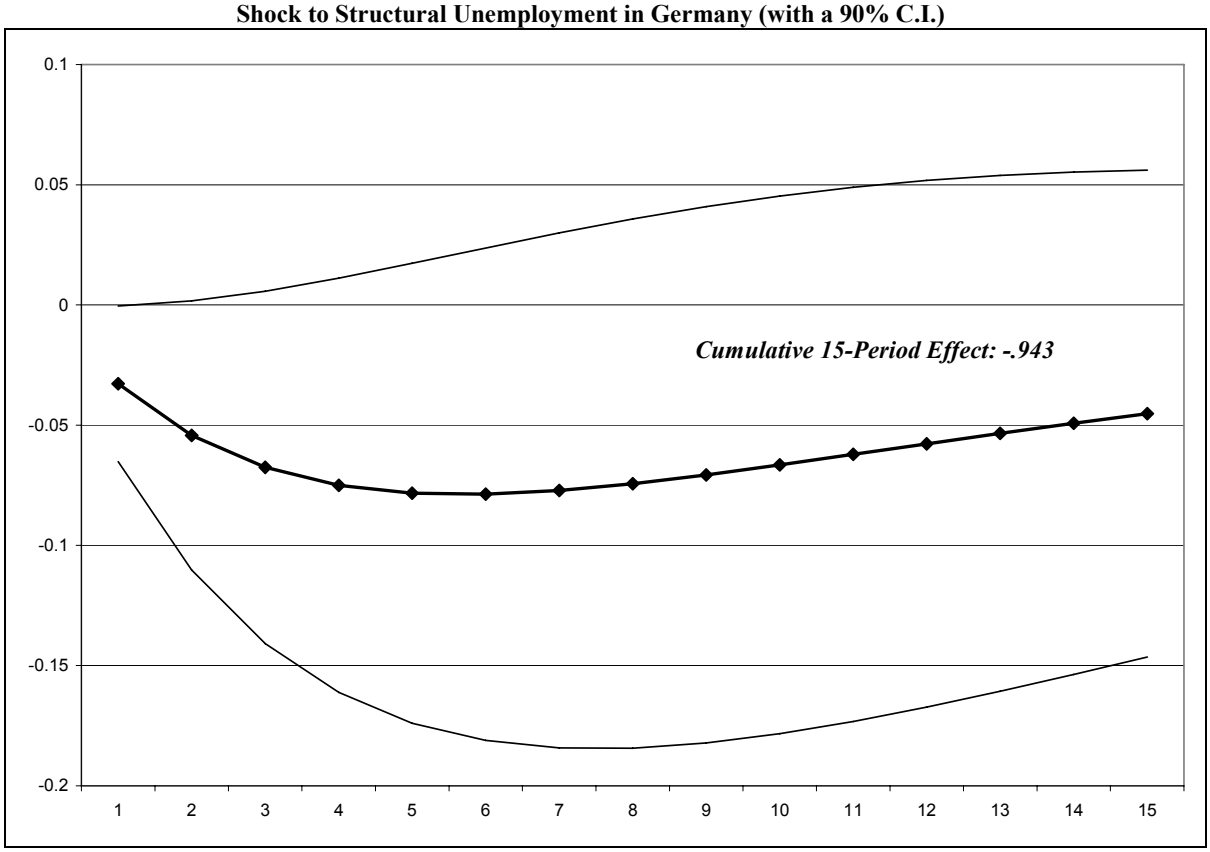


Figure 3: Spatio-Temporal Effects on the French Capital Tax Rate from a Positive One-Unit Counterfactual Shock to Structural Unemployment in Germany (with a 90% C.I.)



V. Conclusion

This chapter first outlined the broad substantive range across comparative politics in which spatial interdependence plays a potentially large role. It did so first by surveying a range of topics studied within comparative politics and noting their interdependence aspects. 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 comparative politics, 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 regarding the explanatory power of spatial-interdependence versus non-spatial factors. Omitting or relatively under-specifying the one tends to induce its underestimation and the other's overestimation. Thus, we conjectured, micro-level and comparative scholars' somewhat natural relative inattention to interdependence will have biased their results in favor of unit-level/domestic explanations whereas macro-level and international-relations scholars' naturally converse emphases will have biased their results in favor of strong interdependence and against the importance of domestic and context-conditional considerations. We discussed one way[32] 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 a replication of Swank & Steinmo's (2002) path-setting study of globalization and taxation in developed democracies, with a re-consideration of Swank's (2006) extension of that agenda to explore interdependence explicitly.

[32] We emphasized fully specified spatial maximum-likelihood (S-ML) and mentioned spatial two-stage-least-squares (S-2SLS) here, and we have also discussed generalized method of moments (S-GMM) extensions of S-2SLS elsewhere (Franzese & Hays 2006a, 2007b, 2008). These are not exhaustive of properly effective estimation strategies however.

From the perspective of that substantive application: Does international economic integration (i.e., globalization) constrain national governments from redistributing income, risk, and opportunity through tax and expenditure policies? We showed that, in overlooking the degree and manner to/in which fiscal policies correlate spatially (i.e., across countries), previous attempts to answer this and related questions empirically have missed important evidence of globalization's sizable influence on domestic policymaking. Theoretically, we had shown that positive and negative cross-jurisdictional externalities of policies should respectively induce negative and positive strategic interdependence of domestic policies. Globalization, and its heightened competition for capital in particular, therefore clearly should imply that domestic capital-tax policy will be positively linked to *neighbors*' policy. Previous regression models that ignored the policy interdependence that globalization implies were therefore seriously misspecified and likely subject to omitted-variable bias which inflated their estimates of domestic and exogenous-external factors' impacts while effectively preventing any empirical manifestation of globalization effects via interdependence. We had shown how to model such strategic policy interdependence with spatial lags, discussed some crucial issues in the specification and estimation of such models related to drawing valid empirical inferences from their estimates, and offered some suggestions on effective presentation of the spatio-temporal dynamic effect-estimates yielded by these models. We used our reanalysis of Swank & Steinmo's influential study of OECD tax-reform to illustrate these practices in specifying, estimating, and presenting the sort of spatial-lag models that reflect more accurately the substance and theory of globalization and interdependence. That re-analysis uncovered that capital-tax-rate policies are indeed highly interdependent, and so that previous estimates do indeed seem to have been misleading in the ways our analysis suggests. Labor being far less mobile across jurisdictions, it is reassuring that we also found far less sign of any significant strategic policy-interdependence in labor tax-rates (and concomitantly no such appreciable biases in previously reported results on that policy dimension).

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