Contagion, Common Exposure, and Selection: Empirical Modeling of the Theories and Substance of Interdependence in Political Science

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I. The Broad Substantive Range of Spatial Interdependence

Social-scientific interest in and applications of spatial modeling have burgeoned lately, due partly to advances in theory that imply interdependence and in methodology to address it; partly to global substantive developments that have raised perception of and attention to interconnectivity, at all levels, from micro/personal to macro/international; and partly to advances in technology for obtaining and working with spatial data. This is a welcome development because the dependence of outcomes in some units on outcomes in others, *spatial interdependence*, is substantively ubiquitous and theoretically quite central across the political and other social sciences.

Perhaps the most-extensive classical and current interest in spatial interdependence surrounds intergovernmental diffusion of policies and institutions among U.S. States.[1] Similar policy-diffusion research has more-recently emerged in comparative studies, but perhaps the closer parallel in terms of classical and current interest in comparative and international politics is institutional/regime diffusion, which dates at least to Dahl's (1971) classic *Polyarchy* and is much invigorated since Starr's (1991)

[1] The ensuing list of topics, subjects, and disciplines corresponds to literature searches for applied work under *contagion*, *spatial interdependence*, or *network dependence*. A web appendix (at www.umich.edu/~franzese/Publications.html) provides full citation to these (*many*) works, with some annotation, topically organized in the order presented here in the text. Likewise, throughout this article, the citations given are often abbreviated versions of fuller reference lists given sequentially in the web appendix. This includes complete references and links to our own work substantiating various conclusions and conducting various methodological and empirical analyses summarized here.

"Democratic Dominoes", Huntington's (1991) *Third Wave*, and the fall of the Soviet Union. The topical range of substantively important spatial-interdependence extends well beyond such inter-governmental diffusion, however, spanning all of political science. Inside democratic legislatures, representatives' votes depend on others' (expected) votes, and, in electoral studies, citizens' votes, election outcomes, or candidate qualities, strategies, or contributions in some contests depend on those in others. In micro-behavioral work, too, much of the surging interest in contextual/*neighborhood* effects surrounds effects on respondents' behaviors or opinions of aggregates of others' (e.g., those of his/her community or social network). Contagion or diffusion in social-movements, national identity, and ideology has also been explored. In comparative and international political economy, too, interdependence is often substantively large and central. Many stress cross-national diffusion as a force behind recent economic liberalizations. Even more broadly, globalization, i.e., international economic integration, arguably today's most-notable (and indisputably its most-noted) political-economic phenomenon, implies strategic (and nonstrategic) interdependence of domestic politics, policymakers, and policies. Likewise, the ignition and outcomes of coups, riots, civil wars, and revolutions in one unit also depend on those in others. Terrorist origins and targets manifest spatial patterns too. As for international relations, the interdependence of states' actions might serve for definition of the subfield. In fact, we might even argue that the interdependence of outcomes across units could serve reasonably as definition for *social* science. Interdependence is indeed studied prominently in geography, regional, and environmental sciences, in regional, urban, and real-estate economics, in medicine, public health, epidemiology, and criminology, and, in its related guise as network-dependence, in medicine, health, and epidemiology again, in education, and, of course, in social-network studies. Topics include, to name just a few, interdependence in macroeconomic performance; microeconomic preferences/utilities; technology, marketing, and other firm strategies; violence and crime; obesity, fertility, birthweight, child development and poverty; marriage; right-wing extremism; (sub)national identity; women's ordainment; and every academic's favorite: citations, placements, and co-authoring.

II. Tobler's Law, the Myriad Mechanisms, and a General Theoretical Model of Interdependence

In short, as *Tobler's Law* (Tobler 1970) aptly sums: "Everything is related to everything else, but near things are more related than distant things." Furthermore, as Beck et al.'s (2006) pithy title reminds in corollary: "Space is More than Geography." The substantive content of the proximity in *Tobler's Law*, and so the pathways along which interdependence between units may operate, extends well beyond physical distance, contact, and contiguity (as several examples above attest). Long literatures in regional science, geography, and sociology carefully elaborate from those disciplinary perspectives the multifarious mechanisms by which contagion may arise. Simmons and colleagues offer a list for international relations: *coercion*, *competition*, *learning*, and *emulation*.[2] In fact, as, e.g., Brueckner (2003) showed, strategic interdependence arises any time some unit(s)'s actions affect the marginal utility of other(s)'s actions. Given such externalities, *i*'s utility depends on both its policy and that of *j*.[3] In environmental policy, for instance, domestic welfare (or net political-economic benefits to policymakers) in each country will depend on the actions of both due to environmental spillovers (e.g., of pollution) and economic ones (e.g., in regulatory costs). Optimizing behavior will yield best-response functions of *i*'s optimal policies as a function of *j*'s and *vice versa*. In this frame, positive externalities create *free-rider* incentives, which induce policies to move in opposite directions (i.e., as *strategic substitutes*), confer late-mover advantages, and make war-of-attrition (strategic delay or inaction) dynamics likely. Conversely, negative externalities create strategic complementarity, with policies moving in the same direction, yielding early-mover advantages and *competitive races*.[4]

III. Empirical Methods for Spatial Interdependence: Specification, Estimation, & Interpretation

Empirically, the clustering or correlation of outcomes on some dimension(s) of proximity, *spatial*

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[2] E.g., Elkins & Simmons (2005) and Simmons et al. (2006). For a fuller, closer match to prior traditions, add *cooperation* and *externality* to *competition*, combine *learning* and *emulation* as one, and add *relocation diffusion* (Haegerstrand 1970)—meaning the direct movement of some components of units *i* into other units *j*, such as by human migration or disease contagion. Note that aspects of these mechanisms may induce spatial association by *common-exposure* or *selection* effects, as opposed or in addition to by *interdependence* (see below). For example, *learning* from other units implies *contagion*, whereas *learning* from one's own experiences could implicate *common-exposure* sources of spatial association insofar as units' experiences and lessons correlate spatially.

[3] In such microeconomic models, externalities could arise from interactions, expectations, and/or preferences (Manski 2000); furthermore, non-strategic interdependence could arise even without externalities. Examples and reviews of micro-theoretical models with explicit interdependence include Akerlof 1997; Glaeser et al. 2000, 2003; Brock & Durlauf 2001;

[4] We eschew the terms *race to the bottom* (or *top*) and *convergence* because these competitive races need not foster convergence to top, bottom, or mean, and could spur divergence (see below and, for related further discussion of the observable regarding convergence, Plümper & Schneider 2006).

association, is also obvious across a vast array of substantive contexts. However, and this is the crux of the great empirical challenge/opportunity represented by the substantive and theoretical ubiquity of interdependence, outcomes may evidence spatial association for at least three distinct reasons, only the second of which is true interdependence (arising by one or more of the mechanisms listed above). First, units may be responding similarly to similar exposure to similar exogenous internal/domestic or external/foreign stimuli (*common exposure*), or, second, unit(s)'s responses may depend on others' responses (*contagion*).[5] We may find states' adoptions of some economic treaty, for example, to cluster geographically or along other dimensions of proximity, e.g., bilateral trade-volume, because proximate states experience similar exogenous domestic or foreign political-economic stimuli or because each state's decision to sign depends on whether proximate others sign. A third possibility arises when the putative outcome affects the variable along which clustering occurs (*selection*). Treaty signatories might also cluster according to some variable on which we observe their proximity (volume of trade between them) because being co-signatories affects that variable (spurs bilateral trade). The theories and policy advice supported by any observed spatial association hinges critically on whether (or the relative degrees to which) state signatories cluster in pockets of dense trade relations because those states tend to experience similar exogenous conditions that favor signing, because the signing by some states spurs their trading partners to sign, or because the treaty fosters trade between co-signatories.

Severe empirical difficulties confront the accurate estimation and distinction of these alternative sources of spatial association: (1) domestic/internal factors, exogenous-external/foreign factors, and context-conditional responses to exogenous-external conditions; (2) cross-unit interdependence; and (3) the effects of interdependence on the proximity of units. We emphasize that, regardless of how one's interests weigh among (exogenous) internal/domestic, external/foreign, or context-condition effects for one, contagion/diffusion for another, and/or network-selection for a third, valid inferences regarding *any* of these possibilities generally requires empirical modeling that specifies and estimates *all* of them well because the three typically look much alike empirically and so the relative omission or inadequacy

[5] This is the famous *Galton's Problem*, and is related to *Manski's Reflection Problem* (1993), which in part is a formalization of Galton's profound comment revealing its full implications.

in the empirical model and estimates of any one will bias inferences in favor of the other(s) most similar to it. We next discuss briefly how to specify and estimate empirical models to make such distinctions and then how to interpret and present effectively the results.

Much of our previous work[6] has focused on estimating and calculating effects in regression models of spatial or spatiotemporal interdependence. The spatiotemporal-lag model, which reflects both spatial and temporal dynamics, can be expressed thus:

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \varphi\mathbf{M}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \qquad (1).$$

The dependent variable, **y**, is an *NTx1* vector of cross sections stacked by period (i.e., all *N* units' first-period observations, then the *N* second period observations, and so on, to the *N* for period-*T*). ρ is the spatial autoregressive coefficient, and **W** is an *NTxNT* block-diagonal spatial-weighting matrix. **Wy** is thus the *spatial lag*; i.e., for each observation, y_{it}, **Wy** is a weighted sum of the other units' outcomes, y_{jt}, with weights $\{w_{ij}\}_t$ reflecting relative connectivity from *j* to *i* (which may be constant or vary across each period *t*). **Wy** thus captures directly the dependence of each unit *i*'s outcome on unit *j*'s; crucially, the researcher prespecifies **W** as the theories and substance at hand suggest. ρ is the strength of interdependence, in that prespecified pattern, to be estimated. **M** is an *NTxNT* matrix with ones on the minor diagonal (i.e., at *(N+1,1), (N+2,2),…(NT,NT-N)*), and zeros elsewhere, so **My** is just the familiar (first-order) time-lagged dependent-variable, with φ its coefficient. **X** contains *NT* observations on *k* independent variables—the exogenous non-spatial explanators, i.e., the *common-exposure* components of domestic/unit-level, contextual/exogenous-external, and context-conditional factors—with $\boldsymbol{\beta}$ their *k*x*1* vector of coefficients. Lastly, $\boldsymbol{\varepsilon}$ is an *NTx1* vector of stochastic components, assumed independent and identically distributed.[7] The spatiotemporal-lag model thus captures temporal and spatial dynamics in familiar form, regressing the outcome, y_{it}, on exogenous non-spatial explanators and controls, $\mathbf{x}_{it}$, a time-lagged dependent-variable, $y_{i,t-1}$, and a weighted average of the dependent variable in other units,

[6] We have recently begun to consider network-selection effects jointly with contagion and common-exposure, and ours is the first such attempt to our knowledge to do so directly. Something similar to incorporating all three is possible in applications of the framework developed by Snijders and colleagues' coevolution-model framework (Snijders 1997, 2005; Leenders 1997), and its accompanying software, SIENA, but only rather indirectly (from our perspective).

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

$\Sigma_j w_{ij} y_{jt}$, with the weights, w_{ij}, reflecting the relative connectivity from units j to unit i.[8]

We have evaluated the bias and efficiency properties several estimators for (1) including non-spatial least-squares (LS), spatial least-squares (S-LS), spatial two-stage least-squares (S-2SLS), and spatial maximum likelihood (S-ML) among others. The first of these estimators (LS) omits spatial lags and is therefore subject to omitted variable bias. S-LS includes spatial lags but ignores their endogeneity, inducing simultaneity bias. S-2SLS avoids the simultaneity bias using spatial instruments (i.e., weighted averages of unit-level variables in neighboring units) to purge the spatial lag of its correlation with the error term, but it is typically inefficient relative to S-ML.

Our central findings are that LS, by ignoring spatial interdependence fosters overestimation of non-spatial effects, i.e., unit-level (domestic, individual) and contextual (exogenous-external) effects. These biases quickly grow substantively sizeable at even very modest interdependence-strength ($\rho > .1\pm$) and become gargantuan at greater ρ. Given any noticeable interdependence, then, non-spatial LS is an unmitigated disaster. S-LS, conversely, suffers simultaneity biases that foster misestimation, usually overestimation, of contagion-strength, usually inducing oppositely signed errors for (i.e., underestimation of) non-spatial factors' roles. These simultaneity biases generally remain mild at weaker interdependence ($\rho < .25\pm$), and S-LS is also rather efficient, but standard-error accuracy is very poor in smaller-T samples (as, in the most-extreme example, in pure cross-sections).[9] The biases of LS concentrate in the unit-level and exogenous-external factors that correlate most with the omitted spatial dependence. Conversely, the simultaneity bias that typically inflates estimated interdependence in S-LS induces corresponding attenuation biases in the estimates of non-spatial explanatory roles, especially for factors exhibiting spatial correlation most similar to the pattern of dependent-variable interdependence. In degree also, relative omission or misspecification of the spatial or non-spatial component of the model fosters underestimation of the strength of the relatively poorly specified component and over-estimation of the better-specified component. Substantively for political scientists, then, relatively poor

[8] Typically, one row-normalizes W such that $\Sigma_j w_{ij}=1$ and so $\Sigma_j w_{ij} y_{jt}$ is a weighted average. This affords certain econometric and substantive conveniences, but is not necessarily substantively neutral (see Pluemper & Neumeyer 2008ab).

[9] An aspect of (one of) *Manski's Reflection Problem*(s) again.

specifications of domestic/micro/individual-level or of exogenous external/macro/contextual-level components (*common exposure*) will tend to bias conclusions to favor *contagion*, and vice versa.[10]

The most important issue methodologically, then, is adequate modeling both of interdependence, including accurate and empirically powerful specification of **W**, and of the non-spatial component of the model (i.e., unit-level and exogenous-external factors). Selecting properly consistent estimators, and which one, is somewhat secondary but also becomes important as interdependence strengthens. In that consideration, S-ML emerges from our explorations as nearly dominating S-LS or S-2SLS. Other issues remain to explore—e.g., relative robustness of the estimators to misspecification or assumption violation—but our analyses so far suggest only simplicity and availability of software to facilitate/automate estimation remain in argument for S-LS or S-2SLS.[11]

Given an estimate of (1), the next step is interpretation of those estimates. Assuming a well-specified model and an effective estimator, one can read the statistical significance of spatial interdependence from $\hat{\rho}$ and of non-spatial factors from $\hat{\beta}$ in the usual manners. However, calculation, interpretation, and presentation of substantive effects in empirical models with spatio-temporal interdependence, as in any model beyond those strictly linear-additive in variables and parameters,[12] involve more than simply considering coefficient estimates. In empirical models with spatio-temporal dynamics, as in those with only temporal dynamics, the coefficients on explanatory variables give only the (often inherently unobservable) pre-dynamic impetuses to outcomes from changes in those variables. To calculate "immediate" spatiotemporal responses—post-spatial but pre-temporal feedback—and the spatiotemporal responses over time (in all N units) to counterfactual shocks to **X** or $\boldsymbol{\varepsilon}$,[13] we need the spatial multiplier, as seen best from the (Nx1) vector form of the model:

[10] *Galton's Problem* (and its related *Manski Problems*) once more.

[11] The first-order concern, though, we reiterate, is not to omit or give short-shrift to interdependence; how best to estimate models that properly include it is secondary.

[12] As familiar examples, linear-interaction models are explicitly nonlinear in variables though linear-additive in parameters; logit/probit models are explicitly nonlinear in variables and parameters; and temporally (or spatially or spatiotemporally) dynamic models are implicitly nonlinear in parameters and variables.

[13] Conceptually useful is to decompose ε into fixed η plus stochastic γ_t and to consider shocks to ε as occurring in η.

$$\mathbf{y}_t = \rho \mathbf{W}_N \mathbf{y}_t + \varphi \mathbf{y}_{t-1} + \mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \Rightarrow$$
$$\mathbf{y}_t = \left(\mathbf{I}_N - \rho \mathbf{W}_N\right)\left[\varphi \mathbf{y}_{t-1} + \mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right] \qquad (2).$$

To find the long-run, steady-state, equilibrium (cumulative) level of **y** (in all **N** units) to permanent counter-factual shocks to **X** and/or **ε** we set $\mathbf{y}_{t-1}$ equal to **y** in (2) and solve:[14]

$$\mathbf{y}_t = \rho \mathbf{W}_N \mathbf{y}_t + \varphi \mathbf{y}_{t-1} + \mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \Rightarrow$$
$$\mathbf{y}_t = \left[\mathbf{I}_{\mathrm{N}} - \rho \mathbf{W}_N - \varphi \mathbf{I}_{\mathrm{N}}\right]^{-1}\left(\mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right) \qquad (3).$$

To offer standard-errors for these effect estimates, we have shown how to use the *delta method*.[15] These formula give the responses of all units $\{i\}$ to hypothetical shocks to **x** or **ε** in any unit(s) $\{j\}$, including possibly shocks in $\{i\}$ itself or themselves, by inserting those counterfactual shocks in $\mathbf{X}_t\boldsymbol{\beta}+\boldsymbol{\varepsilon}$ in the row(s) corresponding to $\{j\}$. These calculations allow interpretation and tabular, graphical, and/or cartographical presentation of substantive spatial effects and dynamics, such as in these (shrunken) examples from our own work (see web appendix):

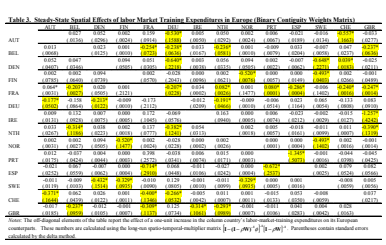
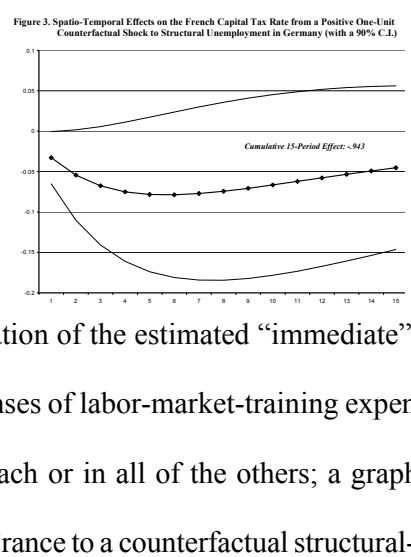
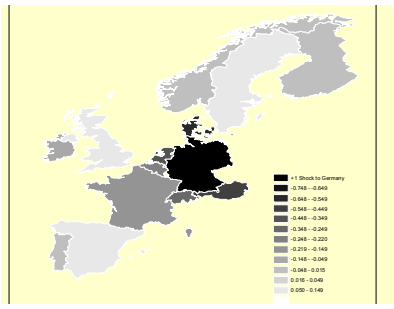


Table 3. Steady-State Spatial Effects of Labor Market Training Expenditures in Europe (Binary Contiguity Weights Matrix)

	AUT	BEL	DEN	FIN	FRA	DEU	IRE	NTH	NOR	PRT	ESP	SWE	CHE	GBR
AUT	0.556	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.0156)	(.0256)	(.0924)	(.0814)	(.1588)	(.0650)	(.0252)	(.0824)	(.0867)	(.0189)	(.0134)	(.1988)	(.0275)	
BEL	0.033	0.633	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.0068)	(.0125)	(.0019)	(.0278)	(.0636)	(.0147)	(.0061)	(.0010)	(.0079)	(.0204)	(.0058)	(.0237)	(.0630)	
DEN	0.032	0.047	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.0607)	(.0160)		(.0385)	(.0395)	(.2118)	(.0038)	(.0315)	(.0245)	(.0027)	(.0062)	(.2411)	(.0161)	(.0211)
FIN	0.062	0.002	0.004		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.0720)	(.0649)	(.0728)		(.0578)	(.2043)	(.0086)	(.0621)	(.0078)	(.0657)	(.0145)	(.0405)	(.5266)	(.0439)
FRA	0.064*	0.209	0.020	0.001		0.229	0.034	0.027	0.001	0.000	0.264	0.006	0.269	0.245
	(.0631)	(.0827)	(.0595)	(.2121)		(.0228)	(.0082)	(.0026)	(.1477)	(.0001)	(.0004)	(.1482)	(.0016)	(.0014)
DEU	0.159	0.156	0.215*	0.049	0.173		0.012	0.319*	0.009	0.000	0.023	0.065	0.133	0.081
	(.0802)	(.0864)	(.0122)	(.0019)	(.2112)		(.0209)	(.0068)	(.0010)	(.0014)	(.1164)	(.0054)	(.0008)	(.0010)
IRE	0.009	0.132	0.007	0.000	0.172	0.009		0.163	0.000	0.006	0.032	0.000	0.015	1.329
	(.0131)	(.0528)	(.0073)	(.0005)	(.1040)	(.0176)		(.0946)	(.0005)	(.0074)	(.0212)	(.0029)	(.0127)	(.2424)
NTH	0.031	0.149*	0.038	0.002	0.137	0.325*	0.054		0.002	0.005	0.018	0.011	0.011	0.290
	(.0267)	(.1188)	(.0223)	(.0019)	(.0777)	(.1240)	(.0113)		(.0019)	(.0017)	(.0161)	(.0099)	(.0007)	(.1139)
NOR	0.002	0.005	0.004	0.000	0.000	0.000	0.000	0.002		0.000	0.000	0.000	0.002	0.001
	(.0033)	(.0027)	(.0034)	(.0000)	(.0000)	(.0000)	(.0000)	(.0002)		(.0001)	(.0001)	(.0001)	(.0002)	(.0001)
PRT	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000
	(.0175)	(.0425)	(.0064)	(.0005)	(.2375)	(.0319)	(.0076)	(.0171)	(.0003)		(.0071)	(.0016)	(.0003)	(.0025)
ESP	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000
	(.0232)	(.0559)	(.0082)	(.0006)	(.2968)	(.0448)	(.0106)	(.0242)	(.0004)	(.2835)		(.0025)	(.0220)	(.0560)
SWE	-0.001	-0.000	0.422*	0.320*	-0.010	0.129	-0.001	-0.011	0.320*	0.000	0.000		-0.000	0.000
	(.0119)	(.0033)	(.0344)	(.0035)	(.0090)	(.0035)	(.0010)	(.0099)	(.0023)	(.0001)	(.0016)		(.0070)	(.0056)
CHE	0.735*	0.062	0.026	0.001	0.600*	0.266*	0.005	0.011	0.001	-0.013	0.053	-0.008		0.017
	(.1669)	(.0429)	(.0122)	(.0011)	(.1280)	(.0725)	(.0042)	(.0007)	(.0011)	(.0131)	(.0220)	(.0029)		(.0127)
GBR	-0.005	0.269	-0.012	-0.001	0.300	0.125	0.314*	0.025*	-0.001	-0.001	0.040	0.004	0.006	
	(.0185)	(.0959)	(.0105)	(.0007)	(.1193)	(.0728)	(.0161)	(.0008)	(.0007)	(.0100)	(.0281)	(.0042)	(.0163)	

Note: The off-diagonal elements of the table report the effect of a one-unit increase in the column country's labor-market-training expenditures on its European counterparts. These numbers are calculated using the long-run spatio-temporal multiplier matrix $\left[\mathbf{I}_N - (\mathbf{I}_N - \rho \mathbf{W}_N)^{-1} \varphi\right]^{-1} \left[\mathbf{I}_N - \rho \mathbf{W}_N\right]^{-1}$. Parentheses contain standard errors calculated by the delta method.





Left to right, these show a tabulation of the estimated "immediate" and long-run-steady-steady-state spatial and spatiotemporal responses of labor-market-training expenditure (LMT) each EU country to counterfactual LMT shocks in each or in all of the others; a graph of the estimated spatiotemporal response-path of capital taxes in France to a counterfactual structural-unemployment shock in Germany (from analyses extending Swank & Steinmo 2002), and a map of the estimated long-run-steady-state LMT responses in Europe to a counterfactual LMT shock in Germany.

Lately, we introduced (to political science) spatial-probit models of interdependence in binary outcomes, exploring Bayesian (MCMC) and frequentist (recursive importance-sampling: RIS)

[14] Given stationarity, the LRSS of any temporary shock is zero. Assuming row-normalization, stationarity requires $|\rho+\varphi|<1$.

[15] That is, we give a first-order Taylor-series linear-approximation to nonlinear (3) around the estimated parameter-values and determine the asymptotic variance of that linear approximation. Parametric bootstrap techniques can also be used to calculate these uncertainty estimates. See web appendix for specific citations.

estimators' performances and (more originally ours) calculation of spatial-dynamic effects in terms of outcome probabilities (with associated certainty estimates), rather than in parameter or latent-variable terms as in existing work. Lastly, we have begun consideration of "multiple-**W**" models, in part as an approach to estimating rather than prespecifying relative connectivities, an approach that, unlike the few extant, more exclusively inductive, approaches, is structural and capable of distinguishing the three sources of spatial association.[16] Multiple-**W** models also allow specification of relative connectivity between units in each **W** according to alternative mechanisms of interdependence, thereby affording direct empirical evaluation of those alternative mechanisms.

Further web appendices to earlier work offer *Stata*™ code for maximum-likelihood estimation of spatial-autoregressive models and for calculating spatial dynamics, effects, and standard errors, etc., plus *MatLab*™ code and *Lotus 1-2-3*™ *.wk1 files of data, including contiguity matrices, for replication of those papers' estimations.[17]

[16] The few existing approaches to estimating **W** are generally spatial-statistical rather than spatial-econometric in philosophy (roughly: non-structural rather than structural), and conditional rather than simultaneous autoregressive (roughly: inductive data-exploratory rather than deductively structured inferential). Network-analytic approaches to estimating ties between units, meanwhile, generally do not consider the *simultaneous* effects of those ties or the structure of those ties on units or of other units' outcomes or characteristics on each unit via the network of ties. (Snijders and colleagues have gone the furthest from this direction, though the approach is rather indirect for our aims: see note 6.)

[17] This code is our own, and does not use spatreg or related third-party Stata™ algorithms because, when last we tried, about four years ago, we had not found it reliable. Our MatLab™ code starts from or borrows with little or no amendment from LeSage's invaluable spatial-econometrics toolbox (Lesage 1999).

REFERENCES

[A web appendix (at www.umich.edu/~franzese/Publications.html) provides full citations for the *many* works corresponding to the topical survey that begins with the second paragraph (see note 1). The following are references for those works explicitly cited here only.]

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