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EDITORIAL

The present issue of Concepts & Methods features a special issue on quantitative methods for the study of spatial interdependence. It is timely for two reasons. First, our columns have recently displayed several essays about conceptualisation of policy learning in qualitative research (see Biegelbauer in 3 (1), 2007; Wieken-kamp as well as Loeber in 4 (1), 2008). Second, there is a growing scientific interest in understanding interdependence due to real or perceived developments of interconnectivity in society and economy (e.g., EU, globalization). Half of the nearly 800 articles referring to the phenomenon of "policy diffusion" that were published in top political science journals in the past half century appeared in the last decade[1].

Much too often, however, the possibility of interdependence is simply neglected in political science research. Robert Franzese and Jude Hays forcefully warn us against such omission, stressing the dire consequences of doing so (i.e., overestimation of non-spatial effects). While providing insights into the bias and efficiency properties of a range of estimators, they remind us of the methodological importance to distinguish the three *sources of spatial association* of common exposure, contagion, and selection, of which only contagion is true interdependence.

Achim Kemmerling illustrates spatial modeling with the example of labor market policies in OECD countries. His study shows not just that there is (some) interdependence in labour market policies of advanced countries, but also makes clear that spatial modeling is a powerful method that allows distinguishing between alternative causal mechanisms. At the same time, he shows the extent to which results depends on the specific weights chosen and hence he warns against an atheoretical modeling approach.

The next essay by Covadonga Meseguer looks at one particular mechanism of interdependence, namely policy learning. She argues that Bayesian updating offers an appropriate approach to the identification and operationalization of learning. Focusing on governments' decision to privatize, she demonstrates that governments in advanced and Latin American countries learn from both the experience in their region and from the experience in the world.

Studying interdependence (or diffusion processes) with spatial lags and spatial weights is not all there is in the quantitative toolkit. Fabrizio Gilardi discusses an alternative dyadic approach. Because the units of analysis are pairs of countries, this approach makes it possible to identify more clearly from which other country a given country is learning.

1 See Graham, Volden and Shipan (2008) "The Diffusion of Policy Diffusion", paper presented at the APSA Annual Meeting 2008, Boston.

All together, the four papers show that spatial modeling can add important insights to time-series cross-section approaches to studying political macrophenomena, but also highlight the fact that no analytical decisions taken in this context are innocuous. While they give an overview of some techniques available for modeling interdependence, it should not be forgotten that the usual datasets on which these techniques can be used are rather small, contain only limited information, and are based on often ambivalent measures. This however, is shared with any other technique that is used to study macrocomparative research questions. Another challenge that has not yet been tackled is the question to what extent process of policy diffusion vary over time. Spatial lags just summarize the relation between two countries over the whole period studied. As periods studied are increasing in length, influence may change. But such thoughts tend to be heretic -- one has to summarize something in order to identify a model.

In the last contribution of this issue, Peter Biegelbauer takes one of Concepts & Methods objectives to heart by engaging Anne Loeber's comments on his earlier thoughts about how to narrow down the concept of learning to render it empirically traceable and hence useful. This discussion highlights differences but also points of agreement or convergence between various approaches to learning.

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

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) "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 intergovernmental 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; micro-

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.

economic 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 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 con-

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)

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.

text-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 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:

$$y = \rho W y + \varphi M y + X\beta + \varepsilon \qquad (1)$$

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 β their *kx1* vector of coefficients. Lastly, ε 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, x_{it}, a time-lagged dependent-variable, $y_{i,t-1}$, and a weighted average of the dependent variable in other units, $\Sigma_j w_{ij} y_{jt}$, 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 (ρ>.1±) 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 (ρ<.25±), 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 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

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 ε are possible but add complication without illumination.

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.

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

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 , 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 and of non-spatial factors from 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 ε,[13] we need the spatial multiplier, as seen best from the (*Nx1*) vector form of the model:

$$y_t = \rho W_N y_t + \varphi y_{t-1} + X_t\beta + \varepsilon_t \Rightarrow \qquad (2)$$
$$y_t = (I_N - \rho W_N)\left[\varphi y_{t-1} + X_t\beta + \varepsilon_t\right]$$

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 y_{t-1} equal to y in and solve:[14]

$$y_t = \rho W_N y_t + \varphi y_{t-1} + X_t\beta + \varepsilon_t \Rightarrow \qquad (3)$$
$$y_t = \left[I_N - \rho W_N - \varphi I_N\right]^{-1}(X_t\beta + \varepsilon_t)$$

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 $X_t\beta+\varepsilon$ 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):

See figures on the next page

Top to down, these show a tabulation of the estimated long-run steady-state responses of labor-market training expenditures (LMT) in each EU country to counterfactual LMT shocks in 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) 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.

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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*.

14 Given stationarity, the LRSS of any temporary shock is zero. Assuming row-normalization, stationarity requires |q+φ|<1.

15 That is, we give a first-order Taylor-series linear-approximation to nonlinear 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.

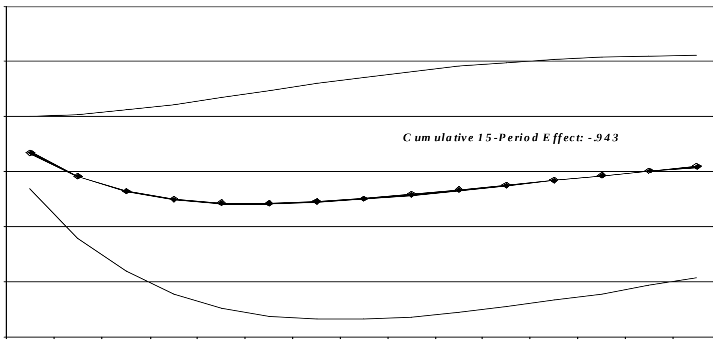
16 The few existing approaches to estimating W are generally spatial-statistical rather than spatial-econometric in philosophy (roughly: non-structural rather than structural), and conditional rather than simultaneous autoregressive (roughly: inductive data-exploratory rather than deductively structured 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.)

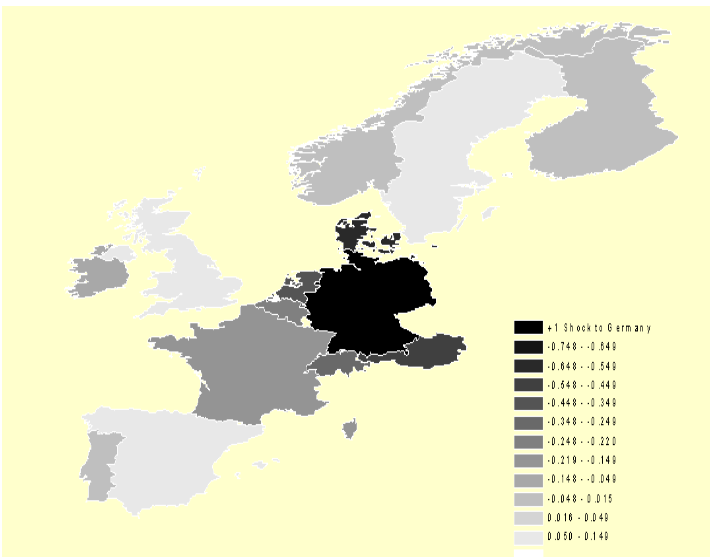
Table 3. Steady-State Spatial Effects of labor Market Training Expenditures in Europe (Binary Contiguity Weights Matrix)

	AUT	BEL	DEN	FIN	FRA	DEU	IRE	NTH	NOR	PRT	ESP	SWE	CHE	GBR
AUT		0.027 (.0136)	0.052 (.0296)	0.002 (.0024)	0.159 (.0914)	-0.530* (.1588)	0.005 (.0050)	0.050 (.0292)	0.002 (.0024)	0.006 (.0067)	-0.021 (.0189)	-0.016 (.0134)	-0.557* (.1663)	-0.033 (.0277)
BEL	0.013 (.0068)		0.023 (.0125)	0.001 (.0010)	-0.254* (.0723)	-0.238* (.0636)	0.033 (.0167)	-0.236* (.0581)	0.001 (.0010)	-0.009 (.0079)	0.033 (.0204)	-0.007 (.0058)	0.047 (.0237)	-0.237* (.0636)
DEN	0.052 (.0407)	0.047 (.0346)		0.094 (.0505)	0.051 (.0305)	-0.640* (.2218)	0.003 (.0038)	0.056 (.0335)	0.094 (.0505)	0.002 (.0022)	-0.007 (.0062)	-0.648* (.2271)	0.039* (.0183)	-0.025 (.0211)
FIN	0.002 (.0785)	0.002 (.0640)	0.094 (.0739)		0.002 (.0570)	-0.028 (.2043)	0.000 (.0096)	0.002 (.0621)	-0.520* (.0076)	0.000 (.0057)	0.000 (.0149)	-0.493* (.0403)	0.002 (.0266)	-0.001 (.0489)
FRA	0.064* (.0031)	-0.203* (.0027)	0.020 (.0505)	0.001 (.2121)		-0.207* (.0228)	0.034 (.0002)	0.082* (.0026)	0.001 (.1477)	0.080* (.0001)	-0.286* (.0004)	-0.006 (.1402)	-0.240* (.0016)	-0.247* (.0014)
DEU	-0.177* (.0502)	-0.158 (.0864)	-0.213* (.0122)	-0.009 (.0010)	-0.173 (.2112)		-0.012 (.0209)	-0.191* (.0466)	-0.009 (.0010)	-0.006 (.0514)	0.023 (.1164)	0.065 (.0054)	-0.133 (.0808)	0.083 (.0910)
IRE	0.009 (.0131)	0.132 (.0928)	0.007 (.0075)	0.000 (.0005)	0.172 (.1045)	-0.069 (.0576)		0.163 (.0940)	0.000 (.0005)	0.006 (.0074)	-0.023 (.0212)	-0.002 (.0029)	-0.015 (.0127)	-1.257* (.4242)
NTH	0.033 (.0267)	-0.314* (.1186)	0.038 (.0223)	0.002 (.0018)	0.137 (.0777)	-0.382* (.1241)	0.054 (.0313)		0.002 (.0018)	0.005 (.0057)	-0.018 (.0161)	-0.011 (.0099)	0.011 (.0007)	-0.390* (.1319)
NOR	0.002 (.0031)	0.002 (.0027)	0.094 (.0505)	-0.520* (.1477)	0.002 (.0024)	-0.028 (.0228)	0.000 (.0002)	0.002 (.0026)		0.000 (.0001)	0.000 (.0004)	-0.493* (.1402)	0.002 (.0016)	-0.001 (.0014)
PRT	0.012 (.0175)	-0.037 (.0424)	0.004 (.0044)	0.000 (.0003)	0.398 (.2572)	-0.038 (.0341)	0.006 (.0074)	0.015 (.0171)	0.000 (.0003)		-1.345* (.5073)	-0.001 (.0016)	-0.044 (.0398)	-0.045 (.0425)
ESP	-0.021 (.0252)	0.067 (.0559)	-0.007 (.0062)	0.000 (.0004)	-0.714* (.2910)	0.068 (.0448)	-0.011 (.0106)	-0.027 (.0242)	0.000 (.0004)	-0.672* (.2537)		0.002 (.0025)	0.079 (.0524)	0.082 (.0566)
SWE	-0.011 (.0119)	-0.009 (.0103)	-0.432* (.1514)	-0.329* (.0935)	-0.010 (.0090)	0.129 (.0805)	-0.001 (.0010)	-0.011 (.0099)	-0.329* (.0935)	0.000 (.0005)	0.001 (.0016)		-0.008 (.0059)	0.005 (.0056)
CHE	-0.371* (.1644)	0.062 (.0439)	0.026 (.0122)	0.001 (.0011)	-0.400* (.1346)	-0.266* (.0532)	-0.005 (.0042)	0.011 (.0007)	0.001 (.0011)	-0.015 (.0133)	0.053 (.0350)	-0.008 (.0059)		0.037 (.0217)
GBR	-0.017 (.0185)	-0.237* (.0959)	-0.012 (.0105)	-0.001 (.0007)	-0.309* (.1137)	0.125 (.0734)	-0.314* (.1061)	-0.293* (.0989)	-0.001 (.0007)	-0.011 (.0106)	0.041 (.0283)	0.004 (.0042)	0.028 (.0163)	

Notes: 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 $\left[\mathbf{I} - (\mathbf{I} - \rho\mathbf{W})^{-1}\phi\right]^{-1}[\mathbf{I} - \rho\mathbf{W}]^{-1}$. Parentheses contain standard errors calculated by the delta method.

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.)





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]

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[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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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).

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ACHIM KEMMERLING

The Weights You Choose, The Odds You Get: Using Different Spatial Weights. The Example Of Labor Market Policies

Introduction

More and more, researchers of comparative and international politics apply spatial econometrics to different causal claims about international diffusion (e.g. Simmons et al. 2006). Usually they estimate a model with a spatial lag and vary the matrix of spatial weights in accordance with the underlying theory. I will use the example of the international interaction between national labor market policies (LMPs) to show that such a methodology bears both opportunities and risks.

For comparative political economists LMPs are no obvious case of diffusion; different welfare state traditions loom large into reform processes. However, policy advisers have increasingly looked for benchmark cases abroad. There is also growing empirical evidence that national LMPs influence each other (Franzese/Hays 2006, Kemmerling 2007). In the following I will look for evidence of international policy diffusion for two different types of reform in LMPs. The first type of reform is 'activation', i.e. shifting passive measures such as unemployment benefits into active schemes of training or job creation. The second type of reform is 'incentivation', i.e. cutting unemployment benefits and thereby increasing pressure on the unemployed to accept new jobs.

Mechanisms of Diffusion

The theoretical literature on policy diffusion, transfer and interaction is very heterogeneous since it taps into many different economic, sociologic and even psychological theories. Arguably because of this heterogeneity, most scholars avoid the term theory, but use the concept of a causal mechanism instead. Mechanisms include different forms of learning, social imitation, or competition. Some scholars have embedded these different mechanisms in a single decision-theoretic framework (Braun/ Gilardi 2006). However, not all of these mechanisms are based on the same meta-theoretical assumptions and can be subjected to the same kind of empirical tests. Moreover, some of these mechanisms produce empirically very similar predictions.

For the sake of simplicity I will assume these theoretical problems away and will focus on three mechanisms for LMPs: competition, learning, and global trends. To begin with the first, one may assume that LMPs have spillover effects from one country to another: if country A enhances employment possibilities for its people, some people from a (neighboring) country B commute or emigrate to A. This reduces both the need for country B to implement similar measures and the effectiveness of the programs in country A. In this case country A's policy leads to opposite reactions in country B. In the long run A also starts cutting its programs. In that sense national LMPs compete with each other (Franzese/Hays 2006). Competition should make activation difficult and incentivation more attractive.

A different mechanism is to think that a government in country A learns from policies in country B (e.g. Meseguer 2006). There may be several forms of learning, but here I simply assume that A's government is uncertain about the effectiveness of a specific LMP. In that case it may use country B's experience as a benchmark: A's government should imitate policies of more successful countries with better labor markets. This could apply to both activation and incentivation policies.

Finally, one may argue that the logic of reforms in LMPs follows more a global trend than strategic or informational concerns. Governments in this sense are highly bounded in their rationality and use international trends in LMPs as crucial cues for their own policies. One may also think of this mechanism as a form of naïve learning in which governments merely emulate the behavior of other countries. Again, common trends serve as key signals for individual governments. Both arguments imply that countries should align their LMPs in activation and incentivation to the global mean.

The use of spatial lags and spatial weights

A spatial lag is an explanatory variable that gives an average of values for the dependent variable for 'neighboring' countries. Spatial lags are similar to temporal lags in time-series analysis in which data for the dependent variable of, say, the previous year is used as an explanation for the current year. The specific nature of the average depends on the weights you choose for all other countries. Hence it depends on the notion of 'neighborhood' and, in particular, on the causal mechanism you assume to be of importance. It is the chosen theory which decides how countries are connected with each other and which countries should matter more for a given country than others.

The typical time-series-cross-section regression with a spatial lag has the form

$$y_{it} = \rho W_t y_{jt} + X_{it}\beta_k + \varepsilon_{it}$$

The dependent variable is y_{it} for N countries (or other units) and T years. The spatial lag is y_{jt}, i.e. observations of y for all countries except for country i at time t. It is convenient to denominate these other countries with a new index j ≠ i. The spatial lag is weighted by a matrix W_t at time t, and ρ measures the spatial coefficient of correlation. X_{it} is the familiar set of K independent variables for each country and year, and the regression coefficients β and the error term ε also follow the familiar model of multiple regressions.

If we omit the time index, the typical matrix for spatial weights for country i has the form

$$W = \begin{vmatrix} w_{11} & \dots & w_{1N} \\ \dots & \dots & \dots \\ w_{N1} & \dots & w_{NN} \end{vmatrix},$$

where the w_{ij}s are usually row-standardized, i.e. . $\sum_1^N w_{ij} = 1$

Each w_{ij} represents the weight of country j on the policy of country i. All diagonal elements w_{ii} are set to zero, since a country cannot spatially affect itself by definition. Row-standardizing means that the spatial lag is a weighted average of the observations of other countries. Compare the following example: The U.S. has only two-contiguous neighbors, Mexico and Canada. If your theory is that only close geographic links matter and you want to describe a U.S. policy as the result of Mexican and Canadian policies you have to ascribe these two countries spatial weights that add up to one. If you further believe that border length proxies strength of influence you will have the following weights for the U.S.:

$$W_{USA} = \left\{ w_{USA \to USA} = 0, w_{CAN \to USA} = \frac{8893}{8893+3141} = 0.74, w_{MEX \to USA} = \frac{3141}{8893+3141} = 0.26 \right\}$$

The U.S.-Mexican border is 3141km and the U.S.-Canadian border 8893km. Hence Canada should have roughly three times as much influence on U.S. policies as Mexico. The weights of both countries add up to one, since by definition the weight of the U.S. on itself is 0.

In my case of LMPs I use four different matrices. The first matrix is based on binary contiguity and attaches positive weight only on neighboring countries. This tries to capture the effect of cross-border movements in employed people and hence the potential competition effects between countries. However, such a crude measure of geographic proximity is a variable that could be employed for many different theories. Therefore I use a second, more specific matrix which takes into consideration the relative length of borders a country shares with others. In this case the rationale is that the longer a common border, the higher the incidence of economic externalities between national LMPs. The validity of border length as a proxy for externalities has a sound basis in the literature (for details cf. Kemmerling 2007). For both matrices I expect that the sign of the coefficient ρ is negative, i.e. if LMPs in neighboring countries increase, the incentive for a given country is to decrease its own LMP.

The third matrix uses differences in unemployment rates between two countries. The argument is that a country copies LMPs from countries that have a better performing labor market and avoids policies of countries with a worse performance. This is my proxy of policy learning and I expect a positive coefficient in the estimations, since countries should copy LMPs of countries that have lower unemployment rates and should avoid policies of countries that have higher unemployment rates. The measure could be more sophisticated, but it catches the gist of the current debate on benchmarking and best practices in LMPs.

The fourth matrix puts equal weight on all countries in the sample. In this case the spatial lag is simply the arithmetic mean of all remaining (K-1) countries, and is meant to capture common (intellectual) trends in LMPs. I expect a negative relationship, since countries with higher (lower) LMPs relative to the mean should decrease (increase) their policies. In all four cases I did row-standardize the data.

Some Results

Using a spatial lag is not without perils, since it introduces endogeneity into the estimation and violates a condition of the classic model of ordinary least-squares (OLS) regression. Franzese and Hays (2006) argue that this disturbance is not very large if the strength of spatial correlation is not very large. This is the case for my analyses and the reason why I only report the results of a simple spatial OLS regression. I operationalized activation as the ratio of active to passive LMP in a country using the OECD Social Expenditure Database for 23 countries over the period 1980-2001. I use Lyle Scruggs' (2004) net replacement rate for unemployment benefits for 18 countries between 1971 and 2002 as a measure of incentivation. Similar to Franzese and Hays I use one regression model for each spatial weight matrix described above. Thus I estimate four regressions all of which also include a temporal lag, fixed time and country dummies and a battery of controls such as the rate of unemployment and the partisan ideology of ruling governments. The table omits all these and focuses directly on the coefficients for the spatial lags (for details cf. Kemmerling 2007).

Table: Abridged Regression Results

Spatial Lag	Activation	Incentivation
Competition		
Binary Contiguity	-0.08 (0.08)	0.041 (0.047)
Metric Contiguity	-0.132 (0.06)**	0.059 (0.044)
Learning		
UR-Weighted Lag	0.001 (0.001)	0.000 (0.000)
Global Trend		
Arithmetic Mean	0.20 (0.16)	-0.009 (0.830)

Levels of significance: * < .1, ** < .05

We see that of all four spatial weights, only metric contiguity produces a significant result and only for the case of activation. We also see that the sign for both border measures is negative, implying a strategic interdependence. Neighbors seem to compete with each other, especially if one takes into consideration the relative length of a shared border: If in neighboring countries the relationship between active and passive LMPs increases by one percent, this relationship drops in the given country by 0.132 percent. Compared to competition we do not see much evidence for a common trend nor the case of learning: both are insignificant and the trend even bears the wrong sign. Let us turn to the second area of reform, incentivation. Here we do not find any significant effects at all. The signs of the coefficients imply that geographic neighbors seem to copy directly from each other and that the case for strategic competition and externalities is much weaker.

Some pitfalls

Given that many recent contributions have found evidence for spatial interdependence future analyses need to shift their focus from omitting diffusion to exaggerating it. Take the example of the often cited tipping-point models in which countries are more likely to join the bandwagon of a new policy innovation if a critical mass of countries has already done so. Empirically these models look very much like an S-curve in which contagion takes off slowly, then accelerates, and finally fades out again. However, a similar S-curve is to be expected if all countries are hit by an international shock and the speed of adjustment after this shock is normally distributed. Deducing diffusion from a simple S-curve may therefore lead to a case of spurious diffusion. Do different spatial lags bear similar risks?

It is obvious that the link between the respective theory and the weights is decisive and that the weights can only be as good as the underlying theory. For instance, my operationalization of the argument about learning was not very sophisticated. Models of Bayesian updating (cf. Meseguer this issue) do much more justice to the way how policy-makers process information. Leaving these theoretical concerns aside, I will focus in the following on some practical problems in the implementation of spatial weights.

First, weights may be endogenous. For instance, unemployment rates could be the result of LMPs. In fact, the theory of externalities needs to assume that policies have an impact on the labor market. The theory is only valid, if activation measures reduce unemployment in both the country from which the policy originates and its neighbors. In that case one would need to endogenize or instrument the weights based on labor market performance (Franzese et al. 2008). An easier, but less satisfactory solution is to use only those weights that are clearly exogenous weights. In our example this means that the matrices based on contiguity are much less vulnerable to endogeneity than the matrix based on the differences between national unemployment rates.

Second, the specification of spatial weights has an enormous influence on the result (e.g. Plümper/ Neumayer 2008). For instance, row-standardization has the advantage that the spatial lag amounts to a weighted average, but it puts strong restrictions on the process of spatial contagion. Take the contiguity data as an example. Since all weights add up to one, a country with one neighbor such as New Zealand receives all its cues from Australia, but is equally dependent on external cues than a European country with 6 or 7 neighbors and many others nearby. We have to judge on basis of our theory whether this is plausible. If theory does not guide your specification it is recommendable to experiment with several modifications to probe the robustness of your results. For instance, the difference between binary and metric weights in the case of contiguity does not affect the sign of the coefficients very much, but it affects its significance.

Third, the small-sample properties of spatial weights have yet to be fully explored. Take the global mean which is strongly influenced by the inclusion or exclusion of a single country in a sample of 20 countries. Say we compute the arithmetic mean of activation for all countries but Sweden. Since Sweden is a well-known case of high levels of activation, the global mean for all other countries drops. Remember that we have to exclude Sweden from the computation of the global mean. In a cross-country comparison there will be a negative spatial correlation, but this correlation is the product of an arithmetic manipulation. We should not confuse this with a theoretically meaningful process of diffusion in which countries want to realign on a global trend. To test the robustness of small and non-random samples bootstrapping is an important tool, but it needs to be adjusted for spatial econometrics.

A last caveat using spatial weights is the temporal stability of the coefficients. Many theories such as strategic learning or competition would actually predict a temporal pattern in which first movers begin to deviate in the short run and only after some time other countries follow. Think again about labor market policies. A country such as Belgium might learn that it benefits from French activation measures. As a consequence it starts cutting its LMP. After some time France will find out that some of the benefits of its LMP go to Belgium and will also start cutting its programs. Hence we would expect a divergence in the short and a convergence of policies in the long run. Temporal stability is also a major issue if the underlying data does not vary enough or if random shocks have lasting effects (so-called non-stationarity). Take the European Union (EU) as an example. If we find that EU members have more similar LMPs nowadays, do we believe that this is due to a process of diffusion or do we believe that EU countries are exposed to a common lasting shock such as the introduction of a monetary union? In the latter case we do not find regional diffusion, but a common (stochastic) trend.

Conclusions

Using spatial lags is an intriguing methodology for the analysis of international policy diffusion. It is important for both econometric and substantive reasons. Since it is a relative newcomer to the field of comparative and international politics, applied research has yet to fully grasp some of the peculiarities of this methodology. Until these problems are fully understood one needs to check the robustness of the results carefully and to improve the links between theory and operationalization.

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Learning from Others[1]

The Problem

In political science, and particularly in International Political Economy, there has been an increasing interest in measuring horizontal influences among countries as determinants of policy choices. One such mechanism of horizontal influence is learning from the experience of others. In its simplest form, learning entails looking at the results (political or economic) of policies carried out by others in order to reduce the uncertainty that usually accompanies the making of economic policy. Whichever the version of political learning one embraces, learning involves politicians holding particular beliefs about the outcomes of a policy. To reduce that uncertainty, politicians look at others' experience. That information is in turn used to revise politicians' initial beliefs and eventually (one can hypothesize) decide on policies on the basis of what has been learned.

Note two important starting assumptions. Learning entails that governments hold beliefs with some uncertainty. If governments do not doubt their beliefs, that is, if they are dogmatic, the motivation to learn vanishes. Thus, for learning to take place, initial beliefs have to be vague. Second, a politician or government interested in learning from others faces several informational constraints: even if she is a rational learner (that is, even if she makes the most efficient use of all available information), there are costs in the acquisition of that information. Hence, governments may not use all potential information simply because it is costly to access it. Beyond this constraint, making the most efficient use of the experience of others implies giving more weight to information that is based on many observations. It also entails giving more value to information that is consistent, that is to say, less noisy information[2]. A particular government that doubts whether to privatize may look at the experience of other countries that privatized before. If in a good number of countries privatization was followed by better economic performance, a rational politician would update its initial beliefs with that information and conclude that privatization is a good way to spur economic growth.[3]

The literature on economic policy making, and in particular, the literature on economic policy reform is pervaded by stories of this type: policies are adopted because they work. Policies are abandoned (providing a policy alternative exists) because they no longer work. Economic policy making is then portrayed as a process of continuity punctuated by moments of policy change. The change is generally associated to deep economic crises that question the validity of previous beliefs (among many others, see Tommasi and Velasco, 1995). The challenge is to test empirically whether this sort of rational behavior has any leverage in explaining actual policy choices against other possible explanations. This test has proved elusive so far given the difficulty in operationalizing learning in a way amenable for cross-national empirical research. I argue that Bayesian updating holds great potential to tackle the operationalization conundrum.

1 This summary is based on Meseguer (forthcoming, 2009)

2 According to theories of bounded learning, there are biases in the processing of information. Actors use several heuristic devices (availability, representativeness and anchoring) which distort the way the experience of others is processed. Applied to policy making, these biases entails that governments pay more attention to experiences that are close, they draw excessive optimistic conclusions on the basis of a limited stream of information and, when adopting policies, policy makers make little adaptations. The most comprehensive application of this model in the policy diffusion literature is Weyland (2007). See also Tetlock (2005).

3 Whether this particular politician will eventually liberalize does not follow immediately, of course. Even if governments are persuaded of the technical virtues of a particular policy, it may not be adopted for a host of political or ideological reasons. Thus, rational policy choices may not automatically follow rational learning.

The Setting

Assume that governments can express their initial uncertainty about the expected economic growth following the implementation of alternative policies, *j* = {*A, B*}, by means of a probability distribution.[4] These alternative policies may be liberalize or protect trade, liberalize or close the capital account, so on and so forth. Growth, *X*, is assumed to be a random variable, normally distributed, with an unknown mean, *M*, and an unknown variance, *V*. Governments learn about these two unknown parameters by observing the results of other countries under alternative policies. These two parameters are random variables, too.

In the specification of prior beliefs for this kind of set up, the conditional distribution of the mean is normally distributed[5]. The marginal distribution of the variance is *scaled Inverse-*χ^2. In this prior *Normal/scaled Inv-*χ^2, the distributions of the mean and the variance are interdependent.[6] Thus, for policies j = {*A, B*}

$$\begin{aligned} &X_j \sim N(M_j, V_j) \qquad (1)\\ &M_j \mid V_j \sim N(\mu_j, \sigma_j^2 / \tau_j)\\ &V_j \sim ScaledInv-\chi^2(\upsilon_j, \sigma_j^2) \end{aligned}$$

The four parameters are the location (μ) and the scale (σ^2/τ) of the mean, *M,* the degrees of freedom (υ) and the scale (σ^2) of the variance, *V*. τ_j is the factor that relates the prior variance of the mean to the sampling variance. At time *t*, governments observe the performance of alternative policies *A* and *B* in other countries. Suppose that n_A countries followed policy *A* and that n_B countries followed policy *B*. Hence, the following information about performance of policies *A* and *B* becomes available at time t.

$$X_j^t = x_{t1}^A, x_{t2}^A, \ldots, x_{tnA}^A, x_{t1}^B, x_{t2}^B, \ldots, x_{tnB}^B,\ j = \{A, B\}. \qquad (2)$$

Assume these new data are drawn from normal distributions. Also, assumed that these observations are independent and identically distributed (i.i.d). The sample mean, $\bar{x}_j$, and the sample sum of squares, S_j, are sufficient statistics to summarize the information in the sample of countries under each of the policies *A* and *B.*

New information in combination with prior beliefs produces posterior beliefs, that is, updated beliefs embodying observed policy results under *A* and *B*. The useful feature of Bayesian updating is that it offers a mechanism of rational learning based on Bayes's theorem. Bayesian updating provides updating equations for the parameters of interest, that is, mean and variance, after observing n_j outcomes of policy. (2)

In common parlance, governments start with certain prior beliefs about average growth and the variability of growth for policies *A* and *B* (for instance, liberalizing and not liberalizing trade). New information is gathered and governments update their beliefs about growth and its variability under alternative policies according to equations (3) - (4) below. Equations (3) and (4) provide the posterior point estimates for the two parameters that can be used as operationalizations of learning in cross national statistical analysis: the posterior for the *location* and the posterior for *the scale.* These posterior beliefs become priors the following year. Under the assumption that samples gathered consecutively are independent, the rational updating of beliefs proceeds sequentially.

With a *Normal/scaled Inv-*χ^2 conjugate prior and a normal likelihood as described above, the posterior value of the location (3) and the posterior value for the scale (4) have the following shapes.[7] For each country *i*, time *t* and policies *j = {A, B}*

$$\mu_{it} = \frac{\tau_{it-1}}{\tau_{it}}\mu_{it-1} + \frac{n}{\tau_{it}}\overline{x_{it}} = \rho\mu_{it-1} + (1-\rho)\overline{x_{it}}; 0 < \rho < 1. \qquad (3)$$

$$s_{it}^2 = \frac{S_{it}}{\upsilon_{it}} \qquad (4)$$

n is the sample size, S_{it} is the posterior for the sum of squares, υ_{it} is the posterior for the degrees of freedom, and τ_{it} is the posterior for the factor that relates the prior variance of the mean to the sampling variance.

The above equations may look rather obscure, and an immediate reaction to them is that no real policy maker would ever undertake the heroic task of calculating posterior beliefs in order to make a decision. Yet, for all its complication, equation (3) implies that posterior beliefs are a compromise between prior beliefs and the information conveyed in the observed sample of countries carrying out alternative policies. The bigger the sample size, *n*, the more weight the sample information has in forming posterior beliefs compared with prior beliefs. Thus, posterior beliefs will be mostly driven by data rather than by prior beliefs. By proceeding in this way, it is possible to generate series of posterior beliefs about expected performance based on past experience and the experience of others and use those posteriors as proxies of learning.

An illustration

Governments' utility can be expressed as a positive function of posterior beliefs about growth, say, privatizing and not privatizing. If governments choose the policy that maximizes their utility, a decision problem can be stipulated based in the comparison of expected utilities under alternative policies. The probability of adopting a particular policy can then be estimated as a function of the difference in posterior beliefs under one and the other pol-

4 Note that this setting assumes that governments want to learn about the success of a particular policy measured in terms of economic growth. Other outcomes of interest, including political outcomes, may be considered, of course.

5 Marginally, the mean has a t-Student distribution.

6 This is a strong assumption but it does not seem to be unrealistic. The dependency means that if σ^2 (which is the sampling variance of growth) is large, then a prior distribution with high variance is induced on *μ.*

7 Gelman et al. (2004: 79).

icy (policies *A* and *B* in a generic way).

The table below shows the results of estimating the impact of learning on the decision to privatize in thirty seven advanced and Latin American countries (Meseguer 2004). The dependent variable is a dichotomous indicator of privatization. The variables OWN RESULTS, AVERAGE REGIONAL RESULTS, AND AVERAGE WORLD RESULTS were calculated using equation (3).[8] I employed as prior beliefs data from actual performance of countries privatizing and not privatizing the year before a particular country enters the database. The information to update prior beliefs was the average growth results for countries that privatized and countries that did not privatize. To account for any possible discrimination of information, I distinguished the own past experience from the experience in the region a particular country belongs to (average growth results in the region) and from the experience in the world (excluding the own and the regional experience).

According to the results (and disregarding the other control variables), in the joint sample, learning from the experience in the region and learning from the experience in the world with privatization is positively related to the probability that a particular country privatizes. In other words, the probability of privatizing is greater if governments' posterior beliefs about performance privatizing exceed the posterior beliefs about performance not privatizing after learning from the experience in the region and in the world. The results change slightly by region, with Latin American learning from their own past experience and the experience in their region and advanced countries being more influenced by the performance beyond their borders.

See table 1 on the next page

More to be learned

Whereas this approach to modeling learning from policy outcomes in the past and in other countries is suggestive, it is certainly only a first step and certainly not problem free. Other questions that I have not addressed here due to space constraints relate to modeling external shocks, how to model the time series component of the updating process, and alternative ways to specify prior beliefs to address similar problems. In any case, Bayesian updating as a tool is a step forward in comparison to the few attempts so far to model learning from others and ideational change and to test its impact on the likelihood of policy switches. In that sense, it is a promising methodological tool for the internationalist interested in spatial interdependence.

8 In this particular illustration, I do not use updates of the variability of growth outcomes.

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Table. 1. Probability of Privatizing

	All Countries (1)	OECD (2)	LA (3)
CONSTANT	-2.60***	-4.56***	-6.45***
	(-5.92)	(-3.72)	(-3.06)
LEARNING FROM OWN RESULTS	0.11	0.04	0.32*
	(1.45)	(0.34)	(1.87)
LEARNING FROM AVERAGE REGIONAL RESULTS	0.16*	-0.63	1.36**
	(1.72)	(-1.22)	(2.55)
LEARNING FROM AVERAGE WORLD RESULTS	0.21**	0.59**	-0.99
	(2.22)	(2.10)	(-1.12)
EMULATION	0.60***	0.49***	1.12***
	(5.06)	(3.39)	(3.60)
COERCION	0.22	-0.08	0.50
	(0.74)	(-0.12)	(1.15)
IDEOLOGY	0.08	0.25*	-0.37
	(0.79)	(1.74)	(-1.59)
REGIME	-0.28E-2	0.02	-0.14**
	(-0.10)	(0.60)	(-2.30)
INFLATION	0.08	1.61	-0.22
	(0.24)	(0.68)	(-0.43)
EU	0.20	0.23	
	(0.71)	(0.78)	
YEAR 1990	0.35	0.45	2.24**
	(0.95)	(0.87)	(2.43)
Log Likelihood	-169.37	-94.02	-48.95
LR Chi-Square	399.15	285.87	165.69
P-Value for F	0.000	0.000	0.000
Observations	533	342	191

*p<.10; **p<.05; ***p<.01; z-scores in parentheses; all variables lagged one year.

FABRIZIO
GILARDI

Interdependence And Policy Diffusion: The Dyadic Approach[1]

Introduction

In recent years, researchers in many political science subfields, including comparative and international political economy, comparative politics, international relations, and public policy, have directed increased efforts to the study of how policy choices in one country are shaped by prior policy choices in other countries, or in other words, how policies diffuse internationally (see for example Simmons, Dobbin and Garrett, 2008). One argument is that countries learn from one another, as foreign experiences supply useful information on the likely consequences of policy change (see Meseguer, this issue), but there are other reasons why policies diffuse, including competition (governments act strategically to attract resources) and emulation (norm dynamics alter the relative attractiveness of policies, regardless of their objective properties).

These ideas are appealing, but how can we know if diffusion really happens, and if it does, what drives it? In the quantitative toolbox, spatial methods are the main option. Diffusion is modeled through spatial lags, namely weighted averages of the lagged dependent variable in which theoretically more relevant countries (e.g. competitors, or more successful examples) have greater influence (see Franzese and Hays, this issue).

In this note, I discuss an alternative, namely the dyadic approach, in which units of analysis are not countries but pairs of countries (dyads). I first outline the logic of this approach, and then I discuss its main advantages and problems.

Basics

In the dyadic approach, the units of analysis are pairs of countries. The first country in each dyad (country$_i$) is defined as the potential "adopter" of a policy, while the second country (country$_j$) is the potential "sender". Each country enters the dataset twice, both as potential "adopter" and as potential "sender". Thus, the France-Germany dyad is different from Germany-France. In the first, France can potentially "receive" a policy from Germany, while in the second it is the other way around. Such a dataset includes all potential combinations of countries, except, of course, same-country dyads (for example, Germany-Germany). The number of dyads is therefore equal to *n* * (*n*-1), where *n* is the number of countries. This approach has been used for a long time in the international relations literature because many outcomes of interests, such as war or trade, are relational, but it has been adapted to the study of policy diffusion only recently (Volden, 2006).

The adaptation comes with a twist. In the context of diffusion, influence, unlike war or trade, cannot be measured at the dyadic level because it is unobservable; indeed, the whole point of the analysis is to find out whether such influence actually exists and what it looks like. Thus, the dependent variable has to be defined in terms of potential influence, or "imitation". Usually, it is coded 1 if, in a given year, country$_i$ takes up a policy that country$_j$ already had in the previous year. In other words, "imitation" so defined is a subset of policy change: it includes only those changes that move country$_i$ closer to country$_j$.

In itself, observing that country$_i$ adopts a policy that country$_j$ already had is of course no evidence of diffusion. It may very well be that country$_i$ changed its policy completely independently for reasons that have nothing to do with mutual influence, and that its increased similarity with country$_j$ is purely coincidental. Therefore, the goal of the analysis is to find out whether there are any systematic patterns of "imitation" For instance, do some characteristics of country$_j$ (such as its "success") or of the relationship between country$_i$ and country$_j$ (such as the similarity of their exports, which is a measure of competition) make imitation more likely? Although mutual influence is unobservable, the detection of systematic patterns of imitation can help make inferences about the underlying diffusion process. The distinct advantage of the dyadic approach is that variables measuring the rela-

1 I thank the editorial team of the C&M Newsletter, and especially Damian Raess, for helpful comments. The note summarizes arguments developed in Gilardi and Füglister (2008).

tionship between the two countries, as well as their individual characteristics, can be easily integrated in the analysis. Thus, diffusion hypotheses can be tested directly.

Concretely, dyadic models have the following form:

$$y_{ijt} = \alpha + X_{ijt}\beta + V_{it\gamma} + W_{jt}\delta + \varepsilon_{ijt},$$

where y_{ijt} is a vector of relational outcomes, *α* is the intercept, X_{ijt} is a matrix of dyadic measures, V_{it} is a matrix of measures for the characteristics of country_i, W_{jt} is a matrix of measures for country_j, ε_{ijt} is the error term, and *β*, *γ*, and *δ* are vectors of coeffcients to be estimated. In other words, the model can include information on the relationship between country_i and country_j, such as the extent to which they compete for the same resources, as well as of the characteristics of country_j, such as the success of its policy, and of course the characteristics of country_i. This means that, provided that good measures and data exist, diffusion hypotheses can be tested directly, and the importance of learning, competition, and emulation can be assessed empirically.

In most cases, the dependent variable is dichotomous, and the model is essentially a time-series cross-section model with a binary dependent variable.

These models can usually be estimated using ordinary logit or probit with corrections for time dependence (Beck, Katz and Tucker, 1998), but the specific dyadic setup introduces additional complications, which I address in the next section.

Pitfalls and promises

It is well-known that time-series cross-section analysis comes with many problems, but the dyadic setup has its own set of issues. A first concern are the complex dependencies that are introduced in the data through the particular construction of the dataset. Observations are non-independent not only within the same dyad over time (for example, France-Germany at time *t*, France-Germany at time *t* + 1, and so on), but also for dyads sharing the same country_i (such as France-Germany and France-Italy) or the same country_j (for instance, France-Germany and Italy-Germany). There is no easy solution, but some help could come from multilevel modeling, which allows the specification of random effects at three levels: country_i, country_j, and year. In other words, the intercept is allowed to vary across these levels, which helps address dependencies as well as cross-sectional (or cross-dyad) heterogeneity, which is another concern of dyadic analyses (King, 2001).

A second problem is linked to the construction of the dependent variable. Given the procedure explained in the previous section, in some cases the probability of imitation is exactly zero. This happens for those observations in which country_j has not (yet) adopted the new policy. This condition may hold for a non-trivial share of observations, which in some way are analogous to observations outside the risk-set in standard event-history analysis. The nature of this problem and its consequences are still unclear, but it seems advisable that such observations be dropped from the analysis (Boehmke, 2008). Intuitively, it makes sense to restrict the analysis to the cases for which imitation is not ruled out by construction.

Despite these problems, the dyadic approach has many advantages. Most notably, the possibility directly to include measures of the characteristics of country_j permits to answer questions such as "are the policies of successful countries more likely to be imitated?" For instance, in his dyadic study of the diffusion of Children's Health Insurance Programs in the U.S., Volden (2006) found that the policies of states that managed to increase the number of insured children, which is a measure of success, were more likely to be adopted elsewhere. Spatial methods can do the same if an indicator of success is used as weight in the spatial lags, but the evidence is more indirect, since spatial lags are averages, that is, aggregated measures of the experience of others. The same logic holds for indicators of the relationship between country_i and country_j, such as geographic proximity or trade patterns.

In my own application of the dyadic approach, I asked whether all policy makers are equally likely to learn, and, to the extent that they do, what they learn about (Gilardi, 2008). First, ideology and prior beliefs regarding the consequences of policy change filter the impact of new information. For instance, right-wing politicians who firmly believe that generous unemployment benefits prevent the labor market from working smoothly will not change their minds easily when confronted with conflicting evidence. By contrast, more moderate policy makers will be more likely to revise their beliefs if new information shows that generous benefits are not associated with high unemployment rates. Second, policy makers certainly care about the policy consequences of reforms (in this example, the unemployment rate), but they are also likely to be concerned about the political fallout. What are the electoral consequences of cutting benefits? Is it compatible with political survival?

The dyadic analysis of 18 OECD countries over 23 years (therefore 18 * (18-1) = 306 dyads and 306*23 = 7038 observations) allowed me to include directly measures of both policy success (measured as change in the unemployment rate) and political success (measured as change in the vote share of the incumbent party) in country_j, as well as a key characteristic of country_i, namely government partisanship. The results show that, as expected, right governments in country_i were more likely to imitate cuts in benefits, but more so if the electoral performance of the incumbent party in country_j was relatively good. By contrast, policy outcomes in country_j were less systematically related to imitation by country_i. These findings suggest that preferences and prior beliefs about the consequences of reforms may lead policy makers to discount information on policy outcomes, while political consequences are taken into account more consistently.

Conclusion

Interdependence and policy diffusion are important social phenomena that have attracted the interest of a growing number of scholars in political science. Spatial models are one quantitative option to analyze policy diffusion processes empirically. This note has briefly presented an alternative, namely the dyadic approach, which takes pairs of countries as units of analysis and asks whether certain theoretically interesting characteristics of the dyad (that is, measures of learning, competition, and emulation) make it more likely that one country takes up the policies of the other. This approach is not unproblematic and, as with any method, unreflective use is to be avoided. However, careful applications can lead to a more direct mea-surement of policy diffusion processes and a better understanding of the mechanisms through which policies spread within and across countries.

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Which Table Should We Take? A Comment On Loeber, On Conceptualisations And Methodologies Of Policy Learning

The C&M Newsletter 1/2007 featured an article of mine on methodological problems of the concept of policy(-oriented) learning (Biegelbauer 2007a) and a response by Loeber in its 1/2008 edition (Loeber 2008). The IPSA Committee on Concepts and Methods, in this case through its Newsletter, thereby provided "a forum of debate between methodological schools who otherwise tend to conduct their deliberations on separate tables" (http://www.concepts-methods.org; retrieved 12-11-2008). At social science faculties we teach a lot, but regrettably not what to do when you find the food on two tables equally enticing.

Loeber conjures up an attractive dish on one of the tables by advancing a broader conception of policy learning than I do. The food I prepared on another table consists of a smaller number of ingredients and is more narrowly focused on the methodological problems a number of contributions utilising policy learning approaches are suffering from.[1] I argue that these are stemming from unclear definitions, shaky operationalisations and little discussion of methodological choices (compare also with James and Lodge 2003, Maier et al 2003). In order to make my point on the two pages provided to me by the editors I followed the overwhelming majority of the policy learning literature and concentrated on the decision-finding and -making phases of the heuristic policy cycle. Furthermore I chose not to discuss how knowledge and action relate to one another and left the relation of power and knowledge as a research desideratum. Loeber challenged me on all of these choices.

Not only does Loeber's dish look attractive, she also cuts the cake that comes for dessert (Loeber 2008, 11) in an interesting way that is much more than just decorative. She locates policy learning as part of a broader understanding of the activities of people based on knowledge that continuously is being tested and assessed when actors negotiate their environment in the framework of their daily activities. Thereby she places her understanding of social actors in a school of thought, which has been termed "social/political practices" (for an overview on political practices see Wagenaar/Cook 2003; on social practices see Reckwitz 2003). The theoretical basis of the rather diverse group of practice approaches often is the work of Giddens (1984; also quoted by Loeber), Bourdieu (1977), but also others (compare Schatzki 1997).

Practice approaches have a number of intellectually enticing features, such as the promise to look at the actual activities of people (and less at how they later on rationalise them or at how others interpret all of these activities). This includes the often ignored daily routines that are structuring our lives and are significant for the ways in which we are dealing with our environments (Wagenaar 2004, Amin/Roberts 2008). What makes practice approaches so interesting for research on policy learning is that one of the defining features of social and political practices is that they are based on a sort of practical knowledge developed and enacted in the doings of actors (Cook/Brown 1999). In the case of policies (but also politics) this means that all practices leading to a policy are indeed based on practical knowledge and are subject to ongoing learning processes, regardless if carried out by relatively speaking powerful or powerless actors, by politicians debating, by civil servants drafting, by journalists writing about or students protesting against a new law proposal.

By making use of the idea of practical knowledge learning becomes the basis of political practices quite naturally and is much more inclusive than is the case for much of the research on policy learning until now. This places the researcher interested in policy learning into an advantageous position, as appropriately described by Loeber. Not only come all political practices by all actors

1 A broader overview on policy learning was published in fall of 2007 (Biegelbauer 2007b).

into the focus adding to our understanding of the relation between knowledge and action, but also the other parts of the heuristic policy cycle command our attention now. After all what difference does it make if political practices based on practical knowledge are changed in the agenda setting, policy making or implementation phases? Thereby also our opportunities to observe policy learning are multiplying in comparison to much of the literature on the topic that is focusing on the policy design phases (as still does most of the policy analysis research, Loeber's comments on Majone and Wildavsky's work aside - regrettably I should say).

Having praised Loeber's take on policy learning I am still tempted to switch tables every now and then. As I have pointed out, on the one hand I do believe that practice approaches are highly interesting and hold a number of promises. Yet some of these promises still have to be realised as the work on social and political practices is at times still quite elusive and sometimes uses concepts focussing on very specific practices. From a position of sympathy[2] I dare to say that this is an innovative school of thought in which a lot of work is waiting to be done in terms of spelling out more completely what social and political practices are and what their explanatory value for social action is.

On the other hand I think that cognitive approaches to policy learning are interesting, too. I agree with Loeber that it is also important that we do not forget the lessons of constructivism regarding the way we interpret the world not on the basis of some objective truth that is “somewhere out there, just waiting for us”, but rather on the basis of our own beliefs about the world - and, in the case of policy communities or subsystems, on the basis of whole belief systems (Sabatier/Jenkins-Smith 1999). Loeber is also right in emphasising that the framing of policies should be factored into an attempt to understand policy learning as it does make a difference what the actual context of a policy is and how the policy relates to the context (Rein/Schön 1994). But there is no reason why the role of attitudes, policy ideas and worldviews as well as framing and meaning-making should have no place in research on policy learning based on a cognitive view.

Moreover I would like to defend the focus on policy design chosen for my article in the Newsletter and by much of the research on policy learning.[3] For reasons of research pragmatism it is often enough the only sensible choice as there is more information on this policy phase than on any other. Decision-finding and decision-making are in the limelight of public discussion and therefore reflected in newspaper and journal articles, TV discussions, books and other potential research material. Researchers utilising an approach such as policy learning which focuses on developments taking place in policy-making over a decade or so (Sabatier/Jenkins-Smith 1999, Bandelow 2003) typically will not be able to rely only on their own original research results, but they often enough will have to use whatever material is available.

A key point for Loeber is the effort to provide insights into the relation between power and knowledge. Indeed she is right that, similar to much literature on policy learning, I left this issue as a research desideratum. Of course the same could be said about many practice approaches, which shy away from dealing with the issue of power (Schatzki 1997, Reckwitz 2003), albeit not all (Hörning 2001). Other interpretative schools of thought have less of a problem with including power as an important category in theory-building. An example is discourse analysis, many proponents of which are building upon the work of Foucault (1980), who understood power as a multidimensional relational concept, with power ubiquitously saturating all social spheres and relations (Hajer 2003, Gottweis 2003).

A final point Loeber takes up in her article is the question of who the subjects of learning are: who does the learning? I am not dealing with that issue in my Newsletter article, although it concerns me in my research on policy learning, in which frequently civil servants play the main role and not politicians (for example Biegelbauer 2007c, Biegelbauer/Mayer 2008). To me there seems to be a tendency in the application of cognitive approaches in research on policy learning to concentrate on the role of individuals. Once again I agree with Loeber, when she states that it is important to understand learning as a social activity, which by definition cannot be carried out by a single person alone. On the same token it is possible to focus on social learning taking place on the level of a policy field, on the organisations and groups of which a policy field consists, or on the individuals, who ultimately are making up organisations and groups. Depending on the level of analysis chosen different insights into mechanisms of policy learning are possible, as are exemplified by the difference between the practical-minded work of Rose (2005), the more academic and theory-driven research of Sabatier/Jenkins-Smith (1999) and the community management-oriented “communities of practice” approach by Wenger (1998). Undoubtedly our understanding of the role of learning in policy-making has increased with the application of each of these theoretical lenses on policies.

In order to find our place in the community/ies in the social sciences we are sometimes expected to find only one sort of foodstuff palatable, quantitative or qualitative, mainstream or interpretive, positivist or constructivist. For the time being I will go on switching tables, catering to my research interests at will. It seems to me that the choosing of different tables every now and then makes my life as a researcher more interesting.

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2 Stemming amongst other things from the fact that I am currently co-editing with Dirk Jörke from Greifswald University a volume of the Austrian Political Science Journal on political practices (Österreichische Zeitschrift für Politikwissenschaft 01/2009).

3 I was lucky enough to find rich material for my own case studies on policy learning and did not have to restrain myself to the policy design phase (see, for example, Biegelbauer 2007c; Biegelbauer/Mayer forthcoming).

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The Committee on Concepts and Methods (C&M) of the International Political Science Association and the Centro de Investigación y Docencia Económicas (CIDE) in Mexico City invite submissions to the third tri-annual Award for Conceptual Innovation in Comparative Politics.

The award is given every three years at the World Congress of the International Political Science Association (IPSA)

2003 Award

The first was awarded in 2003 to Gerardo L. Munck (University of Southern California) and Jay Verkuilen (University of Illinois at Urbana-Champaign) for their article „Conceptualizing and Measuring Democracy: Evaluating Alternative Indices," published in Comparative Political Studies, Vol. 35, No. 1, February 2002, pp. 5-34.

2006 Award

The 2006 Award for Conceptual Innovation in Democratic Studies was granted to James L Gibson, Sidney W. Souers Professor of Government at Washington University in St. Louis, for his book Overcoming Apartheid. Can Truth Reconcile a Divided Nation? (New York: Russell Sage Foundation, 2004).

The third award will be given at the 2009 IPSA World Congress in Santiago de Chile.

CRITERIA

The III CIDE-C&M award will be given to a scholarly work published any time between 1 January 2006 and 31 December 2008.

Any category of formal publication may be submitted, whether it is a book, book chapter, or journal article.

The idea of „conceptual innovation" is to be understood broadly. It is intended to cover concept analysis and concept formation as well as operationalization and measurement.

While the first two IPSA C&M and CIDE awards sought to recognize innovative work in the more narrow field of „democratic studies," the award is now targeting conceptual innovation in the broader field of comparative politics.

SUBMISSIONS

Submissions are open to authors, journal editors, and book publishers. Jury members, too, may suggest candidates.

We encourage self-nominations. When submitting the work of others, please make sure you have obtained the express consent of the author.

Board members of the Committee on Concepts and Methods are banned from participation.

Submissions must include:

- four copies of the work you submit,
- mailing address, phone, fax, and e-mail of the author, and
- mailing address, phone, fax, and e-mail of the person who submits (if different from author).

Please, submit nominations by mail to:

Andreas Schedler
C&M Vice-Chair
CIDE
Centro de Investigación y Docencia Económicas
Department of Political Studies
Carretera México Toluca 3655
Col. Lomas de Santa Fé
Del. Alvaro Obregón
CP 01210 Mexico City
Mexico

All submissions must reach us before 31 December 2008.

JURY

For each award, the Committee on Concepts and Methods nominates a jury composed of three distinguished scholars in field of comparative politics.

The 2009 jury will be formed by James L. Gibson (Washington University in St. Louis), winner of the previous award and chairperson of the jury, John Gerring (Boston University), and Mark Bevir (University of California at Berkeley).

The jury will seek consensual decisions. In case of disagreement, it will rule by majority. Jury decisions are final.

PRICE MONEY

The winner of the price will be awarded 1.500 USD (one thousand five hundred US Dollars). At the jury's discretion, the price is divisible between various winners.

ABOUT C&M

The IPSA Committee on Concepts and Methods (C&M)

The IPSA COMMITTEE ON CONCEPTS AND METHODS (C&M) promotes conceptual and methodological discussion in political science. It provides a forum of debate between methodological schools who otherwise tend to conduct their deliberations on separate tables. It grants the tri-annual "Award for Conceptual Innovation in Democratic Studies," publishes two series of working papers, "Political Concepts" and "Political Methods," and coordinates "Les Intraduisibles: The Dictionary of Untranslatable Terms in Politics".

Chairperson: Andreas Schedler (CIDE, Mexico City), www.concepts-methods.org

Concepts and Methods

Concepts and Methods is the newsletter of the IPSA COMMITTEE ON CONCEPTS AND METHODS (C&M). Its aim is to support discussion and exchange among scholars on conceptual and methodological issues in the social sciences, with a special emphasis on political science. The newsletter is published three times a year and is available in pdf format free of charge after subscription: www.concepts-methods.org/join.php
Free download: www.concepts-methods.org

Chief editor: Bernhard Kittel (Carl von Ossietzky Universität Oldenburg) Editorial team: Rüya Gökhan Koçer, Gerben Korthouwer, Katharina Paul, Nynke Wiekenkamp (all University of Amsterdam www.uva.nl), and Damian Raess (Harvard University)

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Contributions do neither represent the official position of the editorial team nor that of the IPSA COMMITTEE ON CONCEPTS AND METHODS. As an open and plural forum of debate, Concepts and Methods welcomes various kinds of contributions to methodological and conceptual debate: essays, research notes, interviews, data base, literature and book reviews, as well as proposals for thematic issues. All submissions will be carefully considered by the editorial team. For advertisments please contact the editorial team.

Contact: msw@uni-oldenburg.de

C&M working papers

The C&M working paper series are published by the COMMITTEE ON CONCEPTS AND METHODS (C&M), the Research Committee No. 1 of the INTERNATIONAL POLITICAL SCIENCE ASSOCIATION (IPSA), hosted at CIDE in Mexico City. C&M working papers are meant to share work in progress in a timely way before formal publication. The Committee publishes two series of working papers:

Political Concepts contains work of excellence on political concepts and political language. It seeks to include innovative contributions to concept analysis, language usage, concept operationalization, and measurement.

Political Methodology contains work of excellence on methods and methodology in the study of politics. It invites innovative work on fundamental questions of research design, the construction and evaluation of empirical evidence, theory building and theory testing. The series welcomes, and hopes to foster, contributions that cut across conventional methodological divides, as between quantitative and qualitative methods, or between interpretative and observational approaches.

SUBMISSIONS

All papers are subject to review by either a member of the Editorial Board or an external reviewer. Only English-language papers can be admitted. Authors interested in including their work in the C&M Working Paper Series may seek initial endorsement by one editorial board member: www.concepts-methods.org. Alternatively, they may send their paper by e-mail to: workingpapers@concepts-methods.org.

ACCESS

The C&M webpage offers full access to past working papers as well as to commentaries by readers: www.concepts-methods.org

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