The m-STAR Model as an Approach to Modeled, Dynamic, Endogenous Interdependence in Comparative & International Political Economy*

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

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

Aya Kachi
Doctoral Candidate, Department of Political Science
University of Illinois, Urbana-Champaign
akachi2@illinois.edu

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ABSTRACT: Even casual observation reveals obvious spatial patterns in labor-market outcomes and policies across the developed democracies, and within the European Union particularly. Labor-market policies entail significant cross-border spillovers, so strategic interdependence among developed democracies might explain this. However, these countries also faced common or very similar exogenous-external conditions and internal trends, which would also tend to generate spatial patterns in the domestic responses thereto, even without any interdependence. Likewise, membership in the EU itself presents both a series of common external stimuli and a set of strategic interdependencies in common and individual-country labor-market-relevant actions. Additionally, however, labor-market policies will themselves shape the patterns of economic interchange by which some of the interdependencies arise, and entry into the European Union typically presupposes a certain baseline set of shared national characteristics and orientations, raising the possibility that labor-market policies and the pattern of interdependence via institutional co-membership have common origin. That is, the policies of interest may also shape the patterns of connectivity affecting those outcomes, a complex sort of endogeneity known as *selection* in the dynamic networks literature. We have discussed elsewhere the severe empirical-methodological challenges in distinguishing the first two of these possible sources of spatial correlation (Galton's Problem). This paper extends those analyses, applying the *multiparametric spatiotemporal autoregressive* (m-STAR) model as a simple approach to modeling the patterns of interdependence simultaneously with its effects, while recognizing their possible endogeneity (i.e., *selection*). We do so in an empirical application attempting to disentangle the roles of economic interdependence, correlated external and internal stimuli, and EU membership in shaping labor-market policies in recent years.

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I. Introduction

At the Lisbon Summit in March 2000, the EU committed to becoming "the most competitive and dynamic knowledge-based economy in the world by 2010" (European Council 2000:1). Active-labor-market (ALM) policies are a critical part of the plan designed to achieve this objective, the European Employment Strategy (EES). ALM programs aim to improve job seekers' prospects of finding employment and increase the productivity and earning potential of workers. They include spending on public employment, job search assistance, labor market training, and other policies intended to promote employment among the unemployed. While ALM policies—particularly training and education programs—seem almost inherently necessary to create the kind of workforce and economy EU leaders envisage, coordinating these policies through an EES system that relies heavily on the principle of subsidiarity may be problematic. Subsidiarity in the EES means that member states create their own programs and implement them on a mostly voluntary basis, yet individualistic voluntarism leaves policy susceptible to underinvestment due to positive externalities. Has this theoretically possible negative interdependence of European ALM policies actually arisen empirically? If so, are these spillovers and the detrimental interdependence they induce sufficiently sizable to warrant concern and redress?

Building on earlier work (Franzese & Hays 2006b), we argue and present evidence that ALM policies do indeed entail significant externalities that spill across national boundaries and that these spillovers are, apparently, sufficiently sizable to generate appreciable political and economic incentives for European governments to free ride off the efforts of their neighbors. That is, we provide empirical evidence that, on net, the national best-response functions for ALM spending are statistically significantly and substantively appreciably downward sloping: increases in expenditures in one country decrease equilibrium expenditures in most of its neighbors. This leads us to conclude that current levels of ALM expenditures may indeed be too low and that, apparently, the limited (although increasing) coordination of the EES framework is insufficient to internalize positive ALM policy externalities noticeably. Stronger enforcement procedures would seem to be necessary if the European Union is to achieve its EES objectives.

The paper structures these explorations as follows.[1] In the next section, we review the generic theory of strategic policy complementarity and substitutability (positive and negative externalities, respectively). Section three briefly summarizes our previous work and results (Franzese & Hays 2003, 2004, 2006ab, 2007abcd, 2008ab) regarding the specification, estimation, interpretation, and presentation of spatial autoregressive (SAR) and spatiotemporal autoregressive (STAR) empirical models. That work highlighted especially Galton's Problem of distinguishing spatial correlation due to interdependence such from correlation arising from common or correlated exogenous internal or external stimuli. Of first-order importance in drawing such distinctions, we showed, was the relative and absolute empirical accuracy and power with which the model specification reflects the patterns of interdependence on one hand and the exogenous internal and external stimuli on the other. This leads naturally to the extensions offered here, elaborated in section four, of parameterizing and estimating the patterns of interdependence. We suggest an application and interpretation of the multiparametric spatiotemporal autoregressive (m-STAR) model as a simple means of doing this and, with the assumption that temporal precedence entails causal precedence, also of endogenizing the pattern of interdependence dynamically to the outcome-variable of the model (here: ALM policy). Section five contains our illustrative empirical analysis following such a strategy, and section five discusses those results and proffers some (highly) preliminary conclusions.

II. Race-to-the-Bottom Dynamics and Policy Free Riding

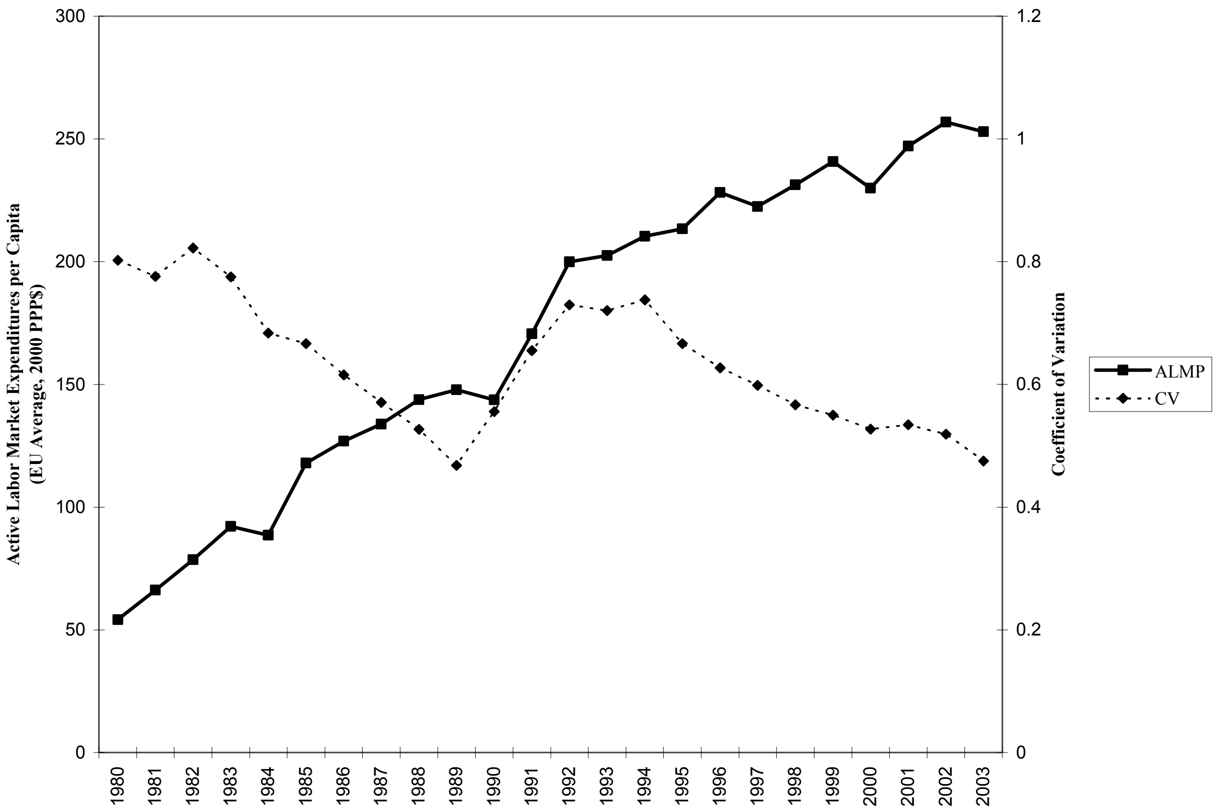
[1] Franzese & Hays (2006b) review the history of the EES starting with the Luxembourg Jobs Summit.

We begin by asking how EU member governments have actually fared in the provision of ALM policies. From a longer historical perspective (1980-2003), the trend looks geneally positive. On average, aggregate ALM expenditures have increased among the EU member states, and, at the same time, the standardized variance (i.e., the coefficient of variation) in spending across countries has decreased (see Figure 1). In 1980, the average total spending on ALM programs among EU member states barely exceeded $54 (2000, PPP$) per capita. By 2003, average spending was almost $253, an increase of roughly 370%.[2] The coefficient of variation (standard deviation) in spending on ALM programs dropped (rose) from .80 (43.5) to .47 (120.1) over the same period. One might see a "*race-to-the-top*" in these trends and be tempted to infer that EU employment-policy coordination has been relatively successful. However, the consensus is that, excepting Scandinavia, EU members lag in designing and implementing policies to upgrade the skills of their workers.[3] According to this view, despite the trends in Figure 1, spending could and should be much higher. If ALM-program spending among EU member states is, in fact, suboptimal, strategic interdependence in the making of active-labor-market policies could explain why. Two kinds of interactions in particular, *race-to-the-bottom* dynamics and *policy free-riding*, would induce suboptimal expenditures on employment policies.

[2] In the post-Lisbon period (1997-2003), average annual per capita ALM spending increased $30.44 (2000, PPP$).

[3] The 2004 Joint Economic Report asked six of the original fifteen members to strengthen their ALM policies. Five of the six later received a C-grade for their response (partial and limited). One received a B (in progress). The Council asked every member country to improve its investment in human capital in one or more ways. The modal response of member governments to these recommendations was "partial and limited" (European Commission, 2005). See Murray and Wanlin (2005) for another disappointing report card.

Figure 1. Aggregate Active Labor Market Expenditures in the *EU*, 1980-2003



In theory, race-to-the-bottom (RTB) dynamics occur when policies are strategic complements across jurisdictions—i.e., when policy changes adopted in one jurisdiction create incentives for other jurisdictions to adopt similar changes. The RTB argument has been applied *inter alia* to capital taxation, environmental regulations, and labor standards. Cuts in taxes and elimination or reduction of regulations and standards in one jurisdiction increase the costs to others of maintaining high taxes, regulations, and standards causing, the effected jurisdictions to follow suit in their own policies. By contrast, free riding occurs when policies are strategic substitutes—i.e., when policy changes in one jurisdiction create incentives for others to adopt change in the opposite direction. For example, an increase in defense expenditures in one country may lower the marginal security benefit of defense spending in its military allies, creating an incentive for them to free ride (see Redoano, 2003).

More formally, consider a two-country world (i,j), each with homogenous populations and domestic welfare that, due to externalities, are a function of government policy in both countries:

$$W^i \equiv W^i(p_i, p_j) \;\; ; \;\; W^j \equiv W^j(p_j, p_i) \qquad (1).$$

When the government in country *i* chooses its policy, p_i, to maximize its own social welfare, this affects the optimal policy-choice in country *j*, and *vice versa*. We can express such *strategic interdependence* between countries *i* and *j* with a pair of *best-response functions*, giving optimal policies of *i*, p_i^*, as a function of the policy chosen in *j*, and *vice versa*:

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

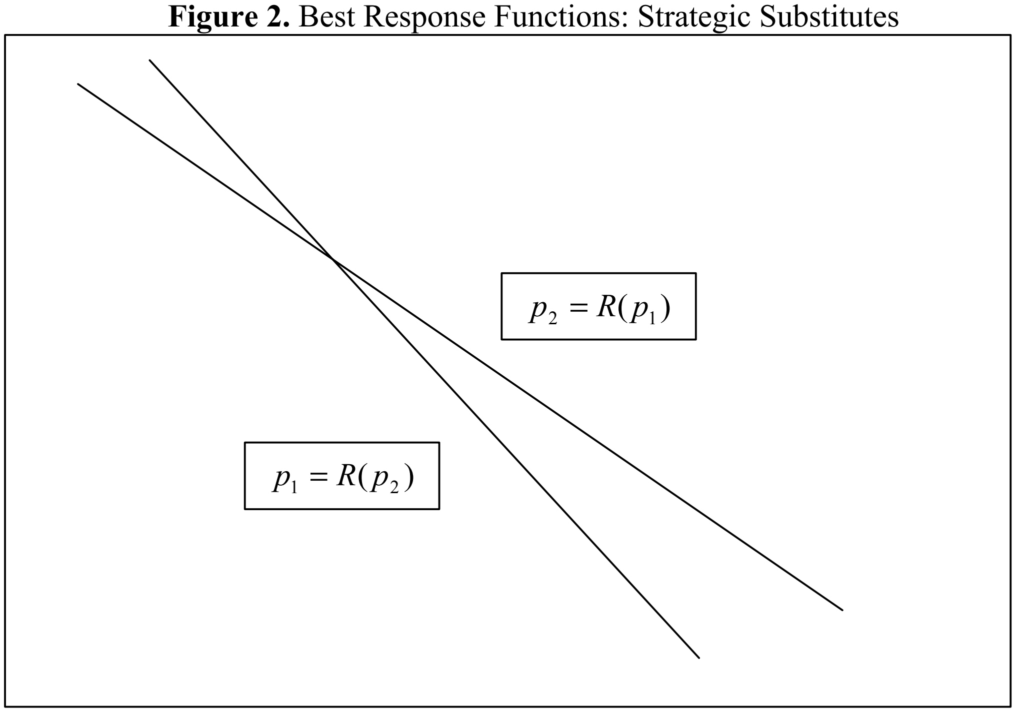
Explicitly, country *i*'s optimum policy is obtained by maximizing $W^i(p_i, p_j)$ with respect to p_i, taking p_j as given (fixed); i.e., setting the first derivative of the welfare function with respect to p_i equal to zero and solving for p_i^* as a function of p_j (and then verifying that the second derivative is negative). Equation (2) expresses the result as the best-response function $p_i^* = R(p_j)$. The slopes of these best-response functions, the signs of which determine whether RTB or free-riding dynamics will occur, depend on the following ratios of second cross-partial derivatives:

$$\frac{\partial p_i^*}{\partial p_j} = -W^i{}_{p_i p_j} / W^i{}_{p_i p_i} \;\; ; \;\; \frac{\partial p_j^*}{\partial p_i} = -W^j{}_{p_j p_i} / W^j{}_{p_j p_j} \qquad (3).$$

If governments are welfare maximizing, the second order condition guarantees the denominators in (3) are negative. Therefore, the slopes will depend directly on the signs of the second cross-partial derivatives (i.e. the numerator). If $W^{i,j}_{p_i p_j} > 0$, policies are strategic complements, and we see from (3) that policy reaction-functions will slope upward. If $W^{i,j}_{p_i p_j} < 0$, policies are strategic substitutes, and the reaction functions slope downward. If the second cross-partial derivative is zero, strategic interdependence does not materialize and the best-response functions are flat (Brueckner, 2003).

Notice that *positive* externalities induce strategic-*substitute* policy-interdependence, and *negative* externalities induce strategic-*complement* policy-interdependence (and lack of externalities yields policy-independence). In the national-defense example discussed above, spending in one country induces free riding in others due to the positive security externalities (among allies) and diminishing returns of military expenditures. If ALM expenditures create positive employment externalities and exhibit diminishing returns, the same problem could arise in this context. In other words, if reducing unemployment requires increasing amounts of spending—e.g., \$1000 per worker to reduce unemployment from 6% to 5%, \$2000 to reduce from 5% to 4%, \$4000 to reduce from 4% to 3%, etc.—and if ALM spending in one country, *i*, helps reduce unemployment in another, *j*, an increase in expenditures in country *i* will reduce the marginal benefit to *j*'s of its (marginal increment of) spending, inducing lower equilibrium spending in *j*. Figure 2 illustrates this situation graphically. This strategic context also creates a first-mover disadvantage—the country that spends first will bear a larger portion of the cost of reducing unemployment—and thus the potential for war-of-attrition dynamics that would delay and push the equilibrium ALM spending of both countries even lower.

Figure 2. Best Response Functions: Strategic Substitutes



Do cross-border positive employment externalities of ALM policies exist among EU countries; and if so are they sufficient to induce this kind of fiscal free-riding in ALM policy? On balance, the evidence suggests that ALM policies may have increased employment in Europe and other OECD countries (see, e.g., Martin 2000; Martin & Grubb 2001; European Commission 2005). A consensus based on micro-level research finds ALM-program participants benefit from an increased probability of employment. In the language of this literature, the average treatment effect among the treated is a positive increase in the probability of employment (Heckman et al. 1999). A weakness of the micro-level research is that it reveals nothing about the effects of ALM programs on non-participants, so saying anything based on these studies about the net employment consequences is impossible. Only aggregate data can clearly exhibit net effects, and much less agreement characterizes studies of the macro-level employment effects of ALM programs implemented on large scales. Several studies find sizeable displacement rates, particularly for subsidized employment programs (e.g., Forslund & Krueger 1997, Calmfors et al., 2001, Dahlberg and Forslund 2005), whereas others find much more positive direct employment effects (Kraft 1998, Estevao 2003). Perhaps the strongest evidence for beneficial ALM policies appears in their mediating influence on adverse macroeconomic shocks. In a seminal paper on the interaction of shocks and institutions in determining employment outcomes, Blanchard and Wolfers (2000) estimate that an adverse shock that would reduce employment by 1% at the sample-mean level of ALM-program expenditures reduces employment by just 0.2% at the sample-maximum level of ALM spending.

That ALM spending would exhibit diminishing returns also seems reasonable. For instance, if labor-market training-programs increase employment by raising workers' marginal productivity, then, in any given macroeconomic conditions, some workers will just miss being employed because their marginal productivity was just below a threshold beyond which firms find hiring them profitable and some whose productivity was far below this threshold. In this case, a little spending might get the first group of workers hired, but much more spending per worker would be required to get members of the less-productive second group employed. If unemployed low- and high-productivity workers are spatially concentrated in regions that span national boundaries, this could create incentives for fiscal free riding. Below, we describe several other mechanisms by which such cross-border spillovers may arise.

A large literature examines the regional patterns of unemployment in Europe (see, e.g., Elhorst, 2003; Puga, 2002; Overman & Puga, 2002). This research shows that, in many cases, differences in employment between bordering regions are much smaller, even if the regions lie in different countries, than the differences between more distant regions within countries. In other words, geographic proximity is more important than nationality in understanding spatial patterns of unemployment in Europe. Labor-market performance in Languedoc-Roussillion in southern France on the Mediterranean, for example, is likely to resemble much more closely that in Cataluna in northeastern Spain than that in Paris. Similarly, employment outcomes in Nord-Pas-de-Calais on the French border with Belgium correlate highly with those in Region Wallonne across the border than with employment patterns in the center of France.[4]

Consider the implications of (effective) French ALM spending for Belgium, for example. Effective French ALM policies enhance Belgian workers' abilities to obtain training in France, and return, more employable, to work in Belgium. Effective French ALM policies also enhance Belgian workers' abilities to find work in France. Effective French ALM policies also enhance the pool of workers (quantity, quality, and diversity) available to employers along the Franco-Belgian border,

[4] Overman & Puga (2002) attribute the growing importance of spatial proximity to changes in the demand for labor. They identify, test, and find empirical support for three sources of demand change over the period 1986-96: the regional concentration of skilled and unskilled labor, the spatial clustering of industries, and what they term *agglomeration effects*. The examples given next in the text illustrate all of these sources.

thereby luring employers to both sides. Finally, effective French ALM policies stimulate the French economy, which, through trade, has positive effects on Belgium's economy. These and other *agglomeration effects* all yield positive externalities of (effective) French ALM policies to Belgian workers (and citizens more generally). Notice, too, that only the first two of these require any cross-national labor mobility, which is notoriously low in Europe, even across common-language borders. Notably, Overman & Puga (2002) find the latter two heavily predominate as sources of the spatial correlation in employment patterns they observed. Of course, Belgians cannot provide political support to French policymakers in response to these spillover effects, so French policymakers ignore these spillover benefits in determining French ALM spending. Accordingly, ALM spending by national policymakers will exhibit negative interdependence, reflecting the positive externalities.

In sum, given what we know about spatial patterns of unemployment in Europe and about the employment effects of ALM policies, fiscal free-riding seems plausible. In our empirical application, we examine the comparative-historical record to gauge the evidence of its existence and magnitude.

III. Spatiotemporal Models of Interdependence: Specification, Estimation, & Interpretation

Analyses that recognize the *interdependence* across units of outcomes —in our case: of ALM policies—must specify empirical models in which outcomes in units *i* and *j* affect each other. We have suggested elsewhere (Franzese & Hays 2004, 2006a, 2007bc, 2008ab), the following generic model of modern, open-economy, context-conditional political-economy with such features:

$$y_{it} = \rho \sum_{j \neq i} w_{ij} y_{jt} + \phi y_{i,t-1} + \boldsymbol{\beta}'_d \mathbf{d}_{it} + \boldsymbol{\beta}'_s \mathbf{s}_t + \boldsymbol{\beta}'_{sd} \left(\mathbf{d}_{it} \otimes \mathbf{s}_t \right) + \varepsilon_{it} \tag{4}$$

where y_{jt} is the outcome in another ($j \neq i$) unit, which in some manner (given by ρw_{ij}) directly affects the outcome in unit *i*. Notice that w_{ij} reflects the *relative degree* of connection from *j* to *i*, and ρ reflects the overall *strength of dependence* of the outcome in *i* on the outcomes in the other ($j \neq i$) spatial units, as weighted by w_{ij}. Substantively for ALM-policy interdependence, for example, the

w_{ij}, could gauge the sizes, geographic contiguity, and/or EU comembership of, and/or the goods or capital trade between *i*'s and *j*'s political economies. The other right-hand-side elements reflect the non-spatial components: unit-level/domestic factors $\mathbf{d}_{it}$ (e.g., government partisanship, election-year indicators), exogenous-external/contextual factors $\mathbf{s}_{it}$ (e.g., oil prices, technology, wars), and context-conditional factors $\mathbf{d}_{it} \otimes \mathbf{s}_t$ (i.e., interactions of the former with the latter).

Distinguishing these spatial (or network) interdependence and non-interdependence sources of spatial correlation is the essence of *Galton's Problem*.[5] A third potential source of spatial correlation, to be introduced later, is that the relative connectivity from *j* to *i*, that is, the w_{ij}, may depend on the outcome(s) in *i* (and/or *j*).[6] As we summarize below (from Franzese & Hays 2004, 2006a, 2007bc, 2008b), obtaining *good* (unbiased, consistent, and efficient) estimates of coefficients and standard errors in such models—more generally, distinguishing open-economy, possibly context-conditional, comparative political economy (CPE) from interdependence (comparative and international political economy: C&IPE) empirically—by any methodological means, including qualitative methods—is *not* straightforward.[7] The first and prime consideration in weighing these alternatives and estimating

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

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

[7] Some might suggest starting with nonspatial models and adding spatial components as the data demand, but tests that can distinguish spatial interdependence from other potential sources of spatial correlation in residuals from non-spatial models are lacking and/or weak (Anselin 2006; Franzese & Hays 2008b).

the role of the corresponding components in (4) are the relative and absolute theoretical and empirical precision and explanatory power of the spatial and non-spatial parts of the model, i.e., of the *interdependence* part and the *common, correlated, or context-conditional responses to common or correlated exogenous-external factors* (henceforth: the *common-shocks*) part. To elaborate: the relative and absolute accuracy and power with which the spatial-lag weights, w_{ij}, reflect and can gain leverage upon the *interdependence* mechanisms actually operating and with which the domestic, exogenous-external, and/or context-conditional parts of the model reflect and can gain leverage upon the true *common-shocks* alternatives critically affect the empirical attempt to distinguish and evaluate their relative strength. The two mechanisms produce similar effects, so inadequacies or omissions in specifying the one tend, intuitively, to induce overestimates of the other's importance.

Secondarily,[8] even with *common-shocks* and *interdependence* mechanisms modeled perfectly, the spatial-lag regressors(s) will be endogenous (i.e., technically, will covary with the residuals), so estimates of ρ (or, equally, qualitative attempts to distinguish interdependence from common shocks) will suffer simultaneity biases. Furthermore, as with the primary concerns of (relative) omitted-variable or misspecification bias, these simultaneity biases in estimated strength of interdependence (usually overestimation) generally induce biases in the opposite direction (usually under-estimation) regarding the importance of common shocks. Thus, researchers who emphasize unit-level/domestic, exogenous-external, or context-conditional processes to the exclusion or relative neglect of interdependence mechanisms (micro-level scholars and comparativists?) will typically be biased in their empirical analyses toward results favoring the former and handicapping the latter sorts of explanations. Conversely, those who stress interdependence to the relative under-specification of

[8] Simulations in Franzese & Hays (2004, 1006a, 2007bc, 2008b) show the omitted-variable/relative-misspecification biases related to neglecting interdependence generally far exceed the simultaneity biases of failing to redress adequately the endogeneity of spatial lags, although the latter becomes appreciable as interdependence grows stronger (e.g., beyond $\rho \approx .3$ for row-standardized $\mathbf{W}$).

domestic/unit-level and exogenous-contextual considerations or who fail to account sufficiently the endogeneity of spatial lags (macro-level and international-relations scholars?) will generally offer empirical analyses biased in the opposite directions, pro-interdependence and anti-common-shock.

Most empirical studies in C&IPE where interdependence may arise, notably the policy diffusion and the globalization, tax-competition, and policy-autonomy literatures, analyze panel or time-series-cross-section (TSCS) data (i.e., observations on units over time). To estimate effects and draw sound causal inferences in such contexts, analysts should specify both temporal and spatial interdependence in their models.[9] The easiest and most straightforward way to incorporate this interdependence is with a spatiotemporal lag model, which we can write as an extension of (4) in matrix notation as:

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \phi\mathbf{M}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{5}$$

where $\mathbf{y}$, the dependent variable, is an $NT \times 1$ vector of cross sections stacked by periods (i.e., the N units' first-period observations, then their second-period ones, and so on to the N period-T ones).[10] ρ is the previously described spatial autoregressive coefficient, and $\mathbf{W}$ is an $NT{\times}NT$ block-diagonal spatial-weighting matrix.[11] If the pattern of connectivity is time-invariance, then this $\mathbf{W}$ matrix can be

[9] Methodologically, two approaches to spatial analysis can be discerned: spatial statistics and spatial econometrics. The distinction, according to Anselin (2002, 2006), lies on the one side in (1) the relative emphasis in spatial econometrics to theoretical models of interdependence processes, (2) wherein space may often have broad meaning, well beyond geography and geometry to encompass all manner of social, economic, or political connection that induces effects from outcomes in some units on outcomes in others (Brueckner 2003; Beck et al. 2006). (3) The spatial-lag regression model plays a starring role in that tradition (Hordijk 1974; Paelinck/Klaassen 1979; Anselin 1980, 1988, 1992; LeSage 1999). In this approach to model specification and estimation, (4) Wald tests of the unrestricted spatial-lag model (top-down) are the main tools and strategy for gauging the importance of spatial interdependence. On the other side, (1) spatial-error models, analysis of spatial-correlation patterns, spatial kriging, and spatial smoothing, e.g., characterize the (2) more-exclusively data-driven spatial-statistics approach, and the (3) typically narrower conception of space in solely geographic/geometric terms in its longer tradition (inspired by Sir Galton's famous comments at the 1888 meetings of the Royal Anthropological Society, and reaching crucial methodological milestones in Whittle 1954; Cliff/Ord 1973, 1981; Besag 1974; Ord 1975; Ripley 1981; Haining 1990; Cressie 1993). (2) Data problems such as measurement error tend to drive spatial analysis in this approach, with spatial correlation often viewed as a *nuisance*. In this approach to model specification and estimation, (4) Lagrange multiplier tests of the restricted non-spatial lag model (bottom-up) are the main tools and strategy.

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

[11] The connectivity matrix is block-diagonal assuming no cross-temporal spatial interdependence. Non-zero off-diagonal elements are possible and manageable, but perhaps unlikely controlling for contemporaneous spatial-lags and time-lags.

expressed as the Kronecker product of a $T\times T$ identity matrix and the constant $N\times N$ weights matrix $\left(\mathbf{I}_T \otimes \mathbf{W}_N\right)$, with the elements w_{ij} of $\mathbf{W}_N$ reflecting the relative connectivity from unit *j* to *i*. $\mathbf{Wy}$ is the *spatial lag*; i.e., for each observation y_{it}, $\mathbf{Wy}$ gives a weighted sum of the y_{jt}, with weights w_{ij}. Notice how $\mathbf{Wy}$ thus directly and straightforwardly reflects the dependence of each unit *i*'s outcome on unit *j*'s. $\mathbf{M}$ is an $NT\times NT$ matrix with ones on the minor diagonal, i.e., at coordinates $(N+1,1)$, $(N+2,2)$, …, $(NT, NT\text{-}N)$, and zeros elsewhere, making $\mathbf{My}$ is just a (first-order) temporal lag[12] and ϕ the temporal autoregressive coefficient. $\mathbf{X}$ contains NT observations on k independent variables, and $\boldsymbol{\beta}$ is a $k\times 1$ vector of coefficients thereupon. In our generic models, $\mathbf{X}$ would contain columns $\mathbf{d}$, $\mathbf{s}$, and $\mathbf{d}\otimes\mathbf{s}$; i.e., $\mathbf{X}$ is the non-spatial part of the model, reflecting domestic/unit-level, contextual/exogenous-external, and context-conditional factors, i.e., the common shocks. Finally, $\boldsymbol{\varepsilon}$ is an $NT\times 1$ vector of stochastic components, assumed to be independent and identically distributed.[13]

Franzese & Hays (2004, 2006a, 2007bc, 2008b) explored analytically and by simulation the properties of four estimators for such models: non-spatial least-squares (i.e., regression omitting the spatial component as is common in most extant research: OLS), spatial OLS (i.e., OLS estimation of models like (5), common in diffusion studies and becoming so in globalization/tax-competition ones: S-OLS), instrumental variables (e.g., spatial 2SLS or S-2SLS), and spatial maximum-likelihood (S-ML). Both OLS and spatial OLS produce biased and inconsistent estimates, OLS due to the omitted-variable bias and spatial OLS because the spatial lag is endogenous and so induces simultaneity bias.

We can view these biases as reflecting the terms of *Galton's Problem*. On one hand, by omitting the spatial lag that would reflect the true interdependence of the data, OLS coefficient-estimates will suffer omitted-variable biases, the familiar formula for which is $\mathbf{F}\boldsymbol{\beta}$, where $\mathbf{F}$ is the matrix of

[12] Higher-order temporal dynamics would simply add further properly configured weights matrices.

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

coefficients obtained by regressing the omitted on the included variables and $\boldsymbol{\beta}$ is the vector of (true) coefficients on the omitted variables.[14] In this case, the omitted-variable bias (OVB) is:

$$\text{OVB}\left(\begin{bmatrix}\hat{\boldsymbol{\beta}}_{\text{OLS}} & \hat{\phi}_{\text{OLS}}\end{bmatrix}'\right)=\rho\times\left(\mathbf{Q}_1'\mathbf{Q}_1\right)^{-1}\mathbf{Q}_1'\mathbf{Wy},\ \text{where } \mathbf{Q}_1\equiv\begin{bmatrix}\mathbf{X} & \mathbf{My}\end{bmatrix}' \qquad (6).$$

$\hat{\rho}_{\text{OLS}}\equiv 0$, of course, which is biased by $-\rho$. Thus, insofar as the spatial lag covaries with the non-spatial regressors, which is highly likely if domestic conditions correlate spatially and is certain for common exogenous-external shocks and, given non-zero spatial correlation arising by any means, for the time lag, OLS will overestimate domestic, exogenous-external, or context-conditional effects, including the temporal adjustment-rate, while ignoring spatial interdependence. Notice (as Sir Galton did) that this applies equally to qualitative analyses that ignore the interdependence of observed phenomena. On the other hand, including spatial lags in models for OLS estimation (or considering qualitatively the observed correlation of outcomes in some units with those in others or tracing putative diffusion processes) entails an endogeneity and so will suffer simultaneity bias. The spatial lag, $\mathbf{Wy}$, covaries with the residual, $\boldsymbol{\varepsilon}$, making S-OLS estimates inconsistent, because the spatial lag is a weighted average of outcomes in other units, placing the left-hand side of some observations on the right-hand side of others: textbook simultaneity. In simplest terms by example: Germany causes France, but France also causes Germany. The asymptotic simultaneity biases (SB) are:

$$\text{SB}\left(\begin{bmatrix}\hat{\rho} & \hat{\phi} & \hat{\boldsymbol{\beta}}\end{bmatrix}'\right)=\left(\mathbf{Q}'\mathbf{Q}\right)^{-1}\mathbf{Q}'\boldsymbol{\varepsilon},\ \text{where } \mathbf{Q}\equiv\begin{bmatrix}\mathbf{Wy} & \mathbf{My} & \mathbf{X}\end{bmatrix} \qquad (7).$$

In the case where $\mathbf{X}$ contains just one exogenous explanator, $\mathbf{x}$, we can rewrite these biases thus:

$$\text{SB}\begin{pmatrix}\hat{\rho}\\ \hat{\phi}\\ \hat{\beta}\end{pmatrix}=\frac{1}{|\boldsymbol{\Psi}|}\begin{pmatrix}\text{cov}(\mathbf{Wy},\boldsymbol{\varepsilon})\times\text{var}(\mathbf{My})\times\text{var}(\mathbf{x})\\ -\text{cov}(\mathbf{Wy},\boldsymbol{\varepsilon})\times\text{cov}(\mathbf{Wy},\mathbf{My})\times\text{var}(\mathbf{x})\\ -\text{cov}(\mathbf{Wy},\boldsymbol{\varepsilon})\times\text{cov}(\mathbf{Wy},\mathbf{x})\times\text{var}(\mathbf{My})\end{pmatrix},\ \text{where } \boldsymbol{\Psi}=\text{plim}\left(\frac{\mathbf{Q}'\mathbf{Q}}{n}\right) \qquad (8).$$

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

With positive interdependence and positive covariance of spatial-lag and exogenous regressors, a likely common case, one would overestimate the interdependence-strength, $\hat{\rho}$, and correspondingly underestimate temporal dependence, $\hat{\varphi}$, and domestic/external/contextual effects, $\hat{\beta}$.

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

Our simulations (Franzese & Hays 2004, 2006a, 2007bc, 20008b) showed the omitted-variable biases of OLS are almost always worse and often far, far worse than S-OLS' simultaneity biases. In fact, S-OLS may perform adequately for mild interdependence strengths ($\rho \times \Sigma_j w_{ij}$ less than about 0.3), although standard-error accuracy can be problematic, and in a manner for which PCSE (Beck &

Katz 1995, 1996) will not compensate. However, S-OLS' simultaneity biases become more sizable as interdependence grows stronger, rendering the use of a consistent estimator, such as S-2SLS or S-ML, highly advisable. Our analyses indicated that, in bias, efficiency, and standard-error-accuracy terms, the choice of which consistent estimator is of decidedly secondary importance. Since S-ML proved close to weakly dominant across all four estimation strategies,[15] we introduce only it here.[16]

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

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \;\heartsuit\; \boldsymbol{\varepsilon} = \left(\mathbf{I} - \rho\mathbf{W}\right)\mathbf{y} - \mathbf{X}\boldsymbol{\beta} \equiv \mathbf{A}\mathbf{y} - \mathbf{X}\boldsymbol{\beta} \qquad (9),$$

where $\mathbf{X}$ now includes $\mathbf{My}$, the time-lag of $\mathbf{y}$, as its first column, and $\boldsymbol{\beta}$ includes ϕ as its first row.[17] Assuming *i.i.d.* normality, the likelihood function for $\boldsymbol{\varepsilon}$ is then just the typical linear-normal one:

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[15] See especially Franzese & Hays (2007b, 2008b) regarding S-ML estimation; they correct some misleading preliminary conclusions, stemming from a coding error (see note 16), from our earlier work on that estimator. The instrumental-variables (IV), two-stage-least-squares (2SLS), generalized-method-of-moments (GMM) family of estimators relies on the spatial structure of the data to instrument for the endogenous spatial lag. On the assumption that what we call *cross-spatial endogeneity*—y's in some units cause $\mathbf{x}$'s in others—does not exist, instruments comprised of $\mathbf{WX}$ are ideal by construction. Cross-spatial endogeneity may seem highly unlikely in many contexts, perhaps, until one realizes that vertical connections from y_i to $\mathbf{y}_j$ and horizontal ones from $\mathbf{y}_j$ to $\mathbf{x}_j$ (the usual sort of endogeneity) combine to give the offending diagonal ones from y_i to $\mathbf{x}_j$. As usual, there are no magic instruments in empirical analysis. On the other hand, S-GMM should improve upon S-2SLS primary weakness in efficiency, so it may compare more favorably to S-ML. We have not yet explored the possibility, in part due to worries about *cross-spatial endogeneity*.

[16] We use J.P. LeSage's MatLab™ code to estimate our spatial models, having found existing Stata™ code for spatial analysis, third-party contributed *.ado* files, untrustworthy and/or extremely computer-time intensive. We have written Stata™ code, which we believe more reliable and efficient, to implement many of our suggestions. Regarding LeSage's MatLab code, *sar.m*, note that the line of code calling the standard errors from the parameter-estimate variance-covariance matrix must be corrected to reference the proper element for the $\hat{\rho}$ estimate. We have made other adjustments to the code to enhance its operation. We will make all of our code publicly available once we have tested its reliability more thoroughly and made it more generic and user-friendly. Currently, some of our application-specific MatLab™ and Stata™ code, and Excel™ spreadsheets, possibly useful as templates, are available at: http://www-personal.umich.edu/~franzese/FranzeseHays.CPS.InterdependenceCP.TemplateImplementationFiles.zip.

[17] We do this because, in translating the likelihood in terms of $\boldsymbol{\varepsilon}_t$ into terms of $\mathbf{y}_t$, $\mathbf{Wy}$ enters but $\mathbf{My}$ does not.

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

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

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

This resembles the typical linear-normal likelihood, except that the transformation from $\boldsymbol{\varepsilon}$ to $\mathbf{y}$ is not by the usual factor, 1, but by $|\mathbf{A}| = |\mathbf{I}-\rho\mathbf{W}|$.[18] Written in ($N\times 1$) vector notation, the spatiotemporal-model conditional-likelihood is mostly conveniently separable into parts, like so:

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

The unconditional (exact) likelihood function, which retains the first time-period observations as non-predetermined, is more complex (Elhorst 2001, 2003, 2005; Franzese & Hays 2007b, 2008b):

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

When T is small, the first observation contributes greatly to the overall likelihood, and scholars should use the unconditional likelihood to estimate the model. In other cases, the more compact conditional likelihood is acceptable for estimation purposes.

One easy way to ease or even erase the simultaneity problem with S-OLS is to lag temporally the spatial lag (Beck et al. 2006; see Swank 2006 for an application). To the extent that temporal lagging renders the spatial lag pre-determined—that is, to the extent spatial interdependence does not incur

[18] This difference complicates estimation in that the determinant $|\mathbf{A}|$ involves ρ, and so requires recalculation at each iteration of the likelihood-maximization routine. Two strategies to simplify are to use an eigenvalue approximation for the determinant (Ord 1975) and to maximize a concentrated likelihood function (Anselin 1988). We discuss both procedures and estimation more generally elsewhere (Franzese & Hays 2004, 2006a, 2007b, 2008b).

instantaneously, where *instantaneous* here means *within an observation period, given the model*—the S-OLS bias disappears asymptotically. In other words, provided the spatial-interdependence process does not operate within an observational period but only with a time lag, and that spatial and temporal dynamics are sufficiently well modeled to prevent the same problem from arising via measurement/specification error, and that T is large, OLS with a temporally lagged spatial-lag on the RHS is a simple and effective estimation strategy. However, even in this best-case scenario, *OLS with time-lagged spatial-lags only provides unbiased estimates if the first observation is non-stochastic* (i.e., if initial conditions are fixed across repeated samples).[19] On the other hand, testing for either or both of remaining temporal or spatial correlation in residuals given the time-lagged spatiotemporal-lag model is possible and highly advisable. Standard Lagrange-multiplier tests for remaining temporal correlation in regression residuals remain valid. (See Franzese & Hays (2004, 2008b) for an introduction to several tests for/measures of spatial correlation, some of which retain validity when applied to estimated residuals from models containing spatial and temporal lags.)

Before proceeding to interpretation and presentation of estimated spatial effects and dynamics, and their certainty estimates, one important estimation issue remains: stationarity. Spatiotemporally dynamic models raise more complicated stationarity issues than do the more familiar solely time-dynamic models. Nonetheless, the conditions and issues arising in the former are reminiscent if not identical to those arising in the latter. Let $\mathbf{A}_1 \equiv \phi\mathbf{I}$, $\mathbf{B}_1 \equiv \mathbf{I} - \rho\mathbf{W}$, and ω as a characteristic root (i.e., eigenvalue) of $\mathbf{W}$, the spatiotemporal process is covariance stationary if

$$\left|\mathbf{A}_1\mathbf{B}_1^{-1}\right| < 1, \quad \text{or, equivalently, if} \quad \begin{cases} |\phi| < 1 - \rho\omega_{\max}, & \text{if } \rho \geq 0 \\ |\phi| < 1 - \rho\omega_{\min}, & \text{if } \rho < 0 \end{cases} \qquad (14).$$

[19] Note that the same condition that complicates ML estimation of the spatiotemporal lag model, namely the first set of observations is stochastic, also invalidates the use of OLS to estimate a model with a temporally lagged spatial lag under those conditions. Hence, asymptotically, this consideration offers no econometric reason to prefer S-OLS over S-ML estimation of spatiotemporal-lag models or the converse. Elhorst (2001:128) derives the likelihood for the spatiotemporal lag model with time-lagged spatial-lag and showed it to retain the offending Jacobian.

For example, in the case of positive temporal and spatial dependence, with **W** row-standardized, the maximum characteristic root is 1, so stationarity requires $\phi+\rho<1$.

Calculation, interpretation, and presentation of effects in empirical models with spatiotemporal interdependence, as in any model beyond the strictly linear-additive (in variables and parameters, explicitly or implicitly),[20] involve more than simply considering coefficient estimates. *Coefficients* do *not* generally equate to *effects* beyond that simplest strictly linear-additive case. In models with spatiotemporal dynamics, as in those with solely temporal dynamics, coefficients on explanatory variables give only the pre-dynamic impetuses to the outcome from changes in those variables. That is, the coefficients represent only the (often inherently unobservable) pre-interdependence impetus to outcomes from each right-hand-side variable. This section discusses calculation of spatiotemporal multipliers, which allow expression of the effects of counterfactual shocks of various kinds to some unit(s) on itself (themselves) and other units over time, accounting the full spatiotemporal dynamics. These multipliers also allow expression of the long-run, steady-state, or equilibrium[21] impact of permanent shocks. We also apply the delta-method to derive analytically the asymptotic approximate standard errors for these response-path and long-run effect estimates.[22]

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

$$\mathbf{y}_t=\rho\mathbf{W}\mathbf{y}_t+\phi\mathbf{y}_{t-1}+\mathbf{X}_t\boldsymbol{\beta}+\boldsymbol{\varepsilon}_t \qquad (15).$$

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

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

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

To find the long-run, steady-state, equilibrium (cumulative) level of $\mathbf{y}$, simply set $\mathbf{y}_{t-1}$ equal to $\mathbf{y}_t$ in (15) and solve. This gives the steady-state effect, assuming stationarity and that exogenous RHS terms, $\mathbf{X}$ and $\boldsymbol{\varepsilon}$, remain permanently fixed to their hypothetical/counterfactual levels:

$$\mathbf{y}_t = \rho\mathbf{W}\mathbf{y}_t + \phi\mathbf{y}_t + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t = \left(\rho\mathbf{W} + \phi\mathbf{I}\right)\mathbf{y}_t + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t = \left[\mathbf{I}_{\mathrm{N}} - \rho\mathbf{W} - \phi\mathbf{I}_{\mathrm{N}}\right]^{-1}\left(\mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right)$$

$$= \begin{bmatrix} 1-\phi & -\rho w_{1,2} & \cdots & \cdots & -\rho w_{1,\mathrm{N}} \\ -\rho w_{2,1} & 1-\phi & & & \vdots \\ \vdots & & \ddots & & \vdots \\ \vdots & & & 1-\phi & -\rho w_{(\mathrm{N}-1),\mathrm{N}} \\ -\rho w_{\mathrm{N},1} & \cdots & \cdots & -\rho w_{\mathrm{N},(\mathrm{N}-1)} & 1-\phi \end{bmatrix}^{-1} \left(\mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right) \equiv \mathbf{S}\times\left(\mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right) \qquad (16).$$

Decomposing $\boldsymbol{\varepsilon}_t = \boldsymbol{\eta} + \boldsymbol{\gamma}_t$ with $\boldsymbol{\eta}$ fixed and $\boldsymbol{\gamma}_t$ stochastic is conceptually useful for considering the responses across units to counterfactual shocks to the outcome(s) in some unit(s). For instance, Franzese & Hays (2006b) report estimates of long-run-steady-state responses across the European Union to counterfactual permanent shocks to labor-market-training expenditures in each member state or in all member states. Such hypotheticals are best understood as permanent changes in $\boldsymbol{\eta}$. The researcher simply fills the $N\times 1$ vector $\boldsymbol{\eta}$ with the desired counterfactual-shock values in the desired units; then $\mathbf{S}\boldsymbol{\eta}$ gives the long-run-steady-state responses to those shocks across the entire vector of units, the one(s) receiving the shock and any or all others.

To offer standard-error estimates for the estimated steady-states, one could use the delta method. I.e., give a first-order Taylor-series linear-approximation to nonlinear (16) around the estimated parameter-values and determine the asymptotic variance of that linear approximation.[23] To find the key elements needed for this, begin by denoting the i^{th} column of $\mathbf{S}$ as $\mathbf{s}_i$ and its estimate as $\hat{\mathbf{s}}_i$. The steady-state spatiotemporal equilibrium effects of a one-unit increase in the i^{th} element of $\boldsymbol{\eta}$ are $\mathbf{s}_i$, so the asymptotic approximate variance-covariance matrix of these estimates by the delta-method are

[23] Higher-order linear-approximations would yield greater accuracy. Simulation may also be advantageous.

$$\widehat{\mathbf{V}(\hat{\mathbf{s}}_i)} = \left(\frac{\partial \hat{\mathbf{s}}_i}{\partial \hat{\boldsymbol{\theta}}}\right) \widehat{\mathbf{V}(\hat{\boldsymbol{\theta}})} \left(\frac{\partial \hat{\mathbf{s}}_i}{\partial \hat{\boldsymbol{\theta}}}\right)' \tag{17},$$

where $\hat{\boldsymbol{\theta}} \equiv \begin{pmatrix} \hat{\rho} & \hat{\phi} \end{pmatrix}'$, $\left(\frac{\partial \hat{\mathbf{s}}_i}{\partial \hat{\boldsymbol{\theta}}}\right) \equiv \begin{pmatrix} \frac{\partial \hat{\mathbf{s}}_i}{\partial \hat{\rho}} & \frac{\partial \hat{\mathbf{s}}_i}{\partial \hat{\phi}} \end{pmatrix}$, and the vectors $\left(\frac{\partial \hat{\mathbf{s}}_i}{\partial \hat{\rho}}\right)$ and $\left(\frac{\partial \hat{\mathbf{s}}_i}{\partial \hat{\phi}}\right)$ are the i^{th} columns of $\hat{\mathbf{S}}\mathbf{W}\hat{\mathbf{S}}$ and $\hat{\mathbf{S}}\hat{\mathbf{S}}$ respectively. Similarly, the steady-state spatiotemporal effects of a one-unit increase in explanatory variable *k* in country *i* are $\mathbf{s}_i\beta_k$, with delta-method standard-errors for those effects of

$$\widehat{\mathbf{V}(\hat{\mathbf{s}}_i\hat{\beta}_k)} = \left(\frac{\partial \hat{\mathbf{s}}_i\hat{\beta}_k}{\partial \hat{\boldsymbol{\theta}}}\right) \widehat{\mathbf{V}(\hat{\boldsymbol{\theta}})} \left(\frac{\partial \hat{\mathbf{s}}_i\hat{\beta}_k}{\partial \hat{\boldsymbol{\theta}}}\right)' \tag{18},$$

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

The spatiotemporal response path of the $N\times 1$ vector of unit outcomes, $\mathbf{y}_t$, to the exogenous RHS terms, $\mathbf{X}$ and $\boldsymbol{\varepsilon}$, could also emerge by rearranging (15) to isolate $\mathbf{y}_t$ on the LHS:

$$\mathbf{y}_t = \left[\mathbf{I}_N - \rho\mathbf{W}_N\right]^{-1}\left\{\phi\mathbf{y}_{t-1} + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right\} = \mathbf{S}\left\{\phi\mathbf{y}_{t-1} + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right\} \tag{19}.$$

This formula gives the response-paths of all unit(s) $\{i\}$ to counterfactual one-unit shocks to $\mathbf{X}$ or $\boldsymbol{\varepsilon}$ (i.e., in $\boldsymbol{\eta}$) in any unit(s) $\{j\}$, including a shock in $\{i\}$ itself/themselves, just by setting $(\mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t)$ to the value reflecting that hypothetical in row(s) $\{j\}$. This formulation is especially useful for plotting estimated response paths in a spreadsheet, for instance. To calculate marginal spatiotemporal effects (non-cumulative) or plot the over-time path of responses to a permanent change in an explanatory variable (cumulative), and their standard errors, working with the entire NT x NT matrix may be easier. Simply redefine $\mathbf{S}$ in (16) as $\mathbf{S} \equiv \left[\mathbf{I}_{\text{NT}} - \rho\mathbf{W} - \phi\mathbf{M}\right]^{-1}$ and follow the steps just outlined. We calculate these effects for the presentation of our empirical reanalysis below, for example.

IV. The Multiparametric Spatiotemporal Model

We explained above how model specifications omitting spatial lags assume zero interdependence by construction, and have shown elsewhere, analytically and in simulation, that this induces omitted-variable biases inflating the estimated effects of non-spatial model-components. Note, e.g., that this means that most extant globalization studies, having neglected spatial lags, likely overestimated the effects of domestic and exogenous-external factors while effectively preventing any globalization-induced interdependence from manifesting empirically. Conversely, we also showed that standard regression estimates of models with spatial lags suffer simultaneity biases. Such models have grown more common recently among researchers interested in interdependence and have been the norm in policy-diffusion and studies of micro-behavioral interdependence. Although our previous analyses have shown that inclusion of spatial lags in regression models is a vast improvement over non-spatial estimation strategies, these simultaneity biases will tend to have inflated estimated interdependence strength at the expense of domestic/unit-level, exogenous-external, and context-conditional factors. The spatial-ML approach just described effectively redresses these simultaneity issues.

Above all, we emphasized that most crucial to proper estimation, distinction, and weighing of the strengths of interdependence and other potential sources of spatial (or network) correlation (i.e., to effective redress of *Galton's Problem*) was the relative and absolute accuracy and empirical power with which the patterns of interconnectivity and of the non-spatial aspects of the model are specified. Given the importance of well-specified connectivity matrices, strategies to parameterize **W** and estimate models in which an *unobserved* pattern of interconnections between units *affects* their choices or outcomes have been of tremendous interest to spatial econometricians, although with only limited progress made so far. For network analysts, contrarily, estimation of the processes generating ties in the *observed* network, as opposed to the effects alters' actions as weighted by the network on unit's choices or outcomes, is typically the *direct object* of the study, i.e., the dependent variable. Usually, network models take the characteristics of actors, including their actions and behaviors, as *given, exogenous* explanators of what ties between actors, typically seen in exclusively binary terms as opposed to possibly (continuous) matters of degree, will form. From the perspective of network analysis, the attempt to parameterize and, ultimately, to endogenize the w_{ij} of spatial-econometric models parallels attempts to model the "coevolution of behavior and networks" in network analysis. The challenges are similar, although spatial-econometric models in C&IPE may raise additional challenges in that relative connectivity may be a matter of continuous degree and, more dauntingly, that the effective connectivity may not be directly observed. Rather, quite commonly, one might observe only some covariates theorized to relate to the effective connection. In the context of interdependent ALM-policymaking for instance, many of the theorized connections arise through inherently unobservable economic competition in labor, capital, or goods markets. We observe only trade or capital flows or other symptoms of or contributors to competition.[24] In the network analysis tradition, Leenders (1995, 1997) and Snijders and colleagues (Snijders 1997, 2001, 2005, Snijders et al. 2007ab) have advanced the furthest on this crucial next task for empirical modeling of networks-cum-interdependence. After very brief review of their approaches, we offer another possible inroad, adapting the *multiparametric spatiotemporal-lag* (m-STAR) model to the purpose, a much simpler and yet perhaps productive approach (we plan future evaluative work).

Leenders (1995, 1997) envisions models of social situations in which "actors will shape their networks and, simultaneously, are influenced by the structure of the network." He terms the effects of networks on actors' *attributes*, understood broadly to mean actions or beliefs or policies as well as

[24] Both of these distinctions may result more from simplifying assumptions typically applied in network analysis than from the underlying substance of the networks and behaviors. For instance, connections in friendship networks are probably in truth a more continuous matter of (relative) degree—closeness of the friendship—and we often may not observe that even as directly as by survey response gauging said closeness.

characteristics, *contagion*. (More exactly, these are the effects of others' (*alters'*) attributes on one's own (*ego*'s) attributes, where the network structure determines which alters matter and how much.) The reverse process, in which the attributes of actors shape the network, he labels *selection*. In his model of selection, the equivalent of w_{ij} arise by a continuous-time Markov process—to be observed at the discrete intervals of measurement given in a particular data set—in which an *arc* (i.e., a binary connection) from j to i forms, w_{ij}=1, or dissolves, w_{ij}=0, at rates, λ_{0ij} and λ_{1ij}, given by some observable attribute(s) of i and/or j. He offers:

$$\lambda_{0ij} = \lambda_0 + \nu_0 d_{ij} \quad ; \quad \lambda_{1ij} = \lambda_1 + \nu_1 d_{ij} \qquad (20),$$

with d_{ij} a measure of similarity of actors i and j. His model of contagion is a spatial-lag model:

$$\mathbf{y} = \rho \mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \qquad (21),$$

which could extend to the standard spatiotemporal model, (15), straightforwardly. Leenders (1997) then integrates his contagion and selection models thus. First, let $\mathbf{A}_t$ be the $N \times N$ matrix current realization of (20), $\mathbf{y}_t$ be the $N \times 1$ vector of attributes for the actors, and $\mathbf{X}_t$ the $N \times k$ matrix of exogenous explanators thereof. Leenders (1997:172) expresses $\mathbf{W}_t$ as the function $\mathbf{W}_t = W(\mathbf{A}_t)$, which would be a very useful extension toward the parameterized modeling of unobserved and potentially continuous degrees of connection as a function of observed binary *arcs* (modeled by (20)) but the function as currently implemented is just the identity. The model is then identified for estimation of $\boldsymbol{\lambda}$, $\mathbf{v}$, ρ, and $\boldsymbol{\beta}$ from $\mathbf{W}_t$ and $\mathbf{y}_t$ observed at discrete intervals t={1..T} by the assumptions that temporal implies causal precedence and that the first observation is fixed and given (i.e., conditional upon the first observation, raising all the issues raised above in that regard). The combined model is then:[25]

$$\mathbf{W}_t = f(\mathbf{W}_{t-1}, \mathbf{y}_t) \quad ; \quad w_{ij,t} \equiv d_{ij,t} = | y_{i,t} - y_{j,t} | \quad ; \quad y_t = \rho_1 \mathbf{W}_t \mathbf{y}_t + \rho_2 \mathbf{y}_{t-1} + \mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \qquad (22).$$

[25] Leenders (1997:173-4) actually converts (21) to a temporally dynamic model like (15) by what amounts to an error-correction model, with equilibrium y being another, constant parameter to be estimated, μ, interpreted as a societal norm for y. We have simplified to a first-order time-lag to facilitate exposition.

He then generates $\mathbf{W}_0$, $\mathbf{y}_0$, $\{\boldsymbol{\varepsilon}_t\}$, and $\{\mathbf{X}_t\}$ randomly, and assesses by simulation the biases entailed in estimating from data collected at intervals of increasing length (measured in numbers of simulation periods) and in erroneously estimating only the selection process, (20), or only the contagion process that is the last expression of (22). The text leaves unclear the exact experiments and estimation procedures, so we can interpret his results with considerable uncertainty. He seems to find, first, that increasing granularity in the periodicity of observation generally causes attenuation bias in estimates of the selection-model parameters and inflation bias in estimates of the contagion-model parameters; second, that estimated contagion is greatly inflated when selection is unmodeled but present; and third, that estimated selection is mildly inflated when contagion is present but unmodeled.

Snijders' and colleagues'[26] approach is more elaborate. In Steglich et al. (2007), they emphasize that the challenge for disentangling the sources of network autocorrelation (a.k.a., spatial correlation) is threefold. One must distinguish *influence* or *contagion* (a.k.a., *interdependence*), from *selection* (e.g., *homophily*), from *social contexts* (i.e., exogenous internal and/or external conditions) because any omissions or inadequacies in modeling those distinct sources of network or spatial correlation will bias conclusions in favor of the included or better-modeled mechanisms. Then, too, they stress three fundamental issues confronting such attempts: observations in discrete time-intervals of continuous-time processes, the need to control for alternative mechanisms and pathways by which observed networks and outcomes may have arisen, and the network dependence of the actors which precludes estimation by common statistical techniques, most of which assume independence.

To surmount these issues in distinguishing these alternative mechanisms, they model the co-evolution of networks and behavior thus. N actors are connected according to an observed, binary, endogenous, and time-variant connectivity matrix, $\mathbf{x}$, with elements $\mathbf{x}_{ij}(t)$—in our notation, $\mathbf{W}$, with

[26] We follow Snijders et al. (1997) and Steglich et al. (2006, 2007) most specifically.

elements w_{ij}(t). The vector of *N* observed, binary behaviors, **z**, at time *t* has elements $\mathbf{z}_i$(t)—in our notation, $\mathbf{y}(t)$, with elements $y_i(t)$. Further exogenous explanators may exist at unit or dyadic level, $\mathbf{v}_i(t)$ or $\mathbf{w}_{ij}(t)$—in our notation, the components of **X**. Actors have opportunities to make changes in their network connections, switching on or off one tie or doing nothing, at fixed rate in continuous time, λ_i^{net}, according to an exponential hazard-rate model. The model may further parameterize λ, but the current implementation assumed the rate constant across all *ij* and *t*. Likewise, opportunities to switch the behavior on or off or do nothing occur at continuous-time rate λ_i^{beh}.[27]

When the opportunity to change network connections arrives for some *i*, s/he chooses to change the status of some one of his/her *N-1* connections, turning it on or off, or leaving them all unchanged. S/he makes this choice by comparing the values of some objective function of the following form:

$$f_i^{net}(\mathbf{x},\mathbf{x}',\mathbf{z})+\boldsymbol{\varepsilon}_i^{net}(\mathbf{x},\mathbf{x}',\mathbf{z})=\sum_h\left\{\boldsymbol{\beta}_h^{net}\times\mathbf{s}_h^{net}(\mathbf{i},\mathbf{x},\mathbf{x}',\mathbf{z})\right\}+\boldsymbol{\varepsilon}_i^{net}(\mathbf{x},\mathbf{x}',\mathbf{z}) \qquad (23),$$ [28]

where $\mathbf{x}'$ is an alternative network under consideration, which can differ from the existing network, **x**, only by changing at most one element of (only) row *i*. $s_h^{net}(\cdot)$ is some statistic, i.e., some function of the data, $\mathbf{x},\mathbf{x}',\mathbf{z}$, that reflects the substantively/theoretically derived objectives of the actors with regard to the network, **x**, and behaviors, **z**. The $\boldsymbol{\beta}_h^{net}$ to be estimated are the relative weights of these objectives. Assuming the $\boldsymbol{\varepsilon}_i^{net}(\mathbf{x},\mathbf{x}',\mathbf{z})$ extreme-value distributed, independently across actors (see note 28) and over time, produces the multinomial-logit model of categorical choice. Similarly, when an opportunity to change behavior arrives, actor *i* compares the value of her/his objective function

[27] We note that, since observation occurs at discrete intervals, the degrees of freedom to vary these continuous-time rates render the assumption of exclusively single actors making single, unit-valued changes in their network connections or behavior essentially inconsequential. As greater frequency and/or magnitude of changes are observed, estimates of these occurrence rates at this unobserved instantaneous level simply rise to compensate.

[28] The Steglich et al. (2007:21) exposition actually omits the stochastic component from the right-hand side of (23), and seems to carry this omission forward into the simulation-model implementation and the associated "method of moments" estimation. We suspect this is highly consequential because it suppresses the dependence across units or dyads of their multinomial choices (see note 30) regarding which if any $\mathbf{x}_{ij}$ to switch on or off.

under each of the three possible actions—switch on, switch off, or leave unchanged. Formally, *i* compares $\mathbf{z}$ to $\mathbf{z}'$ given x, and under analogous assumptions of *i.i.d.* extreme-value stochastic components, the multinomial logit again emerges.[29]

Similarly to Leenders' approach, identification derives from debarring any literal simultaneity in outcomes or networks and assuming that temporal precedence implies causal precedence, and in particular conditioning on the first observation.[30] Given all this, estimation occurs by simulating the sequences of policies $\mathbf{z}$ and of networks $\mathbf{x}$ and searching over possible values of the model parameters, $\boldsymbol{\lambda}$ and $\boldsymbol{\beta}$, to minimize some distance function from the observed sequences of $\mathbf{x}$ and $\mathbf{z}$ to the simulated sequences. Snijders et al. (1997, 2007) label this as an application of 'the method of moments" and an example of a 'third-generation problem' in applied statistics (citing Gouriéroux & Monfort 1996 on the latter); one could also think of it as a calibration exercise. Standard errors could derive from jackknife or bootstrapped resampling (Snijders & Borgatti 1999) if explicit likelihoods or sufficient-statistic moment-equations are unavailable for standard analytic formulae.[31]

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[29] Given the binary behavior and the model set-up, we see only two possible choices: change on or off status of the behavior or leave it unchanged. In this case, the multinomial logit may have reduced to the simple logit.

[30] Some identification problems persist with the current implementations, notwithstanding these strong assumptions. For one, assuming independent multinomial decisions for the endogenous behaviors and network ties and of opportunities for action effectively undoes some of the allowance for dependence in those choices, although it yields the great advantage of seeming to allow estimating standard multinomial logit (and exponential hazard-rate) models for those components of the system. That evasion aside, though, another issue is that included among the unit or dyadic explanators are various measures of network structure. These are various functions of the ties between actors (and possibly also their behaviors), i.e., of the outcomes of the multinomial choices of the actors regarding the connections. In latent-variable models like the multinomial logit, however, one cannot include the actual outcomes on the right-hand side, spatially or temporally lagged and transformed by some network-structure measurement-function as they may be. Only the latent variable or the estimated probabilities can enter those functions. (The problem is that the probabilities predicted of choices on the left-hand side can contradict the actual choices which enter on the right-hand side.) The presence of a stochastic component exhibiting dependence across units, moreover, would render the multinomial logits *N*-dimensional optimization exercises rather than the standard unidimensional. We, however, have no further progress on those problems to offer here, beyond some conjectures we make in the conclusion, nor do we know of any other scholarship that has made greater progress on these issues in this behavior and network co-evolution context. (Spatial econometricians have made considerable progress on this multidimensional optimization issue of interdependent latent-variable models, but entirely outside the co-evolution context to our knowledge.)

[31] The work we read indicated that these explicit likelihoods or proofs of the moment-equations sufficiency were not known, but, at least as of SIENA 3.17a (8 April 2008), estimated variance-covariance of the estimated parameters claim to derive from the appropriate analytic calculations for moments or likelihood estimation.

For C&IPE, some of the features of these approaches, for all the tremendous advances and value they offer network/interdependence scholars, are not ideal as currently implemented. In order of increasing importance and, unfortunately, of height of statistical hurdle represented, first, many behaviors or attributes of interest as dependent variables, as well as the relative connectivity between units, in C&IPE are less likely to be binary or ordinal.[32] For instance, in the perhaps-canonical context of globalization and tax competition, the outcomes of interest are tax rates and many sources of interdependence will derive from the strength of economic competition, which is continuous. Second, in C&IPE contexts, the strengths of relative connectivity are not always observed, or even observable, directly. In the canonical example, strength of competition is not directly observable; we directly observe only some covariates, such as geographic contiguity or proximity or goods or capital flows, theorized to relate to the unobserved strength of economic competition (or substitute or complement relations). Under these conditions, for estimation purposes, the left-hand side of the selection component of the model would have no data. We could estimate the network and its determinants only by estimating its impact on actors' behavior given a specification of how the network matters for that behavior and how the observed covariates relate to the network ties. Third, temporal precedence often will not suffice to assure causal precedence, for many possible reasons. For one, interdependence often operates literally simultaneously in C&IPE. Most political-economy relations are strategic and, in strategic interactions, the effect of alters on ego can be instantaneous or even, frequently, based on estimated futures. In the canonical example, for instance, the strategic interdependence of tax policies across units arises from policymakers engaged in simultaneous play of a strategic game in which the policies of each actor depend on the (expected) policies of others, at

[32] We suspect that the current implementation of SIENA requires only discrete, not necessarily ordinal, behaviors. The requirement seems the sensibility of conceiving an option to increment, leave unchanged, or decrement the behavior by one. If so, rounding and/or rescaling continuous behaviors to render them discrete should suffice. Unbounded behaviors would actually simplify by removing the need to alter the actor's choice problem at upper and lower bounds.

that same time (or even in the future). For another, usually in estimation, *simultaneous* means within an observational period and many C&IPE contexts have high frequency behavior, including changes in networks, relative to much lower observation periodicity. Furthermore, time lagging will suffice to eliminate simultaneity only if and insofar as spatiotemporal dynamics are fully and properly specified in the model. Finally, conditioning on the first observation loses least information and suffers least small-sample bias with long T, which may not always be available.[33]

As Leenders (1997:165) summarized well, most research on network/spatial interdependence either studies the formation of networks (*selection*), taking the attributes and behaviors of actors as fixed and given, or the effects of networks/interdependence on actors' behaviors (*contagion*), taking the pattern of connectivity as fixed and given. Spatial econometricians have primarily worked in the latter mode, whereas network analysts have primarily worked in the former, but both have been eager to combine the combine *contagion* and *selection*. Other differences in tendency seem apparent to us. For instance, spatial econometricians tend primarily to conceive *network effects* as the effects of alters' actions on ego's via their connections, whereas network analysts tend to emphasize the effects of network structure and ego's position in it on ego's actions. However, this difference in the central question—what explains networks vs. how does interdependence affect outcomes—seems most central. Among network analysts, Snijders' and colleagues' co-evolution model represents, to our knowledge, the greatest advances toward this end of combining *contagion* and *selection*.

Our approach comes from a spatial-econometric vantage, so it begins with the spatiotemporal-lag model, (5), and seeks to expand its specification to allow estimation of **W**, the matrix of relative connectivity, i.e., to model it as a parameterized function of covariates observable at unit, dyadic, or exogenous-external level. This model of the w_{ij} corresponds to some sorts of *selection* from the view

[33] These obviously are very general points, hardly restricted to C&IPE.

in the language of network analysts. For instance, the sociologists' *homophily*, if it arises on the basis of fixed or exogenous characteristics of ego and alter, parallels a model from the spatial-econometric perspective of w_{ij} as a function of $\mathbf{x}_i$ and $\mathbf{x}_j$. If, specifically, we consider (some function of) the vector of behaviors of interest, $\mathbf{y}$, among these explanators of $\mathbf{W}$, this parallels a stronger form of *selection*, raising higher statistical hurdles, in which network ties and actor behaviors are endogenous to each other. Thus, the spatiotemporal-lag model with estimated, endogenous spatial-weights is the spatial-econometric analogue to the network co-evolution model, integrating contagion and selection.

Consider, then, the multiparametric spatiotemporal-lag (m-STAR) model—i.e., a spatiotemporal-lag model with multiple spatial-weights matrices:

$$\begin{aligned}\mathbf{y} &= \rho_1\mathbf{W}_1\mathbf{y} + \rho_2\mathbf{W}_2\mathbf{y} + \ldots + \rho_R\mathbf{W}_R\mathbf{y} + \phi\mathbf{M}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \\ &= \mathbf{W}\mathbf{y} + \phi\mathbf{M}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \text{ where } \mathbf{W} \equiv \sum_{r=1}^{R}\rho_r\mathbf{W}_r\end{aligned} \tag{24}$$

Notice that we can also write (24) in scalar notation as:

$$\begin{aligned}y_i &= \rho_1\sum_j w_{ij}^1 y_j + \rho_2\sum_j w_{ij}^2 y_j + \ldots + \rho_R\sum_j w_{ij}^R y_j + \phi y_{i,t-1} + \sum_k x_k^i\beta_k + \varepsilon_i \\ &= \sum_j\left(\rho_1 w_{ij}^1 + \rho_2 w_{ij}^2 + \ldots + \rho_R w_{ij}^R\right) y_j + \sum_k x_k^i\beta_k + \varepsilon_i \\ &= \sum_j\left[\left(\sum_r \rho_R w_{ij}^R\right) y_j\right] + \sum_k x_k^i\beta_k + \varepsilon_i\end{aligned} \tag{25}$$

As the middle version of the expression clarifies most, the term in parentheses, which is row i of $\mathbf{Wy}$, is a parameterized (linear-additive) model of the weights on $y_{j\neq i}$ in affecting y_i. The w_{ij} are the covariates expected to explain the relative strength of interdependence, and ρ the coefficients on them to estimate. In other words, we can conceive the m-STAR model as a spatiotemporal-lag model with estimated $\mathbf{W}$, with $\hat{\mathbf{W}} = \sum_{r=1}^{R}\hat{\rho}_r\mathbf{W}_r$ being a weighted sum of observed "potential" connectors. If, furthermore, the $\mathbf{W}_r$ include any whose elements are (a) function(s) $\mathbf{y}$, then $\mathbf{W}$ and $\mathbf{y}$ are jointly endogenous, and this is essentially the co-evolution model.

The sorts of models of **W**, i.e., of networks, expressible in this form would seem limited, without considerable further complication, to those with continuous w_{ij}, strengths of ties. If we expected truly binary connectivity, e.g., we would need to transform the term in parentheses to binary outcomes in some manner, say by applying the log-odds function and a decision rule to convert probabilities to one. This is not really a limitation, however, if one believes (as we tend to do) that connectivity is a degree, measured at best with error. Non linear-additive models of w_{ij} would also entail some complications, but seem manageable. The costs in terms of estimation complexity of enriching the model of connectivity by adding covariates is also relatively high, at least compared to adding unit, dyad, or exogenous-external factors **x** in **Xβ**. The approach also has some major advantages though. Perhaps most importantly, we have fully developed likelihood for the m-STAR model for the case of exogenous $\mathbf{W}_r$, both the simpler conditional (on the first observation) version, and the unconditional likelihoods, which are important for small-T or true or effectively true simultaneity situations. That is, we can apply all the apparatus for estimation, all the analytically or simulation derived intuitions about biases, efficiencies and sensitivities, all the tools for calculating, interpreting, and presenting spatio-temporally dynamic effects discussed above for spatial-econometric models. The estimated **W**, on the converse side, can be interpreted and presented with standard network-analysis tools. The conditional log-likelihood extends that for the STAR model, (11), intuitively:

$$\ln L(\boldsymbol{\rho},\phi,\boldsymbol{\beta},\sigma;\mathbf{y},\mathbf{X}) = \ln(2\pi\sigma^2)^{-NT/2} + \ln\left|\mathbf{A}\right| - \frac{1}{2\sigma^2}e'e, \quad \text{where } \mathbf{A} = \mathbf{I}_{NT} - \mathbf{W} \text{ and } e = \mathbf{Ay} - \phi\mathbf{My} - \mathbf{X\beta} \qquad (26);$$

the unconditional likelihood extends STAR's (13) analogously; and the estimated variance of $\hat{\mathbf{W}}_{ij}$ is:

$$\hat{\mathbf{W}} = \sum_r \hat{\rho}_r \mathbf{W}_r \Rightarrow \widehat{\operatorname{var}(\hat{\mathbf{W}}^{(i,j)})} = \left(\mathbf{W}_1^{(i,j)}\ \mathbf{W}_2^{(i,j)} \ldots \mathbf{W}_R^{(i,j)}\right)\hat{\boldsymbol{\Omega}}_{\hat{\boldsymbol{\rho}}}\left(\mathbf{W}_1^{(i,j)}\ \mathbf{W}_2^{(i,j)} \ldots \mathbf{W}_R^{(i,j)}\right)' \qquad (27),$$

where $\hat{\boldsymbol{\Omega}}_{\hat{\boldsymbol{\rho}}}$ is the Hessian of likelihood in the usual fashion. Written in $(N\times1)$ vector notation, the STAR-model conditional-likelihood is mostly conveniently separable into parts, as seen here:

$$\begin{gathered}\text{Log} f_{\mathbf{y}_t,\mathbf{y}_{t-1},\ldots,\mathbf{y}_2|\mathbf{y}_1} = -\frac{1}{2}N(T-1)\log\left(2\pi\sigma^2\right) + (T-1)\sum_{r=1}^{R}\log\left|\mathbf{I}-\rho_r\mathbf{W}_r\right| - \frac{1}{2\sigma^2}\sum_{t=2}^{T}\boldsymbol{\varepsilon}_t'\boldsymbol{\varepsilon}_t \\ \text{where } \boldsymbol{\varepsilon}_t = \mathbf{y}_t - \sum_{r=1}^{R}\rho_r\mathbf{W}_{rN}\mathbf{y}_t - \phi\mathbf{I}_N\mathbf{y}_{t-1} - \mathbf{X}_t\boldsymbol{\beta}\end{gathered} \qquad (28).$$

The unconditional (exact) likelihood, which retains first-period observations as non-predetermined, analogously extends the more complicated (13). When *T* is small, the first period contributes greatly to the overall likelihood, so the unconditional likelihood should be used to estimate models. In our case below, *T* is large enough that the more compact conditional likelihood is acceptable.

Co-evolution models, i.e., models with **W** being some function of **y**, present larger challenges. Our simple stratagem for a first cut is to apply the poor man's exogeneity, temporally lagging the **y** in this function explaining **W** and assuming the conditions required for that identification approach hold sufficiently. This, of course, does not address the problem of true simultaneity, or true effective simultaneity due to relative coarseness of the observation frequency, which, as we noted, seems a likely situation for C&IPE contexts at least. Accordingly, we plan to explore a possible two-step estimation-procedure. First, apply spatial-GMM (see, e.g., Anselin 2006, Franzese & Hays 2008b) to obtain by spatial instrumentation consistent estimates of the endogenous w_{ij} and their estimated variance-covariance. We would then take a draw from that estimated multivariate distribution of the instrumented $\hat{\mathbf{W}}$ to insert in the conditional likelihood (26) or its unconditional form (an extension of (13)). We would maximize this likelihood *q* times, each time with new draws from that first-stage S-GMM instrumented $\hat{\mathbf{W}}$. The point estimates of parameters are then just the average of these *q* second stage S-ML estimates, and the estimated variance-covariance of the parameter-estimates is the average of the estimated variance-covariance matrices from each iteration plus (1+*q*) times the sample variance-covariance in the point estimates across iterations (King et al. 2001). This estimator should inherent the nice properties of S-ML and S-GMM as far as we can intuit, but we have not proof of its properties as yet. Accordingly, Monte Carlo assessment of the estimator will be one essential next step; another will be direct comparison of the Snijders et al. approach against this one.

V. Empirical Illustration

To illustrate application of the m-STAR approach (with identification from temporal lagging assumed), we extend our previous ALM-policy analysis (Franzese & Hays 2006b). One extension is of the sample to include observations on both *EU* and non-*EU* countries.[34] This allows distinction of interdependence among *EU* member states due to co-membership from global interdependence.[35]

The OECD ALM-program dataset gives expenditures by five categories: public employment-services and administration, labor-market training, youth measures, subsidized employment, and disability measures. Figure 3 plots the temporal variation in average spending by *OECD* countries on each type. Subsidized employment and labor-market training are the two largest components of ALM spending over the entire sample period, accounting for 26.9% and 26.7% total expenditures.

Table 1 gives the programmatic breakdown in expenditures for each sample country, revealing significant variation across countries. The big spenders on ALM programs per capita were Sweden ($360.88) and Denmark ($287.20), whereas the U.S. ($43.72) and Greece ($34.97) spent the least. This variation is not random. Spatial clustering is evident in the Table 1 data. For example, all four Scandinavian countries spent significantly more than the OECD average. The difference between Portugal and Spain in per capita ALM program spending over the twenty-three year period was less

[34] Annual data from 1980-2003 for 21 OECD countries—Australia, Austria, Belgium, Canada, Denmark, Germany, Greece, Finland, France, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and United States—of which 14 are *EU* member states.

[35] On the temporal dimension, our sample is mostly limited to the period before the Amsterdam Treaty entered into force. This should not affect theoretical conclusions qualitatively since the lack of EES enforcement leaves the pre-Amsterdam strategic incentives largely unchanged. Empirically, the post-Amsterdam behavior of EU member states with respect to employment policy seems to have changed little.

than $1 (2000, PPP$). Both Australia and New Zealand and Canada and the U.S. spent well below the OECD average. What explains the spatial patterns we observe? Do they evidence strategic policy interdependence, common exogenous-external conditions, spatially correlated domestic factors, or some as-yet unconsidered selection process?

Figure 3: Disaggregated Active Labor Market Expenditures in the *OECD*, 1980-2003

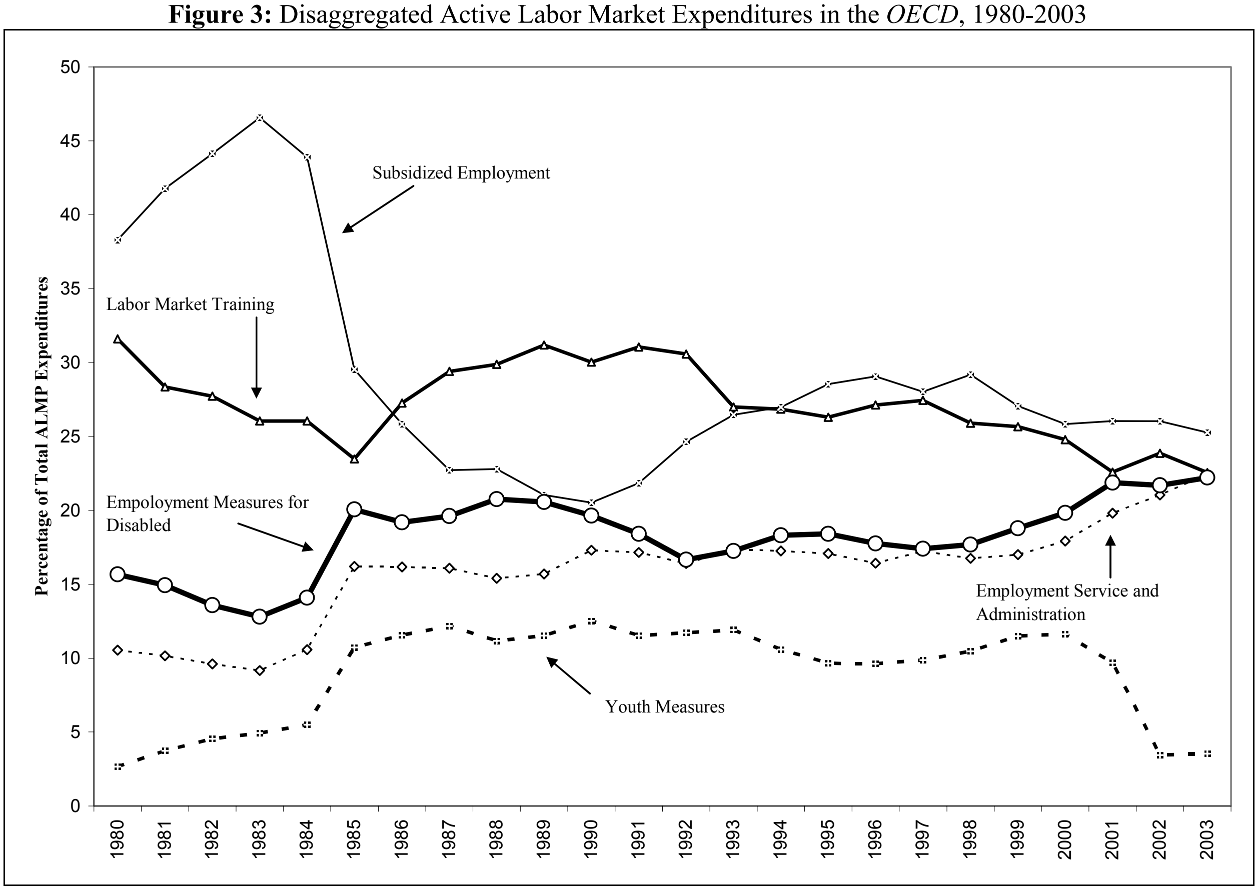

Table 1. Disaggregated Active Labor Market Expenditures per Capita (2000 PPP$)

	AUS	AUT	BEL	CAN	DEN	FIN	FRA	DEU	GRE	IRE	ITA
Employment service and administration	28.85	33.06	41.35	38.44	20.48	22.47	25.98	46.59	10.77	32.36	0
	(37.54)	(29.68)	(15.69)	(39.1)	(7.13)	(10.46)	(14.39)	(19.12)	(30.8)	(15.19)	(0)
Labour market training	10.05	41.58	43.99	46.18	117.32	67	49.74	71.61	7.84	43.26	7.14
	(13.08)	(37.32)	(16.69)	(46.98)	(40.85)	(31.19)	(27.56)	(29.38)	(22.41)	(20.3)	(8.02)
Youth measures	8.36	4.63	3.41	3.92	24.57	17.65	42.47	12.83	6.8	37.11	31.47
	(10.88)	(4.16)	(1.29)	(3.99)	(8.55)	(8.22)	(23.53)	(5.26)	(19.45)	(17.42)	(35.38)
Subsidized employment	21.51	18.62	146.9	7.07	69.26	87.79	49.75	65.7	8.28	87.35	24.68
	(27.98)	(16.71)	(55.73)	(7.19)	(24.12)	(40.87)	(27.56)	(26.96)	(23.67)	(41)	(27.74)
Employment measures for disabled	8.08	13.51	27.94	2.7	55.58	19.12	12.56	46.95	1.28	13	0
	(10.52)	(12.13)	(10.6)	(2.75)	(19.35)	(8.9)	(6.96)	(19.27)	(3.67)	(6.1)	(0)
Total ALMP	76.87	111.41	263.61	98.3	287.2	214.81	180.51	243.72	34.97	213.08	88.97

	JPN	NTH	NWZ	NOR	PRT	ESP	SWE	CHE	GBR	USA	OECD
Employment service and administration	47.65	24.48	17.46	33.36	14.93	12.97	44.98	20.81	36.4	12.1	26.76
	(68.44)	(11.58)	(15.85)	(15.91)	(17.04)	(14.69)	(12.46)	(22.57)	(37.71)	(27.67)	(17.34)
Labour market training	7.48	48.72	39.62	36.28	26.47	19.23	101.86	17.01	15.5	13.48	41.12
	(10.75)	(23.04)	(35.96)	(17.31)	(30.22)	(21.78)	(28.22)	(18.45)	(16.06)	(30.82)	(26.65)
Youth measures	0.24	11.01	10.44	11.53	26.48	7.73	14.32	0.55	28.34	6.68	14.84
	(0.34)	(5.21)	(9.48)	(5.5)	(30.23)	(8.76)	(3.97)	(0.59)	(29.36)	(15.29)	(9.61)
Subsidized employment	12.73	16.69	34.73	23.87	14.77	45.7	91.75	20.05	11.68	2.24	41.44
	(18.28)	(7.89)	(31.53)	(11.39)	(16.86)	(51.77)	(25.42)	(21.74)	(12.1)	(5.13)	(26.86)
Employment measures for disabled	1.53	110.57	7.91	104.59	4.95	2.64	107.98	33.79	4.61	9.22	29.29
	(2.19)	(52.28)	(7.18)	(49.89)	(5.65)	(2.99)	(29.92)	(36.65)	(4.77)	(21.09)	(18.98)
Total ALMP	69.62	211.47	110.15	209.63	87.59	88.28	360.88	92.22	96.52	43.72	154.3

Note: Parentheses contain spending as a percentage of total spending on active labor market programs.

To answer these questions, we estimate a linear multiparametric spatiotemporal autoregressive (m-STAR) lag model.[36] Again, the model, in matrix notation, is

$$\mathbf{y} = \left(\sum_{r=1}^{R} \rho_r \mathbf{W}_r \right) \mathbf{y} + \phi \mathbf{M} \mathbf{y} + \mathbf{X} \boldsymbol{\beta} + \boldsymbol{\varepsilon} \,, \qquad (29),$$

where $\mathbf{y}$, the dependent variable, ALM expenditures, is an $NT \times 1$ vector of cross sections stacked by periods (i.e., the N first-period observations, then the N second-period ones, and so on to the N in the last period, T).[37] ρ_r is the r^{th} spatial autoregressive coefficient, and $\mathbf{W}_r$ is an $NT \times NT$ block-diagonal spatial-weighting matrix. Time-invariant $\mathbf{W}$ matrices are expressible as the Kronecker product of a $T \times T$ identity matrix and the $N \times N$ weights matrix: $\mathbf{I}_T \otimes \mathbf{W}_N$. Each $\mathbf{W}_r$ contains a unique set of elements w_{ij}^r that reflect a particular type of interdependence (e.g., geographic proximity, common membership in groups, and economic interdependence). $\mathbf{W}_r \mathbf{y}$ is thus the r^{th} spatial lag; i.e., for each observation y_{it}, $\mathbf{W}_r \mathbf{y}$ gives a weighted sum of the y_{jt}, with weights, w_{ij}^r, given by the relative connectivity from j to i. $\mathbf{Wy}$ thus directly and straightforwardly reflects the dependence of each unit

[36] Case et al. (1993), Brueckner & Saavedra (2001), Fredriksson & Millimet (2002), Redoano (2003), and Allers & Elhorst (2005) among others have used spatial-lag models to evaluate hypotheses about strategic policy-interdependence, but none of these models have multiple spatial lags.

[37] With some work, nonrectangular panels and/or missing data are manageable, and in our empirical analysis we have missing data, but we assume rectangularity and completeness for simplicity of exposition.

i's policy dependence on unit j's policy, exactly as in the formal model and theoretical arguments reviewed above. ϕ is the temporal autoregressive coefficient, and $\mathbf{M}$ is an $NT\times NT$ matrix with ones on the minor diagonal, i.e., at coordinates $(N+1,1)$, $(N+2,2)$, …, $(NT, NT\text{-}N)$, and zeros elsewhere, so $\mathbf{My}$ is the first-order temporal lag. $\mathbf{X}$ contains $NT\times k$ observations on k independent variables, and $\boldsymbol{\beta}$ is a $k\times 1$ vector of coefficients on them. $\boldsymbol{\varepsilon}$, is an $NT\times 1$ vector of disturbances, assumed *i.i.d.*[38]

Our regression analysis focuses on aggregate ALM program expenditures and the two largest components of ALM spending, labor-market training (LMT) and subsidized employment (SEMP) spending. Our dependent variables are measured per capita (2000, PPP$), and the key independent variables, which allow us to evaluate the nature of the spatial interdependence among the countries in our sample, are the *spatial lags* of ALM spending.

We calculated our spatial lags, $\mathbf{Wy}$, using four different weights matrices ($R = 4$). The first is a standardized *binary contiguity-weights matrix* which begins by coding w_{ij}=1 for countries i and j that share a border and w_{ij}=0 for countries that do not border, with exceptions France, Belgium, and the Netherlands considered contiguous with the U.K, Denmark with Sweden, and New Zealand with Australia. $\mathbf{W}_2$ is an EU co-membership weights-matrix; i.e., w_{ij}=1 if both i and j are EU members and w_{ij}=0 otherwise. $\mathbf{W}_3$ has weights that reflect the historical trade (imports plus exports) shares between sample countries. More specifically, w_{ij} is the historical value (1980-2003) of trade between countries i and j as a proportion of the total value of country i's trade over the same period.[39] The final weights matrix has elements w_{ij} comprised of the dependent variable in unit j in the previous period.[40] For estimation, we *row-standardize* (as commonly done in spatial-econometrics research) all four matrices by dividing each cell in a row by that row's sum.

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

[39] We will ultimately use a time-varying contemporaneous trade based measure; this is merely a preliminary expedience.

[40] XXXX This obviously crude formulation represents our quickest expediency to capturing a co-evolution process. We plan a substantively and theoretically more sensible implementation, $|y_{i,t\text{-}1}\text{-}y_{i,t\text{-}2}|$ for example, for the next revision.

We also include several domestic-level variables. We control for domestic macroeconomic performance with real GDP-growth and the unemployment rate. As their economies grow wealthier, governments might provide more public goods and services (Wagner's Law), suggesting a positive coefficient estimate for GDP per capita. Alternatively, Baumol's Disease, which refers to an argued decreasing relative productivity in service sectors rendering financing of public services increasingly difficult as economies develop and shift toward heavier service-sector employment, would suggest a negative relationship of wealth to ALM expenditures. Most likely, though, our GDP-*growth* measure will capture pseudo-automatic programmatic responses to the macroeconomic cyclical, suggesting a negative coefficient. Unemployment should receive a positive coefficient for the same reason.

Next, we control several structural features of a country's economy related to its labor markets and exposure to external shocks. The labor-market factors are union density and Iversen & Cusak's (2000) deindustrialization measure. Higher union density increases the influence of organized labor, so we expect it to associate closely with greater ALM spending. Regarding deindustrialization, Iversen & Cusak (2000) argued that workers cross significant skill barriers when they shift from manufacturing and agriculture to services. Thus, we expect deindustrialization to spur LMT also. Many scholars argue that international economic exposure favors increased government spending, especially on programs that help workers adjust to external shocks (e.g. Ruggie, 1982; Cameron, 1978; Katzenstein, 1985; Rodrik, 1997; Hays et al., 2005). Others argue that increased international exposure produces competitive pressures that lead to smaller governments, but this mechanism is properly reflected in our model by the third spatial-lag (see Basinger & Hallerberg 2004, Franzese & Hays 2003, 2004, 2006ab, 2007abc, 2008ab). We use trade openness as our measures of exposure.

We also consider several political variables: the working-age population as a percent of the total population, the percent of cabinet seats held by left and Christian Democratic parties, the percent of general-election votes won by left-libertarian parties. Working-age voters are natural constituencies for ALM programs, whereas the benefits for retired voters are indirect at best, so political pressure for ALM programs should increase with the working-age share of the population. Scholars have identified Social Democratic, Christian Democratic, and Left-Libertarian parties as key supporters of active social-policies, albeit of/to/for different precise natures, extents, or reasons (see, e.g., Garrett, 1998; Swank, 2002; and Kitschelt, 1994). Somewhat alternatively, the more traditional left-right ideological dimension may also likely relate to ALM programs.

Table 2: ALM-Spending Models — Estimation Results

DEPENDENT VARIABLE →	**Total ALM**			**LMT**			**SEMP**		
INDEPENDENT VARIABLE ↓	***(1)***	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***	***(7)***	***(8)***	***(9)***
Temporal Lag	0.875***	0.880***	0.892***	0.872***	0.873***	0.865***	0.830***	0.833***	0.822***
	(0.028)	(0.026)	(0.026)	(0.029)	(0.028)	(0.028)	(0.035)	(0.034)	(0.034)
Real GDP Growth Rate	1.365***	1.339***	-0.032	0.269	0.312	-0.445	0.036	0.040	-0.890
	(0.430)	(0.423)	(1.105)	(0.210)	(0.204)	(0.640)	(0.196)	(0.189)	(0.620)
Standardized Unem. Rate	-0.070	-0.074	-0.338	0.361	0.412	0.452	-0.169	-0.187	-0.580
	(0.826)	(0.794)	(0.867)	(0.465)	(0.445)	(0.508)	(0.457)	(0.438)	(0.491)
Union Density	0.888***	0.918***	0.814***	0.205	0.205	0.161	0.567***	0.584***	0.575***
	(0.315)	(0.303)	(0.302)	(0.174)	(0.167)	(0.171)	(0.176)	(0.168)	(0.173)
Deindustrialization	1.259	1.249	0.771	0.106	0.114	-0.220	1.426***	1.413***	1.100**
	(0.820)	(0.783)	(0.776)	(0.469)	(0.448)	(0.454)	(0.455)	(0.437)	(0.442)
Trade Openness	-0.522***	-0.484***	-0.307	-0.187	-0.168*	-0.037	0.018	0.022	0.064
	(0.176)	(0.169)	(0.196)	(0.101)	(0.097)	(0.114)	(0.108)	(0.103)	(0.120)
Working Age Population	0.946	0.916	0.090	2.239**	2.210***	1.819**	-0.139	-0.140	-0.366
	(1.561)	(1.497)	(1.571)	(0.888)	(0.861)	(0.925)	(0.866)	(0.828)	(0.885)
Left Cabinet Seats	-0.024	-0.016	-0.015	0.035	0.036	0.042*	-0.049**	-0.046**	-0.040
	(0.041)	(0.039)	(0.038)	(0.023)	(0.022)	(0.022)	(0.023)	(0.022)	(0.021)
Christian Dem. Cabinet Seats	-0.160	-0.173*	-0.146	-0.070	-0.074	-0.056	-0.032	-0.036	-0.019
	(0.099)	(0.095)	(0.092)	(0.056)	(0.054)	(0.054)	(0.055)	(0.052)	(0.052)
Left Libertarian Vote	-0.285	-0.293	-0.421	-0.316	-0.325	-0.399	-0.248	-0.241	-0.274
	(0.650)	(0.621)	(0.603)	(0.371)	(0.354)	(0.028)	(0.361)	(0.345)	(0.342)
SPATIAL WEIGHTS:									
Borders		-0.004	-0.006		-0.007	-0.008		0.001	-0.002
		(0.007)	(0.007)		(0.007)	(0.007)		(0.007)	(0.007)
European Union Membership		-0.033***	-0.032***		-0.033***	-0.033***		-0.036***	-0.035***
		(0.012)	(0.012)		(0.012)	(0.012)		(0.013)	(0.013)
Trade Shares		0.018	0.025		0.027	0.030*		0.004	0.013
		(0.017)	(0.018)		(0.017)	(0.018)		(0.017)	(0.017)
ALM Program Expenditures		0.008	-0.004		-0.009	-0.015		0.019	0.005
		(0.016)	(0.017)		(0.015)	(0.016)		(0.015)	(0.016)
TIME DUMMIES?	*No*	*No*	*Yes*	*No*	*No*	*Yes*	*No*	*No*	*Yes*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
σ	22.176	21.184***	19.960***	12.604	12.028***	11.664***	12.324	11.765***	11.328***
		(0.785)	(0.739)		(0.452)	(0.436)		(0.436)	(0.419)
Log-Likelihood	-1646.410	-1642.34	-1620.8	-1438.49	-1434.31	-1423.27	-1430.23	-1425.92	-1411.92

Note: All regressions include fixed country effects. In addition to the country fixed effects, Model (3), (6) and (9) also include fixed year effects. All the spatial weights matrices are row-standardized. The parentheses contain standard errors. *** Significant at the .01 level; ** Significant at the .05 level; * Significant at the .10 level.

Table 2 presents our results. We estimate three regressions for each dependent variable: the first non-spatial with country indicators, the second spatial with country indicators, the third spatial with country and time indicators. The period dummies provide a flexible way to model common OECD-wide trends and/or common (random) shocks in ALM expenditures. Recall that the most important issue methodologically in obtaining good estimates of the strength of interdependence, i.e., of $\boldsymbol{\rho}$, is to model well any alternative mechanisms by which the outcomes might correlate spatially, such as common exogenous shocks (e.g., global economic conditions) or correlated domestic factors. From that perspective, the country and year dummies serve as a powerfully conservative way to account for almost any sort of outside shock or spatially correlated domestic factor. Failure to account for such alternative mechanisms will bias spatial-lag coefficient estimates, usually positively.

The non-spatial and spatial estimates suggest subtly different explanations for the spatiotemporal patterns in total ALM-program expenditures. The non-spatial model points to domestic real GDP-per-capita growth, labor-market structures, deindustrialization and especially union density, while the spatial model with period indicators suggests that the effects the other models attributed to domestic growth, deindustrialization, and trade exposure may more effectively be seen as resulting from the spatial diffusion of global economic conditions. More interestingly, perhaps, all three estimation techniques agree on sizable differences in sources of LMT versus SEMP spending. LMT seems closely related to age-demographics of the workforce, not very partisan or only a little left-oriented, and not very closely related to our labor-market structural or institutional measures. SEMP, contrarily, counts strongly left, labor, and deindustrialization, and not at all age-demographic, in its sources. Wald tests of the spatial-lag coefficients—the *t*-test on the EU co-membership coefficient, and joint tests of all four or of the three that are not individually significant—all overwhelmingly reject null hypotheses of zero coefficients, i.e., of the nonspatial model. (Admittedly, likelihood-ratio tests of the models, and observed improvements in residual standard-errors are less overwhelming.) Note in particular, we reiterate, that, while the spatial-lag coefficients for the borders, trade, and the endogenous connectivity matrices are individually insignificant, they are overwhelmingly significant jointly. This means that while the data cannot distinguish well any interdependence by one of these mechanisms from that possibly by another, they strongly reject that all three are absent. In short, ALM policies exhibit considerable spatial interdependence; consequently, coefficient estimates in the non-spatial model almost certainly suffer from omitted variable bias (as discussed above).

We focus, therefore, on the spatial models and, in particular, on the most-conservative time-dummies versions. The estimated GDP-growth coefficient shows weak if any counter-cyclicality in ALM policies. Oddly, total ALM spending seems negatively if at all related to unemployment. We see from the next two models some possible counter-cyclicality in LMT is counteracted by some possible pro-cyclicality in SEMP. None of this is statistically significant, however. We reiterate also the interesting differences in the domestic sources supported empirically for LMT as opposed to SEMP spending. LMT seems primarily a non-partisan-differentiated response to labor-market age-demographics, whereas SEMP seems a left-partisan response to labor-market sectoral-structural and organizational conditions. These strong differences in the explanatory models for the components of ALM urge great caution and care in interpreting the aggregated model. The coefficient on trade openness is negative but insignificant in the ALM and LMT models, slight support for arguments emphasizing competitive pressures. More importantly, we observe strong negative interdependency among the EU countries, and possibly also among bordering countries. This supports, strongly and weakly, respectively, our positive-externalities argument (Franzese & Hays 2006). The negative coefficient on the EU-membership spatial-lag also bolsters the case for those concerned that the EU is not adequately facilitating employment-policy coordination. The positive coefficient for the trade-weights spatial-lag, meanwhile, supports the globalization-induced-competition argument, mildly significantly so for LMT, nearly significantly for total ALM, and insignificantly for SEMP. The coefficients on the endogenous spatial-lag are near-zero and quite insignificant for total ALM and SEMP, and negative and almost as large as its standard error in the LMT case. This indicates, but very dubiously statistically, some small tendency for developed democracies to react negatively to, that is to do the opposite of, high-LMT spenders. Full interpretation of the interdependence effects that these estimates imply, however, requires calculation of the spatial multipliers, which we do next.

We are satisfied, then, that ALM policymaking exhibits statistically significant interdependence, but what do these statistically significant results tell us of the sign and substantive magnitude of this interdependence, i.e. of the effects individual countries' ALM policies have on policymakers in other countries *via* the estimated (network of) interdependencies? The spatial multiplier discussed above enables us to answer this question; in the m-STAR case, we can find it in this reduced form of (29):

$$\begin{aligned} \mathbf{y}_t &= \sum_{r=1}^{R} \rho_r \mathbf{W}_r \mathbf{y}_t + \phi \mathbf{y}_{t-1} + \mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \ \heartsuit \\ \mathbf{y}_t \left(\mathbf{I}_N - \rho_1 \mathbf{W}_1 ... - \rho_R \mathbf{W}_R \right) &= \phi \mathbf{y}_{t-1} + \mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \ \heartsuit \\ \mathbf{y}_t &= \left(\mathbf{I}_N - \rho_1 \mathbf{W}_1 ... - \rho_R \mathbf{W}_R \right)^{-1} \left(\phi \mathbf{y}_{t-1} + \mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \right) \end{aligned} \tag{30}$$

The spatial multiplier, $\left(\mathbf{I}_N - \rho_1 \mathbf{W}_1 ... - \rho_R \mathbf{W}_R \right)^{-1}$, captures the feedback from, say, Belgium on France and other countries, and back from France and those others on Belgium, and so on recursively. The immediate time-*t* effect on the vector of policy-outcomes in the 21 countries, $\mathbf{y}_t$, including that recursive feedback, can now be calculated with this spatial multiplier by considering certain counter-factual shocks to the rest of the right-hand side of (30). To find the long-run, steady-state, equilibrium (cumulative) level of $\mathbf{y}$ (for the case of time-invariant $\mathbf{W}$[41]), simply set $\mathbf{y}_{t-1}$ equal to $\mathbf{y}_t$ in (30) and solve. This gives the steady-state, assuming stationarity and that the exogenous RHS terms, $\mathbf{X}$ and $\boldsymbol{\varepsilon}$, remain permanently fixed to their counterfactual levels (see note 41):

$$\mathbf{y}_t = \left(\mathbf{I}_N - \rho_1 \mathbf{W}_1 ... - \rho_R \mathbf{W}_R - \phi \mathbf{I}_N\right)^{-1} \left(\mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right) \equiv \mathbf{S} \times \left(\mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t\right) \qquad (31).$$

To get standard-error estimates for these steady-state estimates, we use the delta method as detailed above. (We could also simulate them by drawing coefficient estimates from their estimated distribution and calculating (31) repeatedly. Given the nonlinearity of (31), simulated standard-error estimates would likely have better properties.)

Table 3 illustrates calculations for the countries in our sample of first-period effects of a one percentage-point increase in the column country's union density on the row country's SEMP, using (30) and the estimates from the m-STAR model (with time dummies) of SEMP. We apply the delta method for the standard errors, which appear in italics below those entries.

[41] With exogenously time-varying **W**, we need to specify values of **W** to assume to maintain in the long run. With endogenously time-varying **W**, the difference equation is much more complex, but, in principle, we could calculate the equilibrium numerically, assuming stationarity obtains.

Table 3: First-Period Spatial Effects of Union Density on SEMP Spending per Capita (2000 PPP$)

	AUS	AUT	BEL	CAN	DNK	FIN	FRA	GER	GRC	IRE	ITA	JPN	NTH	NWZ	NOR	PRT	ESP	SWE	CHE	GBR	USA
AUS	58.4***	0.03	0.21	0.02	0.05	0.09	0.11	0.1	0	0.13	0.07*	0.09	0.05*	0.08	0.01	0.02**	0.11	0.08	0.04*	0.02	0.06
	(16.83)	(0.03)	(0.17)	(0.02)	(0.04)	(0.07)	(0.08)	(0.07)	(0)	(0.11)	(0.04)	(0.31)	(0.03)	(0.33)	(0)	(0.01)	(0.09)	(0.06)	(0.03)	(0.08)	(0.25)
AUT	0.03	58.4***	0.05	0.01	-0.1*	-0.07	-0.04	0.05	-0.16**	-0.03	-0.06	0.03	-0.11*	0.02	0.01	-0.14**	-0.05	-0.08	0.07	-0.15**	0.02
	(0.02)	(16.83)	(0.14)	(0.01)	(0.06)	(0.07)	(0.06)	(0.34)	(0.07)	(0.1)	(0.09)	(0.02)	(0.06)	(0.02)	(0)	(0.07)	(0.08)	(0.06)	(0.1)	(0.07)	(0.05)
BEL	0.04	-0.12**	58.4**	0.01	-0.09	-0.05	0.02	0	-0.16**	0	-0.07	0.03	-0.06	0.02	0.01	-0.13	-0.03	-0.06	0.06	-0.12	0.02
	(0.03)	(0.06)	(16.83)	(0.01)	(0.07)	(0.08)	(0.09)	(0.11)	(0.07)	(0.11)	(0.06)	(0.02)	(0.09)	(0.02)	(0.01)	(0.06)	(0.08)	(0.07)	(0.04)	(0.08)	(0.07)
CAN	0.03	0.03	0.21	58.4**	0.05	0.09	0.11	0.09	0	0.13	0.06	0.03	0.04	0.02	0.01	0.02**	0.11	0.08	0.05	0.01	0.23
	(0.02)	(0.03)	(0.17)	(16.83)	(0.04)	(0.07)	(0.08)	(0.06)	(0)	(0.11)	(0.05)	(0.05)	(0.03)	(0.02)	(0.01)	(0.01)	(0.09)	(0.06)	(0.04)	(0.03)	(0.58)
DNK	0.03	-0.12	0.06	0.01	58.4**	-0.06	-0.04	0.01	-0.16**	-0.02	-0.09	0.03	-0.1	0.02	0.02	-0.14**	-0.05	-0.03	0.05*	-0.13	0.02
	(0.02)	(0.06)	(0.14)	(0.01)	(16.83)	(0.06)	(0.06)	(0.12)	(0.07)	(0.1)	(0.06)	(0.03)	(0.07)	(0.02)	(0.06)	(0.07)	(0.08)	(0.13)	(0.03)	(0.12)	(0.06)
FIN	0.04	-0.12**	0.06	0.01	-0.09	58.4**	-0.03	-0.03	-0.16**	-0.02	-0.08	0.03	-0.1*	0.02	0.04	-0.14**	-0.04	-0.02	0.05*	-0.13	0.03
	(0.02)	(0.06)	(0.14)	(0.01)	(0.06)	(16.83)	(0.07)	(0.14)	(0.07)	(0.1)	(0.06)	(0.04)	(0.06)	(0.02)	(0.16)	(0.07)	(0.08)	(0.12)	(0.03)	(0.12)	(0.09)
FRA	0.03**	-0.12**	0.09	0.01	-0.1*	-0.06	58.4**	-0.01	-0.16**	-0.02	-0.06	0.03	-0.1*	0.02	0.01	-0.14**	-0.02	-0.07	0.06	-0.12	0.03
	(0.03)	(0.06)	(0.13)	(0.01)	(0.06)	(0.08)	(16.83)	(0.12)	(0.07)	(0.1)	(0.07)	(0.03)	(0.06)	(0.02)	(0.01)	(0.06)	(0.07)	(0.07)	(0.06)	(0.08)	(0.09)
GER	0.03	-0.1*	0.08	0.01	-0.09	-0.06	-0.01	58.4**	-0.16**	-0.02	-0.07	0.03	-0.08	0.02	0.01	-0.14**	-0.04	-0.07	0.07	-0.13	0.03
	(0.02)	(0.06)	(0.14)	(0.01)	(0.09)	(0.07)	(0.07)	(16.83)	(0.07)	(0.1)	(0.08)	(0.04)	(0.06)	(0.02)	(0.02)	(0.06)	(0.07)	(0.06)	(0.05)	(0.11)	(0.1)
GRC	0.03	-0.12**	0.05	0.01	-0.1*	-0.07	-0.03	-0.02	58.4**	-0.03	-0.06	0.03	-0.1	0.02	0.01	-0.14**	-0.05	-0.08	0.05*	-0.14	0.02
	(0.02)	(0.06)	(0.13)	(0.01)	(0.06)	(0.07)	(0.07)	(0.19)	(16.83)	(0.1)	(0.06)	(0.04)	(0.07)	(0.02)	(0)	(0.07)	(0.07)	(0.06)	(0.03)	(0.09)	(0.06)
IRE	0.04	-0.12**	0.08	0.01	-0.1*	-0.06	-0.03	-0.04	-0.16**	58.4**	-0.08	0.03	-0.1*	0.02	0.01	-0.14**	-0.04	-0.07	0.05	-0.03	0.04
	(0.03)	(0.06)	(0.14)	(0.01)	(0.06)	(0.08)	(0.07)	(0.08)	(0.07)	(16.83)	(0.06)	(0.04)	(0.06)	(0.02)	(0.01)	(0.07)	(0.08)	(0.07)	(0.04)	(0.23)	(0.160
ITA	0.03	-0.1	0.06	0.01	-0.1*	-0.07	0	-0.02	-0.16**	-0.02	58.4**	0.03	-0.1	0.02	0.01	-0.14**	-0.04	-0.08	0.07	-0.14	0.03
	(0.02)	(0.13)	(0.13)	(0.01)	(0.06)	(0.08)	(0.08)	(0.2)	(0.07)	(0.1)	(16.83)	(0.02)	(0.06)	(0.02)	(0.01)	(0.06)	(0.06)	(0.06)	(0.11)	(0.1)	(0.09)
JPN	0.05	0.03	0.21	0.02	0.05	0.09	0.11	0.11	0	0.13	0.07*	58.4**	0.05*	0.02	0.01	0.02**	0.11	0.08	0.05*	0.01	0.12
	(0.06)	(0.02)	(0.17)	(0.05)	(0.04)	(0.07)	(0.08)	(0.08)	(0)	(0.11)	(0.04)	(16.83)	(0.03)	(0.02)	(0.01)	(0.01)	(0.09)	(0.06)	(0.03)	(0.06)	(0.53)
NTH	0.03	-0.12**	0.1	0.01	-0.1*	-0.07	-0.03	0.01	-0.16**	-0.02	-0.09	0.03	58.4**	0.02	0.01	-0.14**	-0.04	-0.08	0.05*	-0.12	0.02
	(0.02)	(0.06)	(0.13)	(0.01)	(0.06)	(0.07)	(0.08)	(0.16)	(0.07)	(0.1)	(0.06)	(0.02)	(16.83)	(0.02)	(0.01)	(0.07)	(0.07)	(0.06)	(0.03)	(0.09)	(0.07)
NWZ	0.14	0.03	0.21	0.02	0.05	0.09	0.11	0.1*	0	0.13	0.07*	0.07	0.04	58.4**	0.01	0.02**	0.11	0.08	0.05	0.02	0.05
	(0.24)	(0.03)	(0.17)	(0.02)	(0.04)	(0.07)	(0.08)	(0.06)	(0)	(0.11)	(0.04)	(0.19)	(0.03)	(16.83)	(0)	(0.01)	(0.09)	(0.06)	(0.04)	(0.08)	(0.21)
NOR	0.03	0.03	0.21	0.02	0.06	0.12	0.12	0.12	0	0.13	0.07*	0.03	0.06	0.02	58.4**	0.02**	0.11	0.13	0.05*	0.05	0.02
	(0.03)	(0.02)	(0.16)	(0.03)	(0.05)	(0.2)	(0.08)	(0.13)	(0)	(0.1)	(0.04)	(0.03)	(0.07)	(0.02)	(16.83)	(0.01)	(0.08)	(0.13)	(0.03)	(0.2)	(0.08)
PRT	0.03	-0.12**	0.05	0.01	-0.1*	-0.07	-0.02	-0.03	-0.16**	-0.03	-0.08	0.03	-0.11*	0.02	0.01	58.4**	0.04	-0.08	0.05*	-0.13	0.02
	(0.02)	(0.06)	(0.13)	(0.01)	(0.06)	(0.07)	(0.1)	(0.14)	(0.07)	(0.1)	(0.06)	(0.02)	(0.06)	(0.02)	(0.01)	(16.83)	(0.27)	(0.06)	(0.03)	(0.11)	(0.05)
ESP	0.03	-0.12**	0.07	0.01	-0.1*	-0.06	0.03	-0.03	-0.16**	-0.02	-0.07	0.03	-0.1*	0.02	0.01	-0.1	58.4**	-0.07	0.05	-0.13	0.02
	(0.03)	(0.06)	(0.14)	(0.01)	(0.06)	(0.08)	(0.11)	(0.14)	(0.07)	(0.1)	(0.09)	(0.03)	(0.06)	(0.02)	(0.01)	(0.16)	(16.83)	(0.07)	(0.03)	(0.11)	(0.08)
SWE	0.03	-0.12**	0.06	0.01	-0.07	-0.04	-0.04	-0.03	-0.16**	-0.02	-0.09	0.03	-0.1	0.02	0.04	-0.14**	-0.04	58.4**	0.05*	-0.13	0.03
	(0.02)	(0.06)	(0.14)	(0.01)	(0.1)	(0.12)	(0.06)	(0.14)	(0.07)	(0.1)	(0.06)	(0.03)	(0.07)	(0.02)	(0.08)	(0.07)	(0.08)	(16.83)	(0.03)	(0.12)	(0.09)
CHE	0.03	0.05	0.22	0.01	0.06	0.09	0.15*	0.17	0	0.14	0.1	0.03	0.05	0.02	0.01	0.02**	0.11	0.08	58.4**	0.02	0.03
	(0.02)	(0.08)	(0.16)	(0.01)	(0.04)	(0.07)	(0.09)	(0.22)	(0.01)	(0.11)	(0.07)	(0.04)	(0.04)	(0.02)	(0)	(0.01)	(0.08)	(0.06)	(16.83)	(0.07)	(0.1)
GBR	0.03	-0.12**	0.07	0.01	-0.1*	-0.07	-0.02	-0.04	-0.16**	-0.01	-0.09	0.03	-0.09	0.02	0.01	-0.14**	-0.05	-0.08	0.05*	58.4**	0.04
	(0.02)	(0.06)	(0.16)	(0.02)	(0.06)	(0.07)	(0.07)	(0.13)	(0.07)	(0.11)	(0.06)	(0.04)	(0.07)	(0.01)	(0.02)	(0.07)	(0.07)	(0.06)	(0.03)	(16.83)	(0.16)
USA	0.04**	0.03	0.21	0.13	0.05	0.09	0.11	0.1	0	0.13	0.07*	0.07	0.05*	0.02	0.01	0.02**	0.11	0.08	0.05*	0.02	58.4**
	(0.02)	(0.02)	(0.16)	(0.24)	(0.04)	(0.07)	(0.07)	(0.08)	(0)	(0.1)	(0.04)	(0.21)	(0.03)	(0.02)	(0.01)	(0.01)	(0.08)	(0.06)	(0.03)	(0.08)	(16.83)

Notes: The cells report the first-period spatial effect of a 1% increase in the column country's union density on its own subsidized employment expenditures (×100) and the expenditures (×100) of its OECD counterparts (identified by the rows) based on the model (8) estimates.

Using (27), we can also show the estimated weights matrix, i.e., the estimated pattern of network interdependencies among developed democracies in ALM policy, as in Tables 4-6.

Table 4: Estimated ALM-Policy Interdependencies/Network in 1981

	AUS	CAN	FIN	FRA	NTH	NWZ	ESP	SWE	GBR	USA
AUS	0.000	0.019	0.456	0.022	0.075	0.617	0.09*	0.706	0.225	0.179
	0.000	*0.086*	*0.336*	*0.099*	*0.051*	*0.646*	*0.053*	*0.514*	*0.219*	*0.806*
CAN	0.002	0.000	0.451	0.005	0.064	0.481	0.084	0.697	0.176	0.428
	0.009	*0.000*	*0.348*	*0.023*	*0.041*	*0.373*	*0.062*	*0.537*	*0.107*	*1.135*
FIN	0.008	0.007	0.000	0.044	0.118	0.627	0.126*	1.092	0.300	0.066
	0.035	*0.032*	*0.000*	*0.199*	*0.143*	*0.486*	*0.074*	*0.758*	*0.315*	*0.297*
FRA	0.005	0.009	0.458	0.000	-1.675	0.481	0.202	0.712	-1.49***	0.093
	0.021	*0.042*	*0.332*	*0.000*	*0.605*	*0.372*	*0.206*	*0.500*	*0.569*	*0.415*
NTH	0.004	0.006	0.476	-1.69**	0.000	0.496	0.114	0.744	-1.435**	0.079
	0.018	*0.027*	*0.335*	*0.702*	*0.000*	*0.386*	*0.103*	*0.499*	*0.669*	*0.354*
NWZ	0.243	0.013	0.602	0.013	0.089*	0.000	0.115	0.931	0.265	0.118
	0.464	0.060	0.461	0.058	0.051	0.000	0.077	0.703	0.174	0.529
ESP	*0.003*	*0.005*	*0.477*	*0.249*	*0.102*	*0.503*	*0.000*	*0.739*	*0.250*	*0.060*
	0.014	0.024	0.351	0.478	0.147	0.389	0.000	0.533	0.291	0.270
SWE	0.008	0.009	0.836	0.052	0.150	0.751	0.148*	0.000	0.353	0.082
	0.034	*0.041*	*0.787*	*0.235*	*0.212*	*0.581*	*0.085*	*0.000*	*0.351*	*0.366*
GBR	0.011	0.016	0.504	-1.67***	-1.621***	0.528	0.121	0.784	0.000	0.122
	0.048	*0.071*	*0.356*	*0.620*	*0.608*	*0.401*	*0.110*	*0.535*	*0.000*	*0.547*
USA	0.014	0.311	0.454	0.031	0.082	0.483	0.092*	0.704	0.217	0.000
	0.062	*0.672*	*0.342*	*0.139*	*0.077*	*0.367*	*0.052*	*0.518*	*0.189*	*0.000*

Note: Dependent variable: SEMP. Actual weights multiplied them by 100 (and standard errors adjusted accordingly) to improve table formatting. [XXXX: These are for c-dums, no t-dums model]

Table 5: Estimated ALM-Policy Interdependencies/Network in 1991

	AUS	BEL	CAN	DEN	FIN	FRA	DEU	IRE	ITA	JPN	NTH	NWZ	NOR	PRT	ESP	SWE	CHE	GBR	USA
AUS	0.000	0.458	0.022	0.201	0.312	0.070	0.126	0.130	0.040	0.160	0.036	0.215	0.115	0.025	0.218	0.101	0.008	0.047	0.105
	0.000	*0.339*	*0.041*	*0.150*	*0.233*	*0.045*	*0.091*	*0.093*	*0.056*	*0.523*	*0.026*	*0.578*	*0.085*	*0.017*	*0.159*	*0.062*	*0.023*	*0.137*	*0.426*
BEL	0.029	0.000	0.018*	-0.140	0.401	-0.232	-0.165	-0.227	-0.345**	0.060	-0.275	0.139	0.149	-0.365***	-0.110	0.131	0.009	-0.320**	0.040
	0.018	*0.000*	*0.010*	*0.203*	*0.303*	*0.192*	*0.208*	*0.144*	*0.138*	*0.037*	*0.194*	*0.107*	*0.107*	*0.131*	*0.190*	*0.079*	*0.025*	*0.152*	*0.121*
CAN	0.023*	0.453	0.000	0.199	0.309	0.062	0.108	0.128	0.029*	0.059	0.032*	0.107	0.115	0.024***	0.215	0.096	0.004	0.025	0.401
	0.013	*0.345*	*0.000*	*0.152*	*0.238*	*0.037*	*0.065*	*0.097*	*0.017*	*0.073*	*0.018*	*0.082*	*0.082*	*0.018*	*0.164*	*0.070*	*0.006*	*0.039*	*0.982*
DEN	0.025*	0.111	0.016	0.000	0.353	-0.311**	-0.153	-0.255*	-0.353***	0.058	-0.342**	0.119	0.150	-0.370*	-0.155	0.196	0.010	-0.341*	0.035
	0.015	*0.343*	*0.010*	*0.000*	*0.236*	*0.131*	*0.223*	*0.144*	*0.135*	*0.052*	*0.145*	*0.091*	*0.096*	*0.132*	*0.179*	*0.207*	*0.033*	*0.199*	*0.108*
FIN	0.029	0.544	0.018	0.251	0.000	0.093	0.191	0.153	0.048	0.065	0.055	0.127	0.188	0.031***	0.262	0.210	0.011	0.064	0.047
	0.017	*0.383*	*0.014*	*0.151*	*0.000*	*0.089*	*0.281*	*0.108*	*0.072*	*0.068*	*0.081*	*0.097*	*0.316*	*0.018*	*0.175*	*0.201*	*0.035*	*0.202*	*0.158*
FRA	0.023*	0.115	0.016	-0.192	0.318	0.000	-0.199	-0.264*	-0.311*	0.054	-0.345**	0.110	0.121	-0.369***	-0.134	0.104	0.030	-0.329**	0.047
	0.014	*0.281*	*0.014*	*0.170*	*0.238*	*0.000*	*0.246*	*0.138*	*0.166*	*0.048*	*0.144*	*0.084*	*0.079*	*0.131*	*0.148*	*0.062*	*0.070*	*0.153*	*0.165*
DEU	0.024*	0.121	0.016	-0.167	0.328	-0.262	0.000	-0.261*	-0.330	0.060	-0.309**	0.112	0.126	-0.370***	-0.158	0.111*	0.042	-0.343*	0.052
	0.014	*0.317*	*0.013*	*0.228*	*0.238*	*0.172*	*0.000*	*0.138*	*0.197*	*0.070*	*0.149*	*0.086*	*0.078*	*0.131*	*0.151*	*0.063*	*0.080*	*0.196*	*0.190*
IRE	0.024*	0.099	0.016	-0.184	0.330	-0.310**	-0.250	0.000	-0.359***	0.058	-0.348**	0.114	0.124	-0.373***	-0.163	0.107	0.010	-0.175	0.072
	0.014	*0.309*	*0.013*	*0.174*	*0.248*	*0.139*	*0.162*	*0.000*	*0.130*	*0.060*	*0.137*	*0.087*	*0.084*	*0.134*	*0.172*	*0.066*	*0.031*	*0.405*	*0.278*
ITA	0.025	0.075	0.017	-0.195	0.313	-0.230	-0.199	-0.268*	0.000	0.051	-0.347**	0.108	0.116	-0.371***	-0.160	0.102	0.062	-0.350**	0.047
	0.015	*0.289*	*0.016*	*0.167*	*0.234*	*0.212*	*0.386*	*0.140*	*0.000*	*0.039*	*0.142*	*0.083*	*0.083*	*0.131*	*0.140*	*0.061*	*0.259*	*0.174*	*0.166*
JPN	0.047	0.464	0.031	0.204	0.315	0.072	0.136	0.132	0.035	0.000	0.041	0.113	0.117	0.025	0.221	0.100	0.009	0.037	0.214
	0.107	*0.339*	*0.078*	*0.149*	*0.237*	*0.051*	*0.122*	*0.092*	*0.036*	*0.000*	*0.042*	*0.075*	*0.084*	*0.016*	*0.159*	*0.065*	*0.030*	*0.089*	*0.916*
NTH	0.023	0.139	0.015	-0.193	0.315	-0.300*	-0.156	-0.267*	-0.352**	0.050	0.000	0.108	0.120	-0.372***	-0.173	0.105*	0.009	-0.315**	0.039
	0.014	*0.284*	*0.009*	*0.163*	*0.231*	*0.176*	*0.310*	*0.138*	*0.141*	*0.037*	*0.000*	*0.084*	*0.076*	*0.133*	*0.160*	*0.060*	*0.030*	*0.173*	*0.131*
NWZ	0.212	0.480	0.022	0.210	0.325	0.070*	0.125	0.135	0.037	0.117	0.035*	0.000	0.120	0.026	0.228	0.104	0.006	0.047	0.089
	0.399	*0.352*	*0.036*	*0.157*	*0.248*	*0.040*	*0.077*	*0.101*	*0.039*	*0.322*	*0.021*	*0.000*	*0.090*	*0.018*	*0.168*	*0.067*	*0.014*	*0.133*	*0.356*
NOR	0.023	0.486	0.024	0.234*	0.375	0.089	0.164	0.138	0.039	0.055	0.060	0.113	0.000	0.028*	0.232	0.191	0.006	0.092	0.039
	0.015	*0.344*	*0.046*	*0.132*	*0.435*	*0.103*	*0.222*	*0.094*	*0.047*	*0.047*	*0.121*	*0.087*	*0.000*	*0.016*	*0.160*	*0.208*	*0.016*	*0.333*	*0.131*
PRT	0.022	0.070	0.015	-0.195	0.313	-0.287	-0.226	-0.269*	-0.345**	0.048	-0.348**	0.108	0.119	0.000	-0.027	0.103*	0.010	-0.345**	0.029
	0.014	*0.299*	*0.009*	*0.166*	*0.233*	*0.223*	*0.272*	*0.144*	*0.156*	*0.032*	*0.139*	*0.083*	*0.077*	*0.000*	*0.470*	*0.060*	*0.033*	*0.190*	*0.087*
ESP	0.025	0.119	0.016	-0.174	0.347	-0.209	-0.215	-0.253*	-0.325	0.056	-0.348***	0.120	0.129	-0.310	0.000	0.112	0.010	-0.343**	0.040
	0.015	*0.337*	*0.010*	*0.182*	*0.260*	*0.222*	*0.268*	*0.143*	*0.206*	*0.043*	*0.134*	*0.092*	*0.092*	*0.291*	*0.000*	*0.069*	*0.030*	*0.190*	*0.132*
SWE	0.025*	0.489	0.017	0.264	0.373	0.085	0.175	0.136	0.043	0.055	0.056	0.112	0.181	0.028*	0.232	0.000	0.011	0.060	0.047
	0.015	*0.325*	*0.015*	*0.206*	*0.295*	*0.090*	*0.275*	*0.094*	*0.065*	*0.049*	*0.102*	*0.086*	*0.150*	*0.016*	*0.155*	*0.000*	*0.035*	*0.192*	*0.165*
CHE	0.023*	0.462	0.015	0.202	0.310	0.131	0.254	0.131	0.093	0.056	0.047	0.107	0.114	0.026*	0.222	0.102	0.000	0.044	0.048
	0.013	*0.316*	*0.012*	*0.142*	*0.230*	*0.132*	*0.382*	*0.088*	*0.131*	*0.064*	*0.069*	*0.082*	*0.083*	*0.015*	*0.145*	*0.060*	*0.000*	*0.125*	*0.174*
GBR	0.026	0.095	0.020	-0.194	0.314	-0.277*	-0.234	-0.230	-0.351**	0.057	-0.315**	0.109	0.124*	-0.371***	-0.170	0.107*	0.015	0.000	0.071
	0.020	*0.349*	*0.032*	*0.161*	*0.226*	*0.142*	*0.243*	*0.175*	*0.144*	*0.066*	*0.149*	*0.079*	*0.071*	*0.132*	*0.150*	*0.061*	*0.054*	*0.000*	*0.273*
USA	0.029	0.459	0.224	0.200	0.309	0.076	0.133	0.132	0.039	0.125	0.041	0.108	0.115	0.025	0.219	0.100	0.010	0.045	0.000
	0.029	*0.327*	*0.409*	*0.149*	*0.234*	*0.065*	*0.119*	*0.086*	*0.052*	*0.367*	*0.045*	*0.079*	*0.081*	*0.016*	*0.154*	*0.063*	*0.031*	*0.128*	*0.000*

Note: Dependent variable: SEMP. Actual weights multiplied them by 100 (and standard errors adjusted accordingly) to improve table formatting. [XXXX: These are for c-dums, no t-dums model]

Table 6: Estimated ALM-Policy Interdependencies/Network in 2001

	AUS	AUT	BEL	CAN	DEN	FIN	FRA	DEU	GRE	IRE	ITA	JPN	NTH	NWZ	NOR	PRT	ESP	SWE	CHE	GBR	USA
AUS	0.000	0.060	0.359	0.028	0.094	0.156	0.194	0.174*	0.001	0.228	0.120*	0.157	0.080*	0.142	0.009*	0.034	0.189	0.136	0.084	0.039	0.103
	0.000	*0.042*	*0.262*	*0.039*	*0.067*	*0.111*	*0.119*	*0.103*	*0.003*	*0.169*	*0.068*	*0.521*	*0.046*	*0.559*	*0.005*	*0.024*	*0.136*	*0.089*	*0.051*	*0.139*	*0.423*
AUT	0.055	0.000	0.088	0.021*	-0.180*	-0.120	-0.073	0.086	-0.274***	-0.048	-0.104	0.048	-0.189**	0.035	0.010	-0.241***	-0.082	-0.138	0.127	-0.253**	0.028
	0.039	*0.000*	*0.240*	*0.012*	*0.096*	*0.123*	*0.108*	*0.590*	*0.095*	*0.172*	*0.145*	*0.040*	*0.083*	*0.026*	*0.007*	*0.090*	*0.129*	*0.103*	*0.169*	*0.104*	*0.087*
BEL	0.065	-0.204**	0.000	0.024*	-0.164	-0.093	0.030	0.004	-0.274***	-0.002	-0.130	0.053	-0.104	0.042	0.012	-0.234***	-0.045	-0.113	0.099	-0.208	0.037
	0.046	*0.090*	*0.000*	*0.014*	*0.103*	*0.141*	*0.147*	*0.185*	*0.095*	*0.184*	*0.090*	*0.034*	*0.155*	*0.031*	*0.010*	*0.088*	*0.141*	*0.111*	*0.061*	*0.128*	*0.120*
CAN	0.054	0.058	0.350	0.000	0.091	0.151	0.183	0.154	0.001	0.222	0.107	0.056	0.075	0.035	0.010	0.033	0.183	0.130	0.079	0.017	0.399
	0.037	*0.043*	*0.265*	*0.000*	*0.069*	*0.115*	*0.128*	*0.099*	*0.001*	*0.171*	*0.072*	*0.073*	*0.050*	*0.026*	*0.008*	*0.024*	*0.139*	*0.096*	*0.056*	*0.041*	*0.979*
DEN	0.057	-0.212**	0.096	0.021*	0.000	-0.108	-0.067	0.010	-0.273***	-0.042	-0.151*	0.052	-0.177*	0.036	0.033	-0.240***	-0.079	-0.053	0.088*	-0.228	0.033
	0.038	*0.088*	*0.240*	*0.012*	*0.000*	*0.104*	*0.109*	*0.204*	*0.095*	*0.169*	*0.086*	*0.051*	*0.100*	*0.027*	*0.107*	*0.089*	*0.133*	*0.217*	*0.051*	*0.185*	*0.107*
FIN	0.061	-0.209**	0.109	0.023	-0.162*	0.000	-0.061	-0.048	-0.273***	-0.035	-0.147*	0.057	-0.179**	0.037	0.063	-0.238***	-0.071	-0.042	0.091*	-0.223	0.044
	0.036	*0.086*	*0.247*	*0.015*	*0.084*	*0.000*	*0.111*	*0.245*	*0.095*	*0.175*	*0.086*	*0.068*	*0.089*	*0.028*	*0.276*	*0.089*	*0.132*	*0.205*	*0.052*	*0.202*	*0.155*
FRA	0.059	-0.209**	0.155	0.023	-0.173*	-0.110	0.000	-0.020	-0.273***	-0.030	-0.101	0.053	-0.174*	0.038	0.013	-0.235***	-0.032	-0.130	0.112	-0.214	0.045
	0.040	*0.088*	*0.223*	*0.015*	*0.097*	*0.130*	*0.000*	*0.214*	*0.095*	*0.174*	*0.109*	*0.047*	*0.097*	*0.028*	*0.019*	*0.087*	*0.122*	*0.107*	*0.096*	*0.129*	*0.162*
DEU	0.059	-0.179*	0.139	0.022	-0.158	-0.111	-0.016	0.000	-0.272***	-0.034	-0.126	0.056	-0.145	0.037	0.015	-0.237***	-0.065	-0.128	0.118	-0.231	0.048
	0.039	*0.097*	*0.239*	*0.014*	*0.143*	*0.123*	*0.122*	*0.000*	*0.094*	*0.171*	*0.136*	*0.065*	*0.100*	*0.028*	*0.027*	*0.088*	*0.119*	*0.098*	*0.079*	*0.171*	*0.176*
GRE	0.053	-0.214**	0.084	0.020*	-0.180**	-0.123	-0.061	-0.039	0.000	-0.054	-0.100	0.055	-0.176	0.035	0.010	-0.242***	-0.082	-0.142	0.085*	-0.239	0.031
	0.038	*0.085*	*0.218*	*0.011*	*0.090*	*0.118*	*0.125*	*0.336*	*0.000*	*0.164*	*0.275*	*0.073*	*0.111*	*0.025*	*0.007*	*0.091*	*0.114*	*0.100*	*0.048*	*0.145*	*0.102*
IRE	0.061	-0.210**	0.132	0.023	-0.171*	-0.106	-0.049	-0.070	-0.275***	0.000	-0.147	0.057	-0.175*	0.039	0.013	-0.238***	-0.064	-0.127	0.094*	-0.061	0.071
	0.041	*0.093*	*0.242*	*0.014*	*0.098*	*0.133*	*0.115*	*0.136*	*0.096*	*0.000*	*0.088*	*0.060*	*0.090**	*0.029*	*0.016*	*0.091*	*0.140*	*0.110*	*0.055*	*0.401*	*0.276*
ITA	0.058	-0.179	0.106	0.023	-0.177*	-0.117	0.006	-0.028	-0.269***	-0.041	0.000	0.048	-0.179	0.036	0.010	-0.238***	-0.063	-0.136	0.127	-0.237	0.044
	0.036	*0.218*	*0.224*	*0.015*	*0.095*	*0.127*	*0.143*	*0.345*	*0.095*	*0.171*	*0.000*	*0.037*	*0.094*	*0.027*	*0.008*	*0.088*	*0.111*	*0.106*	*0.177*	*0.151*	*0.158*
JPN	0.079	0.060	0.358	0.036	0.095	0.154	0.194	0.182	0.002	0.227	0.114*	0.000	0.084*	0.039*	0.010	0.034	0.188	0.134	0.085*	0.028	0.211
	0.097	*0.040*	*0.256*	*0.076*	*0.064*	*0.112*	*0.116*	*0.124*	*0.005*	*0.166*	*0.066*	*0.000*	*0.049*	*0.022*	*0.008*	*0.023*	*0.133*	*0.091*	*0.049*	*0.092*	*0.909*
NTH	0.056	-0.213**	0.163	0.021*	-0.177*	-0.118	-0.052	0.014	-0.273***	-0.044	-0.148	0.047	0.000	0.035	0.014	-0.240***	-0.078	-0.135	0.086*	-0.200	0.037
	0.039	*0.087*	*0.224*	*0.012*	*0.091*	*0.122*	*0.131*	*0.281*	*0.095*	*0.166*	*0.089*	*0.036*	*0.000*	*0.027*	*0.024*	*0.089*	*0.125*	*0.098*	*0.050*	*0.151*	*0.129*
NWZ	0.242	0.059	0.357	0.027	0.093	0.153	0.189	0.168*	0.002	0.225	0.115*	0.112	0.077	0.000	0.009*	0.034	0.187	0.134	0.081	0.038	0.087
	0.397	*0.042*	*0.257*	*0.034*	*0.067*	*0.114*	*0.122*	*0.095*	*0.005*	*0.171*	*0.066*	*0.321*	*0.047*	*0.000*	*0.005*	*0.024*	*0.136*	*0.090*	*0.053*	*0.136*	*0.354*
NOR	0.053	0.060	0.356	0.029	0.114	0.199	0.205*	0.204	0.002	0.225	0.115*	0.049	0.101	0.035	0.000	0.036*	0.188	0.218	0.081	0.082	0.038
	0.038	*0.039*	*0.244*	*0.044*	*0.088*	*0.341*	*0.119*	*0.212*	*0.005*	*0.161*	*0.065*	*0.047*	*0.109*	*0.026*	*0.000*	*0.020*	*0.126*	*0.215*	*0.052*	*0.334*	*0.130*
PRT	0.054	-0.215**	0.090	0.020*	-0.180*	-0.122	-0.042	-0.057	-0.275***	-0.051	-0.144	0.045	-0.182**	0.035	0.013	0.000	0.064	-0.139	0.085*	-0.231	0.028
	0.038	*0.089*	*0.222*	*0.011*	*0.093*	*0.123*	*0.174*	*0.247*	*0.096*	*0.169*	*0.103*	*0.031*	*0.093*	*0.026*	*0.021*	*0.000*	*0.459*	*0.100*	*0.049*	*0.175*	*0.087*
ESP	0.059	-0.209**	0.118	0.022*	-0.174*	-0.109	0.043	-0.045	-0.273***	-0.030	-0.118	0.051	-0.179**	0.038	0.011	-0.179	0.000	-0.130	0.091*	-0.230	0.038
	0.041	*0.088*	*0.245*	*0.013*	*0.099*	*0.130*	*0.192*	*0.243*	*0.095*	*0.176*	*0.154*	*0.042*	*0.087*	*0.028*	*0.010*	*0.276*	*0.000*	*0.108*	*0.054*	*0.174*	*0.130*
SWE	0.059	-0.210**	0.110	0.023	-0.124	-0.066	-0.063	-0.051	-0.274***	-0.038	-0.150*	0.052	-0.175**	0.037	0.070	-0.239***	-0.075	0.000	0.090*	-0.225	0.045
	0.037	*0.087*	*0.231*	*0.016*	*0.166*	*0.202*	*0.110*	*0.237*	*0.095*	*0.172*	*0.085*	*0.048*	*0.099*	*0.027*	*0.133*	*0.089*	*0.133*	*0.000*	*0.052*	*0.194*	*0.163*
CHE	0.057	0.095	0.372	0.021	0.098	0.158	0.249*	0.293	0.003	0.233	0.166	0.054	0.091*	0.036	0.010	0.036*	0.197	0.139	0.000	0.035	0.046
	0.037	*0.128*	*0.249*	*0.013*	*0.063*	*0.113*	*0.135*	*0.369*	*0.008*	*0.168*	*0.107*	*0.060*	*0.063*	*0.027*	*0.007*	*0.021*	*0.127*	*0.088*	*0.000*	*0.122*	*0.166*
GBR	0.058	-0.216**	0.112	0.026	-0.179**	-0.122	-0.035	-0.067	-0.274***	-0.014	-0.150	0.054	-0.150	0.036	0.018	-0.240	-0.080	-0.137	0.089*	0.000	0.069
	0.033	*0.089*	*0.274*	*0.030*	*0.089*	*0.115*	*0.121*	*0.218*	*0.095*	*0.198*	*0.091*	*0.066*	*0.114*	*0.023*	*0.043*	*0.088*	*0.113*	*0.093*	*0.052*	*0.000*	*0.270*
USA	0.060	0.059	0.355	0.228	0.092	0.151	0.196*	0.179	0.001	0.226	0.117*	0.121	0.084	0.036	0.010	0.034***	0.186	0.133	0.084*	0.037	0.000
	0.035	*0.040*	*0.246*	*0.407*	*0.066*	*0.111*	*0.112*	*0.121*	*0.003*	*0.158*	*0.066*	*0.365*	*0.050*	*0.023*	*0.010*	*0.023*	*0.129*	*0.087*	*0.049*	*0.131*	*0.000*

Note: Dependent variable: SEMP. Actual weights multiplied them by 100 (and standard errors adjusted accordingly) to improve table formatting. [XXXX: These are for c-dums, no t-dums model]

We can also illustrate our estimated patterns of interdependence, i.e., ALM-policy network, using graphical techniques familiar to network analysts. Figures 4-6 graph the estimated patterns and strengths of interdependence in 1981, 1991, and 2001 thus. First, they show only the statistically significantly estimated ties (p<.10) edges. The circle nodes are EU member-countries; others are squares. Red arrows represent negative interdependence, indicative of net-positive externalities between those countries and consequent free-riding among them. Blue arrows are positive interdependence, indicative of net-negative externalities and net-competitive relations. The thickness of the arrows represents the estimated strength of the relationship. Nodes with all estimated dependencies insignificant at the .10 level appear as singletons.

Figure 4: The Estimated Network of ALM-policy Interdependence, 1981

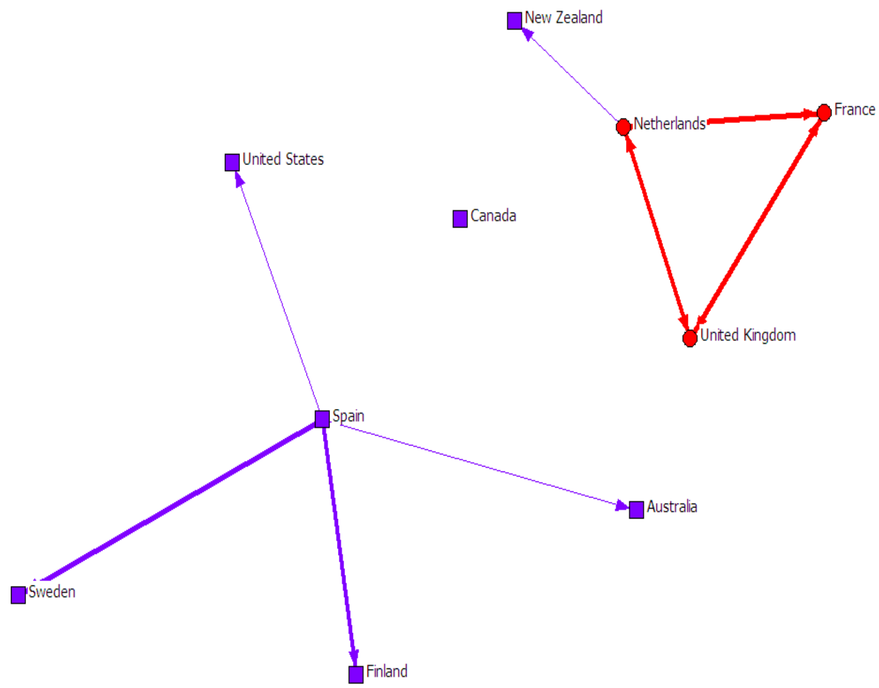


Figure 5: The Estimated Network of ALM-policy Interdependence, 1991

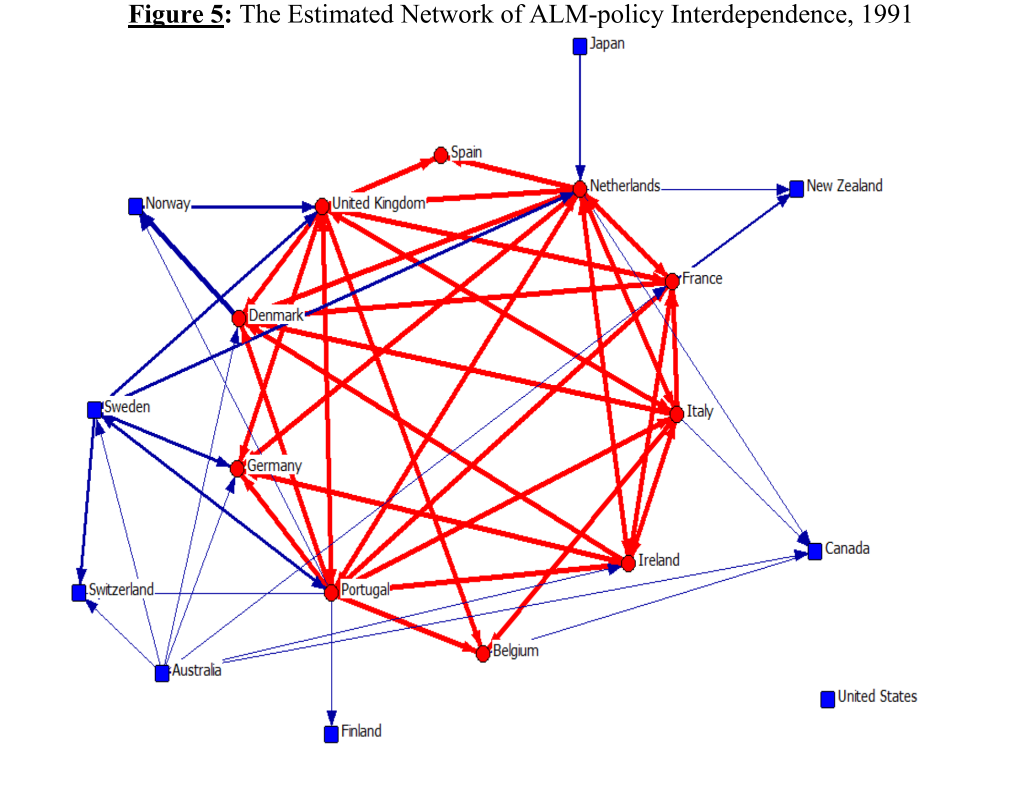
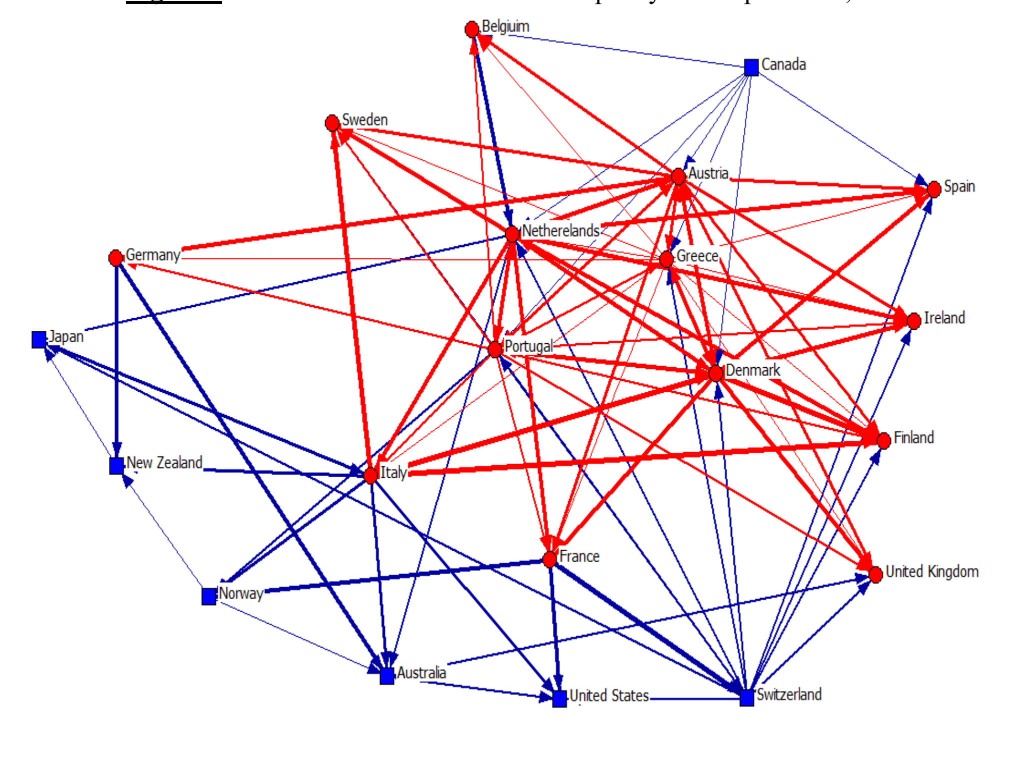


Figure 6: The Estimated Network of ALM-policy Interdependence, 2001



AS OF THIS WRITING, WE HAVE NOT YET CALCULATED SPATIOTEMPORAL DYNAMIC EFFECTS OR LONG-RUN STEADY-STATE EQUILIBRIUM EFFECTS (OR THEIR STANDARD ERRORS). THESE REQUIRE ADDRESSING THE ENDOGENOUS FEEDBACK OF THE CO-EVOLUTION PROCESS.

VI. Conclusion and Discussion

In Franzese and Hays (2006), we estimated single lag STAR models using binary contiguity (borders) weights matrices and a sample of European countries over the period 1987-1998. Our estimated coefficients on the spatial lags in those regressions were negatively signed and statistically significant, and we argued that these results suggested that there was ALM policy free-riding in the European Union. The results here, using an m-STAR model to consider multiple possible patterns and pathways of ALM-policy interdependence among the developed democracies in general, are strongly consistent with the conclusion that free-riding dynamics dominate among EU-member countries. It also supports, but considerably less strongly, that these dynamics emerge specifically in great extent due to cross-border spillovers as we had suggested. We also find now some suggestions in the evidence of negative externalities via trade-related competition, although again neither strongly significantly nor sizably. Methodologically, we have offered here a simple way to model and estimate networks/patterns-of-interdependence simultaneously with estimation of the effect of those networks/interdependencies on units' actions. Within this framework, we have suggested and started on the more ambitious agenda of endogenizing those two components of the co-evolution of networks/interdependence-patterns and unit behavior/actions.

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