<u>Project Description</u>: Spatial-Econometric Models for the Political & Social Sciences

Robert J. Franzese, Jr. Jude C. Hays

0. Project Overview

The interdependence of outcomes across units of observation, *spatial interdependence*, is substantively ubiquitous and theoretically quite central across the social sciences. Empirically, the clustering or correlation of outcomes on some dimension(s), *spatial association*, is also obvious in most contexts. However, outcomes may evidence spatial association for at least two distinct reasons. Units may be responding similarly to similar exposure to similar exogenous internal/domestic or external/foreign stimuli (*common exposure*), or units' responses may depend on others' responses (*interdependence*, or *contagion*). We may find states' adoptions of some economic treaty, e.g., to cluster geographically or along other dimensions of *proximity*, e.g., bilateral trade-volume, because proximate states experience similar exogenous domestic or foreign political-economic stimuli or because each state's decision to sign depends on whether proximate others sign. The theories and policy implications that these alternative sources of spatial association support obviously differ starkly.

In previously funded research,[1] we explored the specification, estimation, interpretation, and presentation of spatial- and spatiotemporal-lag linear-regression models, which reflect spatial interdependence directly and which therefore can distinguish common exposure from contagion as alternative substantive sources of observed spatial association. For such models, we gauged analytically and by simulation the biases of omitting interdependence or of including spatial lags to reflect it but ignoring the lags' simultaneity, finding the former a typically far graver concern, but that the latter becomes one too as interdependence strengthens. We explained maximum-likelihood and moment estimators that redress the simultaneity, and our simulations showed them near-dominant as estimators. We explored various model-specification tests and the sensitivity of the estimators' performance to misspecification of the non-spatial component, of the pattern of spatial-connectivity, or of the strict assumptions of the consistent estimators. Finally, we showed how to calculate spatial and spatiotemporal dynamics and initial and equilibrium effects, along with their certainty estimates.

We propose next to undertake a like set of tasks for two further, and more challenging, classes of models: those with interdependence among qualitative, limited, or systems of dependent variables (*S-QualDep* or *S-SysEq* models), and those that estimate jointly the connectivity pattern and the strength of contagion by that pattern (*Estimated*-**W** models), including the case where connectivity is endogenous to the dependent variable (*Endogenous*-**W** models). Section 3 details our specific plans in these regards and offers preliminary analyses suggesting their likely fruitfulness. As before, we stress substantively-theoretically guided (i.e., structural) specifications that can support counterfactual analyses of spatial or spatiotemporal responses in dependent-variable terms and that can distinguish the possible sources of spatial association, now three: common exposure, contagion, and *selection*. The last possibility arises with endogenous-**W**, i.e., when the putative outcome affects the variable along which clustering occurs. Continuing the example, treaty signatories might also cluster according to some variable on which we observe their proximity (e.g., volume of trade between them) because being co-signatories affects that variable (e.g., spurs bilateral trade). Again, the theories and policy-advice supported by the observation of spatial association hinge critically on whether (or gauging the relative degrees to which) state signatories cluster in pockets of dense trade relations because those states tend to experience similar exogenous domestic or internal conditions favoring signing, because the signing by some states spurs their trading partners to sign, or because the treaty fosters trade between co-signatories.

1. The Theoretical and Substantive Centrality of Spatial Interdependence and the Empirical Ubiquity of Spatial Association

Interdependence of outcomes across units of observation (*spatial interdependence* or *contagion*) is ubiquitous and quite central across the theory and substance of social science. In a tour across political/social science:[2] Globalization inherently implies the interdependence of domestic politics, policymakers, and policies. Policies, institutions, and regimes diffuse across (sub)national governments. Legislators' votes

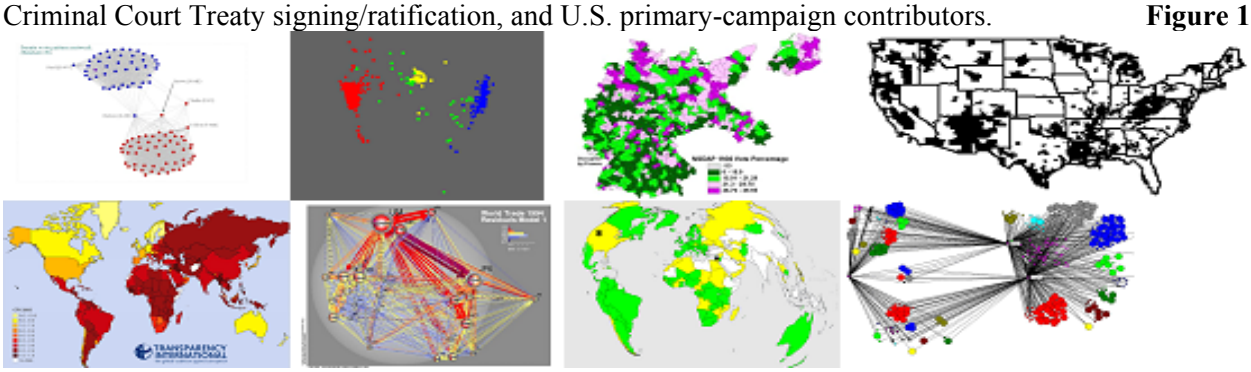
[1] Franzese & Hays (2003, 2004ab, 2005ab, 2006abc, 2007abcd, 2008abcd) and Franzese et al. (2008).

[2] The ensuing list of topics, subjects, and disciplines corresponds to literature searches for applied work under *spatial interdependence*, *contagion*, or *network dependence*, extensive citation to which works appear at the top of the proposal's Reference List. Citations for the broader subjects and disciplines listed are limited to works specifically on the narrower topics, the broader subject and disciplinary literatures being too large even simply to list citations.

depend on the (expected) votes others, as do citizens' votes and turnout. The *contextual* or *neighborhood* effects of micro-level studies often refer to effects on individuals' behaviors and opinions of aggregates of others'. Election outcomes and candidate qualities, contributions, and strategies in one contest depend on those in others. The probabilities and outcomes of coups, riots, civil wars, or revolutions in one unit depend on those in others. States' entry in wars, alliances, organizations, or treaties depend heavily on how many and which others (are expected to) enter. Terrorism is interdependent by source and target. Interdependence is also studied prominently in geography, regional, and environmental sciences, in regional, urban, and real-estate economics, in medicine, public health, and epidemiology, and, in its related guise as *network-dependence*, in medicine, health, and epidemiology again, in education, and, of course, in social-network studies. Other topics have included macroeconomic performance; microeconomic preferences; technology, marketing, and other firm strategies; obesity, fertility, birthweight, child development and poverty; marriage; ideology, right-wing extremism, (sub)national identity; women's ordainment; and faculty coauthoring, citations, placements.

In short, as *Tobler's Law* (Tobler 1970) aptly sums: "Everything is related to everything else, but near things are more related than distant things." Furthermore, as Beck et al.'s (2006) pithy title reminds in corollary: "Space is More than Geography." I.e., the substantive content of the proximity in *Tobler's Law*, and so the pathways along which interdependence between units may operate, extend well beyond physical distance, contact, and contiguity (as several examples above attest).[3] Long literatures in regional science, geography, and sociology carefully elaborate from those disciplinary perspectives the multifarious mechanisms by which contagion may arise. Simmons and colleagues (Elkins & Simmons 2005, Simmons et al. 2006) offer a list for international political-economy/relations: *coercion*, *competition*, *learning*, and *emulation*.[4] Indeed, one can show (see, e.g., Brueckner 2003), that strategic interdependence arises whenever some unit(s)'s actions affect the marginal utility of other(s)'s actions. Given such externalities, *i*'s utility depends on both its policy and that of *j*.[5] In environmental policy, e.g., domestic welfare (or net political-economic benefits to policymakers) in each country will depend on the actions of both due to environmental spillovers (e.g., of pollution) and economic ones (e.g., in costs of regulations). Optimizing behavior will yield best-response functions, giving *i*'s optimal policies as a function of *j*'s, and *vice versa*.

Spatial association, clustering, or correlation is also empirically obvious across political/social science. Figure 1, e.g., shows clustering in several topics listed above; top-left to bottom-right: U.S. Senate votes, U.K. MP votes, Weimar votes for Nazis, U.S. unemployment, government transparency, trade, International Criminal Court Treaty signing/ratification, and U.S. primary-campaign contributors. **Figure 1**



[3] Beck et al. (2006) are addressing scholars of international politics. Getis & Aldstadt (2004) similarly address regional scientists: "while most spatial analysts recognize that [connectivity] is supposed to be a theoretical conceptualization…, these same analysts more often than not use in their work a [form] which is at best empirically convenient" (p. 91). The examples listed next are all physical-distance based. Geographers, including Tobler (see 2004, e.g.), likely least needed the reminder. Haegerstrand (1967, 1970) and Gatrell (1983) are the classic geography references on the rich conceptualizations of distance and, correspondingly, of the processes by which interdependence may arise.

[4] For a fuller, closer match to prior traditions, add *cooperation* and *externality* to *competition*, combine *learning* and *emulation* as one, and add *relocation diffusion* (Haegerstrand 1970)—the last meaning the direct movement of some components of units *i* into other units *j*, such as by human migration or disease contagion.

[5] In such microeconomic models, externalities could arise from interactions, expectations, and/or preferences (Manski 2000); furthermore, non-strategic interdependence could arise even without externalities. Examples and reviews of micro-theoretical models with explicit interdependence include Glaeser et al. 1992, 1996; Akerlof 1997; Durlauf 1997, 2004; Brock & Durlauf 2001ab; Conley & Ligon 2002; Conley & Topa 2002.

However, outcomes may show such spatial association for three fundamental reasons. The units may respond similarly to similar exposure to similar exogenous internal/domestic or external/foreign stimuli (*common exposure*); units' responses may depend on other(s)'s responses (*interdependence* or *contagion*); or outcomes in the units may cause the variable underlying the dimension along which clustering is observed (*selection*). For instance, the geographic clustering of ICC signing and ratification (penultimate map) could reflect locations rich in natural resources and the operation of a resource curse in regime type (*common exposure* to resource-richness) or a tendency for contiguous states to influence each other's behavior (*contagion* among neighbors). As plausibly, a resource curse in regime type may produce a geographic concentration of certain kinds of autocracies and, in complement, of democracies and other types (*common exposure*). Influence may occur among states of common regime-type (*contagion*). The third possibility then becomes (marginally) plausible (perhaps, in a long-run analysis): treaty ratification affects regime type. The clustering by regime type arises not by contagion among or common exposures of like regimes but because treaty ratification helps determine regime type. In other contexts, the relative plausibility of the mechanisms can fall differently, but the general point is that our approach to empirical modeling must address this difficult but crucial task of distinguishing and weighing the strengths of the alternative processes by which spatial association may arise. The approach also should afford estimation of the kinds of spatial and spatiotemporal effect-estimates of most substantive interest to political/social science, namely the responses across the units and over time to counter-factual shocks to explanatory variables in some units. The kind of structural models we prefer and propose first take these two aims as essential; then, secondarily, simplicity is also desirable, as we wish to facilitate and foster widespread proper use of spatial-analytic methods among applied researchers.

2. <u>Project Foundations</u>: Work Completed under Previous Grant (*Results of Prior Support*)

Social-science interest in and applications of spatial analysis in general and spatial-econometric modeling in particular have boomed lately, spreading rapidly and broadly from the longer-historied of the substantive-disciplinary areas listed above and associated methodological traditions in spatial econometrics, spatial statistics, and network analysis.[6] This explosion of spatial-analytic research seems due partly to advances in theory that imply interdependence and in empirical methodologies to address it; partly to global substantive developments that have raised the degree and extent of interconnectivity, at all levels, from micro/personal to macro/international; and partly to technological advances in spatial/network-data collection and management. This boom is a very welcome development because socio-politico-economic phenomena entail substantively central interdependence and because omitting such interdependence empirically can bias inferences badly.

In a series of articles, chapters, papers, and a book-manuscript yielded from previously funded research (NSF 0318045),[7] we demonstrated this ubiquity and prominence of spatial interdependence across social-science theory and substance. In this work, we explored spatial or spatiotemporal interdependence almost exclusively in linear-regression models. For these, 1) we derived analytically in simple cases the biases given interdependence of non-spatial least-squares (LS) and of spatial least-squares (S-LS: i.e., of omitting spatial lags or of including them but ignoring their endogeneity), these being by far the most-common (almost *only*) estimators used in applied research (the "ubiquity and centrality…" notwithstanding). 2) We explored in simulations under richer, more-realistic, and limited-sample conditions the properties of the biased LS and S-LS estimators and of the consistent and asymptotically efficient spatial method-of-moments (S-MoM: S-IV, S-2SLS, S-GMM) and maximum-likelihood (S-ML) estimators. 3) We showed how to calculate, interpret, and present estimated spatial/spatiotemporal effects and dynamics, with appropriate certainty-estimates. We gave delta-method asymptotic-approximation standard errors for estimated initial responses, response-paths, and steady-state effects. (They can be simulated too.) Additionally, 4) we explored sensitivity of estimator performance to misspecification of the non-spatial component, of the spatial-connectivity matrix, **W**, and of the identification and distributional assumptions of the S-MoM and S-ML estimators, respectively; and 5) we explored specification tests for alternative spatial-lag or spatial-error models. Most recently, 6) Franzese &

[6] An appendix (at http://www-personal.umich.edu/~franzese/Publications.html) discusses subtle differences in emphases regarding typical questions asked, sorts of answers sought, and so methodological approaches adopted of the spatial-statistical, spatial-econometric, and network-analytic traditions. Regarding these boundaries, which are fuzzy, imperfect, permeable, and increasingly subject to productive crossing and blurring, we most-fit the spatial-econometric tradition.
[7] Franzese & Hays (2003, 2004ab, 2005ab, 2006abc, 2007abcd, 2008abcd) and Franzese et al. (2008)

Hays (2008d) introduced spatial probit (*S-Probit*), with preliminarily exploration of extant Bayesian and frequentist (recursive importance-sampling: RIS) estimators' performances and calculation of spatial-dynamic effects *in terms of outcome probabilities* (with associated certainty estimates), rather than in parameter or latent-variable terms as in prior literature. 7) Franzese et al. (2008), finally, began our consideration of a simple approach to estimated-**W** models that estimate rather than prespecify the relative connectivity, **W**. This proposal's next steps build from these last two, and from Hays & Kachi's (2008) seemingly-unrelated, limited-, and full-information ML estimators for simultaneous systems of duration equations (*cf.*, the extant frailty approach: Banerjee et al. 2004, Boehmke 2006, Boehmke & Meissner 2008, Darmofal 2008).

Our central findings are that LS, by ignoring spatial interdependence, suffers omitted-variable biases that foster overestimation of non-spatial effects, i.e., unit-level (domestic, individual) and contextual (exogenous-external) effects.[8] These biases quickly grow substantively sizeable at even very modest interdependence-strength ($\rho>.1\pm$) and become gargantuan at greater ρ. Standard errors for these overestimated effects are also dramatically underestimated in these ranges, and PCSE (Beck & Katz 1995, 1996) offers little amelioration. Given any noticeable interdependence, then, non-spatial LS is an unmitigated disaster. S-LS, conversely, suffers simultaneity biases that foster misestimation, usually overestimation, of contagion-strength, usually inducing oppositely signed errors for (i.e., underestimation of) non-spatial factors' roles. These simultaneity biases generally remain mild at weaker interdependence ($\rho<.25\pm$), and S-LS is also rather efficient, but standard-error accuracy is very poor in smaller-T samples (as, in the extreme, in pure cross-sections).[9] The biases of LS concentrate in the unit-level and exogenous-external factors that correlate most with the omitted spatial dependence. Conversely, the simultaneity bias that typically inflates estimated interdependence in S-LS induces corresponding attenuation biases in the estimates of non-spatial explanatory roles, especially for factors exhibiting spatial correlation most similar to the pattern of dependent-variable interdependence. In degree also, relative omission or misspecification of the spatial or non-spatial component of the model fosters underestimation of the strength of the relatively poorly specified component and overestimation of the better-specified component. Substantively for political scientists, then, relatively poor specifications of domestic (or micro/individual-level) components or of exogenous-external (macro/contextual-level) components (common shocks/stimuli) will tend to bias conclusions to favor contagion, and *vice versa*.

The most important issue, then, is adequate modeling both of interdependence, including accurate and empirically powerful specification of **W**, and of the non-spatial component of the model (i.e., unit-level and exogenous-external factors). Selecting appropriately consistent estimators (and which consistent estimator[10]) also become(s) important as interdependence strengthens. The equal criticality of well-specified non-spatial and spatial model-components underscores strongly the importance of the estimated-**W** (and endogenous-**W**) models part of our proposal,[11] and reinforces commitment to our approach stressing structural models and estimators capable of distinguishing the alternative possible sources of spatial association.

Some of our analytic results,[12] some of our simulation designs and results regarding estimators' small-sample properties and sensitivity/robustness to certain forms of misspecification,[13] and some of our work on

[8] This is *Galton's* famous *Problem*, and related to Manski's *Reflection Problem* (1993, 1995, 2000), which in part is a formalization of Galton's profound comment revealing its full implications.

[9] Given this performance of S-LS, only its poor standard-error accuracy would seem to argue strongly against it as a simple-but-effective option for small-ρ, large-T contexts. Programs and instruments to implement S-ML or S-2SLS, each consistent and asymptotically normal and efficient under its assumptions, and each proven solid redress of the simultaneity issue, are readily available for other contexts. However, S-ML and S-MoM estimators nearly dominate across all ρ and T settings and do so more decisively in larger-ρ, smaller-T contexts. As software to implement S-ML and S-MoM becomes more accessible to practitioners, therefore, argument for the simpler S-LS estimator will diminish.

[10] Simulations showed S-2SLS unbiased in both parameter and standard-error estimation, even in smaller samples, but inefficiency is an issue. S-ML nearly weakly dominates in mean-squared-error terms across sample dimensions and parameter values, especially in smaller samples with smaller ρ. (Comparing S-GMM to S-ML might be fairer, however.)

[11] The relative concentration of S-LS' simultaneity-induced ills in the standard errors (under large-T, small-ρ) indirectly adds to the case for exploring *S-QualDep* models. The additively separable stochastic components of linear-regression underlie this result. Spatial linear-regression undermines that separability somewhat, but *S-QualDep* models will undermine it more completely, via the qualitative and the spatial aspect.

[12] E.g., the precise terms of the simultaneity biases of S-LS estimation.

[13] E.g., we crafted simulation data-generating processes, sample dimensions, and specification errors to reflect typical

calculating and presenting estimated counterfactual spatial/spatio-temporal dynamics and effects,[14] with associated certainty estimates,[15] seem to have been new to the spatial-statistical, spatial econometric, and/or network-analytic literatures. Most certainly, applied work underutilized and/or underappreciated some of these conclusions. However, methodological innovation *per se* was not our primary aim in these earlier stages of the project. . Rather, we aimed centrally to introduce and explicate these techniques for political-science and related social-science applied researchers and political/social-science methodologists less familiar with them (occasionally, this required adapting methods for typical political/social-science research contexts); to demonstrate the empirical, substantive, theoretical, and methodological importance of interdependence for these audiences; to explore the utility and performance of extant spatial methods and approaches for the kinds of questions, and in sample-size, dimension, and other data characteristics typical of political/social science; and, most especially, to instruct these audiences on specifying spatial models, estimating and evaluating them, and interpreting and presenting the substantive spatial and spatiotemporal effects that their estimates imply.

3. Project Preview: Work Proposed for Next Stages

The next stages that we propose will involve greater shares of methodological innovation *per se*, working as they will from at or nearer the spatial-statistical, spatial-econometric, and/or network-analytic frontiers. Still, the core aims will remain exploration, for the same primary target-audience, of specification, estimation, interpretation, and presentation of empirical models of interdependence. As before, we will stress structural approaches that can distinguish and weigh the strengths of common exposure, contagion, and (now) selection as alternative sources of observed spatial association, and that can support calculation of estimated spatial or spatiotemporal responses to substantively motivated counterfactuals, with associated certainty estimates. These next steps also respond directly to the most-common requests from audiences of our prior work: "We're convinced, …but what do I do about interdependence among qualitative dependent variables?" and "…but the whole trick is the *prespecification* of an *exogenous* **W**: can we estimate and/or endogenize it?"[16]

First, we will explore from this perspective spatial qualitative- and limited-outcome (*S-QualDep*) models (e.g., *S-Probit*[17]) and spatial systems-of-equations (*S-SysEq*: e.g., Kelejian & Prucha 2004; Rey & Boarnet 2004), including systems of *QualDep* equations (Hays & Kachi 2008). We introduce and adapt these models[18] for political/social-science applications, or, where needed, we will develop them. In this, we will follow our usual sequence of emphases: theoretically informed specification, appropriate estimation, and substantive interpretation and presentation of dependent-variable effects (rather than parameter or latent-variable effects), with corresponding certainty estimates. We include under *appropriate estimation* the exploration, in typical political/social science contexts, of small-sample performance and sensitivity to misspecification and other assumption-violations. Section 3a elaborates our specific *plan of work* and gives some *proof of concept*.

Second, we will explore prospects for parameterizing and estimating, and ultimately endogenizing, the connectivity matrix, **W**, consensus priorities for spatial and network methodological research.[19] Scholars have

---

conditions in comparative-and-international-political-economy research.

[14] E.g., effect (and certainty) calculations in terms of outcome-probabilities in S-Probit.

[15] E.g., some of the delta-method approximations we give do not seem to have been given explicitly before.

[16] Actually, even more common was the request: "We're convinced, but have you programmed it in Stata™ for us?" Our affirmative response will come with completion of the previous grant later this academic year.

[17] McMillen 1992, 1995; Bolduc et. al. 1997; Pinkse & Slade 1998; LeSage 1999, 2000; Beron et al. 2003; Beron & Vijverberg 2004. Spatial logit also exists (Dubin 1997; Lin 2003; Autant-Bernard 2006), but *S-Probit* dominates applied and methodological work, and will receive primary focus. Also mooted and to receive attention are models of spatial sample-selection (i.e., spatial Tobit or Heckit: McMillen 1995, Smith & LeSage 2004, Flores-Lagunes & Schnier 2006), spatial multinomial-probit (McMillen 1995, Bolduc et al. 1997, Autant-Bernard et al. 2008), and spatial discrete-duration (Phaneuf & Palmquist 2003), all of which closely resemble *S-Probit*, and models of spatially dependent counts (Bhati 2005a), including related zero-inflated (Rathbun & Fei 2006) and rare-events (Bhati 2005b), and, finally, models of survival with spatial frailty (Banerjee et al. 2004, Boehmke 2006, Darmofal 2008, Boehmke & Meissner 2008).

[18] I.e., those listed in note 17. Also, spatial model-averaging (LeSage & Parent 2007) and spatial missing-data procedures (e.g., LeSage & Pace 2004), in addition to their intrinsic interest, may prove synergistically useful for approaching the challenges of the second strand of proposed work.

[19] Some exemplary statements: "One key problem facing analysts is how to construct and treat connectivities among observations… They should be based on theory… In practice, [they are] often based on convenience or common

made great and productive efforts to systematize the substantive-theoretical specification of connectivity.[20] Likewise, the sensitivity of results to misspecified **W** has drawn great attention to specification tests for and to simulation explorations of errors in **W**, to which we have also contributed.[21] Nonetheless, Anselin (2005:10) concludes: "There is very little formal guidance in the choice of the *correct* spatial weights for…model specification." Griffiths (1996) concurs, finding only five banal general rules emerge from extensive review of studies (essentially: more data, better measures, and simpler models are good).[22] Aldstadt & Getis identify three general strategies regarding **W**—we label them *theory*, *convenience*, or *estimation*—before naming estimation best (2006:328-9). Indeed, as Fernandez-Vazquez & Rodriguez-Valez (2007:2) ask: "Why not estimate both the elements of **W** and the other parameters of the spatial model?" One answer is because *estimated*-**W** models raise thorny methodological challenges. For starters, **W** has generically N^2-N parameters, which (often greatly) exceeds N. However, several possible approaches to redressing these complications are evolving in spatial statistics/econometrics (see subsection 3b). Unfortunately for our purposes, the existing strategies, while highly technically sophisticated, tend toward the inductive and non-structural, and, as such, generally do not afford distinction between alternative sources of spatial association or support estimation of the substantive counterfactuals we seek. Our more-structural approach would be simpler, make these kinds of distinctions, and support such counterfactual analyses. We start by using multi-parametric spatiotemporal-lag (m-STAR) models, i.e., those with more than one **W**, to express the w_{ij} as a function of observed covariates theorized to explain (the strength of) connectivity. Combining this more-deductive approach with the more-inductive strategies currently being developed by others is planned for future exploration.

Endogenous-**W** models, in which the connectivity between units may depend upon units' actions, i.e., on the outcome variable, are even thornier. In spatial econometrics or statistics, both the pre-specified **W** and the extant estimated-**W** approaches assume **W** exogenous. In network analysis, contrarily, the challenges tend to arise in reverse order. The more-central issue has been the generation of networks, i.e., what explains the (set of) ties between units, i.e., estimation of **W**. In this, the attributes of actors, which may include their *behavior*, i.e., the dependent variables from our perspective, are usually taken as exogenous explanators of ties, i.e., of **W**. The ultimate challenge is thus very similar. From a spatial-econometric view, the aim is joint estimation of the connectivity matrix and of the effects via those ties of units' actions on other units. From the network-analytic perspective, the core aim is joint estimation of the network ties and the effects of network structure and the units' positions in it on units' actions, and sometimes also the effect of *alters*' actions on *ego*'s via the network of connections.[23] Snijders and colleagues' *coevolution model*[24] advances furthest with a network-analytic approach to these problems. Our initial approach to such *endogenous*-**W** models is again simpler, being an extension of our approach to estimated-**W** models generally. Namely: given multiple $\mathbf{W}_z$, with some $\mathbf{W}_z$ exogenous, and given some exogenous covariates, **X**, spatial-moment strategies (i.e., instrumentation) can offer consistent estimates of the endogenous **W**. These estimates and the other **W** can then enter the m-STAR likelihood. Section 3b elaborates our specific *plan of work* and offers some *proof of concept* in these regards.

3.a. S-QualDep & S-SysEq Models: Plan of Action & Proof of Concept

In brief and in general, difficulties arise for *S-QualDep* models as the endogenous spatial and/or temporal lags of latent-outcomes, y_j^* and/or y^*_{t-1}, on their right-hand sides (RHS) are converted to observed quantities by computation of an integral (e.g., the cumulative normal in probit). Since observations are spatially and/or

---

approaches thought to be state of the art" (Ward & Gleditsch 2008:77). "…the specification of the weight matrix is a matter of some arbitrariness and is often cited as a major weakness of the lattice approach" (Anselin 2002:257).

[20] Getis & Aldstadt (2004) list 12 formulations of (geographic) contiguity or distance. Leenders (2002) offers several based on sociological and economic considerations. Snijders (2005) specifies 17, designed for social-network processes.

[21] See, e.g., Stetzer 1982, Anselin 1985, Anselin & Rey 1991, Florax & Rey 1995, Griffith 1996, Bavaud 1998, Getis & Aldstadt 2004, Florax et al. 2006, Conley & Molinari 2007.

[22] These are: (1) Better to posit some reasonable **W** than assume independence. (2) Tessellation between square and hexagonal seems optimal. (3) Large samples of spatial units are greatly desirable. (4) Lower-order models should have preference over higher-order ones. (5) Better to err toward under- than over-specification.

[23] In one sense, then, the network-analytic approach takes a larger set of questions, including as it does more ways structure may affect units, although the central ones from our perspective tend to be less central there.

[24] Snijders 1997, 2001, 2005; Snijders & Borgatti 1999; Snijders & Steglich 2006; Snijders et al. 2006, 2007; see also Leenders 1995, 1997, 2002.

temporally interdependent, log-likelihoods (or log-posteriors) of realized data (times priors) are single, non-separable logs of *n*-dimensional integrals rather than sums of logs of *n* unidimensional integrals as usual when assuming conditional independence of observations. The *n*-dimensional cumulative-normal of *S-Probit*, e.g., is exponentially more intense to compute than the non-spatial unidimensional ones, which prohibits direct optimization even in small samples. Bayesian (Metropolis-Hastings-within-Gibbs-sampling: LeSage 2000) or simulated-likelihood (recursive importance-sampling: Beron et al. 2003) techniques can do the calculations in acceptably burdensome time.[25] Likewise, estimating spatial dynamics and effects, and their certainties, in terms of *QualDep* outcomes, rather than in parameter or latent-variable terms as is current practice, requires calculation of more *n*-dimensional integrals. We suggest similar integration-by-simulation strategies for these.

The large, current, and rapidly growing *S-QualDep* literature, with the notable exception of *S-Probit*, orients mostly Bayesian, CAR (conditional autoregressive) rather than SAR (simultaneous autoregressive), and squarely within the spatial-statistics tradition. Our contribution is more to the spatial-econometric analysis of *S-QualDep* models.[26] That is, we seek 1) estimators for the structural parameters of theoretically derived *S-QualDep* regression models, which will 2) allow estimates of the effects of counterfactual changes in explanatory variables, based on the estimated parameters of these models, in terms of the outcomes of interest, and 3) that will also yield estimates of the uncertainty of these parameter and effect estimates. We seek estimates optimizing the usual desirable properties (unbiased, consistent, efficient, accurate standard-errors) in sample dimensions and research contexts typical of political/social science, of course, but we also prefer estimators be simple to implement, given that one of our core goals to spur and empower applied empirical researchers. We intend to begin this pursuit with spatial-count, -duration, and -probit models (see notes 17 and 25 for additional *S-QualDep* models slated for exploration).

3.a.1 Spatial Poisson Models

Besag's (1974) introduced spatial Poisson (*S-Poisson*) as one of his *auto-models*.[27] Auto-models conquer the estimation challenges of *S-QualDep* by making assumptions that allow variables' joint distributions to be expressed as products of their conditional distributions. Auto-models are conditional autoregressive (CAR), and, like all such, the required assumptions can be very restrictive. They usually require symmetric spatial-interdependence structures (Anselin 2006): implausible in many social-science applications (Belgium and the US must affect each other equally, for instance). CAR models also usually require exclusively non-negative interdependence, although auto-Poisson requires non-positive (Besag 1974); either can be highly confining. Recent advances to redress the latter limitation include Kaiser and Cressie's (1997) suggestion of Winsorizing counts (restricting them to finite sets of integers), which affords limited positive interdependence within an auto-Poisson CAR framework. The Winsorized model is computationally intense though (Griffith 2003), and it retains the problematic symmetry restriction. Griffith (2002, 2003) propose a spatial-filtering approach to simultaneous autoregressive (SAR) Poisson in which each unit's mean is a function of the respective element of the eigenvector of the inverse spatial-covariance matrix. This seems promising, but eigenvector calculation heightens estimation demands, and this is especially so for the counterfactual effect-estimates with certainty-estimates that we seek. Moreover, by design, spatial-filtering tends to deter or debar attempts to distinguish alternative sources of spatial association. "Spatial filtering seeks to transform a variable containing spatial dependence into one free of it by partitioning the original georeferenced attribute variable into two synthetic variates: a spatial filter variate capturing latent spatial dependency that otherwise would remain in the

[25] Alternative approaches worth considering apply approximate respecifications of *S-QualDep* models, e.g., (non)linear probability models (Fleming 2004), to allow spatial (generalized) linear-modeling, and/or apply the concept of generalized-residuals to allow, *for spatial-error* QualDep *models only*, spatial-GMM strategies (Pinkse & Slade 1998). Either strategy evades the intensive multidimensional integration. McMillen 1992 suggested an EM algorithm, which afforded direct maximization of *S-Probit* log-likelihoods, but with certain other limitations. Superseding this, McMillen 1995 and Bolduc et. al. 1997 applied simulated-likelihood strategies to estimate spatial-multinomial-probit (S-MNP) models, Beron et al. 2003 and Beron & Vijverberg 2004 advanced a recursive-importance-sampling (RIS) estimator, and LeSage 1999, 2000 introduced a Bayesian strategy of Markov-Chain-Monte-Carlo (MCMC) by Gibbs and Metropolis-Hastings sampling. Fleming 2004 reviews these two families and the aforementioned simpler approximation strategies.
[26] We view the Bayesian aspect as more a practical than a philosophical issue, although sustaining both Bayesian and frequentist tools seems wisely prudent to us. Our aims depart more importantly from the literature in the other regards.
[27] Griffith & Haining (2006) give excellent summary of the history and recent developments in *S-Poisson*.

response residuals and a nonspatial variate that is free of spatial dependence" (Griffith 2006: 166). Thus, problematically from the perspective of our aims, spatial-filtering, and CAR approaches also, generally tend 1) to treat spatial dependence as nuisance, 2) to stress spatial-error or spatial-heterogeneity models as opposed to spatial-lag models, and 3) to treat all observed spatial association as arising by one undifferentiated source, characteristically dependence in spatial econometrics, common shocks in spatial statistics, and selection in network analysis. Available estimators were simply not designed to address our aims, neither to distinguish alternative mechanisms by which spatial association arises nor to answer the counterfactual questions of our interest. Give that and their computational intensity, we propose to start with a simpler, structural approach, offering a maximum-likelihood estimator (with instruments) for a *S-Poisson* model that is so-designed.

The Poisson regression model expresses observed counts as draws from a Poisson distribution with parameter $\lambda_i(\mathbf{x}_i)$, the instantaneous rate at which the counted event occurs:

$$\Pr(Y_i = y_i) = e^{-\lambda_i}\lambda_i^{y_i} \big/ y_i! \quad \text{, with } y_i \in \{0,1,2,...,\infty\}. \qquad (1).$$

A typical log-linear model of λ_i specifies it as $\ln \boldsymbol{\lambda} = \mathbf{X}\boldsymbol{\beta}$ (2), with $\mathbf{X}$ an *NxK* matrix of explanators and $\boldsymbol{\beta}$ a *K*-vector of coefficients on $\mathbf{X}$. The log-likelihood for estimating the parameters in (2) is thus:

$$\ln L(\mathbf{y}) = \sum_i \{-\lambda_i + y_i \boldsymbol{\beta}'\mathbf{x}_i - \ln y_i!\} \qquad (3);$$

In the *S-Poisson* model, the structural version of equation (2) takes the form:

$$\ln \boldsymbol{\lambda} = \rho \mathbf{W}(\ln \boldsymbol{\lambda}) + \mathbf{X}\boldsymbol{\beta} \qquad (4),$$

where ρ is the spatial autoregressive coefficient and $\mathbf{W}$ is an *NxN* spatial-weights matrix.

The $\ln(\boldsymbol{\lambda})$ on the right-hand-side of the *S-Poisson* (4), being both unobserved and endogenous, raises the previously described estimation difficulty of *S-QualDep* models. One strategy would be to write the spatial structure directly into the likelihood, as has been done for *S-Probit* (subsection 3c). A second estimates the parameters indirectly using instruments. Following this second strategy as a first cut, we want to *purge* $\ln(\boldsymbol{\lambda})$ of its spatial feedback to isolate its exogenous component, i.e., the $\mathbf{X}\boldsymbol{\beta}$ part. The exactly identified case with a single exogenous regressor illustrates. Substitution gives:

$$\ln \boldsymbol{\lambda} = \rho \mathbf{W}(\beta \mathbf{x}) + \beta \mathbf{x} = \rho\beta \mathbf{W}\mathbf{x} + \beta \mathbf{x} = \phi \mathbf{W}\mathbf{x} + \beta \mathbf{x} \qquad (5)$$

The structural parameter, ρ, in (4) is estimated indirectly: $\hat{\rho} = \hat{\phi} / \hat{\beta}$. Its (first-order) delta-method asymptotic-approximate variance is: $\left[\frac{\hat{\phi}}{\hat{\beta}}\right]^2 \times \left[\frac{V(\hat{\phi})}{\hat{\phi}^2} + \frac{V(\hat{\beta})}{\hat{\beta}^2} - 2\frac{C(\hat{\phi},\hat{\beta})}{\hat{\phi}\hat{\beta}}\right]$. The overidentified case should extend intuitively from this. The opportunity to distinguish alternative sources of spatial association and to calculate estimated spatial (and, ultimately, spatiotemporal) responses to substantive counterfactuals arises from the direct specification of the structural model (4) (in its instrumented form (5)) into the estimator (the likelihood, (3)). As seen in our previous work, the qualities of these inferences and estimates will then hinge most crucially on the accuracy and power with which the researcher can specify both the spatial and non-spatial components of the model.

Table 1 presents some preliminary simulation results. We intend these simply, first, to show that the proposed estimator gives the right answers on average in its parameter and in its standard-error estimates, and, second, to compare it with a naïve estimator that treats the spatial lag as an exogenous right-hand-side variable. The latter reflects actual practice in much applied research, where theorized contagion of counts is correctly understood to imply dependence of *i*'s count on *j*'s, and so to require spatial-lag specifications, but the resulting simultaneity is unrecognized or ignored. We generate the data in two steps. First, values of $\boldsymbol{\lambda}$ were determined using the reduced form of (4). We fixed β to 0.6 and set ρ first to 0.1 (low interdependence) and then to 0.3 (high interdependence). The sample size is 960 (20x48). The row-standardized 960x960 weights matrix has the 48x48 binary borders weights matrix for the contiguous US states along the block diagonal and zeros elsewhere. Then we draw

Table 1: Spatial Poisson Model (980 Obs, 250 Trials)			*Low Interdependence*		*High Interdependence*	
			β	*ρ*	*β*	*ρ*
	TRUE	*Coeff.*	*0.6*	*0.1*	*0.6*	*0.3*
Proposed	*ESTIMATE*	*Coeff.*	0.6025	0.1063	0.6267	0.3629
Estimator	*ACTUAL*	*Std.Dev.*	0.0158	0.0361	0.0140	0.0345
	ESTIMATE	*Std.Err.*	0.0161	0.0354	0.0133	0.0330
Naïve	*ESTIMATE*	*Coeff.*	0.6168	0.0205	0.6669	0.0535
Estimator	*ACTUAL*	*Std.Dev.*	0.0151	0.0087	0.0143	0.0051
	ESTIMATE	*Std.Err.*	0.0137	0.0076	0.0120	0.0044

from the respective Poisson distributions. The results of 250 trials show the proposed estimator is unbiased[28] and clearly outperforms the naïve estimator. Compared to the simultaneity biases of S-OLS that we studied before, these for S-Poisson are negative and larger at lower ρ.[29]

Further explorations will follow our usual sequence: emphasizing effective substantive-theoretical specification of structural *S-Poisson* models; proper estimation; and calculation of spatial dynamics, immediate and steady-state effects of substantive counterfactuals, along with associated certainty estimates. *Proper estimation* again includes evaluation of the small-sample performance of the estimators—Winsorized auto-Poisson, Eigenvector spatial-filtering, our spatial-instrumented-ML, as well as the naïve estimator and the non-spatial one—and sensitivity to misspecification or assumption-violations in experiments designed to reflect typical social-science research. It will also include in this case development of the full ML estimator. Finally, after generalizing the just-identified case shown here and developing the pure likelihood estimator, we will extend the analysis to *S-SysEq* models involving *S-Poisson* along the lines of Hays & Kachi (2008).

3.a.2 Spatial Duration Models

For spatial duration also, log-linearization offers an easy way to specify structural equations:[30]

$$\mathbf{d} = \rho\mathbf{W}\mathbf{d} + \mathbf{X}\boldsymbol{\beta} + \mathbf{u} \qquad (6).$$

d is the vector of log durations and **u** a vector of structural disturbances drawn *iid* from an extreme-value distribution, making this an exponential duration model. This is easily relaxed by, e.g., scaling **u** with the inverse shape parameter of a weibull, e.g. The reduced form of this model (the DGP) is:

$$\mathbf{d} = (\mathbf{I} - \rho\mathbf{W})^{-1}(\mathbf{X}\boldsymbol{\beta} + \mathbf{u}) \qquad (7),$$

and the likelihood for estimating the parameters in (6) using data generated from (7) is:

$$L(\mathbf{d}) = \prod_i (1-\rho\omega_i)\exp\left[-\left[(\mathbf{I}-\rho\mathbf{W})_i\,\mathbf{d} - \mathbf{X}_i\boldsymbol{\beta}\right] - e^{-\left[(\mathbf{I}-\rho\mathbf{W})_i\mathbf{d}-\mathbf{X}_i\boldsymbol{\beta}\right]}\right] \qquad (8),$$

where ω_i are the eigenvalues of **W**. This likelihood assumes that we have observed failures for each unit in the dataset—i.e., no right-censoring. If there is right-censoring, the likelihood becomes:

$$L(\mathbf{d}) = \prod_i (1-\rho\omega_i)\left\{\exp\left[-\left[(\mathbf{I}-\rho\mathbf{W})_i\,\mathbf{d} - \mathbf{X}_i\boldsymbol{\beta}\right] - e^{-\left[(\mathbf{I}-\rho\mathbf{W})_i\mathbf{d}-\mathbf{X}_i\boldsymbol{\beta}\right]}\right]\right\}^{\delta_i}\left\{\exp\left[-e^{-\left[(\mathbf{I}-\rho\mathbf{W})_i\mathbf{d}-\mathbf{X}_i\boldsymbol{\beta}\right]}\right]\right\}^{1-\delta_i} \qquad (9),$$

where δ is a censoring indicator that takes a value of 0 if the observation is censored and 1 otherwise.

Table 2 presents preliminary simulations serving to show that the estimator *works* (in bias, efficiency, and standard-error-accuracy) and that it compares well to the naïve estimator. Data are generated data using (7) with one regressor and with sample size, β and ρ values, and **W**, as in Table 1. The 250 trials show the proposed estimator having minuscule bias, accurate standard-errors and greater efficiency than the naïve estimator, which overestimates ρ (simultaneity bias) and underestimates β (induced bias).

Table 2: Spatial Duration Model (980 Obs, 250 Trials)			Low Interdependence		High Interdependence	
			β	ρ	β	ρ
	TRUE	Coeff.	0.6	0.1	0.6	0.3
Proposed Estimator	ESTIMATE	Coeff.	0.5990	0.0990	0.6033	0.2977
	ACTUAL	Std.Dev.	0.0267	0.0275	0.0281	0.0232
	ESTIMATE	Std.Err.	0.0265	0.0281	0.0287	0.0237
Naïve Estimator	ESTIMATE	Coeff.	0.5815	0.1215	0.5491	0.3510
	ACTUAL	Std.Dev.	0.0310	0.0339	0.0322	0.0274
	ESTIMATE	Std.Err.	0.0285	0.0314	0.0306	0.0267

Our explorations of *S-Duration* and of the other *S-QualDep* models (see notes 17, 18, 25) will parallel those of the *S-Count* models, comparing our more-structural, spatial-econometric approach to spatially blind and naïve estimators, and to extant Bayesian, CAR, and spatial-statistical approaches. We will continue to stress substantive-theoretical specification, proper estimation, and calculation of substantive counterfactuals

[28] The seeming small bias in the high-interdependence case actually reflects the high degree of noise in our simulation since the process is non-stationary for many values of x for these parameter values.

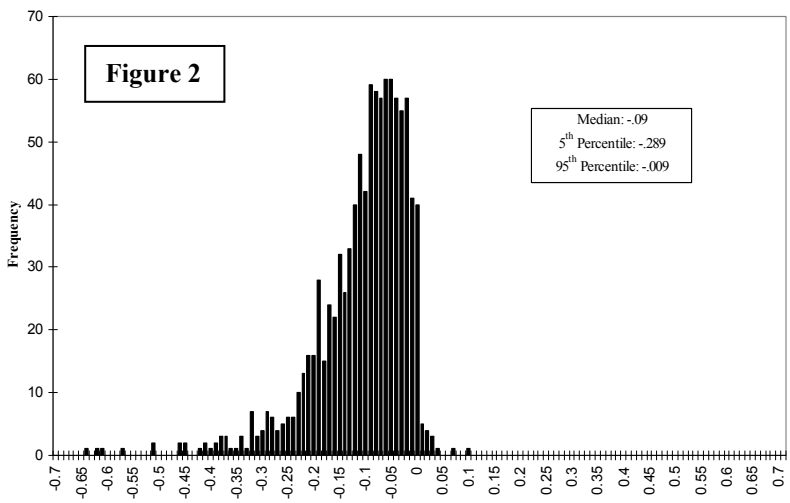
[29] Regarding the seemingly lesser induced biases (though these are oppositely signed as before), note that these x exhibit no spatial association unlike the regressors in those experiments.

[30] That we cannot find this seemingly obvious and easy approach to structural *S-QualDep* models in the extant literature perhaps highlights the difference in goals of spatial-statistical and spatial-econometric approaches.

with associated certainty estimates. In all cases, we will also explore extensions to *S-SysEq* models involving such *S-QualDeps* along the lines of Hays & Kachi (2008).

3.a.3 Spatial Probit Models

Relative to other *S-QualDep* models, research on *S-Probit* is extensive, includes a spatial-econometric strand, and, despite the challenges, both Bayesian and frequentist estimators formulated and employed.[31] Lacking, though, is clear strategy for evaluating counterfactuals in terms of estimated changes in probabilities and for calculating the associated certainty estimates. Beron et al. (2003), e.g., report counterfactual effects, which is itself rare, but in terms of the latent y^* instead of probabilities, and without standard-error estimates. The reason is clear. Calculating probabilities (and standard errors for them) requires integrating over an *n*-dimensional multivariate normal distribution (many times), the same complication of *S-Probit* estimation itself. We therefore propose applying the same methods used to estimate the likelihood (i.e., calculate *factual* probabilities given observed *X*'s) to calculate these *counterfactual* probabilities. In Franzese & Hays (2008), e.g., we estimate by recursive importance sampling (RIS) an *S-Probit* of the determinants of states' term-limit adoptions. We then applied the RIS logic again to the S-Probit estimates to calculate substantively interesting counterfactuals in dependent-variable terms, and a parametric bootstrap to obtain uncertainty estimates for them. Specifically, we asked: how would substantial decreases in the propensities of Oregon and Idaho to adopt term limits have affected the probability that Washington adopted them? Figure 2 shows our answer. The median effect in our set of simulations was a 9-point decrease, and fewer than 5% of the simulations (each trial draws from the multivariate normal sampling distribution of the RIS estimator) found effects greater than zero. We propose to apply such strategies also to calculate substantive counterfactual spatial and spatiotemporal effects and certainties for the other *S-QualDep* models, and to evaluate the strategy's performance for *S-Probit* and these others in typical social-science contexts.



*3.b. Estimated-**W** & Endogenous-**W** Models: Plan of Action & Proof of Concept*

From a spatial-econometric view, estimating the connectivity matrix, however desirable one may find it, raises high statistical hurdles. First, the w_{ij} elements of **W** that one might wish to estimate generally greatly outnumber observations,[32] so some reduced-parameterization, i.e., a model of w_{ij}, is essential. Second, the parameters to estimate in these w_{ij} models will themselves enter as elements of the **W** term in the Jacobian transformation, $|\mathbf{I}-\rho\mathbf{W}|$, which complicates spatial estimation in the first place. Some progress has been made, though. Recognizing the crucial substantive, theoretical, and empirical importance of **W**'s pre-specification, yet also the great practical uncertainty involved, Conley (1999) proposed an instrumental-variables strategy robust to imperfectly measured *distances*. Chen & Conley (2002) and Pinkse et al. (2002) extend this line, adopting semi-parametric approaches that approximate the unknown functions of the distance metric(s), *d*, that determine w_{ij} by some flexible sequence of parametric families (e.g., polynomials in *d*) which they estimate consistently by spatial instrumentation (so-called *sieve* estimation: Grenander 1981). Bhattacharjee & Jensen-Butler (2006) go further, building from Meen (1996) to estimate $\rho\mathbf{W}$ in a spatial-error model without prespecifying a distance metric (i.e., non-parametrically), directly from observed spatial association among residuals from a first-stage non-spatial model. This strategy is limited to the spatial-error model[33]—as

[31] Note 25 gives a brief history. Franzese & Hays (2008d) reviews and applies these approaches more fully.

[32] The w_{ij} number N^2-N for cross-sections or time-series cross-sections with time-invariant asymmetric **W**, ½N(N+1) for these data formats with symmetric **W**, and T times those numbers for the time-variant W cases.

[33] Franzese & Hays (2003) takes a very similar tack; as Anselin (1988) emphasizes, however, the first-stage non-spatial

currently implemented, it seems also to require symmetric-**W** and constant-ρ—nor can it separately identify ρ and **W** (at present, our approach shares this last limitation). Moreover, the crucial feature that identifies the joint estimation of patterns and strengths of interdependence from observed spatial association is that $\rho\mathbf{W}$ fully captures *all* spatial association. Thus, the identification strategy directly prevents one of our central goals: distinguishing alternative sources of spatial association. The other, calculating responses to substantive counterfactuals, is also limited by construction to shocks to error terms. Fernandez-Vazquez & Rodriguez-Valez (2007) take a different tack. Assuming row-normalization and exclusively non-negative w_{ij}, they note the rows of **W** can be seen as probability distributions for maximum-entropy estimation of w_{ij} simultaneously with spatial-lag parameter ρ and non-spatial covariate coefficients $\boldsymbol{\beta}$. This approach would seem to make addressing the possibility of *selection*, i.e., endogenous w_{ij}, more difficult than would the instrumentation strategies; the limitation to non-negative w_{ij} can be constraining; and identification off the row-normalization (a convenience) may seem questionable. Our approach is simpler and parametric, but otherwise similar to these other spatial-econometric ones. Possibilities of merging them with our strategy merits exploration.

Approaches we would characterize as spatial statistical are still more inductive and ill-addressed to our aims. Kooijman (1976), e.g., proposed choosing **W** to maximize Moran's I, a univariate test-statistic of spatial association. Openshaw (1977) argued similarly to choose **W** to optimize univariate spatial-lag models. Boots & Dufournaud (1994) specify binary-contiguity matrices by a procedure marking dyads as contiguous or not to maximize or minimize spatial-association. Griffith (1996, 2003) and Getis & Griffith (2002) use spatial-filtering strategies designed to find **W** that maximally purge spatial association from **y**. Getis & Aldstadt (2004, 2006) similarly seek to separate the "variables being adjusted for spatial effects" into one component subject to spatial-lag autocorrelation and one not. The procedure finds a maximum distance, d_c, beyond which spatial correlation is negligible and sets weights w_{ij} in row i equal to a function of the Getis-Ord (1995) statistic of local association, $G_i^*(d_c)$, to 1, or to 0.[34] Coefficients on dummies for rows with all w_{ij}=0 estimate the non-spatial component. Aldstadt & Getis (2006) write a genetic algorithm to optimize the procedure. The recent of these spatial-statistical estimators are highly sophisticated, but, ultimately, none addresses our aims so well for the now-familiar reasons: univariate, filtering, or non-parametric strategies tend to treat spatial effects as nuisance to be purged, to treat all spatial association as arising from a single source, and/or to model association in ways that complicate or debar consideration of the sorts of substantive counterfactuals we seek.

Efforts to parameterize and ultimately to endogenize w_{ij} in spatial-econometrics/statistics mirror efforts in the network-analytic tradition to model the *coevolution of behavior and networks*.[35] *Coevolution* approaches stress (see esp. Steglich et al. 2007) as we do the challenge of disentangling the sources of network (spatial) association—*influence* (*interdependence* or *contagion*), *social context* (*common exposure*), and *selection* (e.g., *homophily*)—recognizing that any omissions or inadequacies in modeling one will bias conclusions to favor the included or better-modeled mechanisms. Leenders (1995, 1997), e.g., envisioned models where "actors will shape their networks [*selection*] and, simultaneously, are influenced by the structure of the network [*contagion*]." In his selection model, the equivalent of w_{ij} arises by a continuous-time Markov process where *arcs* from j to i form, w_{ij}=1, or dissolve, w_{ij}=0, at rates modeled as functions of observable attribute(s) of i and/or j, say a distance metric d_{ij}. He models contagion as a spatial lag. The combined model,

$$w_{ij,t} \equiv d_{ij,t} = \alpha \,|\, y_{i,t} - y_{j,t} \,| \quad ; \quad y_t = \rho_1 \mathbf{W}_{t-1}\mathbf{y}_t + \rho_2 \mathbf{y}_{t-1} + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \qquad (10),$$

is identified for estimation of α, $\boldsymbol{\rho}$, and $\boldsymbol{\beta}$ from $\mathbf{W}_t$ and $\mathbf{y}_t$ observed at discrete intervals t={1..T} by assuming time lags and the first observation to be predetermined. Conditioning on first observations entails inefficiency and a small-sample bias of order *1/T*. In large-*T* panel data, though, insofar as interdependence does not incur instantaneously, where *instantaneous* means *within an observational period, given the model*—this can work. I.e., provided that the interdependence process does not operate within an observational period but only with at least a one-period lag, and that spatial and temporal dynamics are modeled sufficiently well to prevent

estimated errors are consistent only under the spatial-error and not under the spatial-lag model.

[34] Specifically: w_{ij}=1 for nearest-neighbors if d_c suggests spatial effects negligible beyond that; w_{ij}=0 if d_c=0, meaning only negligible local association exists; and $w_{ij}=\{G_i^*(d_c)-G_i^*(d_{ij})\}/\{G_i^*(d_c)-G_i^*(0)\}$ otherwise.

[35] The exponential random-graph models (ERGM's: Carrington et al. 2005, Hunter 2007, Hunter et al. 2008, Lubbers & Snijders 2007, Morris et al. 2008, Robins & Morris 2007, Robins et al. 2007ab) of current great interest in network analysis would seem of limited utility to our aims because they do not actually model the ties of i to j, the w_{ij}, but rather some sufficient statistic(s) of the network given some expected pattern(s) of dependency.

time-lagged contagion from leaking into contemporaneous due to measurement/specification error—and that T is large, time-lagging can serve as a simple and effective *poor man's exogeneity*.[36] However, observational periods are often too few and/or too long relative to interdependence processes, and much substantive interdependence operates literally instantaneously (as most strategic interdependence does, for instance), so the effective applicability of such approaches in many social-science contexts is questionable.

Snijders' & colleagues'[37] approach is similar, though more elaborate. Adapting their notation, they model N actors connected by an observed, binary, endogenous, time-variant connectivity matrix $\mathbf{W}(t)$. The observed, binary behaviors at time t are $\mathbf{y}(t)$. Exogenous unit or dyadic covariates $\mathbf{X}$(t) may also exist. Opportunities arise for actors to alter their network connections, switching on or off one tie or doing nothing, at a continuous rate, λ_i^{net}, according to an exponential-duration mode (*with hazard rates independent across actors and over time*). Opportunities to augment or reduce by one or not change the behavior also arise (*independently*) at rate, λ_i^{beh}. These λ_i^m can be parameterized. When opportunity to act arrives for some i, she chooses to alter one or none of her N-1 connections or behaviors by evaluating objective functions of this form: [38]

$$f_i^{net}(\mathbf{W},\mathbf{W}',\mathbf{y}) = \sum_h \left\{\boldsymbol{\beta}_h^{net} \times \mathbf{s}_h^{net}(\mathbf{i},\mathbf{W},\mathbf{W}',\mathbf{y})\right\} + \boldsymbol{\varepsilon}_i^{net}(\mathbf{W},\mathbf{W}',\mathbf{y}) \quad (11).$$

$$f_i^{beh}(\mathbf{W},\mathbf{y},\mathbf{y}') = \sum_h \left\{\boldsymbol{\beta}_h^{beh} \times \mathbf{s}_h^{beh}(\mathbf{i},\mathbf{W},\mathbf{y},\mathbf{y}')\right\} + \boldsymbol{\varepsilon}_i^{beh}(\mathbf{W},\mathbf{y},\mathbf{y}') \quad (12).$$

The alternative networks or behaviors to weigh, $\mathbf{W}'$ or $\mathbf{y}'$, can differ from the existing network and behaviors, $\mathbf{W}$ or $\mathbf{y}$, only by at most one element of only i's row. The $s_h^m(\cdot)$ are some statistics, i.e., some functions of data $\{\mathbf{W},\mathbf{W}',\mathbf{y},\mathbf{y}'\}$, that reflect the actors' substantively/theoretically derived objectives regarding networks and behaviors. The $\boldsymbol{\beta}_h^m$ to be estimated are the relative weights of these objectives. With $\boldsymbol{\varepsilon}_h^m(\cdot)$ extreme-value distributed, *independently across actors and over time*, standard multinomial-logit models of categorical choice emerge for network ties and behavior. Similarly to Leenders' approach, identification derives from assuming no literal simultaneity in outcome or network-tie decisions, assuming time-lags to be pre-determined, and conditioning on first observations.[39] Given all this, estimation occurs by simulating the sequences of actions and of networks and searching over possible values of the model parameters, $\boldsymbol{\lambda}$ and $\boldsymbol{\beta}$, to minimize some distance function from the observed sequences of $\mathbf{W}$ and $\mathbf{y}$ to the simulated sequences.[40]

For our purposes, some features of extant network-analytic coevolution approaches are not ideal (see also note 39). In order of increasing importance and height of statistical hurdle presented: first, many behaviors and connectivities of interest are not binary or ordinal.[41] Second, relative connectivity strengths are not always directly observed, or even observable. Where not, the selection model would have no left-hand-side data, so networks could only be estimated as we propose: through their impact on actors' behavior given a structural specification of how the network matters for that behavior and how the observed covariates relate to the

[36] Testing for either or both of remaining temporal or spatial residual-correlation given a time-lagged spatiotemporal-lag model is possible and highly advisable. Franzese & Hays (2004, 2008b), e.g., discuss some valid tests.

[37] We follow Snijders et al. (1997) and Steglich et al. (2006, 2007) most closely. See note 24 for fuller citation list.

[38] In the expositions we have read, Snijders and colleagues omit the stochastic terms in (11) and (12) or assume them *i.i.d.*, and likewise those in the hazard models of opportunities to act. On the critical implications of this, see note 39.

[39] Despite these strong assumptions, some identification problems persist in the current implementation. First, assuming independent multinomial decisions for the endogenous behaviors and network ties and opportunities for action allows estimation of standard (non-spatial, independent) multinomial logit and hazard-rate models for those system components, but only by debarring stochastic dependence in those choices. Even then, the measures of network structure included among the unit or dyadic explanators to account/model the lagged dependencies are various functions of the ties between actors (and/or of their behaviors), i.e., of the outcomes of the multinomial choices of the actors regarding the connections (and/or behaviors). In latent-variable models like the multinomial logit, however, the actual outcomes cannot logically enter the right-hand side, spatially or temporally lagged and transformed by some network-structure measurement-function as they may be. Only (functions of) the latent variable can enter those functions. (The problem is that the probabilities of predicted choices on the left-hand side logically contradict the actual choices on the right-hand side.)

[40] Standard errors could derive from jackknife or bootstrapped resampling (Snijders & Borgatti 1999) if likelihoods or sufficient-statistic moment-equations for the analytic formulae are unavailable or inconvenient.

[41] We suspect the current implementation actually requires discrete, not ordinal, behaviors. Since the hazard rates are free parameters that can be set arbitrarily high or low to reflect total movements of any size from unit steps, at issue seems the sensibility of conceiving options as incrementing or decrementing the behavior by one. If so, rounding and/or rescaling continuous behaviors to render them discrete should suffice, and unbounded behaviors would actually simplify matters.

network ties. Third, as previously elaborated, time-lagging often will not suffice, and conditioning on the first observation is least inefficient and suffers least small-sample bias with long T, which is rarely available. A simultaneous and unconditional version of the Snijders *coevolution* model, however, would have to apply spatial multinomial-logit and hazard-rate models in those components, massively increasing complexity.

Our simple spatial-econometric approach begins with the spatiotemporal-lag model, expanding it to allow estimation of $\rho\mathbf{W}$ as a parameterized function of observed unit, dyadic, or exogenous-external variables. This model of the w_{ij} can reflect the *selection* stressed in network analysis. For instance, *homophily*—tendency for similar actors to form ties—if it arises on the basis of exogenous characteristics of those actors, yields a model of w_{ij} as a function of $\mathbf{x}_i$ and $\mathbf{x}_j$. If we consider among these explanators of $\mathbf{W}$ (some function of) the vector of behaviors of interest, $\mathbf{y}$, this yields a stronger form of *selection* where network ties and actor behaviors are jointly endogenous, raising higher statistical hurdles. Thus, the spatiotemporal-lag model with estimated, and possibly endogenous, spatial-weights is the spatial-econometric analogue to the network *coevolution* model, integrating contagion, selection, and common exposure. Our start is the multiparametric spatiotemporal-autoregression (m-STAR) model—i.e., a spatiotemporal-lag model with multiple spatial-weights matrices:

$$\mathbf{y} = \rho_1\mathbf{W}_1\mathbf{y} + \rho_2\mathbf{W}_2\mathbf{y} + \ldots + \rho_R\mathbf{W}_R\mathbf{y} + \phi\mathbf{M}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} = \mathbf{W}\mathbf{y} + \phi\mathbf{M}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \text{ with } \mathbf{W} \equiv \sum_{r=1}^{R}\rho_r\mathbf{W}_r \qquad (13).$$

Notice that we can also write (13) in scalar notation as:

$$\begin{aligned} y_i &= \rho_1\sum_j w_{ij}^1 y_j + \rho_2\sum_j w_{ij}^2 y_j + \ldots + \rho_R\sum_j w_{ij}^R y_j + \phi y_{i,t-1} + \sum_k x_k^i\beta_k + \varepsilon_i \\ &= \sum_j\left(\rho_1 w_{ij}^1 + \rho_2 w_{ij}^2 + \ldots + \rho_R w_{ij}^R\right)y_j + \sum_k x_k^i\beta_k + \varepsilon_i = \sum_j\left\{\left(\sum_r \rho_R w_{ij}^R\right)y_j\right\} + \sum_k x_k^i\beta_k + \varepsilon_i \end{aligned} \qquad (14).$$

Note that the parenthetical term in (14), the sum of row i of $\rho\mathbf{W}$, is a parameterized (linear-additive) model of the weights on y_j in affecting y_i. The w_{ij} are the covariates expected to explain the strength of ties from j to i, and $\boldsymbol{\rho}$ are the coefficients on them to estimate. Thus, the m-STAR model is an estimated-$\mathbf{W}$ model, with the $\hat{\mathbf{W}} = \Sigma_r(\hat{\rho}_r\mathbf{W}_r)$ being weighted sums, weights to be estimated, of observed (pre-specified) potential connectors. If the $\mathbf{W}_r$ include any whose elements are functions of $\mathbf{y}$, then $\mathbf{W}$ and $\mathbf{y}$ are jointly endogenous, and the m-STAR model expresses the jointly endogenous coevolution of networks and behaviors.

The sorts of models of $\mathbf{W}$, i.e., of networks, expressible without considerable further complication in this form would seem limited to those with linear-continuous w_{ij}, strengths of ties. If we expected truly binary ties in sum, i.e., in $\mathbf{W}$, we would need to transform the parenthetical term to binary outcomes in some manner, say by applying the log-odds function and a decision rule to convert probabilities to (0,1). (Other non linear-additive models of $\mathbf{W}$ would also entail some such complications. Note: explanators of total connectivity, $\mathbf{W}_r$, *can* be binary in the unmodified m-STAR model.) However, this is not a limitation if one believes (as we tend to do) that connectivity is a degree, only measured as binary only with error. 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 $\mathbf{x}$ in $\mathbf{X}\boldsymbol{\beta}$. The approach has some major advantages too, though. For one thing, likelihoods already exist for the simultaneous m-STAR model with exogenous $\mathbf{W}_r$, both the simpler conditional (on the first observation) likelihoods,

$$\begin{gathered} \ln L(\boldsymbol{\rho},\phi,\boldsymbol{\beta},\sigma;\mathbf{y},\mathbf{X}) = \ln(2\pi\sigma^2)^{-NT/2} + \ln|\mathbf{A}| - \tfrac{1}{2\sigma^2}e'e, \\ \text{where } \mathbf{A} = \mathbf{I}_{NT} - \mathbf{W} \text{ and } e = \mathbf{A}\mathbf{y} - \phi\mathbf{M}\mathbf{y} - \mathbf{X}\boldsymbol{\beta} \end{gathered} \qquad (15),$$

and the unconditional ones, which are crucial for small-T or true or effectively-true simultaneity situations:

$$\begin{aligned} \operatorname{Log} f_{\mathbf{y}_t,\ldots,\mathbf{y}_1} &= -\frac{1}{2}NT\log\left(2\pi\sigma^2\right) + \frac{1}{2}\sum_{i=1}^{N}\log\left(\left(1-\sum_r\rho_r\omega_i^r\right)^2 - \phi^2\right) + (T-1)\sum_{i=1}^{N}\log\left(1-\sum_r\rho_r\omega_i^r\right) \\ &- \frac{1}{2\sigma^2}\sum_{t=2}^{T}\boldsymbol{\varepsilon}_t'\boldsymbol{\varepsilon}_t - \frac{1}{2\sigma^2}\boldsymbol{\varepsilon}_1'\left((\mathbf{B}-\mathbf{A})'\right)^{-1}\left(\mathbf{B}'\mathbf{B} - \mathbf{B}'\mathbf{A}\mathbf{B}^{-1}\left(\mathbf{B}'\mathbf{A}\mathbf{B}^{-1}\right)'\right)^{-1}(\mathbf{B}-\mathbf{A})^{-1}\boldsymbol{\varepsilon}_1 \end{aligned} \qquad (16),$$

where $\boldsymbol{\varepsilon}_t \equiv \mathbf{y}_t - \mathbf{W}\mathbf{y}_t - \mathbf{A}\mathbf{y}_{t-1} - \mathbf{X}_t\boldsymbol{\beta}$, $\boldsymbol{\varepsilon}_1 \equiv \mathbf{y}_1 - \mathbf{W}\mathbf{y}_1 - \mathbf{A}\mathbf{y}_1 - \mathbf{X}_1\boldsymbol{\beta}$, ω_i^r is the ith characteristic root of $\mathbf{W}_r$, $\mathbf{A}\equiv\varphi\mathbf{I}_N$, $\mathbf{B}\equiv\mathbf{I}-\mathbf{W}$, and $\mathbf{W} \equiv \Sigma_r(\rho_r\mathbf{W}_r)$ and $\mathbf{W}_r$ are $N\times N$ spatial-weights matrices. The estimated variance of

$\hat{\mathbf{W}}_{ij}$—i.e., of the estimated strength of the ij^{th} tie—is:

$$\hat{\mathbf{W}} = \sum_r \hat{\rho}_r \mathbf{W}_r \Rightarrow \widehat{\text{var}(\hat{\mathbf{W}}^{(i,j)})} = \begin{bmatrix} \mathbf{W}_1^{(i,j)} & \mathbf{W}_2^{(i,j)} & \dots & \mathbf{W}_R^{(i,j)} \end{bmatrix} \hat{\mathbf{\Omega}}_{\hat{\rho}} \begin{bmatrix} \mathbf{W}_1^{(i,j)} & \mathbf{W}_2^{(i,j)} & \dots & \mathbf{W}_R^{(i,j)} \end{bmatrix}' \quad (17),$$

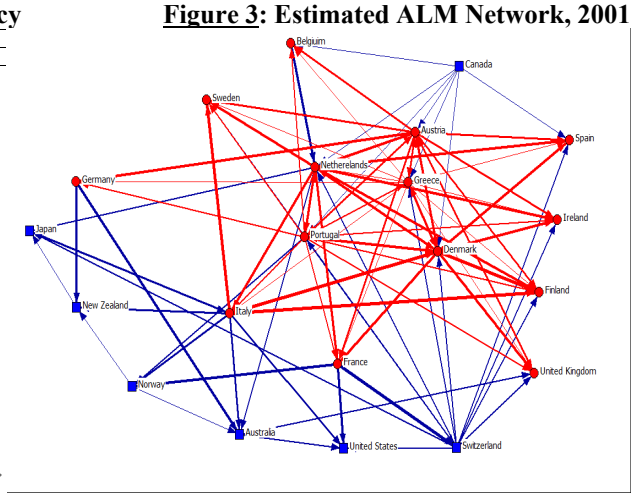
where $\hat{\mathbf{\Omega}}_{\hat{\rho}}$ is the Hessian of the likelihood as usual. Thus, we can apply all the estimation techniques, all the intuitions about biases, efficiencies and sensitivities, all the tools for calculating, interpreting, and presenting spatiotemporally dynamic effects discussed in our previous work for spatial linear-regression models. The estimated **W**, conversely, can be interpreted and presented with all the standard tools of network analysis.

Table 3: m-STAR model of Active-Labor-Market Policy

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*
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.

Figure 3: Estimated ALM Network, 2001



Endogenous coevolution models, i.e., models with some $\mathbf{W}_r$ being some function of **y**, present larger challenges. One simple stratagem, which we applied in our first cut at an m-STAR approach to estimated-and-endogenous-**W** models (Franzese et al. 2008) that Table 3 and Figure 3 illustrate, is to apply the *poor man's exogeneity*, temporally lagging the **y** in this $\mathbf{W}_y$ and assuming the conditions required for that strategy of identification hold sufficiently. (This gives essentially Leenders' model.) It 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. Accordingly, we propose to explore a 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. For this, we would use other $\mathbf{W}_r$ that are functions of exogenous variables only and exogenous regressors **X**, to create spatial instruments $\mathbf{W}_r\mathbf{X}$. Then, draw from the estimated multivariate distribution of the instrumented $\mathbf{W}_y$ to insert in the conditional likelihood (15) or the unconditional one (16). Maximize this likelihood q times, each time with new draws from that first-stage S-GMM instrumented $\mathbf{W}_y$. 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 neither proof nor simulation of its properties as yet. Accordingly, Monte Carlo assessment of the estimator will be one essential next step; two others will be to compare this approach to the Snijders et al. one and to attempt to add robustness against specification error in m-STAR models of **W** by adding some features of the spatial-instrumentation estimators described above (Conley 1999, Chen & Conley 2002, Pinkse et al. 2002) to this one.

4. Summary of Proposed Research & Deliverables

I. Develop or Introduce, and Explore, *S-QualDep* & *S-SysEq* Models
   A. Introduce: Spatial-GMM for the Spatial-Error Probit Model (following Pinkse & Slade 1998)
   B. Introduce/Develop: Approximate-Respecification Approaches to *S-QualDep* Models (building from

Fleming 2004, extend to other *S-QualDep* beyond *S-Probit*)

C. Develop: Temporal- and Spatiotemporal-Lag Probit Model (extends *S-Probit* literature)

D. Develop: Structural Spatial-Lag and Spatiotemporal-Lag Models for:
   1. S-Count (Poisson, Negative-Binomial, Zero-Inflated, etc.)
   2. S-Duration (Exponential, Weibull, etc.)
   3. Relatives of S-Probit: S-Logit, S-Tobit, S-Heckit, S-MNP, S-MNL, S-Event-History, etc.

E. *S-SysEq* Models:
   1. Introduce: Spatial Linear-Regression Systems (Kelijian & Prucha 2004, Rey & Boarnet 2004)
   2. Develop: S-SysEq for Structural S-QualDep Models (builds from Hays & Kachi 2008)

F. Explore Small-Sample Properties and Sensitivity/Robustness to Misspecification & Assumption-Violation, and Compare to the Extant Less-Structural Approaches

G. Develop Tools for Calculating & Presenting Counterfactual Spatiotemporal Dynamics & Effects

II. Estimated-**W** & Endogenous-**W** Models:

A. Introduce: m-STAR Model as an Approach to Estimated-**W** Models

B. Develop: Qualitative and Nonlinear Estimated-**W** in an m-STAR Approach

C. Develop: Simultaneous Endogenous-**W** (Coevolution) Models in an m-STAR Approach (i.e., the proposed S-GMM within S-ML Estimator Sketched in Section 3b)

D. Explore: Small-Sample Properties & Sensitivity/Robustness to Misspecification & Assumption-Violation; Compare to Extant Network-Analytic (Coevolution) & Less-Structural Approaches

E. Develop Tools for Calculating & Presenting Counterfactual Spatiotemporal Dynamics & Effects in Dependent-Variable Terms, with Associated Certainties, for These Models

III. **Supplements:** Provide MatLab, R, and Stata code to implement all specification, estimation, testing, and presentation procedures described in the project, and all data & code to replicate empirical work.

5. Results of Prior Support

The co-PI's received prior support from NSF #0318045, "Diagnosing, Modeling, Interpreting, and Leveraging Spatial Relationships in Time-Series-Cross-Section Data," originally funded in 2003, and in a total amount of approximately $285,000. We described the substantive content of the research products of that grant extensively above. As cited here, the work products are Franzese & Hays (2003, 2004ab, 2005ab, 2006abc, 2007abcd, 2008abcd): a book manuscript, three journal articles, three book chapters, a working paper, and eight conference papers (as cited here; we estimate well over twice that number of presentations & presentation-papers). We have worked varyingly closely with four graduate students over this period: one US citizen (Bryce Corrigan), one Japanese (Aya Kachi), one Chinese (Xiaobo Lu), and one South Korean (Nam Kyu Kim); three male and one (Kachi) female; three at the University of Michigan and one (Kachi) at the University of Illinois. We expect the work of this grant to be completed, and its funds depleted, by the spring of 2008, before the requested start-period of the current grant-proposal. The remaining funded task (<10% of the total) is the translation from MatLab™ to (R™ and) Stata™ of our code for estimating these previous models and for calculating spatial dynamics, effects, and standard errors. (About half of our code is original, and the rest starts from or borrows with little or no amendment from LeSage's MatLab™ code (Lesage 1999).