MOSTLY POINTLESS SPATIAL ECONOMETRICS?*

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ABSTRACT. We argue that identification problems bedevil applied spatial economic research. Spatial econometrics usually solves these problems by deriving estimators assuming that functional forms are known and by using model comparison techniques to let the data choose between competing specifications. We argue that in many situations of interest this achieves, at best, only very weak identification. Worse, in many cases, such an approach will be uninformative about the causal economic processes at work, rendering much applied spatial econometric research "pointless," unless the main aim is description of the data. We advocate an alternative approach based on the "experimentalist paradigm" which puts issues of identification and causality at center stage.

1. INTRODUCTION

The last two decades have seen economists become increasingly interested in geographical issues (Martin, 1999; Behrens and Robert-Nicoud, 2009). This has been variously attributed to theoretical developments, a growing interest in cities or simply the greater availability of geo-referenced data. The result has been greater interaction between economic geographers, regional scientists, and economists interested in spatial aspects of the economy. More recently, a similar process has seen mainstream econometric theorists becoming increasingly interested in spatial processes, traditionally the preserve of a group of spatial econometricians.[1] One might think that the next step would be convergence between the tools developed by spatial econometricians and the methods used by applied economists to assess the empirical validity of models of spatial economics. We argue that this is unlikely because, while there may have been convergence between mainstream and spatial econometric theory, most applied economic research is taking a different path.

In many (micro) economic fields—particularly development, education, environment, labor, health, and public finance—empirical work is increasingly concerned with questions about causality (Angrist & Pischke, 2010). If we increase an individual's years of education, what happens to their wages? If we decrease class sizes, what happens to student grades? These questions are fundamentally of the type "if we change x, what do we expect to happen to y." Just as with economics more generally, such questions are fundamental

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*The title is a reference to Angrist and Pischke's (2009) "Mostly Harmless Econometrics" which outlines the experimentalist paradigm and argues that fancier econometric techniques are unnecessary and potentially dangerous.

[1] See Anselin (2010). Many of the specialized econometricians who developed the field are recognized by Fellowship of the Spatial Econometric Association. See http://spatialeconometr.altervista.org/

to our understanding of spatial economics. When more skilled people live in an area, what happens to individual wages? If a jurisdiction increases taxes, what happens to taxes in neighboring jurisdictions?

In an experimental setting, agents (individuals, firms, governments) would be randomly assigned different x and the outcomes y observed. Measuring whether different x are associated with different outcomes would then give the causal effect of x on y. The fundamental challenge to answering these questions for (most) economic data is that x is not randomly assigned. Instead, we jointly observe x and y so we lack the counterfactual, that is, what would have happened if x had not been changed. Fortunately, applied economics has come a long way in its efforts to find credible and creative ways to answer such questions by constructing counterfactuals from observational data.

A good starting point for thinking about whether a question about causality can be answered and how to answer it, is to consider an ideal experiment. The experiment may not be feasible, but with the design in mind it is easier to think of ways to find sources of variation in the data that mimic or approximate the ideal experiment. The "experimentalist paradigm" (Angrist and Krueger, 1999; Angrist and Pischke, 2009, 2010) does this by using simple linear estimation methods, taking care to pinpoint and isolate sources of variation in x that can plausibly be considered exogenous. The aim of these methods is to mimic, as far as possible, the conditions of an experiment in which agents are randomly assigned different x and outcomes y observed. The central idea is to find otherwise comparable agents (e.g., twins, siblings, neighbors, regions) who for some reason have been exposed to different x. This approach is still "econometric"—it draws on theory to guide the questions asked and thinking about the causal processes at work. However, the fundamental attraction is that the assumptions required for identification of causal effects are usually clearly specified and understandable without reference to specific (and untested) economic theories. Put another way, the aim is to obtain plausible estimates of causal effects without relying on *ad hoc* functional forms and exclusion restrictions imposed arbitrarily, or derived from untested theories about which there is no consensus.[2] This approach is particularly attractive in areas, like much of spatial economics, where available structural models do not closely capture the complexities of the processes for which we have data.[3] Unfortunately, although these issues may be well understood by more experienced practitioners, they are not widely discussed in many of the "standard" spatial econometrics references (including, for example, Arbia, 2006 and LeSage and Pace, 2009). For this reason there is a danger that people entering the world of applied economic research using spatial econometrics will ignore these insights into framing questions and achieving credible research designs.

Why is it the case that the spatial econometrics literature often ignores these issues? We suspect this is partly because the underlying theory developed from time-series foundations, so that questions about causality have not been center stage. The standard approach to spatial econometrics has been to write down a spatial model (e.g., the spatial

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[2] The reliance on simple linear methods may seem a strong functional form assumption. However, the assumption of a linear structural relationship—the Conditional Expectation Function (CEF)—is "not really necessary for a causal interpretation of regression" (Angrist and Pischke, 2009, p. 69). If the CEF is causal, then linear regression is informative about causality because it provides the best linear approximation to the CEF.

[3] Sutton (2002) makes a similar argument about structural modeling when models are "far from reality." This is not to say that theoretical structure has no place in empirical spatial economics. Particularly when general equilibrium considerations are important, there may be a greater role for theory (preferably based on micro-economic behavioral foundations). See Combes, Duranton, and Gobillon (2011) for discussion. Later in the paper we briefly discuss the use of spatial econometrics in the estimation of structural econometric models.

autoregressive model), to assume it accurately describes the data generating processes and then to estimate the parameters by nonlinear methods such as (quasi) maximum likelihood (ML). Because estimation is not always simple, much effort has gone in to developing techniques that allow estimation of a range of models for large data sets. Questions of identification (i.e., does an estimated correlation imply that x *causes* y?) have been addressed by asking which spatial processes best fit the data. While this sounds straightforward, in practice, as we discuss below, it is hard to distinguish between alternative specifications that have very different implications for which causal relationships are at work.

In this paper we explain why the standard spatial econometric toolbox is unlikely to offer a solution to the problem of the identification of causal effects in many spatial economic settings. Of course, much standard (i.e., nonspatial) empirical economic analysis falls someway short of the lofty ideals of identifying causal effects from random variation in the variable of interest (x). Finding sources of truly exogenous or random variation in x is difficult, but good applied work aimed at causal analysis must surely make some credible attempt to do so. This is not to say that noncausal associations are never without merit, because description and correlation can provide essential insights. However, identification of causal effects remains the gold standard to which many economists claim to aspire. We will argue that this should also be the case in applied spatial economic research.

The rest of this paper is structured as follows. Section 2 provides a basic overview of standard spatial econometric models, while Section 3 discusses problems of identification. Section 4 returns to the relationship between the spatial econometrics and the experimentalist paradigm. Section 5 concludes.

2. SPATIAL ECONOMETRIC MODELS AND THEIR MOTIVATION

This section provides an introduction to spatial econometric models, of the type popularized by Anselin (1988). It is not comprehensive but provides enough background so that someone unfamiliar with spatial econometrics should be able to follow the arguments made later. We generally use the model terminology of LeSage and Pace (2009) and refer the reader there for details.

To develop ideas, start with a basic linear regression:

$$(1) \qquad\qquad\qquad y_i = \mathbf{x}_i' \boldsymbol{\beta} + u_i,$$

where i indexes units of observation, y_i is the outcome of interest, $\mathbf{x}_i$ is a vector of explanatory variables (including a constant), u_i is an error term, and $\boldsymbol{\beta}$ is a vector of parameters. The most basic regression specification assumes that outcomes for different units are *independent*. This is a strong assumption and there may be many reasons why outcomes are not independent, particularly when observations are for geographically referenced events, agents, or places. In a spatial setting, this model is often not very interesting. There are many contexts in which estimating and interpreting the parameters that characterize this dependence is of academic and policy interest.

Estimating the complete between-observation variance-covariance structure is infeasible. However, if the data are spatial so can be mapped to locations, relative positions (and direction) may restrict the connections between observations. For example, outcomes may depend on outcomes in "nearby" locations but not those further away. A simple way to capture these restrictions is to define a vector $\mathbf{w}_i$ where the jth element is bigger, the more closely connected j is with i (e.g., $1/\text{distance}_{ij}$). With n observations, multiplying $\mathbf{w}_i'$ by the nx1 vector of outcomes $\mathbf{y}$ gives a value $\mathbf{w}_i'\mathbf{y}$ that spatial econometricians refer to as a spatial lag. For each observation, $\mathbf{w}_i'\mathbf{y}$ is a linear combination of all y_j with which the ith

observation is connected. If, as is usually the case, $\mathbf{w}_i$ is normalized so that the elements sum to 1, then $\mathbf{w}_i'\mathbf{y}$ is a weighted average of the "neighbors" of i.

What now if we want to know whether the outcome y_i is related to outcomes at locations to which i is connected? Ord (1975) proposes a simple solution, to assume that the effect of the spatial lag of y_i is linear and constant across observations. This gives the spatial autoregressive model (SAR):

(SAR) $\qquad y_i = \rho\,\mathbf{w}_i'\mathbf{y} + \mathbf{x}_i'\boldsymbol{\beta} + u_i.$

LeSage and Pace (2009) suggest a "time dependence motivation" for the SAR model. Assume fixed across time exogenous variables $\mathbf{x}_i$ determine outcome y_i. Now assume that when determining their own outcome, agents take in to account both their own characteristics and recent outcomes for other "nearby" agents. We might think of y_i as the price of a house, $\mathbf{x}_i$ as the fixed characteristics (number of rooms) and assume that when agreeing a sale price, people consider both the characteristics of the house and the current selling price of nearby houses. In this case $\boldsymbol{\beta}$ captures the causal effect of house characteristics and ρ represents the causal effect of neighboring prices (conditional on observed housing characteristics).

We could drop the assumption that y_i is affected by the spatial lag of y_i and instead assume that y_i is affected by spatial lags of the explanatory variables. If $\mathbf{X}$ denotes the matrix of explanatory variables and $\boldsymbol{\gamma}$ a vector of parameters, this gives the spatial (lag of) X model (SLX):

(SLX) $\qquad y_i = \mathbf{x}_i'\boldsymbol{\beta} + \mathbf{w}_i'\mathbf{X}\boldsymbol{\gamma} + u_i.$

LeSage and Pace (2009) provide an "externality motivation" for this model. Continuing with the housing example, this assumes the characteristics of nearby houses, e.g., their size, directly determine prices (rather than working through observed sales prices). Of course, an externality motivation could justify the SAR model if the externality works through the spatial lag of y_i

Next, drop the assumption that outcomes are affected by spatial lags of the explanatory variables and instead assume a SAR-type spatial autocorrelation in the error process. If $\mathbf{u}$ denotes the vector of residuals, this gives a spatial error model (SE):

(SE) $\qquad y_i = \mathbf{x}_i'\boldsymbol{\beta} + u_i\;;\;u_i = \rho\,\mathbf{w}_i'\mathbf{u} + v_i.$

Alternative SE specifications are available, but this version is sufficient for our purposes. Finally, combining the SAR and SLX models gives us the Spatial Durbin Model (SD):

(SD) $\qquad y_i = \rho\,\mathbf{w}_i'\mathbf{y} + \mathbf{x}_i'\boldsymbol{\beta} + \mathbf{w}_i'\mathbf{X}\boldsymbol{\gamma} + u_i,$

which assumes dependence between y_i and the spatial lags of both the outcome and explanatory variables, but drops the assumption of spatial autocorrelation in the error process. Alternatively, the SD model can be motivated by simply rearranging the SE model in a "spatial" Cochrane–Orcutt transformation:

(2) $$u_i = y_i - \mathbf{x}_i'\boldsymbol{\beta},$$

(3) $$y_i - \mathbf{x}_i'\boldsymbol{\beta} = \rho\,\mathbf{w}_i'\mathbf{y} - \rho\,\mathbf{w}_i'\mathbf{X}\boldsymbol{\beta} + v_i,$$

(4) $$y_i = \rho\,\mathbf{w}_i'\mathbf{y} + \mathbf{x}_i'\boldsymbol{\beta} - \rho\,\mathbf{w}_i'\mathbf{X}\boldsymbol{\beta} + v_i.$$

This idea provides another motivation for including spatial lags, as a "solution" to the omitted variables problem. See the appendix for further discussion.

These five processes are not exhaustive of all possible models, and we consider a particularly important generalization further below, but for the moment they are sufficient for our purposes. In the text, we use the acronyms (SAR, etc.) to refer to the specifications above.

Estimation using OLS gives inconsistent parameter estimates if the models include a spatial lag of y_i and ρ is nonzero (e.g., the SAR and SD models). This inconsistency arises because of a mechanical link between u_i and $\mathbf{w}_i'\mathbf{y}$ for most specifications of $\mathbf{w}_i$. Standard errors are also inconsistently estimated for these models, as well as for models including a spatial lag in u_i (e.g., the SE model). OLS provides consistent parameter estimates if the spatial correlation occurs only through the error term (SE model) or exogenous characteristics (SLX model). In both cases, standard errors are inconsistent, and OLS estimation of the SE model is inefficient. In contrast, Lee (2004) shows that (quasi) ML estimation provides consistent estimators for all these models *conditional on the assumption that the spatial econometric model estimated is the true data generating process*. Alongside theoretical developments, advances in computational power and methods have made ML estimation feasible for large datasets.[4] As a result, it is preferred in the spatial econometrics literature. The SAR and SLX models are nested within the SD model and as shown the SE model can be rearranged to give the SD model. The fact that the SD model nests many of the other models provides an argument for estimating the SD model and then testing this against the nested models through the use of likelihood tests. Model comparison techniques can be used to compare models based on different weight matrices and explanatory variables. This is the approach advocated by LeSage and Pace (2009).

To begin to understand the problems with this approach it is useful to see how these models are related to each other. Consider the reduced form (expressing y_i in terms of exogenous factors) of the SAR model. If the model is correct, the only exogenous factors affecting y_i are $\mathbf{x}_i$ and u_i, so the only factors affecting $\mathbf{w}_i'\mathbf{y}$ are $\mathbf{w}_i'\mathbf{X}$ and $\mathbf{w}_i'\mathbf{u}$. The spatial lag $\mathbf{w}_i'\mathbf{y}$ also depends on the *second-order* spatial lag of $\mathbf{w}_i'\mathbf{W}\mathbf{y}$, that is, on outcomes for the "neighbors of my neighbors." By repeated substitution the reduced form is:

$$(5) \qquad y_i = \mathbf{x}_i'\boldsymbol{\beta} + \rho\,\mathbf{w}_i'\mathbf{X}\boldsymbol{\beta} + \rho^2\mathbf{w}_i'\mathbf{W}\mathbf{X}\boldsymbol{\beta} + \rho^3\mathbf{w}_i'\mathbf{W}^2\mathbf{X}\boldsymbol{\beta} + [\cdots] + v_i,$$

where $v_i = \rho\,\mathbf{w}_i'\mathbf{v} + u_i$, $\mathbf{W}$ is the matrix of stacked weight vectors ($\mathbf{w}_i'$), and $\mathbf{W}^2 = \mathbf{W}\mathbf{W}$.

Notice that, in the reduced form, the only thing that distinguishes this from the SLX model is the absence of terms in $\rho^n\mathbf{w}_i'\mathbf{W}^{n-1}\mathbf{X}\boldsymbol{\gamma}$ for $n > 1$. As we explain in the next section, in practice these two models will often be hard to tell apart.

It is also informative to derive the reduced form for the general SD model. Substituting for y_i we get

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\begin{aligned}
(6) \qquad y_i \;&= \rho\,\mathbf{w}_i'(\rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\mathbf{X}\boldsymbol{\gamma} + \mathbf{u}) + \mathbf{x}_i'\boldsymbol{\beta} + \mathbf{w}_i'\mathbf{X}\boldsymbol{\gamma} + u_i \\
&= \rho^2\mathbf{w}_i'\mathbf{W}\mathbf{y} + \rho\,\mathbf{w}_i'\mathbf{X}\boldsymbol{\beta} + \rho\,\mathbf{w}_i'\mathbf{W}\mathbf{X}\boldsymbol{\gamma} + \mathbf{x}_i'\boldsymbol{\beta} + \mathbf{w}_i'\mathbf{X}\boldsymbol{\gamma} + v_i \\
&= \rho^2\mathbf{w}_i'\mathbf{W}\mathbf{y} + \mathbf{x}_i'\boldsymbol{\beta} + \mathbf{w}_i'\mathbf{X}(\rho\boldsymbol{\beta} + \boldsymbol{\gamma}) + \rho\,\mathbf{w}_i'\mathbf{W}\mathbf{X}\boldsymbol{\gamma} + v_i \\
&= [\dots] \\
&= \rho^n\mathbf{w}_i'\mathbf{W}^{n-1}\mathbf{y} + \mathbf{x}_i'\boldsymbol{\beta} + \mathbf{w}_i'\mathbf{X}(\boldsymbol{\beta}\rho + \boldsymbol{\gamma}) \\
&\quad + \rho\,\mathbf{w}_i'\mathbf{W}\mathbf{X}(\boldsymbol{\beta}\rho + \boldsymbol{\gamma}) + \rho^2\mathbf{w}_i'\mathbf{W}^2\mathbf{X}(\boldsymbol{\beta}\rho + \boldsymbol{\gamma}) + [\cdots] + v_i
\end{aligned}
$$

where v_i denotes the spatial lag terms in u_i. Under standard regularity conditions on ρ and $\mathbf{w}_i$, $\lim_{n\to\infty}\rho^n\mathbf{w}_i'\mathbf{W}^{n-1}\mathbf{y} = 0$ so that term can be ignored. In the reduced form, the only

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[4] "These improvements allow models involving samples containing more than 60,000 U.S. Census tract observations to be estimated in only a few seconds on desktop [...] computers" (LeSage and Pace, 2009, p. 45).

thing that distinguishes this from the SLX model is the cross-coefficient restrictions on the terms in $\mathbf{w}'_i\mathbf{W}^{n-1}\mathbf{X}$ for $n>1$.

In short, spatial interaction in y_i, spatial externalities in $\mathbf{x}_i$, or spatially omitted variables lead to different spatial econometric specifications. These models have different implications for the economic processes at work. However, the reduced form for all these models is

$$(7) \qquad y_i = \mathbf{x}'_i\boldsymbol{\beta} + \mathbf{w}'_i\mathbf{X}\pi_1 + \mathbf{w}'_i\mathbf{W}\mathbf{X}\pi_2 + \mathbf{w}'_i\mathbf{W}^2\mathbf{X}\pi_3 + [\cdots] + v_i,$$

and the only differences arise from how many spatial lags of $\mathbf{x}_i$ are included, constraints on the way the underlying parameters determine the composite parameters $\boldsymbol{\Pi}$, and whether the error term is spatially correlated. Distinguishing which of these models generates the data that the researcher has at hand is going to be difficult as the specification of $\mathbf{W}$ is often arbitrary, and because the spatial lags of $\mathbf{x}_i$ are just neighbor averages that are almost always very highly mutually correlated. Put another way, these different specifications are generally impossible to distinguish without assuming prior knowledge about the true data generating process that we often do not possess in practice. In short contrasting motivations lead to models that cannot usually be easily distinguished. It would be useful if these problems were more generally recognized by *all* researchers working with spatial data, but we think they generate particular problems for the spatial econometrics approach as outlined in this section. We now consider these difficulties in detail.

3. THE REFLECTION PROBLEM AND CRITIQUE OF SPATIAL ECONOMETRIC MODELS

Readers familiar with the "neighborhood effects" literature will see immediate parallels between the spatial econometrics models (SAR, etc.) and "linear-in-means" neighborhood effects models (or "peer effects" models). The parallels between these fields have already been highlighted by Lee (2004, 2007) and others. The generic neighborhood effects model described by Manski (1993, 2000) and used by countless applied economics papers on neighborhood effects, takes the form

$$y_i = \rho_1 E[y_i|a] + \mathbf{x}'_i\boldsymbol{\beta} + E[\mathbf{x}'_i|a]\boldsymbol{\gamma} + v_i,$$

$$(8) \qquad v_i = \rho_2 E[v_i|a] + u_i,$$

where y_i is the outcome of interest, $\mathbf{x}_i$ a vector of exogenous variables, and u_i and v_i are error terms representing unobservables. Variable a indexes locations, usually nonoverlapping "neighborhoods" in the neighborhood effects literature. This specification allows for three sources of neighbor influence. Parameter ρ_1 captures the "endogenous" effect of neighbors' expected outcome on own outcomes. Parameter γ captures the "contextual" or "exogenous" effect of mean group characteristics on individual outcomes. Parameter ρ_2 captures the "correlated" effects of unobserved (at least to the econometrician) mean characteristics of agents in location a or factors affecting agents in location a.

There are inherent identification problems in estimating (8), even assuming that v_i and $\mathbf{x}_i$ are independent. First, ρ_1 and ρ_2 cannot be separately identified without data on v_i. This is clear if we substitute $E[v_i|a]$ and (using the law of iterated expectations) rewrite (8) as

$$(9) \qquad y_i = (\rho_1 + \rho_2 - \rho_1\rho_2)\, E[y_i|a] + \mathbf{x}'_i\boldsymbol{\beta} + E[\mathbf{x}'_i|a](\boldsymbol{\gamma} - \rho_2\boldsymbol{\beta} - \rho_2\boldsymbol{\gamma}) + u_i,$$

to see that the parameter on $E[y_i|a]$ is a composite of the causal "endogenous" and incidental "correlated" effects. What then can be identified from the observable characteristics?

Taking expectations of (8) and rearranging gives a reduced form version of (8)

$$(10) \qquad y_i = \mathbf{x}'_i\boldsymbol{\beta} + E[\mathbf{x}'_i|a](\rho_1\boldsymbol{\beta} + \boldsymbol{\gamma})/(1 - \rho_1) + \rho_1/(1 - \rho_1)E[v_i|a] + v_i.$$

Equation (10) shows that the causal effects of neighborhood mean outcomes (ρ_1) and of neighborhood mean characteristics (γ) cannot be separately identified from the reduced form parameters, even when there is no spatial autocorrelation in the unobservables ($\rho_2 = 0$). Only $\boldsymbol{\beta}$ and the composite parameter vector $(\boldsymbol{\gamma} + \boldsymbol{\beta}\rho_1)/(1 - \rho_1)$ are identified. This is Manski's "reflection problem": only the *overall* effect of neighbors' characteristics is identified, not whether they work through exogenous or endogenous neighborhood effects. These issues are intuitive: How can you distinguish between something unobserved and spatially correlated driving spatial correlation in y from the situation where y is spatially correlated because of direct interaction between outcomes? Further, how can you tell whether an individual is affected by the behavior of their group, or by the characteristics of their group when group behavior depends on the characteristics of the group? In many circumstances you cannot, without imposing further restrictions, either assuming away one or more of the sources of neighborhood effects, or by imposing nonlinear theoretical relationships between $E[y_i|a]$ and $E[\mathbf{x}'_i|a]$ (e.g., as in Brock and Durlauf, 2001, when the outcome is discrete, and the researcher imposes a logit or probit functional form). In some situations, however, experimental data (of the real or natural variety) can remove the need for such arbitrary restrictions. We discuss further and provide some concrete examples in Section 4.

In practice, the neighborhood effects literature uses empirical counterparts to (8) and (10):

$$(8a) \qquad y_i = \rho_1\mathbf{w}'_i\mathbf{y} + \mathbf{x}'_i\beta + \mathbf{w}'_i\mathbf{X}\gamma + v_i,$$

$$(10a) \qquad y_i = \mathbf{x}'_i\boldsymbol{\beta} + \mathbf{w}'_i\mathbf{X}(\boldsymbol{\gamma} + \boldsymbol{\beta}\rho_1)/(1 - \rho_1) + \rho_1/(1 - \rho_1)\mathbf{w}'_i\mathbf{v} + v_i,$$

where $\mathbf{w}_i$ is the spatial weight vector that creates "neighborhood averages" as estimates of $E[\cdot|a]$ (as noted by Pinkse and Slade, 2010; McMillen, 2010b; and others). For neighborhoods, where groups are contiguous and nonoverlapping, the jth element of $\mathbf{w}_i$ takes value $1/n_a$ if i and j are in the same neighborhood a, of size n_a. In these specifications, u_i and ω_i are potentially spatially autocorrelated error terms (when $\rho_2 \neq 0$ in equation (8)). Note that (8a) is identical to the SD model and (10a) is an SLX model (with a spatially autocorrelated error term).

Applied economists usually worry a lot about identification issues when they take (8) and (10) to the data using specifications like (8a) and (10a). Why then, are these issues considered far less in applications of the SAR, SD and SE models? This question has been the subject of surprisingly little discussion (Lee, 2004, 2007 and Pinkse and Slade, 2010 are notable exceptions).

One important difference is that, in spatial econometrics, equations like (8a) are treated as the population data generating process, rather than an empirical analogue to (8). Parameter ρ_1 is taken to be the effect of the observed sample mean neighborhood outcome, rather than the effect of an unobserved population mean estimated from the data. As a consequence, repeated substitution of y in (10a) leads to a reduced form as in Equation (6):

$$(11) \quad y_i = \mathbf{x}'_i\boldsymbol{\beta} + \mathbf{w}'_i\mathbf{X}(\boldsymbol{\beta}\rho_1 + \boldsymbol{\gamma}) + \rho_1\mathbf{w}'_i\mathbf{W}\mathbf{X}(\boldsymbol{\beta}\rho_1 + \boldsymbol{\gamma}) + \rho_1^2\mathbf{w}'_i\mathbf{W}^2\mathbf{X}(\boldsymbol{\beta}\rho_1 + \boldsymbol{\gamma}) + [\cdots] + \omega_i.$$

Now all the structural, causal parameters ρ_1, $\boldsymbol{\beta}$ and γ are, in theory identified, because there are only three parameters, but an infinitely large number of spatial lags of $\mathbf{x}_i$. The parameters can, in principle be estimated by nonlinear methods (including

maximum likelihood), or by linear instrumental variables (IV, or 2SLS) estimation of (8a), using the linear first stage predictions from

$$(12) \qquad \mathbf{w}'_i y_i = \mathbf{w}'_i \mathbf{W} \hat{\boldsymbol{\beta}} + \mathbf{w}'_i \mathbf{W} \mathbf{X} \hat{\pi}_1 + \mathbf{w}'_i \mathbf{W}^2 \mathbf{X} \hat{\pi}_2 + \mathbf{w}'_i \mathbf{W}^3 \mathbf{X} \hat{\pi}_3 + [\cdots],$$

where the econometrician can choose an arbitrary number of spatial lags of $\mathbf{x}_i$ as instruments.[5]

So why do spatial econometricians argue that (8a) is identified, by virtue of (11), when other economists would argue that (8a) isn't identified, by virtue of (10a)? The crucial difference is that spatial econometrics assumes that $\mathbf{W}$ is known and represents real-world linkages. Neighborhood effects researchers argue that the true $\mathbf{W}$ is almost never known, and is, at best, a means of estimating $E[\cdot|a]$. In other words, the assumption of knowledge about $\mathbf{W}$ is critical.[6]

If $\mathbf{W}$ takes the typical block-diagonal structure used in neighborhood effects studies (or $\mathbf{W}$ is otherwise idempotent) then (11) collapses to (10a) and the parameters are no longer separately identified. But even if $\mathbf{W}$ is not idempotent, there are serious problems in relying on (11) and (12) for identification of the parameters in (8a). First, if the exact structure of $\mathbf{W}$ is not known then identification breaks down because $\mathbf{w}'_i \mathbf{W}$, $\mathbf{w}'_i \mathbf{W}^2$ etc. may better capture the connections between observation i and its neighbors than does $\mathbf{w}_i$ (e.g., $\mathbf{x}_i$ has an effect up to 5 km, but $\mathbf{w}_i$ incorrectly restricts effects to within 2 km). If the higher order lags $\mathbf{w}'_i \mathbf{W} \mathbf{X}$, $\mathbf{w}'_i \mathbf{W}^2 \mathbf{X}$ affect y directly, they cannot provide additional information to identify ρ_1. It is easiest to think about this in the context of the linear (2SLS) IV estimator implicit in (11) and (12) (e.g., Kelejian and Prucha, 1998): If the exclusion restrictions on $\mathbf{w}'_i \mathbf{W} \mathbf{X}$, $\mathbf{w}'_i \mathbf{W}^2 \mathbf{X}$ etc. in (8a) are invalid, then these spatial lags are not suitable as instruments, nor as sources of identification more generally.

Second, even if $\mathbf{W}$ is assumed known (and is not idempotent) there are serious estimation problems because the spatial lags $\mathbf{w}'_i \mathbf{X}$, $\mathbf{w}'_i \mathbf{W} \mathbf{X}$, $\mathbf{w}'_i \mathbf{W}^2 \mathbf{X}$, etc. are likely to be highly correlated. In the IV context, there is a "weak instruments/identification" problem, because there is little independent variation (and hence little additional information) in the higher order spatial lags of $\mathbf{x}_i$, conditional on $\mathbf{w}'_i \mathbf{X}$. Since Bound, Jaeger, and Baker (1995) and Staiger and Stock (1997), applied researchers worry about the strength of the instruments in IV regressions, because weak instruments can lead second stage coefficient estimates to be severely biased and imprecisely estimated. This issue has certainly been recognized in the spatial econometrics literature but the profound consequences do not appear to have had much influence on applied research.

In theory, the degree of collinearity between spatial lags depends on sample size, sampling frame and how $\mathbf{W}$ changes as observations are added.[7] In practice, in large samples (and using standard $\mathbf{w}_i$), $\mathbf{w}'_i \mathbf{X}$, $\mathbf{w}'_i \mathbf{W} \mathbf{X}$, etc. are likely to be highly correlated for

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[5] In principle, when $\boldsymbol{\beta}$ and γ are zero, the parameter ρ_1 can also be identified from the error structure $\omega_i = \rho_1 \mathbf{w}'_i \mathbf{v} + \rho_1^2 \mathbf{w}'_i \mathbf{W} \mathbf{v} + \rho_1^3 \mathbf{w}'_i \mathbf{W}^2 \mathbf{v} + [\cdots] + v_i$ using maximum likelihood, although this identification is clearly purely parametric in the sense that it relies on the empirical model being an exact representation of the data generating process.

[6] Interestingly, the idea of putting more structure on neighborhood effects (e.g., by assuming a hierarchical network) has recently been suggested as a way of solving the identification problem. See Lee, Liu, and Lin (2010).

[7] In theoretical analysis it is usual to distinguish between increasing domain asymptotics (adding observations expands the space over which we estimate) and infill asymptotics (increasing sample size means sampling more observations in a given area). The latter makes more sense in many micro-econometric settings, which is problematic because general results are not available for MLE under infill asymptotics (see Lee, 2004). Our intuition is that consistency under infill asymptotics will be difficult to derive precisely because, for many common W matrices, infill asymptotics increases the correlation between x and its spatial lags.

the simple reason that they are a weighted average (and consistent estimates of the mean) of $\mathbf{x}_i$ in some neighborhood of i. As a result in many applications the parameters on $\mathbf{w}_i'\mathbf{X}$, $\mathbf{w}_i'\mathbf{WX}$, etc. are likely to be imprecisely measured and/or severely biased. Earlier versions of this paper provide an example which demonstrates these problems are important in practice (Gibbons and Overman, 2010).

To summarize, in theory if $\mathbf{W}$ is not idempotent, identification is possible, but the parameters in the SD model are likely only weakly identified in practice. Even this weak identification depends on the strong assumption that $\mathbf{W}$ is correctly specified so that higher order spatial lags of $\mathbf{x}_i$ provide additional information (e.g., satisfy the exclusion restrictions required to make them valid instruments). It is not clear how this assumption could ever be evaluated.[8]

It should be clear therefore, that there are fundamental problems in using assumptions on the spatial structure to generate instruments. The problems are even more profound if we allow for spatial autocorrelation in the error terms, and drop the assumption of the exogeneity of $\mathbf{x}_i$ to give a more general spatial model:

$$(13) \qquad\qquad y_i = \rho\,\mathbf{w}_i'\mathbf{y} + \mathbf{x}_i'\boldsymbol{\beta} + \mathbf{w}_i'\mathbf{X}\boldsymbol{\gamma} + u_i,$$

$$(14) \qquad\qquad u_i = \rho\,\mathbf{w}_i'\mathbf{u} + v_i,$$

$$(15) \qquad\qquad x_{ik} = \mathbf{z}_i'\boldsymbol{\delta}_1 + \delta_2 u_i + e_{ik},$$

where x_{ik} is an element of $\mathbf{x}_i$ and $\mathbf{z}_i$ is a vector of factors determining x_{ik}, which may include elements of $\mathbf{x}_i$. This general spatial model presents all the challenges described above, plus the additional problem of one (or more) explicitly endogenous explanatory variables. Typical spatial ML methods simply assume away (15) and treat $\mathbf{x}_i$ as exogenous. True, the parameters of this model could all, in principle, be estimated by ML or spatial IV, imposing all the restrictions implied by the specification of $\mathbf{W}$ and the way the model is written down. Fingleton and Gallo (2010) discuss various approaches along these lines. Nevertheless, this mechanical approach to estimation will not appeal to applied economics researchers who view minimal assumptions on functional forms and explicit sources of exogenous variation as necessary conditions to infer causality.

We say more about these issues in the next section, where we argue that a better approach to estimating parameters that represent spatial interactions (such as the SAR, SD, or SLX models) or to deal with omitted variables in spatial contexts, is to precisely delineate the research question, and focus on the key parameter of interest. The experimentalist paradigm insists that a satisfactory strategy must use theoretical arguments or informal reasoning to make a case for a source of exogenous variation that can plausibly be used to identify this parameter of interest. In addition, this mode of research would expect rigorous empirical testing to demonstrate, as far as possible, the validity of these assumptions. We now consider these issues in more detail.

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[8] Statistical tests for overidentifying restrictions (e.g., Sargan and Hansen tests, see Angrist and Pischke, 2009, p. 143–146) are not very robust evidence for the validity of instruments, unless simply as auxiliary support for a convincing case of their theoretical validity. These statistics, in effect, provide tests for equality of the IV estimates from each potential instrument, but will be prone to Type II errors (failing to reject the null of the validity of the over-identifying restrictions) in situations, like the one faced here, where instruments are either weak (because IV coefficients for each instrument are then imprecisely estimated) or endogenous for similar reasons (because IV coefficients for each instrument will be similarly inconsistent).

4. THE EXPERIMENTALIST PARADIGM AND SPATIAL ECONOMETRICS

The discussion so far has been critical of the spatial econometrics approach, particularly regarding the crucial issue of identification of causal parameters. Others have made similar arguments although perhaps not as forcefully (see, for example, McMillen, 2010a, 2010b). Of course, any alternative approach also has to solve the identification problems that plague spatial economic analysis. Our argument is that these problems are so fundamental that they must sit at centre stage of applied work, not be shunted to the sidelines through the use of ML that assumes knowledge of the appropriate functional forms and spatial weights. In this section we argue that spatial research would be best served by turning away from the application of generic spatial models and attempts to distinguish between observationally equivalent models using contestable parameter restrictions that only emerge from the assumed model. Instead, we advocate strategies that are carefully designed to answer well-defined research questions using insights from the experimentalist paradigm.

We start with the situation where we are interested in estimating parameters in a SAR or SD specification to test for direct spatial interactions between outcomes y_i. It is hard to imagine situations in which this *is* the true data generating process because simultaneous decisions based on y_i must rely on expectations (as in the neighborhoods effect literature), but let us suppose that estimation of ρ is the goal. As argued above, there is a central conceptual problem about identification of the linear dependence y_i on $\mathbf{w}_i'\mathbf{y}$ in an SAR-style specification, which follows from the "reflection" problem. Specifically, if the model properly specifies how y is determined, how can we induce exogenous change in $\mathbf{w}_i'\mathbf{y}$ that is not caused by changes in elements of either $\mathbf{w}_i'\mathbf{X}$ or $\mathbf{w}_i'\mathbf{u}$? Maximum Likelihood solutions seem unconvincing for reasons discussed extensively above. In some settings, the spatial econometrics literature offers interesting insights in to the potential for using specific restrictions on $\mathbf{w}_i$ to achieve identification, where these restrictions arise from the institutional context, for example from the directed structure of friendship networks, or the spatial scope of area targeted policies (e.g., see Calvó-Armengol, Patacchini, and Zenou, 2009). For most applied problems, however, uncertainty about functional forms and lack of information on the true spatial weights mean alternative strategies are more appropriate.

An alternative strategy is to use panel data and to difference the data over time to provide fixed effects or "difference-in-difference" estimates. Differencing removes unobservables that are fixed over time, and that the researcher considers to be potential sources of endogeneity. While this is a very useful strategy in many contexts (some of which are mentioned below), it does not, on its own, offer a way to identify the *causal* effects of $\mathbf{w}_i'\mathbf{y}$ on y_i in SAR/SD type models because the "reflection" issues simply transfer to the differenced specification. The question now becomes how to distinguish changes in $\mathbf{w}_i'\mathbf{y}$ (i.e., in $\mathbf{w}_i'\Delta\mathbf{y}$) that are not caused by elements of $\mathbf{w}_i'\Delta\mathbf{X}$ and/or $\mathbf{w}_i'\Delta\mathbf{u}$. For similar reasons, even randomization offers limited scope for distinguishing group effects arising from the spatial interaction in outcomes $\mathbf{w}_i'\mathbf{y}$ from those arising from group characteristics $\mathbf{w}_i'\mathbf{X}$ because if a group has randomly higher $\mathbf{w}_i'\mathbf{y}$, it will have randomly higher $\mathbf{w}_i'\mathbf{X}$ too.

Given these limitations, is there any hope for the SAR specification, and estimation of "endogenous" neighborhood effects? Some settings do appear to offer explicit sources of randomization in $\mathbf{w}_i'\mathbf{y}$ due to institutional rules and processes. Sacerdote (2001), for example, uses the random allocation of college dorm-mates to dorms to break the correlation between individual student unobservables and dorm-mates' group characteristics, to get estimates of peer-group effects on students' college achievement. De Giorgio, Pellizzari, and Redaelli (2010) use a similar strategy in the context of random class assignments.

Although both papers make claims that are probably too strong in terms of their ability to solve the reflection problem (because randomization also changes $\mathbf{w}_i'\mathbf{X}$ and $\mathbf{w}_i'\mathbf{u}$ as discussed above), randomization does at least reduce the problems induced by self-selection into groups and consequent correlation between individual and group characteristics. Field experiments designed for purpose are also clearly very useful. However, big ones like the Moving to Opportunity Program (Kling, Ludwig, and Katz, 2005; Kling, Liebman, and Katz, 2007) are rare, costly and often suffer from unavoidable design flaws, and small ones suffer from concerns about external validity. It would also be very difficult to design experiments to answer many spatial questions and we do not see this as a way forward for many problems of interest.

One alternative is to re-consider instrumental variables (IV/2SLS) estimation, either in cross-sectional or time differenced specifications. As shown above, *if* the SAR model is correctly specified, then $\mathbf{w}_i'\mathbf{X}$ provides instruments for $\mathbf{w}_i'\mathbf{y}$ and this forms the basis for the traditional "spatial IV" method. Most applied micro-econometric researchers would expect very careful arguments to justify the exclusion of $\mathbf{w}_i'\mathbf{X}$ from the estimating equation.[9] In practice, many papers that use spatial econometrics do not do this. To take just one example, in the tax competition literature characteristics of neighboring areas $\mathbf{w}_i'\mathbf{X}$ are often used to instrument for neighbors' tax rates $\mathbf{w}_i'\mathbf{y}$ in a regression of own tax rate y_i on neighbors tax rates. A run through some of the references in a recent review (Revelli, 2005) suggests that these exclusion restrictions receive little, if any consideration. Besley and Case (1995) appear to be one of the first to adopt this strategy by using demographics of neighbors to instrument for neighbors' tax rate. They do provide a brief discussion of whether this restriction is valid, but mostly rely on overidentification restrictions imposed by their theoretical model to justify this assumption. Brett and Pinske (2000) use a similar approach and justify their exclusions by noting: "While there could be reasons why municipal business tax rates depend on wealth directly, such reasons are less obvious than dependence through their effect on capital base" (p. 701). Buettner (2001) claims to pay careful attention to whether the instruments are endogenous (by examining spatial autocorrelation in the residuals) but has no discussion of how this relates to the validity of the exclusion restrictions. Hayashi and Boadway (2001) do not instrument at all, instead using restrictions from a theoretical model to achieve identification. Turning to more recent papers, we find little evidence that much has changed. Leprince, Madies, and Paty (2007) has no discussion of the exclusion restrictions. Charlot and Paty (2007) use ML. Edmark and Agren (2008) do discuss the strength of their instruments, but not the exclusion restrictions. Feld and Reulier (2009) use IV but do not discuss either problem. None of these papers discuss the problem specific to the spatial setting, that spatially lagged exogenous variables may better capture the connections between observation i and its neighbors than the incorrectly specified first-order spatial lag of y_i. This list of papers is not exhaustive and inclusion in it is not intended as a specific criticism of the particular paper (after all, these papers have all been published in respectable journals after peer review).[10] But we do think that the list serves to illustrate the problems that arise when the spatial IV/2SLS approach, of Anselin (1988), Kelejian and Prucha (1998), and others, is used in practice. The same issues arise with spatial GMM, which are simply efficient versions of IV estimators.

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[9] Of course, if $\mathbf{w}_i'\mathbf{X}$ can be excluded then this solves the identification problem for ML as well. Even in this case, we still think that the case for switching to ML is weak because it relies on precise knowledge of $\mathbf{w}_i$.

[10] Indeed, one of the authors has at least one older paper that similarly adopted the Kelejian and Prucha (1998) IV approach.

So what ways forward are there for IV strategies? Potentially, institutional arrangements *can* provide exogenous variation in one (or more) elements of $\mathbf{w}_i'\mathbf{X}$ that has no direct influence on y_i.[11] For instance, a researcher might argue that there are no direct impacts on outcomes in a district from a policy intervention in neighboring districts (an element of $\mathbf{w}_i'\mathbf{X}$), but the policy does have effects via its influence on neighboring outcomes. As just discussed, this is the strategy adopted by some papers in the tax competition literature (e.g., Besley and Case, 1995; and Brett and Pinske, 2000), although whether a researcher can convince others that there are no direct effects from neighbors' policies depends on the policy in question (and whether they make any attempt to justify the exclusion restrictions!). Sometimes, however, changing institutional arrangements can offer more convincing "natural experiments." A particularly nice example is provided by Lyytikäinen (2011) who argues that changes in the statutory lower limit to property tax rates induces exogenous variation in tax rates, which can be used to study tax competition among local governments in Finland. Specifically, policy changes to minimum tax thresholds interacted with previous tax rates, can be used to instrument for the changes in tax rates in neighboring districts. In this case, the exclusion restrictions are more plausible: a district tax authority is not likely to care how changes in tax threshold policy affected neighbors, except in so far as it changed these neighbors' tax rates. Particularly interesting, for our purposes, is that Lyytikäinen compares his estimates to those based on spatial lags and traditional spatial IV applied to the same data (using lags of all the determinants of tax rates, not just the policy-induced changes). While he finds no evidence of interdependence in property tax rates from his policy-based IV research design (which contradicts much of the literature), his spatial IV estimates are large and significant. He concludes, with a degree of understatement, "that the standard spatial econometrics methods [. . .] overestimate the degree of interdependence in tax rates."

Another interesting possibility for SAR-type models emerges when $\mathbf{w}_i'\mathbf{y}$ represents expectations about y_i in some spatial group, since the expectation could be changed by additional information about $\mathbf{w}_i'\mathbf{y}$, without directly changing y_i itself. For example, suppose the registry of house prices becomes publicly available, providing individuals with new information that allows them to react to the sale prices of nearby houses. Or police forces introduce crime mapping, which allows closer monitoring of the activities of criminals. Sometimes, however, it may still be difficult to justify that other neighborhood characteristics captured in $\mathbf{w}_i'\mathbf{X}$ do not simultaneously become observable (e.g., the characteristics of local houses are recorded in the local registry) and drive any observed changes in y.

Unfortunately, examples such as these where there are plausible instruments for $\mathbf{w}_i'\mathbf{y}$ in SAR-type models are still rare, and looking for ways to estimate the causal effect of $\mathbf{w}_i'\mathbf{y}$ on y_i appears to leave a fairly limited range of questions that can be successfully answered. We remain more hopeful for the role of differencing, IV and "natural experiments" in isolating exogenous variation in one or more of the observable factors that drives the outcome of interest, i.e., elements of $\mathbf{w}_i'\mathbf{X}$—whether directly, or indirectly via $\mathbf{w}_i'\mathbf{y}$. But, given the difficulty in justifying the exclusion restrictions on $\mathbf{w}_i'\mathbf{X}$, coupled with the conceptual problems in terms of what the SAR model implies about underlying causal relationships, we argue that many situations may call for abandoning the SAR model altogether. In these situations, we advocate the path taken by most recent neighborhood effects research and argue for estimation of reduced form SLX models in $\mathbf{x}_i$ and spatial lags of $\mathbf{x}_i$, rather than direct estimation of the SAR or SD model. Given the identification problems in the alternative specifications, we believe that in many situations this

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[11] In other words, in components of $\mathbf{w}_i'\mathbf{X}$ where the corresponding element of $\gamma = 0$. An alternative formulation would use Z to denote these observable characteristics that have no direct effect on y other than through their effect on X.

"reduced form" approach is simply more credible. The composite reduced form parameter that describes the influence of neighbors' characteristics *or* outcomes is itself a useful and policy-relevant parameter. With this in hand judgments can be made based on theory and institutional context about the likely channels through which the effects operate. The key estimation challenge that remains is the one discussed above. That is, the fact that $\mathbf{x}_i$ and $\mathbf{w}_i'\mathbf{X}$ are unlikely to be exogenous, and will be correlated with the unobserved determinants of y_i via causal linkages or because of the sorting of agents across geographical space. Estimation of the reduced form SLX models, sets aside the challenge of estimating ρ directly leaving the researcher free to focus on the remaining threats to consistent estimation of the composite parameters in the reduced form, which are still formidable.

How then should researchers working on spatial empirical analysis proceed? One possibility is to use "natural experiments" which offer channels for identification of interesting spatial parameters, even when estimation of SAR-type spatial dependence is infeasible. For example, changes over time in the connections between places or agents may allow identification of causal spatial interactions. A good example is provided by Redding and Sturm (2008), who use the reunification of East and West Germany to study the impact of market access on outcomes. The idea here is that before reunification, the East and West German border prevented market interactions and restricted the economic connections between places, but reunification opened up new possibilities. Reunification thus created a change in the $\mathbf{w}_i$ matrix that can be used to explore the role of spatial interactions. Similar ideas have been used in the literature on schools and house prices, using school attendance zone boundary changes (Bogart and Cromwell, 2000; Salvanes and Machin, 2010). Changes to the $\mathbf{w}_i$ matrix caused by exogenous changes in transport networks have also been used to investigate the effects of employment or population accessibility on firms or households (e.g., Holl, 2004; Gibbons et al., 2010; Ahlfeldt, 2011).

A second possibility is to use the standard toolkit of IV and differencing based strategies employed by researchers in many other fields of applied economics. This tool kit can be used effectively, if applied carefully with attention to the identification of specific causal parameters rather than an arbitrarily specified system of equations. For an IV strategy to give consistent estimates of the parameters of interest in these reduced form SLX models, instruments must satisfy the usual relevance and exclusion restrictions. We have said enough already about exclusion restrictions and weak instrument problems for it to be clear that we do not think that IV strategies based on using higher order spatial lags of $\mathbf{x}_i$ as instruments are a very good idea.[12] For these reasons, we believe that standard IV strategies which pay careful attention to the omitted variables and clearly justify the validity of instruments represent a more appropriate way to address the problem of spatially correlated omitted variables.[13] Many effective IV strategies of this type make use of policy designs, institutional rules and natural environmental features (or even better, changes in these factors).

There are many examples of these kinds of well-thought-through instrumenting strategies applied to spatial problems, by researchers working outside the traditional spatial econometric mould. For example, Michaels (2008) notes that the U.S. highway system was planned on a regular East-West, North-South grid connecting major cities,

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[12] Note, however, that while the spatial structure of the data does not help, neither does it especially hinder the search for a suitable instrument. If we have an instrument that is independent of u_i, then it is also independent of $\mathbf{w}_i'\mathbf{u}$, (unless the weights are endogenous) so the fact that x_i and u_i are both spatially correlated is irrelevant (aside from the implications for standard errors).

[13] Control function approaches may also be equally valid, but require instruments too, and generally require more assumptions than IV.

implying that towns located due East, West, North or South of a major city incidentally experienced large changes in transport accessibility by virtue of their position relative to major cities. Luechinger (2009) uses the sites of installation of SO2 scrubbers and prevailing wind directions to predict pollution levels, in order to estimate the effects of pollution on individual well-being. The idea here is that people living downwind of emissions sources experience big improvements in pollution levels relative to those living upwind, when emissions reduction technologies are installed, but that these directions are otherwise unrelated to well-being. Gibbons, Machin, and Silva (2008) use distances to school admissions district boundaries to predict levels of choice and competition in school markets. This works because students do not attend schools on the opposite side of district boundaries, so the number of schools from which students can choose (within a given distance) is truncated. Earlier examples of the creative use of IV in spatial analysis are found in Cutler and Glaeser (1997) and Hoxby (2000), who use the number of rivers cutting across cities as instruments. In both cases, rivers are assumed to bisect communities leading to greater racial segregation within cities (Cutler and Glaeser, 1997) or more school districts and more choice and competition in school markets (Hoxby, 2000).

Another alternative to IV is *spatial* differencing to remove relevant omitted variables, e.g., through difference-in-difference, fixed effects or regression discontinuity designs. In this case, the fact that the unobserved component is spatially correlated helps because spatial differencing (of observations with their "neighbors") is likely to be effective in removing it. Holmes (1998) provides an early example. Gibbons, Machin, and Silva (2009) provide more recent discussion. Other differencing strategies drawing on a "case-control" framework may also be appropriate, for example the "million dollar plant" analysis of Greenstone et al. (2010) which compares the effect of large plant relocations on destination U.S. counties, using their second ranked preferences—revealed in a real estate journal feature—as a counterfactual. Both Busso, Gregory, and Kline (2010) and Kolko and Neumark (2010) evaluate the effects of spatial policies by comparing policy-treated areas with control areas that were treated in later periods, as a means to generating plausible counterfactuals. Spatial differencing can also be combined with instrumenting as discussed in, for example, Duranton, Gobillon, and Overman (2011) and Gibbons, McNally, and Viarengo (2011). Lee and Lemiuex (2010) provide further examples of regression discontinuity designs, many of them relevant to spatial research.

The "experimentalist" strategies set out above may not be without their problems (see, for example, Kean, 2010), but at least provide some hope of uncovering causal relationships in the spatial context, which off-the-shelf spatial econometrics techniques do not. One common criticism of the experimentalist style of research, as represented by these examples, concerns the generalizability of the estimates. These designs seek out sources of exogenous, pseudo-random variation in the variables of interest, and inevitably end up estimating causal effects for some sub-group of the population, exposed to, and responding to a specific intervention or difference in environment. If responses are heterogeneous, there is therefore no guarantee that the estimated response is representative of a more general population. This issue is well known in the context of IV, giving rise to Local Average Treatment Effects (Imbens and Angrist, 1994). Even so, we would argue that it is better to have plausibly causal estimates for a specific group in the population, than to have noncausal parameter estimates of unknown meaning, estimated by other methods. Our remarks about the validity of exclusion restrictions in spatial IV above also apply to experimentalist designs, because we still have to be sure that whatever causes random variation in $\mathbf{x}_i$, affects y_i only through $\mathbf{x}_i$ and not through other channels. To deal with these threats, spatial research designs in the experimentalist mode must think through the specific institutional details very carefully, and provide clear statements and tests of the identifying assumptions, and be cautious in generalizing results too widely.

To summarize, different economic motivations lead to spatial econometric specifications that will be very hard to distinguish in practice. Add to the mix the fact that in (nearly) all applications we face uncertainty about the endogeneity of $\mathbf{x}_i$, the appropriate functional form and spatial weights and it becomes clear why many applied researchers find ML or IV estimation of some assumed spatial econometric specification uninformative. Instead, we support a focus on attempting to solve identification problems using empirical strategies that have been carefully designed for the specific application. Further, if empirical strategies cannot be devised that satisfactorily identify the causal impact of the spatial lag in the endogenous variable (i.e., many applied situations) then we advocate a reduced form approach paying particular attention to the problems raised by endogeneity of the $\mathbf{x}_i$.

Opponents of our advocacy of experimentalist approaches to spatial questions might argue that places are unique because of their unique spatial position, and so not amenable to these kinds of research designs. They may argue that it is infeasible to find a comparator location for any location, given differences in spatial location. This position is surely too pessimistic, since it rules out any form of causal empirical analysis on spatial data, given that no counterfactual can ever be constructed. On the contrary, in all these examples discussed above, the purpose in thinking through experimental settings to find "comparator" or control groups is not necessarily to find control places that are identical in every way to the "treatment" places. Nor is the aim necessarily to find sources of variation that are completely random (i.e., instruments that are uncorrelated with every other characteristic), although this might be the ideal. Instead, the goal is more modest—to find "control" and "treatment" places that are comparable along the dimensions that influence the outcome being studied. Similarly, instruments should be uncorrelated with the unobserved factors that influence the outcome. In short, even when we are concerned that there are unobserved aspects of spatial location that do influence outcomes and make places unique, there are still potentially causally informative comparisons that can be made between neighboring places, which, while not identical are potentially very similar along salient dimensions.

So far we have said little about the role of theory. Many spatial econometricians are defensive about the role theory plays in the construction of their empirical models and see comments about the lack of theory as a misguided criticism of their work (e.g., see Corrado and Fingleton, 2010). But the role played by theory is not our main criticism, rather it is the failure to adopt a careful research design that solves the problems specific to the research question being addressed, and the lack of attention to finding credible sources of random or exogenous variation in the explanatory variables of interest. This is not to say we do not think that theory is very important, or that empirical work that has proper behavioral structural foundations is uninformative (see Holmes, 2010 for examples in regional economics). Theorizing, of a formalistic or more heuristic type, is of course essential in organizing thoughts about how to design a research strategy and theory and assumptions at some level are necessary for any empirics. Theory is also useful once you have these causal parameter estimates to hand, when it comes to making predictions about general equilibrium effects, as long as it is made clear that these predictions are valid only for that theoretical view of the world.

Consistent with our overall approach, we argue that testing theories means correctly estimating the coefficients on specific causal variables (as suggested by the theory). This provides another point of contrast to most applied spatial econometrics where the role of theory is to derive a generic functional form, with ML applied to give the parameters that ensure the best "fit" to readily available data. For example, to test the predictions of NEG models, our approach insists on a research strategy to identify whether market potential has a causal impact on wages while recognizing that no model is going to completely

explain the spatial distribution of wages. This contrasts strongly with the applied spatial econometrics approach which uses the extent to which different spatial econometric models "fit" the data as a way to test competing theories. This has the unfortunate side effect of encouraging the inclusion of endogenous variables in empirical specifications as, for obvious reasons, these tend to increase the fit of the spatial model with the data.

In many spatial economic problems, theory may thus play an important role in revealing variables for which we would like to know the causal effects. But empirical implementation requires careful research design if the results are to have any general scientific credibility or to be considered trustworthy for policy making. It is surely wrong to use specialized theory alone to impose specific restriction on the research design (e.g., by assuming away potentially confounding sources of variation) unless you have reasonable confidence that the theory is correct and that it is demonstrably so to a general audience. Unfortunately, this is the role played by theory in much applied spatial econometric research. Theory is used to justify the inclusion of a spatial lag, assumptions are made about the form of the spatial weight matrix (possibly derived from theory), ML is used to achieve "identification" and then model "fit" is used as a basis for testing the theory which justified the inclusion of the spatial lag. It should be clear by now that, for most spatial problems, we simply do not find this a convincing approach. Without wishing to weigh further into the vigorous debate on structural versus experimental approaches to empirical work (e.g., Angrist and Jorn-Steffen, 2010) we simply make the point that whatever method is adopted (structural, experimental, qualitative or any other) any empirical research that aims to find out if x causes y needs to find a source of exogenous variation in x!

5. CONCLUSIONS

We have argued that identification problems bedevil most applied spatial econometric research. Many spatial econometricians are surely aware of these problems but the literature (inadvertently) downplays their importance because of the focus on deriving estimators assuming that functional forms are known and by using model comparison techniques to choose between competing specifications. While this raises interesting theoretical and computation issues that have been the subject of a growing and thoughtful formal econometric literature, it does *not* provide a toolbox that gives satisfactory solutions to these problems for applied researchers interested in causality and the economic processes at work. It is in this sense that we call into question the approach of the burgeoning body of applied economic research that proceeds with mechanical application of spatial econometric techniques to causal questions of "spillovers" and other forms of spatial interaction, or that estimates spatial lag models as a quick fix for endogeneity issues, or that blindly applies spatial econometric models by default without serious consideration of whether this is necessary given the research question in hand. While the question we pose in the title to our paper is deliberately provocative and tongue-in-cheek, we maintain that this mode of spatial econometric work, while maybe not "pointless," is of limited value when it comes to providing credible estimates of causal processes that can guide understanding of our world, and guide policy makers on how to change it. We urge those considering embarking down this route to think again.

Paradoxically, we think that using the standard spatial econometric specifications (adapted, as we have done throughout the text, to reinforce the focus on the causal factors that drive outcome y_i) helps clarify identification problems for those researchers who are interested in causality. In particular, we think that closer attention to model specification will be helpful in understanding the exclusion and relevance assumptions that underlie IV approaches. Spatial econometrics also provides important insights on

the interpretation of parameters in spatial models. In short, there are lessons to be learnt from the spatial econometrics literature but for most applied economic researchers the appropriate strategy should be based on the experimentalist paradigm which puts issues of identification and causality at center stage.

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APPENDIX: SPATIAL ECONOMETRICS AS A "SOLUTION" TO THE OMITTED VARIABLES PROBLEM

Assume y_i depends on exogenous x_i and unobservable z_i. That is:

$$(A1) \qquad y_i = x_i\beta + z_i.$$

Further, assume that the unobservable z_i is both spatially correlated and partly determined by x_i:

$$(A2) \qquad z_i = \rho w_i'\mathbf{z} + \gamma x_i + v_i.$$

Substituting $z_i = y_i - x_i\beta$ into (6) and rearranging gives

$$(A3) \qquad y_i = \rho \mathbf{w}_i'\mathbf{y} + (\gamma + \beta)x_i - \rho\mathbf{w}_i'\mathbf{x}\boldsymbol{\beta} + v_i.$$

From (4) and (A3) note that the presence of a spatially correlated error term, whether correlated with $\mathbf{x}_i$ or not, leads to the SD model involving a spatial lag in $\mathbf{y}$ and $\mathbf{X}$. It is important to emphasize, however, that in this motivation for the SD model the spatial lags of $\mathbf{y}$ and $\mathbf{X}$ are simply being used to control for spatial correlation in the error term, so ρ reveals nothing about the causal effect of the spatial lags on outcomes. This hints at the problems of identification in spatial models discussed at length in the text.

If there are standard omitted variables problems (an unobserved variable correlated with one or more of the explanatory variables) then we know estimates of $\boldsymbol{\beta}$ are biased. Spatial autocorrelation in the explanatory and omitted variables is likely to exacerbate this bias. Increasingly, the presence of spatially correlated omitted variables is used in spatial econometrics to justify estimation of the SD model to "solve" these kinds of omitted variable problem (LeSage and Pace, 2009). The reasoning follows the derivation in Equations (A1)–(A3). However, there are surely some doubts about this method as a solution to omitted variables problems. If it was a general solution, it would also work for nonspatial panel data. For example, the equivalent of Equations (A1)–(A3) with panel data is:

$$(A4) \qquad y_{it} = \beta x_{it} + z_{it},$$

$$(A5) \qquad z_{it} = \rho z_{it-1} + \gamma x_{it} + v_{it},$$

$$(A6) \qquad y_{it} = \rho y_{it-1} - \rho\beta x_{it-1} + (\gamma + \beta)x_{it}' + v_{it}.$$

This equation can be estimated consistently by ML or nonlinear least squares, or estimates of the various parameters retrieved from the OLS coefficients. Although endogeneity problems of this type might be mitigated by this strategy, it is certainly not a complete fix. To see this, modify the set up in Equations (A1)–(A3) slightly to cope with more general endogeneity in that x_i is partly determined by the omitted variable (f_i). In this case we have

(A7)
$$y_i = \beta x_i + z_i$$

$$z_i = \rho \mathbf{w}'_i \mathbf{z} + \gamma f_i + v_i$$

$$x_i = f_i + u_i$$

$$y_i = \rho w'_i \mathbf{y} + (\gamma + \beta) x_i - \rho \beta w'_i \mathbf{x} + (v_i - \gamma u_i).$$

The error term now has a component u_i that is negatively correlated with x_i, so the coefficients cannot be estimated consistently by OLS, NLS or ML. In this more general setting, the SD model does not provide a solution that gives consistent estimates for the parameter of interest (β). See, for example, Todd and Wolpin (2003) for a related discussion in the context of "value-added" models in the educational literature. In short, the SD model should not be seen as a general solution to the omitted variable problem in spatial research, and it is inadvisable to proceed as if it is one. A better solution is to treat this as a standard endogeneity problem that makes $\mathbf{x}_i$ correlated with the error, and to bring to bear tools for dealing with such problems as discussed further in the text.