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Economic Benefits of Investments in Transport Infrastructure

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ABSTRACT

This paper begins by motivating the need for including “wider economic effects” when conducting transport infrastructure appraisal, followed by a discussion of various techniques to do so. The major focus is on studies from the cost function perspective that incorporate spillover benefits from public infrastructure capital, with a presentation of applications on highways, airports, and ports infrastructure stocks. The substantial differences between approaches focusing on “narrow” and “wider” impacts is evaluated, along with discussion of how application of the tools of spatial econometrics has facilitated estimation of models that capture wider economic benefits.

1. INTRODUCTION

There are many studies since the 1980’s that attempt to quantify the effects of public infrastructure on the U.S. economy. There are a broad range of findings in these studies, including large positive, small positive, as well as negative effects. In recent years, research on the impacts of public infrastructure capital has started to incorporate assessments of the spillover benefits and costs across geographic boundaries. This revolution in the field comes at approximately the same time as growth in the area of spatial econometrics, which has facilitated the development of this strand in the infrastructure literature.

Despite these recent advances, there is still more that could be done, some of which depends on data availability. Namely, applying the approaches of recent cost function studies to other industries besides the manufacturing sector would require detailed data on input prices at the industry level. Another aspect that is worthy of additional attention is modeling cross-boundary spillovers in a general equilibrium framework that accounts for both consumers and firms.

In this paper, first I begin by introducing and motivating the need for incorporating measures of "wider" benefits of transport infrastructure in studies of the impacts of public infrastructure capital. In the context of this paper, “wider” benefits refer to the benefits beyond the geographic region in which the investment is undertaken. This motivation is followed by a description of several techniques used in the literature for measuring the "wider" (or spillover) benefits and how these measurement techniques differ from those for local benefits, for a variety of types of transportation infrastructure in general. These techniques include spatial spillovers (or lags) and spatial autocorrelation, both of which can be addressed through the empirical tools of spatial econometrics. Next I describe results of a variety of studies in the literature on highways, airports, ports, and various combinations of more than one type of transportation infrastructure. Finally, I elaborate on possible extensions and future work in this area, including research in progress and data sources that could be useful for addressing these issues.

2. MOTIVATION

An economic principles approach (supply and demand analysis) is instructive to motivate the problem of transportation infrastructure spillovers. Consider an average manufacturing firm in New York. The equilibrium amount of goods produced by this firm is given by the intersection of its supply and demand curves. What causes a shift in these curves? For the supply curve, holding all else constant, a decrease in the cost of "inputs" (such as wages, or the cost of private capital machinery or equipment) is one possibility. Another potential cause of a shift in supply is an improvement in technology. Finally, a "spillover" benefit (or a positive spillover) can shift the supply curve to the right.

A positive spillover occurs when other agents' actions confer benefits on an individual while the individual does not provide any compensation for these benefits. For example, if Connecticut improves its roads, the employees that travel to work from Connecticut to New York may have shorter commuting times, which would be expected to enhance productivity of workers in New York. Similarly, the cost of shipping goods out of New York can be expected to go down when Connecticut improves its roads, so this would be another way in which better roads in Connecticut would confer spillover benefits on New York firms. The key difference between the roads in Connecticut and those in New York are that the Connecticut roads may not be financed by the firms in New York. While a portion of highway infrastructure is paid for by the federal government, a major portion of road financing in a neighboring state is paid for (indirectly) by residents and firms in that neighboring state, opposed to individuals in other states who pass through on a regular basis.

So when Connecticut expands its stock of public infrastructure, it causes the supply curve for firms in New York to shift to the right (see Figure 1). The new equilibrium level of production in New York is now higher than previously. In our analysis, the number of workers employed in New York is not changed, so output per worker, or productivity, now increases.

Researchers implicitly use similar reasoning to explain the impacts of public infrastructure within a particular geographic region while ignoring the impacts of spillovers across boundaries. Accordingly, much of the empirical literature on public infrastructure is concerned with the question of: by how much is productivity enhanced when the stock of public infrastructure increases? In other words, by how much does the supply curve shift, and how large is the associated output change, when public infrastructure increases?

The early empirical literature focused on national-level data using a production function approach of Aschauer (1989), and found a tremendous effect of infrastructure on productivity. Subsequent studies, such as Munnel (1990) assessed state-level data (Munnel), followed by studies that focused on the cost impacts of infrastructure (Morrison and Schwartz, 1996; Nadiri and Mameaunus, 1994). These subsequent studies found a range of infrastructure elasticities that were more reasonable than the initial Aschauer findings. Although the cost function study results are not directly comparable with the earlier production function studies, it is expected that they should be roughly in line with the production function results.

But most of these studies ignore an important aspect of public infrastructure. The network structure of many types of public infrastructure might imply that there are benefits to individuals beyond the state or locality where the infrastructure is located. On the other hand, better infrastructure in one location could assist firms in neighboring locations with drawing away the most productive resources, which could be detrimental to firms in the locality with the enhanced infrastructure. These network effects (both positive and negative) could have significant ramifications for the infrastructure elasticities worth examining in studies of state or county level infrastructure. A major focus of this paper is on the research, most of which developed in the late 1990's and 2000's, of the spatial spillover effects of public infrastructure capital.

At this point, it is also worth noting that most infrastructure productivity studies are done in a partial equilibrium context. Haughwout (2002) is an exception. He estimates a general equilibrium model of production and consumption, with public infrastructure as a local public good for several large U.S. cities. He finds that public infrastructure is beneficial to firms and consumers, but a significant expansion of infrastructure capital would leave producers and consumers worse off. However, Haughwout's model does not incorporate spatial spillovers across different cities due to public infrastructure, and estimating the net benefits of such a spillover model in a general equilibrium framework is worthy of attention.

Unlike Haughwout's study, most of the partial equilibrium studies in the literature ignore the impact of the demand curve on the equilibrium change in production from public infrastructure. In other words, the researchers really are concerned with the magnitude of the rightward shift of the supply curve from improvements in public infrastructure (Figure 2), opposed to the change in the equilibrium level of output resulting from the supply curve shift (Figure 1). This implies that the researchers assume a flat demand curve. Thus, there may be an overstatement of the impacts of public infrastructure in partial equilibrium studies, assuming the "true" private demand curve slopes downward. Another aspect deserving of greater attention in the infrastructure literature is the wider benefits to other sectors, such as the approach of Lakshmanan *et. al.* (2007). Studies that ignore these benefits may underestimate the impacts of public infrastructure investment. Overall, the net effect is unknown, but it would need to be determined empirically. Although describing the models behind such a general equilibrium approach are beyond the scope of the present paper, they are worthy of attention, and the reader is encouraged to see Lakshmanan *et. al.* (2007) for additional details.

3. GENERAL BACKGROUND

There are at least a couple of ways researchers attempt to quantify the changes in productivity from greater infrastructure investments in neighboring jurisdictions. One of these approaches is the production function approach, which incorporates the stock of infrastructure in neighboring jurisdictions as a "shift" factor in the production function. The production function approach requires panel (cross-section and time series) data on the amount of output (Y), labor (L), other "variable" factors such as materials (M), the stock of fixed factors such as private capital stocks (K), and measures for public capital stocks for neighboring (G) and within-locality (I).

The production function from the early studies on infrastructure that ignore inter-jurisdictional spillovers could be written (in vector notation) as the product of two functions, as follows:

(1) $Y = h(I) f(K, L, M) + u$,

where u is a stochastic error term, which in general is implicitly assumed to have the desirable properties of zero mean, constant variance, and zero correlation across observations. Possible violation of the last of these assumptions can lead to inefficient estimates for the parameters, in which case their statistical significance may be understated. This potential problem is described in the spatial autocorrelation section below. The production function in (1) allows for infrastructure to shift the production function.

The more recent production function studies that incorporate spatial spillovers across jurisdictions (such as Boarnet, 1998) use a more general production function, such as the following:

(2) $Y = h(I, G) f(K, L, M) + u$

In this specification, infrastructure in the own-jurisdiction, as well as in neighboring jurisdictions, can cause a shift in the production function.

Another approach, often referred to as a cost function approach, relies on duality theory. Duality theory (Varian, 1992) tells us that if we assume firms minimize costs, then cost minimization is essentially the same problem as profit maximization (which is based on the production function). The cost function approach is appealing because it incorporates optimizing behavior by firms, and it estimates an implied reduced-form cost function. This approach requires information on factor prices (such as P_{LP}, the wages of production workers; P_{LN} , the wages of non-production workers; and P_M , the price of materials inputs); the stock of fixed factors (such as private capital, K) and their associated prices (P_K); output (Y); as well as separate measures of infrastructure stocks for within-jurisdiction (I) and in other jurisdictions (G). Specifically, the total cost (TC) function model that ignores inter-jurisdictional infrastructure spillovers (similar to Morrison and Schwartz, 1996) can be written as follows:

(3) $TC = VC(Y, P_{LP}, P_{LN}, P_M, K, I, t) + P_K K + u$,

where $VC(\cdot)$ is the variable cost function, and t is a “time” counter representing the passage of time.

Incorporating neighboring jurisdictions’ infrastructure (G), such as in Cohen and Morrison Paul (2004), yields

(4) $TC = VC(Y, P_{LP}, P_{LN}, P_M, K, I, G, t) + P_K K + u$

A useful rule (called Shepard’s Lemma) that is a special case of the envelope theorem (see Varian, 1992) states that the derivative of VC with respect to any of the input prices yields a demand function for that particular input. So as an example, for production labor (L_P),

(5) $L_P = \partial VC(\cdot)/\partial P_{LP}$

With both the cost function and production function approaches, regression analysis is used to estimate parameters necessary to obtain elasticities of the infrastructure variables. For the cost function approach, an input demand function similar to (5) is derived for each of the variable factors, and a stochastic error term is appended to each of these equations. These input demands are estimated together with the variable cost function, using Seemingly Unrelated Regression (SUR) techniques.

In terms of assessing spillover benefits, with the production function approach the goal is to obtain estimates of the elasticity of output with respect to neighboring jurisdictions' infrastructure:

(6) $\varepsilon_{Y,G} = [\partial Y/\partial G][G/Y]$

For the cost function analysis, in assessing the wider benefits of infrastructure, one objective is to estimate the elasticity of variable costs with respect to neighbors' infrastructure:

(7) $\varepsilon_{VC,G} = [\partial VC/\partial G][G/VC]$

When researchers compare results from production function studies with cost function studies, they tend to compare elasticities (6) and (7), respectively. However, the comparison is not completely valid since (6) shows the impact of neighbors' infrastructure on output, while (7) shows the effect of neighbors' infrastructure on variable costs.

A similar way of writing (7) is as the "shadow" value of neighboring localities' public infrastructure stocks (Z_G), as it reveals how additional infrastructure in neighboring localities affects a particular locality's variable costs:

(8) $Z_G = [\partial VC/\partial G]$

For $Z_G < 0$, neighboring jurisdictions' public infrastructure can be thought of creating "value" for firms in a particular jurisdiction, since variable costs fall as the size of the public infrastructure stock in neighboring jurisdictions increases.

The cost function approach also enables an examination of other revealing elasticities that provide insight into the wider benefits of public infrastructure. For instance, the elasticity of labor demand with respect to neighboring jurisdictions' infrastructure, which for production labor (LP) is (building on the result from equation (5), which is based on Shepard's Lemma):

(9) $\varepsilon_{LP,G} = \partial L_P / \partial G = \partial(\partial VC(\cdot))/\partial P_{LP} \partial G$

Also, the elasticity of the "shadow" value of the neighbors' infrastructure with respect to the own-jurisdiction infrastructure is written as:

(10) $\varepsilon_{G,I} = [\partial Z_G/\partial I][I/Z_G]$

This shadow value elasticity (10) is useful in determining whether infrastructure in neighboring jurisdictions is a substitute for or complement to an individual jurisdiction's infrastructure stock. Namely, if greater infrastructure in a particular jurisdiction increases the value of neighboring jurisdictions' infrastructure, then the two are complements. On the other hand, if greater infrastructure in a jurisdiction decreases the value of neighboring jurisdictions' infrastructure, the two are substitutes. The outcome for this elasticity can have important implications for regional infrastructure coordination policies.

Since it is clear that estimating these elasticities is an objective of the analysis, now a major question is how to construct the "neighbor" infrastructure stocks, test for and possibly adapt the model for spatial autocorrelation, and estimate the resulting equations. This is the focus of the next section on spatial econometrics.

4. SPATIAL ECONOMETRICS

Spatial Econometrics (Cliff and Ord, 1981, Anselin, 1981) has grown in popularity over the past 25 years, and only recently has been applied in the area of infrastructure studies. There are two aspects of spatial econometrics, commonly referred to as spatial autocorrelation and spatial lags (Kelejian and Prucha, 1999).

4.1. Spatial Autocorrelation

Spatial autocorrelation occurs when one locality's error term in the regression depends on "neighboring" localities' shocks or innovations, instead of merely being normally distributed with zero mean, constant variance, and zero covariances over time and space. Spatial autocorrelation implies interdependencies among different localities, and in general researchers can accommodate for spatial autocorrelation after conducting a procedure that generates an estimate of the magnitude of the autocorrelation. The word "neighboring" is in quotations because the word does not necessarily imply that the neighbor is at a contiguous location. That is, it could imply that localities are similar (or dissimilar) in other ways, such as average incomes of residents, volume of trade between individual locations, or other demographic characteristics.

Mathematically, spatial autocorrelation is represented in the following form:

(11) $u_i = \lambda \Sigma_j w_{i,j} u_j + \gamma_i$

or, in vector notation,

(11') $u = \lambda Wu + \gamma$

In equation (11), u_i is the error term for locality i, λ is the spatial autocorrelation coefficient, $w_{i,j}$ is the weight that locality j's error term has on locality i's error term (described as W in matrix notation), and γ_i is locality i's error term with the "desirable" properties (described below). Depending on the estimation technique for λ, researchers impose different assumptions on the distribution of γ_i. Namely, the Generalized Moments (GM) approach of Kelejian and Prucha (1999) assumes that γ_i is independently, identically distributed with zero mean, constant variance, and zero covariances across observations. The other commonly used approach, known as maximum likelihood (ML) estimation (Anselin, 1981), assumes normality of the γ_i, along with the same assumptions of zero mean, constant variance, and zero covariances.

Before the estimation can be implemented, researchers must choose the specification for the spatial weights, $w_{i,j}$. One common approach is contiguity weights, where all jurisdictions that are contiguous geographic neighbors to a particular jurisdiction are weighted equally. In other words,

(12) $w_{i,j} = 1/c$ if j is a contiguous neighbor to i

$= 0$ otherwise,

where c is the total number of i's contiguous geographic neighbors.

Other approaches, such as that of Boarnet (1998), specify more complicated spatial weight structures. One common example is the following:

(13) $w_{i,j} = [1/|D_i - D_j|] / [\ 1/\ \Sigma_j\ |D_i - D_j|\ ]$

In this weights specification, D_i and D_j can represent demographic variables, such as population, per capita income, or others (Boarnet, 1998). Intuitively, this gives greater weight to jurisdictions that are "similar" to each other, and less weight to jurisdictions that are "dissimilar". Since two jurisdictions (i and j) that are similar based on some demographic information will have D_i and D_j relatively close together, the inverse of the absolute value of their difference will be a large number, so jurisdiction j will have greater weight on jurisdiction i. The term involving the summation in the denominator is a normalization to ensure that $\Sigma_j\ w_{i,j} = 1$.

The next step after specification of the spatial weights is the estimation. Often, researchers estimate the production or cost function (along with the associated input demand equations), and perform a test for spatial autocorrelation (such as the Moran I test). Assuming the null hypothesis of no spatial autocorrelation is rejected, the next step is to determine the appropriate estimation technique for λ. One approach is to test whether the fitted residuals are normally distributed, using a test for normality (such as the Jarque-Bera test). If normality is rejected, the GM approach is followed to appropriately estimate λ, otherwise the ML estimation approach is used. Finally, once an estimate of λ is obtained, researchers use it to perform a spatial Cochrane-Orcutt transformation (analogous to a time-series Cochrane-Orcutt transformation) before re-estimating the transformed system.

Namely, to demonstrate this process consider the production function $Y = h(I,G)f(K,L)$, which we rewrite as:

(14) $Y = X\beta + u$,

where X represents a matrix of the explanatory variables (I,G,K,L), β is a vector of parameters to be estimated (and subsequently used to obtain the infrastructure elasticities), and u is as represented in the spatial autocorrelation error process described in (11') above. Substituting equation (11') into equation (14) yields:

(15) $Y = X\beta + \lambda\ Wu + \gamma$

Also, since we can rewrite the production function equation as:

(14') $u = Y - X\beta$,

then multiplying through both sides by □W yields

(14'') $\lambda\ Wu = \lambda\ WY - \lambda\ WX\beta$,

and substituting this result into the equation (15) above,

$$(15') \quad Y = X\beta + \lambda WY - \lambda WX\beta + \gamma$$

and rewriting:

$$(15'') \quad Y - \lambda WY = X\beta - \lambda WX\beta + \gamma$$

or

$$(16) \; Y^* = (X^*)\beta + \gamma$$

where $Y^* \equiv Y [I_N - \lambda W]$,

$X^* \equiv X [I_N - \lambda W]$

and I_N is an N by N identity matrix (where N is the number of observations in the sample).

After obtaining parameter estimates for λ and substituting them into equation (16) above, the resulting estimation equation has an error term (γ) that does not exhibit spatial autocorrelation, and thus yields efficient parameter estimates for the elasticities of output or costs with respect to infrastructure (either in the own or neighboring jurisdictions).

There are a number or potential reasons why a model might be expected to exhibit spatial autocorrelation. These include possible omitted variables that vary spatially; decisions in one location that are made for entities in other locations; and/or common shocks that spill over across geographic boundaries. An example of the latter is the weather and its impact on firms' costs or production process. A weather "shock" (for instance, either a storm or a heat wave) hitting some states and impacting production or costs can spill over to an adjacent state, and thus there can be some degree of persistence over geographic space that may lead to spatial autocorrelation.

Ignoring spatial autocorrelation can lead to parameter estimates with higher standard errors than if spatial autocorrelation had not been present. These higher standard errors can translate into t-statistics that are smaller than they should be. In other words, ignoring significant spatial autocorrelation can impact hypothesis testing, as researchers might fail to reject a null hypothesis that is actually a true hypothesis. In the context of infrastructure, ignoring spatial autocorrelation can lead a researcher to erroneously accept a null hypothesis that the infrastructure elasticity is equal to zero.

One of the first known infrastructure studies that addressed spatial autocorrelation is Kelejian and Robinson (1997). They estimate a Cobb-Douglas production function and incorporate a spatial autocorrelation adjustment, and they are careful to try many other specifications as well. They find that there can be a wide range of estimates on the infrastructure elasticities, depending on the econometric specification employed by the researchers.

Two subsequent studies find less convincing evidence of spatial autocorrelation. Holtz-Eakin and Schwartz (1995) test for spatial autocorrelation but find no evidence of its presence in their model. Boarnet (1998) finds no evidence that accommodation of spatial autocorrelation affects the sign and significance of the infrastructure elasticity estimates in his model.

The form of spatial autocorrelation in equation (11) is analogous to a first-order time series autoregressive process. Just as there are much more complicated time series processes in the econometrics literature, there are now some more complicated spatial processes addressed in the infrastructure literature to allow for more general forms of spatial autocorrelation. Cohen and

Morrison Paul (2007) address the problem of higher order spatial autocorrelation in the context of assessing the impacts of transportation infrastructure on manufacturing costs. Namely, they consider more general forms for the spatial process, such as:

$$(17)\ u_i = \Sigma_m \lambda_m \Sigma_j w_{m,i,j} u_j + \gamma_i$$

where m represents the "order" of the neighbor. Equation (17) is similar to but more general than equation (11), since here $w_{m,i,j}$ stands for the weight that state j has on state i in neighbor band m. Also, λ_m is the spatial autocorrelation parameter for the impact of the weighted average of errors in neighbor band m on state i's error term. For instance, at the state level and using contiguity weight matrices, New York, Connecticut, Rhode Island, New Hampshire, and Vermont would be first-order neighbors (m=1) to Massachusetts; New Jersey, Maine, and Pennsylvania would be second-order neighbors (m=2) to Massachusetts, etc. Such an error structure allows for more complex interactions among error terms for states (or other geographic units), so that in the previous example, shocks hitting New Jersey, Maine, and Pennsylvania might spill over to Massachusetts, whereas they would not with the first order contiguity neighbor matrix. Also, since each order neighbor has a separate spatial autocorrelation coefficient, it is possible in models of higher order spatial autocorrelation that the shocks hitting Massachusetts' second order neighbors have different impacts on the state than the shocks that hit its first-order neighbors. This error structure can be preferable to an approach where all other units are neighbors in varying degrees but with the same spatial autocorrelation coefficient. With higher order spatial autocorrelation, one can test whether the autocorrelation impact dissipates (or even dies out) beyond a certain range, instead of merely imposing a cutoff distance for neighbors to be included in the weighted average.

In determining the appropriate number of neighbors (m), Cohen and Morrison Paul (2007) apply a variation of the Kelejian and Robinson (1992) test for spatial autocorrelation as follows. First, Cohen and Morrison Paul test for first order spatial autocorrelation. When they find evidence of first order spatial autocorrelation, they proceed to test for second order, otherwise they stop. If they find second order spatial autocorrelation, they proceed to test for third order, otherwise they stop. They perform these tests on each of the estimation equations (the variable cost and the 3 input demands) separately. They find evidence of first order spatial autocorrelation in the non-production labor demand equation; second order spatial autocorrelation in the materials demand and variable cost equations; and third order spatial autocorrelation in the production labor demand equation. Accordingly, they estimate the spatial autocorrelation coefficients for each equation using the Kelejian and Prucha (2004) Generalized Moments techniques for systems of equations, then use these estimates to perform a spatial Cochrane-Orcutt transformation on each equation, before estimating the transformed system to obtain consistent parameter estimates.

Cohen and Morrison Paul (2007) find that the magnitude of the spatial autocorrelation coefficients for each equation decreases as the order of the neighbors increases. In other words, the impact of a "band" of neighbors' error terms on a particular state's error term is higher for states that are closer neighbors to a particular state, and it dissipates for bands of states that are more distant neighbors.

4.2. Spatial Lag

The other form of spatial spillovers that can be assessed with spatial econometrics is known as a spatial lag. A spatial lag (or spatial dependence) occurs when the "neighbors" of a particular geographic unit's variable(s) are included as explanatory variables in a regression. These spatially lagged variables can be of the dependent variable, as in Boarnet (1998), who includes a spatial lag of output. Such a spatial lag is interpreted as the weighted average of other jurisdictions' dependent variable. It is also common for researchers to include a spatial lag of some variable(s) other than the dependent variable. Examples of such spatial lags described below in more detail include Cohen and Morrison Paul (2003a, 2004), who include the weighted average of other states' airports, and highways, respectively.

A production function regression equation with a spatial lag can be written as follows:

(18) $Y = \rho WY + X\beta + u$,

where ρ and β are parameters to be estimated. In this equation, WY is the spatial lag, and it represents the weighted average of other jurisdictions' endogenous variable (which is output in the case of the production function). In Boarnet (1998), the endogenous variable is output. Since we know that Y is correlated with the error term u, it follows that WY is also correlated with u. Thus, WY is also an endogenous variable. In this case, ordinary least squares (OLS) is not the appropriate estimation technique. Instead, two-stage least squares (2SLS), or instrumental variables (IV) should be used to estimate equation (18). It can be shown (Kelejian and Prucha, 1998) that X is the appropriate instrument for itself, and WX is an instrument for WY. It is also possible, but not necessary, to include additional instruments for WY, such as WWX, WWWX, etc.

In situations where there is a spatially lagged dependent variable and spatial autocorrelation in the same model (that is, when equation (18) has the error structure described in equation (11')), the procedure for estimating λ described above is somewhat different. The first step is to estimate equation (18) by 2SLS, using X and WX as instruments. The second step is to retrieve the fitted values of the error terms u, and use them in either the GM or ML procedure described above to generate an estimate for λ. The final steps are to transform (18) with a spatial Cochrane-Orcutt transformation, plug in the estimate for λ, and estimate the transformed equation(s) by 2SLS, using X and WX as instruments for X and WY, respectively. This process yields efficient parameter estimates for β and ρ, and in turn, estimates for the infrastructure elasticities.

It is also possible to model spatial dependence by including spatial lags of other exogenous variables in the model. One example is the weighted average of other jurisdictions' public infrastructure stocks. In such a situation, the production function is written as:

(19) $Y = X\beta + WZ\delta + u$,

where Z is some subset of the variables included in X (such as the stock of public infrastructure), and β and δ are parameters to be estimated. It is also possible, but not necessary, to add a spatially lagged dependent variable in the model. Once the estimates of β and δ are obtained, either through OLS, the spatial autocorrelation adjusted OLS procedure, or 2SLS (if there is a spatially lagged dependent variable), it is possible to generate insights on the wider benefits of infrastructure. By calculating the elasticity of output with respect to neighboring jurisdictions' infrastructure ($\varepsilon_{Y,G}$), or the elasticity of variable costs with respect to neighbors' infrastructure ($\varepsilon_{VC,G}$), it is possible to assess these wider benefits. Also, if spatial autocorrelation is found to be present in the earlier estimation stages, that can provide additional information about wider benefits by shedding light on the innovations that spill over among "neighboring" jurisdictions.

5. APPLICATIONS

Recent applications of spatial lags and spatial autocorrelation in U.S. public infrastructure capital studies (both production function and cost function) have been done at the state and county levels, and have focused on airports, ports, highways and roads. Boarnet (1998) includes a spatial lag of the public infrastructure variables (roads and highways). He conducts an analysis of California counties with a Cobb-Douglas production function, allowing the infrastructure and neighboring county infrastructure stocks to be "free" variables that would shift the production function. Boarnet also tries a variety of different spatial weights matrices, and he finds significantly negative spatial lags with the weights for counties with more similar population densities ($\varepsilon_{Y,G} = -.307$), as well as those with similar levels of per-capital income ($\varepsilon_{Y,G} = -.806$). The magnitudes of these effects seem quite large, as the impacts of own-state infrastructure $\varepsilon_{Y,I}$ are 0.268 and 0.300 for the population and income weights, respectively.

Boarnet's results represent evidence of leeching behavior. Namely, improved infrastructure in neighboring counties would enable firms in those neighboring counties to draw away productive resources from a nearby county, leaving less productive workers in the nearby county. Thus, he finds some evidence showing that improvements in infrastructure in neighboring counties lead to a decrease in output in a particular county, assuming that workers are mobile.

Other subsequent state-level infrastructure studies by Cohen and Morrison Paul (2003a, 2004) find evidence of positive spillovers across states. The former paper focuses on airports, while the latter on highways. These studies incorporate spatial autocorrelation adjustments as well. They estimate cost functions and input demand equations for the U.S. manufacturing sector, so any benefits that they find accrue only to this particular sector.

Cohen and Morrison Paul (2003a) is motivated by the hub and spoke structure of the U.S. air transportation network. This system consists of airlines transporting passengers and freight from spoke airports to hub airports, followed by the passengers and cargo deplaning at the hubs and boarding other flights that transport them to their final destinations. With such a system, a delay at any particular node in the network can have system-wide effects, since passengers and cargo waiting to be transported by connecting flights at other nodes can be delayed as well. Improving infrastructure at a particular airport may reduce congestion throughout the entire system, leading to a decrease in travel time for business travelers and for cargo throughout the country. This lower travel time can translate into a decrease in firms' costs and enhance worker productivity.

A distinctive characteristic of the Cohen and Paul (2003a) analysis is that external benefits are different for airports than for highways or roads. In order for an airport to generate any benefits at all, there must be another node somewhere in the system for departing planes to land. Highways or roads infrastructure, on the other hand, can provide benefits with as little as several miles length within one city. Thus, one might expect the out-of-state-benefits for airports to be relatively large compared with those of highways, since better infrastructure at congested airports in other states should have a similar impact on travel savings (and in turn, costs) as if the improvements had been made at a congested departure airport in the firm's state.

Cohen and Morrison Paul (2003a) estimate a state-level variable cost function (which is the VC(·) expression in equation (4) above) and input demand equations similar to equation (5), where I represents within-state airport infrastructure stocks, and G represents a weighted average of airport infrastructure stocks in other states. They use Seemingly Unrelated Regressions (SUR) to estimate the system of equations, and they also find that applying a spatial autocorrelation adjustment to this system based on parameter estimates from the Kelejian and Prucha (2004) Generalized Moments approach does not substantively affect their results. They obtain the data for I by applying the perpetual inventory method to state-level capital spending data on air transportation, for the years 1982-1996. They obtain an estimate of the average service life of airports of 25 years, which they multiply by the average air transportation capital spending from 1977 to 1981, to obtain a base-year airports capital stock. Their depreciation rate is obtained by the inverse of the estimated average service life, and their investment deflator is from the *2000 Economic Report of the President*.

Their G variable is based on the extent of the interaction between a particular state and other states. This interaction is measured by the number of person-trips by air between individual states, from data in the 1995 American Travel Survey (Bureau of Transportation Statistics). So, as an example, a destination-state (j) with fewer person trips ($a_{i,j}$) between it and an origin state (i) has a lower weight on the origin state than another destination state with a larger number of person trips between it and the origin state. They define the weight that a particular destination state has on an individual state i as:

(20) $w_{i,j} = a_{i,j}/\Sigma_j(a_{i,j})$

with the term in the denominator ensuring that the $w_{i,j}$ sum to 1 (and $w_{i,j}$ represents the (i,j) element of the spatial weight matrix, W). Equation (20) represents the spatial weights that they use to perform a spatial autocorrelation adjustment in the variable cost and each of the input demand equations.

They also construct R_j , the ratios of Gross State Product (GSP) in state i to GSP in state j in a given year. Then, they define the average "neighbors'" airport infrastructure, G_i , in any given year as

(21) $G_i \equiv \Sigma_j \, w_{i,j} \, I_j \cdot R_j$,

where I_j is the airport infrastructure stock in state j in a given year. The intuition behind R_j is that one might expect a disproportionately large number of flights in larger states (such as Texas) to enter into G for smaller states (such as Rhode Island). Multiplying each "neighbor" state's infrastructure stock (I_j) by the inverse of its GSP times state i's GSP essentially eliminates the size effect arising due to the large neighbor states.

Cohen and Morrison Paul note that many large hub airports in the U.S. are facing more congestion during the period of their sample than airports that are not large hubs. Thus, it might be expected that the cost elasticities with respect to own-state and other state airports are not the same for states with at least one hub airports opposed to states with no hub airports. So they present two sets of elasticity results, for states with hub airports and for states with no hub airports.

First, for states with large hubs, the $\varepsilon_{VC,I}$ and $\varepsilon_{VC,G}$ elasticities are very similar and significant, with values of -0.113 and -0.116, respectively. This implies that better airports in other hub states are just as effective as airports in the origin state at reducing costs for manufacturing firms in that particular state. As discussed above, this supports the notion that unlike highways, airport improvements at origin and destination points should provide approximately the same level of cost-reduction benefits. In other words, for states with large hubs, an out-of-state airport can be just as important as the origin airport because two points are necessary to complete a trip.

For the input demand elasticities with respect to G for states with large hub airports, both production and non-production labor demand are negative and significant. These imply that increased airport infrastructure stocks in other states leads to lower demand for both types of labor in an individual state with large hub airports. With these lower numbers of workers, increased marginal product of labor is implied as a result of the higher levels of G. The results are similar in direction for materials inputs, while the magnitude of the effect of G on materials demand is smaller than the impacts for both types of labor.

The results are somewhat different for states with no major hubs. Namely, while $\varepsilon_{VC,G}$ and $\varepsilon_{VC,I}$ are negative and significant, $\varepsilon_{VC,G}$ is much larger in magnitude. The authors explain this difference by the fact that G includes states with large hubs, many of which are congested, while I represents airport infrastructure stocks for non-hub origin states, which in general are not as congested. Thus, the cost savings from expanding airports in other states is much larger in magnitude than the cost savings from larger airports in the origin states. Furthermore, the negative and significant shadow value elasticities $\varepsilon_{I,G}$ and $\varepsilon_{G,I}$ imply that G and I are substitutes, as increases in I imply lower Z_G (and vice-versa for G and Z_I).

Cohen and Morrison Paul (2004) focus on highway interdependencies across state borders. They note that the magnitudes and directions of such network effects have been elusive in previous infrastructure studies. The highways problem is motivated by the possibility of travel time savings for firms' workers in a particular state who travel through neighboring states on their way to and from work. Also, firms generate cost-saving benefits from shipment of materials through neighboring states with improved infrastructure stocks.

The authors estimate a variable cost function for the U.S. manufacturing industry similar to that of Cohen and Morrison Paul (2003a), except here I represents within-state highways infrastructure (obtained from Paul et. al., 2001, who apply the perpetual inventory method to state-level investment data); and G is the weighted average of neighbors' highway infrastructure. They calculate the spatial weights $w_{i,j}$ as in equation (20) above, where here $a_{i,j}$ is the average value of goods shipped from state i to state j, and j consists of states that are contiguous neighbors of state i. After the $w_{i,j}$ are determined, G is calculated as in equation (21).

Another element of the Cohen and Morrison Paul (2004) estimation system is that they allow for first order spatial autocorrelation in the cost function and input demand equations, by appending an error structure to each estimation equation similar to (11). They estimate a Generalized Leontief variable cost function, as well as input demand functions based on (5) for production labor, non-production labor, and materials inputs. Their annual data are for the manufacturing industry at the state level, covering the period 1982-1996. They find that the parameters for the terms involving G are jointly significant, which justifies their inclusion of spatial spillover effects in the variable cost function model. They also reject the hypothesis that the I and G parameters together are jointly zero. They find that the mean of the elasticity $\varepsilon_{VC,I}$ = -0.230 and is statistically significant, while the mean of $\varepsilon_{VC,G}$ = -0.011 and is statistically insignificant. The inconsistency between the joint significance of the terms involving G in the regressions and the insignificance of the mean $\varepsilon_{VC,G}$ elasticity may be explained by the difference in how the standard errors are calculated for $\varepsilon_{VC,G}$. Namely, the latter are based on the mean of the data over the entire sample.

The authors also find that when spatial effects (both G and spatial autocorrelation) are not recognized, the $\varepsilon_{VC,I}$ is only about -0.15, so they conclude that incorporating G and spatial autocorrelation increases the absolute value of the magnitude of the own-state infrastructure elasticity. Furthermore, the combined effect of G and I is approximately -0.24, which is about 50% larger in magnitude than when both G and spatial autocorrelation are ignored. The upshot is that accounting for these spatial effects appears to have a substantial effect on estimates of the cost-saving impacts of public infrastructure.

Another finding is that several of the inputs (namely, private capital, materials, and non-production labor) are substitutes with I, while production labor is a complement with I. The finding that private capital and I are substitutes is consistent with other findings in the public infrastructure literature.

There are somewhat different relationships between G and the inputs. Namely, capital, non-production labor and production labor are substitutes with G, while materials and G are complements. Cohen and Morrison Paul (2004) note that the substitutability between G and both types of labor is similar to the Boarnet (1998) findings.

Interestingly, Cohen and Morrison Paul (2004) note differences in the regional elasticities involving G. They find that $\varepsilon_{VC,G}$ is slightly positive for the Pacific states, implying that within-state infrastructure is more important than inter-state infrastructure improvements for those states. This may be partly because California, a relatively large state, is included in the Pacific region. On the other hand, $\varepsilon_{VC,G}$ is largest for states in the Mountain and West North Central regions. The authors note that since these states have relatively small populations, interstate highways may be more important for manufacturing firms in those states.

Cohen and Monaco (2007) examine the impacts of ports on manufacturing costs at the state level. They look at the within-state port effects (through I) and the inter-state port effects (through G) based on estimating a Generalized Leontief variable cost function, with I and G as shift factors. They construct ports capital stocks using the perpetual inventory method on state-level ports investment data. The authors also incorporate highway infrastructure variables to test for complementarity or substitutability between ports and highways. They test for and allow for spatial autocorrelation in their analysis as well. The spatial autocorrelation parameters are positive and significant, implying that a shock to states neighboring a particular state spill over to the particular state.

Regarding their elasticity estimates, Cohen and Monaco find that increases in ports infrastructure within a particular state decrease variable costs, with a variable cost elasticity of about -0.04 and statistically significant. The results for the variable cost elasticity with respect to neighboring states' ports infrastructure are quite different. Namely, greater levels of ports infrastructure in neighboring states leads to a rise in variable costs in a particular state. The variable cost elasticity with respect to neighboring states' ports is 0.129. The authors argue that these inter-state findings are consistent with Boarnet (1998), and imply that improved ports in nearby states may draw away the most productive workers from a particular state, leading to higher manufacturing costs in that particular state. In other words, the positive and significant infrastructure elasticity is evidence of external diseconomies of scale. From the perspective of manufacturing firms in a particular state, neighboring states may have too much ports infrastructure during the sample period, and lower ports infrastructure in neighboring states may be expected to lower manufacturing costs in a particular state.

Cohen and Monaco (2007) also find that the elasticity of the shadow value of neighbors' ports with respect to the own state's ports infrastructure is negative and significant. This result implies that states with decreasing ports infrastructure face larger external diseconomies of scale resulting from changes in ports infrastructure in neighboring states. On the other hand, they find that the elasticity of the own state's ports shadow value with respect to the stock of ports in neighboring states is insignificant, implying that additional ports infrastructure in neighboring states has no significant impact on the shadow value of ports infrastructure in a particular state.

Based on the elasticities relating ports and highways, the authors find no significant relationship between the shadow value of ports (highways) and additional highways (ports). The ports shadow value elasticities with respect to both types of labor (production and non-production labor) are positive. In other words, the cost-reduction potential (or shadow value) of ports increases with more workers, so there appear to be some complementarities between workers and ports. Finally, the shadow value of ports increases over time, after controlling for all factor prices and other shift factors, as is seen by the sign and significance of the elasticity of the ports shadow value with respect to the time counter (t).

The functional forms for the cost function studies discussed so far all are Generalized Leontief. Also, the focus of most previous spatial cost function studies is on the impacts of various types of infrastructure on the U.S. manufacturing sector. Another recent study by Moreno et. al. (2004) assesses spillovers for 15 Spanish regions over the years 1980 to 1991, for 12 manufacturing industries. They estimate a translog variable cost function, for two separate classes of models. They classify the first type of model as the "sectoral" case, where the weighted average of other industries' and/or geographic regions' output are included as external inputs. Their sectoral case is similar in spirit to the approach of Morrison and Siegel (1999), who incorporate external shift variables in the cost function for other industries' output. Moreno et. al.'s other group of models is the "regional" case, where they add measures of public capital for neighboring regions. They include measures of public capital (I) within a particular region for each industry, by apportioning the aggregate infrastructure stock to the individual industries based on the output share of each manufacturing industry in total manufacturing output. For the regional case, the authors have a somewhat different specification of G than the spatial lag approach of the other cost function studies described above. Namely, they denote G as W times ln(I), where ln(I) represents the natural logarithm of I, and W is a contiguity matrix based on geographic neighboring Spanish regions. Then, total public capital (which here will be called "T") is assumed to be a geometric mean of the own-region public capital (I) and the neighbors' public capital (G):

$$(22) \qquad T \equiv I^{\theta} G^{1-\theta},$$

where θ is a parameter between 0 and 1 to be estimated empirically together with the rest of the cost function. They argue that one advantage of such a specification for public capital is that it allows for complementarities between I and G. This specification also averts the need to add several additional interaction terms for both I and G, while instead interaction terms for only one infrastructure variable (T) needs to be added to the basic cost function. They argue that inclusion of minimal interaction terms mitigates potential multicolinearity problems. A disadvantage of this approach, however, is that now with the addition of T the model must be estimated with nonlinear regression techniques.

For their regional case, Moreno et. al. build up their model by starting with a translog variable cost function model containing input prices for labor and intermediate materials, an output measure, and a fixed factor for capital. They also perform 3 tests for spatial autocorrelation, and find significant evidence of spatial autocorrelation in this basic model with one of the 3 tests. Next, they add public capital (I), and find that all of the parameters that are involved with terms for I are jointly significant.

Once again, they find evidence of spatial autocorrelation with one of their 3 tests for this specification. They find that on average over all Spanish regions, $\varepsilon_{VC,I}$ =-0.034. Their estimates for input demand elasticities imply that labor and infrastructure are complementary, while infrastructure and intermediate materials are substitutes. Finally, when they add cross-region externalities in the form of G and the weighted average of neighboring regions' output, they find no evidence of spatial autocorrelation, but they find that θ = 0.58. This value for θ (and the associated value for (1-θ)) implies that both G and I are important determinants of variable costs, and supports the notion that transportation networks are present. But the elasticity of variable costs with respect to the composite infrastructure measure is now positive, which leads to a conclusion that these Spanish regions may have too much infrastructure during the 1980's. Also, the elasticity of labor with respect to the composite infrastructure measure T is now negative, implying that workers and infrastructure are now substitutes. Furthermore, the elasticity of intermediate materials with respect to infrastructure also switches signs, with an interpretation that these two inputs are now complements. The authors also note, however, that the spatial weight matrix specification may be driving their results with this particular estimation approach, but they do not report results of testing with alternative weight matrices.

In the sectoral case, they assume that θ = 1, so that they do not incorporate public capital spillovers across regions. First, they find that $\varepsilon_{VC,I}$ = 0.305, implying once again that there is an excess of public infrastructure capital during the 1980's in Spain. They also find strong evidence of spatial autocorrelation across sectors (which they call "sectoral autocorrelation") based on all 3 tests. Finally, in a separate estimation procedure they add the weighted average of neighboring regions' output as a fixed factor. This additional fixed factor, together with the inclusion of public capital (I), completely eliminates the evidence of significant "sectoral autocorrelation". They also find that the average $\varepsilon_{VC,I}$ = -0.341, implying that public infrastructure capital in Spain confers cost-saving benefits on manufacturing firms in that country. In both of the estimation procedures that incorporate public capital for the sectoral case, they find that labor and public infrastructure capital are complements, while intermediate materials and public capital are substitutes.

6. CONCLUSIONS AND FUTURE WORK

Recent advances in spatial econometrics have facilitated analysis of the wider benefits of public infrastructure. In particular, researchers over the past decade have assessed both the impacts of spatial autocorrelation and spatial lags on estimates of the benefits of public infrastructure capital. Various modes of transportation infrastructure have been studied, including highways, air, and ports. Coverage has focused on U.S. counties, states, as well as regions of Spain. Studies have been conducted using both production function and cost function approaches, and have led to a broad range of results. Namely, some studies have found that additional infrastructure capital leads to greater output or lower costs, while others have found the opposite. Despite this lack of consensus on infrastructure's impacts, it is clear that incorporating measures of "wider benefits" has enhanced the precision of the effects of infrastructure relative to the state of the art in the early 1990's. Thus, the innovations in the tool set of spatial econometrics have contributed to understanding in this field. However, there is still more that can be done in future research to improve the accuracy of impact measures for public infrastructure.

One area of potential further work would be to utilize firm-level manufacturing data to estimate the elasticity of variable costs with respect to public infrastructure. Such a disaggregate analysis would allow for greater heterogeneity among the individual agents, which may generate different results for the infrastructure elasticities. Such data are housed at the U.S. Census Bureau Research Data Centers (RDC's). There are a number of obstacles to overcome before obtaining these data, but the potential richness of the data may be worth the effort needed to gain access to the RDC's resources. One potential benefit of the firm-level analysis is that once elasticities are estimated, one could impute for each firm a dollar value of the estimated cost-reduction resulting from additional infrastructure. Such an approach could lead to innovative alternative approaches for financing infrastructure improvements by charging firms based on their expected (or realized) benefits from infrastructure improvements.

Along with the advances in the area of spatial econometrics over the last 15 years, Geographic Information Systems software has grown in popularity and usage in the economics profession. While its usage in other areas within the economics profession has become common, such as in hedonic housing price studies, there is much that could be done with GIS software in infrastructure studies. For example, researchers could utilize GIS more heavily so as to generate more sophisticated spatial weights in assessing the spillover benefits from "neighboring" jurisdictions. Constructing a greater variety of spatial weights and estimating either the cost function or production function for several different weights specifications can provide a robustness check for the spatial modeling.

Related to the notion of checking robustness of using different spatial weights matrices is incorporating alternative variations of the measure of other localities' infrastructure stocks. Namely, many studies calculate G for a particular locality as the weighted average of other localities' infrastructure, and G enters as a separate shift factor in the analysis. One exception is Moreno *et. al.* (2004), who instead use I and G to derive a net infrastructure measure, which we call T in equation (22) above. As noted by Moreno *et. al.*, using T instead of separate terms for both I and G reduces the number of interaction terms (and in turn, the number of parameters to estimate with the more sophisticated functional forms), although it introduces nonlinearities that preclude classical linear estimation techniques. But it would be a worthwhile exercise to compute such a composite infrastructure measure and check the robustness of results. One potential drawback, however, is that such a structure imposes additional interdependencies between G and I instead of testing for such interrelationships empirically.

While there have been studies of public infrastructure impacts on manufacturing costs involving multi-modal transportation, such as Cohen and Morrison Paul (2007) for airports and highways, and Cohen and Monaco (2007) for ports and highways, a large scale intermodal study would generate new insights on the complementarity and/or substitutability between different types of infrastructure. A more detailed analysis of spillovers from intermodal transportation at the disaggregate (county) level, incorporating ports, rail, air, and highways would integrate the more complex structure of transportation networks into the current literature.

Another possible extension would be to examine the impacts of infrastructure on other sectors besides manufacturing. Cohen and Monaco have work in progress that explores the impacts of ports on the textiles and wholesale goods sectors, at the California county level. Studies for additional industries and locations that examine other types of infrastructure as well could be insightful.

In addition to looking at the benefits across sectors, another possibility would be to examine the general equilibrium impacts of G along the lines of Haughwout (2002). Namely, this would consist of a model with consumers making consumption choices while minimizing their total expenditures, with infrastructure as an exogenous shift factor. Additionally, the model would have a production side, with firms choosing inputs to minimize production costs, and infrastructure would also enter the cost function. Here, "infrastructure" could consist of both I and G, so one might assess the general equilibrium impacts on welfare from infrastructure spillovers, both across jurisdictions as well as within a particular jurisdiction.

Another more macro approach would be to look at benefits across countries, such as individual European countries that are highly interdependent, along with benefits across regions that are within countries. Cohen and Morrison Paul (2003b) assess production-related spillovers across EU countries, but they do not incorporate infrastructure. Yet another aspect would be having different layers of G that start at micro level, and then aggregate up. This approach would avoid missing spillovers that accrue within individual countries when doing a cross-country spillover analysis. While the spillover public capital stocks (G) would likely be larger here, this does not necessarily imply that the benefits would be greater as well. The sign of the net benefits would depend on the sign of the elasticities with respect to infrastructure based on the econometric estimation of the model.

Finally, rolling up many of these ideas and examining them together would be a complex exercise. But it would also be an excellent springboard for introducing CGE models, as presented by Lakshmanan, *et. al.* (2007). Needless to say, there is much more work that still can be done in assessing the wider benefits of public infrastructure capital.

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Figure 1 - Change in Equilibrium Output from an Increase in Public Infrastructure Stock in a Neighboring Locality

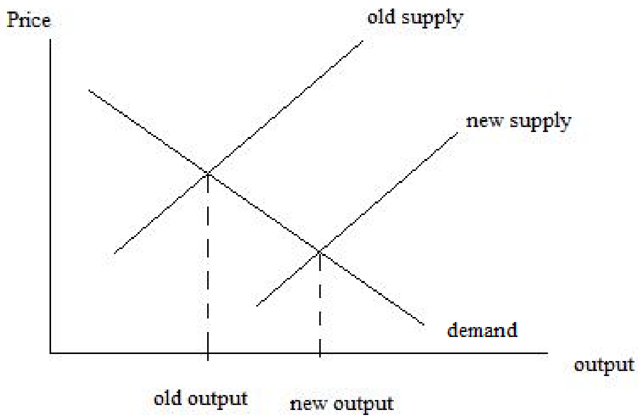

Figure 2 - Change in Supply from an Increase in Public Infrastructure Stock in a Neighboring Locality