PUBLIC INFRASTRUCTURE INVESTMENT, INTERSTATE SPATIAL SPILLOVERS, AND MANUFACTURING COSTS

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Abstract—Effects of public infrastructure investment on the costs and productivity of private enterprises have proven difficult to quantify empirically. One piece of this puzzle that has received little attention is spatial spillovers. We apply a cost-function model to 1982–1996 state-level U.S. manufacturing data, to untangle the private cost-saving effects of inter- and intrastate public infrastructure investment. We implement two spatial adaptations—including a spatial spillover index in the theoretical model, and allowing for spatial autocorrelation in the stochastic structure. Recognizing such spillovers both increases the estimated magnitude and significance of cost savings from intrastate public infrastructure, and augments these productive effects.

I. Introduction

THE size and significance of the effects of public infrastructure investment on the economic performance of the private sector have been debated at least since Aschauer (1989). The early literature on public infrastructure and growth linkages suggests a close correlation for many developed countries between reductions in public capital investment and declining private-sector productivity. Most of the econometric investigations in the subsequent literature on this *public capital hypothesis* have been aimed at gaining consensus about the extent of these effects, but the question remains contentious.

Literature surveys by Gramlich (1994), Sturm and De Haan (1995), and Sturm, Kuper, and De Haan (1998) identify many early studies that found a strong productive effect of public infrastructure investment. Estimates presented by Aschauer (1989), Reich (1991), and Deno (1988), for example, indicate that public investment has a much greater return to private-sector economic performance than does private capital investment. These findings imply that policy measures to augment public infrastructure investment could dramatically enhance U.S. productivity and competitiveness.

Subsequent studies raised serious questions about the robustness of the empirical results on which this story was based.[1] In particular, refining the econometric structure by incorporating state and time fixed effects caused the estimated effects of public infrastructure investment on private-sector productivity to virtually disappear (Holtz-Eakin, 1994; Hulten & Schwab, 1991; Garcia-Mila & McGuire, 1992). Accommodating spatial correlation also reduced the magnitude and significance of the estimated productivity effects, suggesting sensitivity to stochastic specification (Kelejian & Robinson, 1997).

Relaxing restrictive assumptions in the theoretical framework by incorporating behavioral responses, and recognizing various scale and homogeneity properties and dynamics, yielded further insights (Conrad & Seitz, 1992; Morrison & Schwartz, 1996a,b; Shah, 1992). Such dual formulations facilitate the representation of input substitution and scale economy responses to external factors, which are key to evaluating productivity patterns deriving from public capital investment (Morrison & Schwartz, 1996b; Batina, 2001). Empirical results from such models suggest smaller, but statistically significant and more robust, estimates of infrastructure effects on overall productivity growth than found in the initial studies.

Other researchers explored the consequences of industrial aggregation. Hulten and Schwab (1991), Shah (1992), Nadiri and Mamuneas (1994), and Morrison and Schwartz (1996a,b) estimated returns to manufacturing industries from public infrastructure investment, and found that focusing on a particular sector resulted in more plausible and interpretable results than taking a macro perspective. Paul et al. (2001) found similar implications for the agricultural sector, and Sturm (2001) found significant differences in returns to "sheltered" and "nonsheltered" sectors.[2]

Regional disaggregation also provided insights into public infrastructure benefits to the private sector. Studies estimating state-specific effects, such as Munnell (1990) and Morrison and Schwartz (1996a,b), obtained smaller (but still significant) estimates of infrastructure effects than those using national data. The size and significance of these estimates were also found to differ regionally, and over time (Hulten & Schwab, 1991; Aschauer, 2001).

Other issues that may complicate the estimation of public infrastructure investment effects have been raised in the literature. In particular, the existence of spatial spillovers from public capital investment in geographically linked areas has been postulated, along with temporal dependence of estimated infrastructure effects (Kelejian & Robinson, 1997; Holtz-Eakin & Schwartz, 1995; Boarnet, 1998).[3] The potential endogeneity of infrastructure investment decisions has also been targeted, which would imply inconsistent estimates if not accommodated in the estimation procedures.

In this study we further investigate the infrastructure question, with a focus on spatial spillovers in a dual framework.

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[1] Sturm et al. (1998) overview the criticisms of studies in this literature.

[2] Nonsheltered sectors are those more open to global influences, which include both manufacturing and agriculture.

[3] Kelejian and Robinson (1997) allow for spatial lags of dependent and independent variables along with spatial correlation of the error terms, Holtz-Eakin and Schwartz (1995) consider interstate spillovers in a production-oriented model based on long differences to accommodate long-run adjustment, and Boarnet (1998) measures cross-county spillovers using a Cobb-Douglas production function approach.

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We estimate a cost-function model by maximum likelihood techniques, using updated and refined[4] state-level data on prices and quantities of aggregate output and (capital, production and nonproduction labor, and materials) inputs for U.S. manufacturing, and stocks of public highway infrastructure. This framework directly characterizes overall private cost savings and underlying input demand effects from public infrastructure investment; the estimated effects take the form of cost (shadow value) and input-specific (substitution) effects. The model also distinguishes intra- and interstate effects of public infrastructure stock levels and their interdependences; the stochastic and cost specifications are adapted (using spatial-econometrics procedures and incorporating a spatial spillover index) to measure the extent and significance of spatial spillovers.

We find a significant contribution of intrastate public infrastructure investment to manufacturing production that is both enhanced and augmented by cross-state spillovers. That is, recognizing spatial linkages increases the estimated effects of within-state infrastructure investment, and between-state effects cause the combined effect to be even greater. We also find increasing intra- and interstate public-capital effects over time, coinciding with a somewhat declining return to private capital investment. The benefits of public capital investment are further enhanced by scale economies, in the form of implied output growth, but the effect of short-run private-capital fixities is negligible. The overall cost effects suggest some substitutability of private and public capital, but are driven largely by materials substitution. Finally, allowing for serial correlation has very little influence on estimated intrastate public investment effects, but reduces the measured effect of interstate spillovers.

II. The Model

Our analysis of the cost-saving productive effects of public infrastructure investment is based on a cost-function model applied to a state-by-year panel of U.S. manufacturing industry data. We assume that manufacturing firms minimize short-run costs by choosing a combination of inputs, given input prices, existing demand (output) and capacity (capital) levels, and (external) technological and environmental conditions. The total cost function embodying these decisions is expressed in the general form

$$TC_{i,t} = R_{i,t}(Y_{i,t}, K_{i,t}, \mathbf{p}_{i,t}, \mathbf{r}_{i,t}) + p_{K,i,t}K_{i,t}, \tag{1}$$

where $i = 1, 2, \ldots, 48$ represents the state (spatial dimension) and $t = 1982, 1983, \ldots, 1996$ the year (temporal dimension), $TC_{i,t}$ is the total cost in state i at time t, $R_{i,t}(\cdot)$ is the restricted cost function in state i at time t incorporating short-run constraints from fixed capital stocks, $Y_{i,t}$ is the aggregate output in state i at time t, $K_{i,t}$ is the fixed (private) capital in state i at time t,[5] $\mathbf{p}_{i,t}$ is a vector of variable input prices in state i at time t, and $\mathbf{r}_{i,t}$ is a vector of external shift factors for state i at time t. The variable inputs are nonproduction labor $L^N_{i,t}$, production labor $L^P_{i,t}$, and intermediate materials $M_{i,t}$, with prices $p^N_{L,i,t}$, $p^P_{L,i,t}$, and $p_{M,i,t}$, respectively; $\mathbf{p}_{i,t} = (p^N_{L,i,t}, p^P_{L,i,t}, p_{M,i,t})$. The external factors are a standard time trend ("technical change") variable t,[6] the public infrastructure stock $I_{i,t}$, in state i, and public infrastructure levels $G_{i,t}$ in states geographically connected to state i; $\mathbf{r}_{i,t} = (t, I_{i,t}, G_{i,t})$.

The measure $I_{i,t}$, as in Bell and McGuire (1994), was constructed by applying standard perpetual inventory techniques to data on state-level public highway infrastructure investment (see the data appendix for further discussion of the data construction). The measure $G_{i,t}$ was computed as a weighted sum of highway infrastructure stocks in neighboring states,[7] where the weight for each neighboring state is the value of goods shipped to it as a share of the value of goods shipped to all neighboring states (see below for details). Including $I_{i,t}$ as a cost-function argument follows Conrad and Seitz (1992), Lynde and Richmond (1992), Nadiri and Mamuneas (1994), and Morrison and Schwartz (1996a,b). Including the spatial spillover index $G_{i,t}$ allows for spatial spillovers to also directly affect the productive contribution of public infrastructure stocks.[8]

Empirical implementation of such a model requires specific assumptions to be made about the forms of the cost function and stochastic structure. We approximate $R_{i,t}(\cdot)$ by a generalized Leontief function, where the factors expressed in levels are included in quadratic form (Paul, 2001). We also allow for first-order autocorrelation and a spatial autoregressive structure in the error specification, to accommodate temporal and spatial lags (Berndt, 1991, and Boarnet, 1998, respectively).[9] The resulting model is

[4] Our data are refined in the sense that the capital stocks are constructed on a state-by-state basis, instead of apportioning national stock data to the states as was done in many previous studies. See the data appendix for additional details.

[5] This is a beginning-of-the-year stock level, representing the fixed capital stock for the year.

[6] The t effect is generally interpreted in this literature as representing technical change, although technical change more justifiably should be recognized as endogenous (resulting from R&D and other internal and external technological factors) rather than exogenous.

[7] The stock levels are relative in the sense that if Nevada, for example, has one-tenth the manufacturing production of California, it is assumed to benefit only from that fraction of California's I stock. We used these relative stock levels because some states (Nevada and Vermont in particular) had unreasonably large $G_{i,t}/R_{i,t}(\cdot)$ ratios if the full I stock in the neighboring state was assumed to provide economic benefits.

[8] This adaptation is similar to models allowing for (supply- and demand-driven) agglomeration effects, such as Bartlesman, Caballero, and Lyons (1994) and Morrison and Siegel (1999) (although Bartlesman et al. incorporated this index into a first-order logarithmic production function in differenced form, rather than a cost function).

[9] The extension to apply stochastic spatial econometric techniques to a system of cost and input demand equations is, to our knowledge, novel in the literature.

$$
\begin{aligned}
RC_{i,t} &= R_{i,t}(Y_{i,t}\, K_{i,t},\, \mathbf{p}_{i,t},\, I_{i,t},\, G_{i,t},\, t) \\
&\equiv \sum_n \sum_i \delta_{n,i}\, p_{n,i,t}\, DUM_i + \sum_n \sum_m \alpha_{nm}\, p_{n,i,t}^{0.5}\, p_{m,i,t}^{0.5} \\
&\quad + \sum_n \delta_{nY} p_{n,i,t} Y_{i,t} + \sum_n \delta_{nK} p_{n,i,t} K_{i,t} + \sum_n \delta_{nI}\, p_{n,i,t} I_{i,t} \\
&\quad + \sum_n \delta_{nG} p_{n,i,t} G_{i,t} + \sum_n \delta_{nt}\, p_{n,i,t} t + \sum_n p_{n,i,t} (\delta_{YY} Y_{i,t}^2 \\
&\quad + \delta_{KK} K_{i,t}^2 + \delta_{YK} K_{i,t} Y_{i,t} + \delta_{IY} I_{i,t} Y_{i,t} + \delta_{IK} I_{i,t} K_{i,t} \\
&\quad + \delta_{IG} I_{i,t} G_{i,t} + \delta_{It}\, I_{i,t} t + \delta_{II}\, I_{i,t}^2 + \delta_{GY}\, G_{i,t} Y_{i,t} \\
&\quad + \delta_{GK} G_{i,t} K_{i,t} + \delta_{Gt} G_{i,t} t + \delta_{GG} G_{i,t}^2 + \delta_{tY} Y_{i,t} t \\
&\quad + \delta_{tK} K_{i,t} t + \delta_{tt} t^2) + u_{i,t},
\end{aligned} \tag{2a}
$$

where

$$u_{i,t} = \rho_s \sum_j w_{i,j} u_{j,t} + \psi_{i,t}; \tag{2b}$$

$$\psi_{i,t} = \rho_\theta \psi_{i,t-1} + \phi_{i,t}; \tag{2c}$$

$\phi_{i,t} \sim N(0,\, \sigma^2)$; $w_{i,j}$ is the weight that state j has on state i; $w_{i,i} = 0$; $-1 < \rho_s < 1$; $-1 < \rho_\theta < 1$; n, $m = (L^N,\, L^P,\, M)$, $n \neq m$; i, $j = (1, 2, \ldots, 48)$; $t = (1982, 1983, \ldots, 1996)$; and DUM_i is a dummy variable for state i. The elements of $\phi_{i,t}$ are assumed to be independently, identically distributed (i.i.d.), the elements of $\psi_{i,t}$ are assumed to be i.i.d., and $\phi_{i,t}$ and $\psi_{i,t}$ are assumed to be independent.

Our system of estimating equations includes both the cost function (2) and demand equations for the three variable inputs derived from equation (2) via Shephard's lemma: $v_{n,i,t} = \partial R_{i,t}/\partial p_{n,i,t}$ $(n = L^N,\, L^P,\, M)$. Each of these equations thus takes the form

$$
\begin{aligned}
qv_{n,i,t} &= v_{n,i,t}(Y_{i,t},\, K_{i,t},\, \mathbf{p}_{i,t},\, I_{i,t},\, G_{i,t},\, t) \equiv \frac{\partial R_{i,t}(\cdot)}{\partial p_{n,i,t}} \\
&= \sum_i \delta_{n,i} DUM_i + \sum_m \alpha_{nm}\, p_{n,i,t}^{-0.5} p_{m,i,t}^{0.5} + \delta_{nY} Y_{i,t} \\
&\quad + \delta_{nK} K_{i,t} + \delta_{nI} I_{i,t} + \delta_{nG} G_{i,t} + \delta_{nt} t + \delta_{YY} Y_{i,t}^2 \\
&\quad + \delta_{KK} K_{i,t}^2 + \delta_{YK} K_{i,t} Y_{i,t} + \delta_{IY} I_{i,t} Y_{i,t} + \delta_{IK} I_{i,t} K_{i,t} \\
&\quad + \delta_{IG} I_{i,t} G_{i,t} + \delta_{It} I_{i,t}\, t + \delta_{II} I_{i,t}^2 + \delta_{GY} G_{i,t} Y_{i,t} \\
&\quad + \delta_{GK} G_{i,t} K_{i,t} + \delta_{Gt} G_{i,t} t + \delta_{GG} G_{i,t}^2 + \delta_{tY} Y_{i,t}\, t \\
&\quad + \delta_{tK} K_{i,t}\, t + \delta_{tt}\, t^2 + u_{n,i,t},
\end{aligned} \tag{3a}
$$

where

$$u_{n,i,t} = \rho_{s,n} \sum_j w_{i,j} u_{n,j,t} + \psi_{n,i,t}; \tag{3b}$$

$$\psi_{n,i,t} = \rho_{\theta,n} \psi_{n,i,t-1} + \phi_{n,i,t}; \tag{3c}$$

$\phi_{n,i,t} \sim N(0,\, \sigma_n^2)$; $qv_{n,i,t}$ is the demand for input n in state i in year t; and $-1 < \rho_{s,n} < 1$, $-1 < \rho_{\theta,n} < 1$. We assume that the elements of $\phi_{n,i,t}$ are i.i.d., the elements of $\psi_{n,i,t}$ are i.i.d., and $\phi_{n,i,t}$ and $\psi_{n,i,t}$ are independent, as are $\phi_{L,i,t}^N$ and $\phi_{L,i,t}^P$, $\phi_{L,i,t}^N$ and $\phi_{M,i,t}$, and $\phi_{M,i,t}$ and $\phi_{L,i,t}^P$.

We summarize the cost function as $RC_{i,t} = R_{i,t}(\cdot) + u_{i,t}$, where $RC_{i,t} = \sum_n p_{n,i,t} qv_{n,i,t}$ $(n = L^N,\, L^P,\, M)$, and the input demand functions as $qv_{n,i,t} = v_{n,i,t}(\cdot) + u_{n,i,t}$. Stacking the observations for all states for each year, and using equations (2b), (2c), and (3b), (3c) to transform equations (2a) and (3a) analogously to a Cochrane-Orcutt procedure, results in the four-equation system

$$
\begin{aligned}
RC_t &= \rho_\theta RC_{t-1} + R_t(\cdot) + \rho_s[WRC_t - WR_t(\cdot)] \\
&\quad - \rho_\theta[\rho_s WRC_{t-1} + R_{t-1}(\cdot) - \rho_s WR_{t-1}(\cdot)] \\
&\quad + \Phi_t,\; qv_{n,t} = \rho_{\theta,n} qv_{n,t-1} + v_{n,t}(\cdot) \\
&\quad + \rho_{s,n}[Wqv_{n,t} - Wv_{n,t}(\cdot)] - \rho_{\theta,n}[\rho_{s,n} Wqv_{n,t-1} \\
&\quad + v_{n,t-1}(\cdot) - \rho_{s,n} Wv_{n,t-1}(\cdot)] + \Phi_{n,t},
\end{aligned} \tag{4}
$$

where $\Phi_t \sim N(0,\, \sigma^2 \mathbf{I}_{48})$, $\Phi_{n,t} \sim N(0,\, \sigma_n^2 \mathbf{I}_{48})$; W is a 48×48 weighting matrix with (i,j) element $w_{i,j}$; and $\mathbf{I}_{48}$ is a 48×48 identity matrix. We specify RC_t as a 48×1 vector of $RC_{i,t}$ at time t; $R_t(\cdot)$ as matrix notation for $R_{i,t}(\cdot)$ at time t; WRC_t as W times RC_t at time t; $WR_t(\cdot)$ as W times $R_t(\cdot)$ at time t; $qv_{n,t}$ as a 48×1 vector of $qv_{n,i,t}$ at time t; $v_{n,t}(\cdot)$ as matrix notation for $v_{n,i,t}(\cdot)$ at time t; $Wqv_{n,t}$ as W times $qv_{n,t}$ at time t; and $Wv_{n,t}(\cdot)$ as W times $v_{n,t}(\cdot)$ at time t.

A spatial autoregressive (SAR) error specification is thus incorporated by the spatially lagged error terms; ρ_s and $\rho_{s,n}$ represent linkages with neighboring states [similar in spirit to Kelejian and Robinson (1997)]. The temporal dimension of the panel data is recognized by accommodating first-order serial correlation [AR(1)] through the ρ_θ and $\rho_{\theta,n}$ terms [as in Holtz-Eakin and Schwartz (1995) and Kelejian and Robinson (1997)].

Defining the *connecting* states or geographic neighbors and their weights is key to implementing the SAR approach. For the spatial autocorrelation specification we define the weight that neighboring state j has on state i, $w_{i,j}$, as the share of the value of goods shipped from state i to state j in the total value of goods shipped from state i to all of its neighbors:[10]

$$w_{i,j} = a_{i,j} \Big/ \sum_j a_{i,j}, \tag{5}$$

where $a_{i,j}$ is the value of goods originating in state i with destination in neighboring state j.[11,12] To weight the sum of

[10] This is similar to Cohen and Paul's (2003) treatment of airport network interdependences.

[11] No corresponding time series is available. However, given the concern about potential endogeneity of the weights, we followed an approach similar to Case, Rosen, and Hines (1993) by using an average of the shares for 1977, 1992, and 1996 as the weights. Case et al. argue that when using

state j's relative infrastructure investment for construction of $G_{i,t}$, we combine these weights with information on differences in the relative sizes of state-level economic activity [measured by the gross state product (GSP)]:

$$G_{i,t} \equiv \sum_j w_{i,j} I_{j,t} \frac{GSP_{i,t}}{GSP_{j,t}}, \tag{6}$$

where $GSP_{i,t}$ is the GSP of state i in year t. The GSP multiplicative factor reflects the relatively large effect that highway infrastructure stocks in state j, which shares a large value of goods shipments with state i, will have on state i's manufacturing costs. Also, if state j, say, has a high level of economic activity relative to state i, it will constitute an overly large portion of $G_{i,t}$ unless this size effect is counteracted through multiplication by $GSP_{i,t}/GSP_{j,t}$.[13]

Based on the parameter estimates from our model, the contributions of the external and internal shift factors $I_{i,t}$, $G_{i,t}$, t, and $K_{i,t}$ to overall and input-specific cost savings may be measured and evaluated. These effects are expressed as the (negative) shadow values $Z_I = \partial R/\partial I$, $Z_G = \partial R/\partial G$, $Z_t = \partial R/\partial t$, and $Z_K = \partial R/\partial K$ (hereafter the time and state subscripts are suppressed for expositional simplicity).[14] In particular, Z_G quantifies the cost savings for manufacturing firms in a given state from a marginal increase in infrastructure investment in neighboring states, or the extent of interstate spillovers. Z_I similarly reflects intrastate public infrastructure effects. We express these cost measures also in elasticity form to represent their proportional effects; for example, $\varepsilon_{RC,I} = \partial \ln R/\partial \ln I = Z_I \cdot I/RC$.

Our flexible cost-function framework allows us to evaluate not only these first-order (overall) cost effects, but also second-order effects reflecting input substitution and output valuation. That is, in addition to the I, G, K, and t shadow values, first derivatives of the cost function capture demands for variable inputs, $v_n = \partial R/\partial p_n$, and the marginal cost of output, $MC = \partial R/\partial Y$. In proportional (elasticity) terms these derivatives, $\varepsilon_{RC,pn} = \partial \ln R/\partial \ln p_n$ and $\varepsilon_{RC,Y} = \partial \ln R/\partial \ln Y$, reflect (short-run) input cost shares and scale economies. Input-specific and output marginal cost effects of I (and analogously G, K, t) changes are thus represented through elasticities such as $\varepsilon_{vn,I} = \partial \ln v_n/\partial \ln I$ and $\varepsilon_{MC,I} = \partial \ln MC/\partial \ln I$. In reverse—and equivalently, due to Young's theorem—the effects on Z_I and Z_G from changes in p_n and Y are measured as $\varepsilon_{ZI,pn} = \partial \ln Z_I/\partial \ln p_n$ and $\varepsilon_{ZI,Y} = \partial \ln Z_I/\partial \ln Y$. Similarly, the elasticities of I, G, and K changes on their respective shadow values, such as $\varepsilon_{ZI,G} = \partial \ln Z_I/\partial \ln G$ or $\varepsilon_{ZK,I} = \partial \ln Z_K/\partial \ln I$, reflect complementarity or substitutability among these public and private productive factors.

We use such measures to explore how intra- and inter-state public infrastructure investment affect capital investment, production and nonproduction labor employment, and intermediate materials use, which has important implications for productivity and growth. For example, growth theory suggests that the relation of I to K (and in our scenario also of G to K) is important for determining whether ongoing growth may stem from public infrastructure investment (Batina, 2001). If increasing intra- and inter-state infrastructure expenditures stimulate private capital investment ($\varepsilon_{ZK,I}$ and $\varepsilon_{ZK,I}$ are positive), then public expenditure provides a stronger growth mechanism than if they act as substitutes. The relationships among the private inputs and public capital also have implications about input-specific productivity. For example, it has been hypothesized that labor productivity rises with greater public infrastructure investment (Pereira, 2001). In our framework this means $\varepsilon_{LN,I}$ and $\varepsilon_{LP,I}$ are negative (and similarly for G), because labor use must fall for a given output level to increase its productivity; L^N and L^P must be substitutable with I.

Finally, recall that these measures directly reflect short-run cost responses at existing output levels. A short-run perspective on the evaluation of infrastructure benefits was in fact supported by Berndt and Hansson (1992), Shah (1992), and Morrison and Schwartz (1996a,b), but Nadiri and Mamuneas (1994) suggested that accommodating utilization changes may be important for appropriate analysis of public infrastructure benefits. It is thus useful to assess whether K adjustment from its short-run fixed level substantively affects input demands and thus costs. Similarly, to increase the comparability of our measures with their primal counterparts, it is informative to infer Y changes from infrastructure investment rather than just focusing on costs at given output levels.

To pursue this, first note that we have presented all our elasticity expressions in terms of short-run restricted costs. To facilitate making the K and Y adjustments, we can instead characterize the elasticities in terms of total costs by computing, for example, $\varepsilon_{TC,I} = \partial \ln TC/\partial \ln I = (\partial R/\partial I)I/TC$, or $\varepsilon_{TC,I} = \varepsilon_{RC,I} \cdot (RC/TC)$ [where $TC = RC + p_K K$, from equation (1)].

Further, if capital fixities preclude immediate adjustment to equilibrium K levels, the shadow value of capital (in absolute value), $-Z_K$, will deviate from its market price p_K. This deviation represents the cost effect of subequilibrium,

averages over several years for the weights, the weights and the explanatory variables are orthogonal to each other. Thus for our weights, which do not vary over time, the residuals and the independent variables are not correlated.

[12] We initially estimated the system using only the 1996 shipments data to construct the weights, and found that $\varepsilon_{RC,G}$ was negative and significant (but, due to concerns about endogeneity of the weights, we chose to use the econometrically preferable average weights).

[13] An alternative assumption about the weights, where all neighbors of a particular state received equal weight, was tried in preliminary investigation. This assumption did not affect the model results substantively, except that the shadow value of G was significant. Such a simple weighting specification does not seem, however, to fully reflect the nature of the spatial interactions that we are attempting to capture, so we chose not to present the results of this alternative weighting specification.

[14] Note that K may be thought of as a shift factor similar to the external factors in the vector $\mathbf{r}$, because K changes toward the long run involve shifts in the short-run cost curves along the long-run cost-curve envelope.

or the extent of capital utilization, and the direction of K adjustment to its long-run level. As shown in Berndt and Hansson (1992) and Morrison (1985), imputing cost effects net of capacity utilization fluctuations involves defining shadow costs, $TC^* = R(\cdot) - Z_K K$, to construct the cost-side capacity utilization (CU) ratio TC^*/TC.[15] The reciprocal of the CU then becomes a multiplicative adjustment factor to represent full utilization cost elasticities, such as $\varepsilon_{TC^*,I} = \varepsilon_{TC,I} \cdot (TC/TC^*)$.

Finally, accommodating scale economies recognizes the output growth stimulus of lower costs. Such an adaptation follows Ohta (1975), who showed that a primal measure of technical progress, defined as $\varepsilon_{Y,t} = \partial \ln Y/\partial t$ for the production function $Y(\mathbf{V}, \mathbf{x}, t)$, may be inferred from the dual as a combination of the cost-based technical change measure $\varepsilon_{TC,t} = \partial \ln TC/\partial t$ and the scale economy measure $\varepsilon_{TC,Y} = \partial \ln TC/\partial \ln Y$: $\varepsilon_{Y,t} = -\varepsilon_{TC,t}/\varepsilon_{TC,Y}$.[16] Equivalent adaptations may be made for the I and G cost elasticities through multiplication by $AC/MC = 1/\varepsilon_{TC,Y}$, or, representing long-run (full utilization) scale economies as $\varepsilon_{TC^*,Y} = \varepsilon_{TC,Y} \cdot (TC/TC^*)$, by AC^*/MC (where $AC^* = TC^*/Y$).

III. Empirical Implementation and Results

We estimated our model using a two-step maximum likelihood (ML) procedure, by generalizing the approach of Upton and Fingleton (1985). We first obtained a set of fitted residuals from seemingly unrelated regression (SUR) estimation of the equations (2a) and (3a), using ML methods. After confirming their statistical significance, we incorporated these estimates into our equation system (4) and estimated the remaining parameters by seemingly unrelated regression (SUR) techniques.[17] This approach provides us with ML estimates for all of the parameters in the system.

To check for robustness of these ML estimates we also estimated our model using spatial autocorrelation parameters obtained from a generalized moments approach for systems of equations that was developed, and shown to be consistent, by Kelejian and Prucha (2004).[18] The signs and significance of the elasticity estimates obtained from this approach were not substantively different from the ML estimates. This similarity of results supports the accepted view in the spatial econometrics literature that ML estimates are consistent for this type of model.[19] Thus, we have chosen, following the suggestion of an anonymous referee, to present our results based on the ML estimates.

To test for the potential endogeneity of I and G we initially used instrumental variables (IV) techniques to conduct a Hausman (1978) specification test.[20] We found we could not reject the null hypothesis of I and G exogeneity, consistent with our a priori conjectures that manufacturing-sector activity is unlikely to drive policy decisions across states (or even within a state), due to the small share of manufacturing production in states' overall GSP. Also, to recognize potential heteroskedasticity we computed the standard errors in a robust White form, but this had a negligible effect, so we maintained the usual standard-error computations.

Parameter estimates for our final empirical specification, presented in appendix table A1 (without the dummy variables, to keep the presentation manageable), document the statistical significance of most parameters of this complex model. The R^2's for all equations are nearly 1.0, and all of the spatial and temporal autocorrelation parameter estimates are highly significant.

To evaluate the importance of including neighboring states' infrastructure in the model, we performed joint significance tests for the infrastructure parameters by conducting likelihood ratio tests, and rejected the null hypothesis that the G parameters were jointly zero. We also rejected the null hypotheses that the I parameters, or the I and G parameters together, were jointly zero.[21]

The primary public and private capital shadow values and elasticities computed from our parameter estimates are presented in table 1, both on average over the entire sample, and divided into the two decades covered by our data to identify time trends. The corresponding standard errors for these and additional cost and input elasticities over the whole sample, computed by using the delta method to

[15] Thus, if $p_K < -Z_K$, so $TC/TC^* < 1$, then there are incentives for K investment, and movement toward the long run causes marginal costs to fall; it reduces the overutilization of capital. See Morrison (1985) for further discussion of the construction and use of this measure.

[16] For an extensive discussion of this and other manipulations of the cost compared with primal-based measures, and short- compared with long-run measures, see Paul (1999).

[17] This procedure was suggested by Clint Cummins at TSP International.

[18] Kelejian and Prucha (2004) prove that the spatial autocorrelation parameter estimates obtained from the generalized moments technique are consistent. Although they do not incorporate serial (temporal) autocorrelation, it is possible (but beyond the scope of the present paper) to extend their results to hold in a model such as ours.

[19] See Kelejian and Prucha (1999) for a discussion of the conditions required for consistency of the ML estimator for a spatial model, and references to the literature.

[20] An anonymous referee noted that there may be difficulties with using IV techniques after a spatial Cochrane-Orcutt transformation. Thus, we imposed the assumption on our model that all of the ρ parameters were equal to 0, and conducted a Hausman (1978) test for the null hypothesis that $I_{i,t}$ and $G_{i,t}$ are exogenous (H_0), versus endogenous (H_1), assuming all other arguments of the function and $p^N_{L,i,t-1}$, $p^P_{L,i,t-1}$, $p_{M,i,t-1}$ are exogenous. One-period-lagged input prices were used as instruments for $I_{i,t}$ and $G_{i,t}$, and contemporaneous output levels, input prices, and private capital stocks were instruments for themselves. We found for our base model, for which the number of parameters $k = 176$, that the test statistic was equal to 203.05, and $\chi^2_{176,0.95} = 207.95$. So we could not reject the null hypothesis of $I_{i,t}$ and $G_{i,t}$ exogeneity.

[21] For the full model, $\ln L = -19{,}067.6$. For the model where all I parameters are jointly set equal to 0 (involving eight restrictions), $\ln L = -19{,}146.1$. For the model where all G parameters are jointly set equal to 0 (involving eight restrictions), $\ln L = -19{,}132.5$. For the model where all I and all G parameters are jointly set equal to 0 (involving a total of fifteen restrictions), $\ln L = -19{,}242.4$.

TABLE 1.—PUBLIC AND PRIVATE CAPITAL SHADOW VALUES AND ELASTICITIES, AND ADJUSTMENTS

	Entire Sample	1980s	1990s
Z_I	−0.387	−0.311	−0.463
Z_G	−0.024	−0.002	−0.046
Z_K	−0.252	−0.285	−0.218
$\varepsilon_{RC,I}$	−0.230	−0.202	−0.259
$\varepsilon_{RC,G}$	−0.011	−0.001	−0.021
$\varepsilon_{RC,K}$	−0.122	−0.145	−0.100
RC/TC	0.892	0.886	0.897
TC/TC^*	1.001	0.987	1.015
AC^*/MC	1.603	1.676	1.531

TABLE 2.—COST ELASTICITIES AND INPUT-SPECIFIC G, I ELASTICITIES, ENTIRE SAMPLE (AVERAGED DATA)

	Mean	Std. Error		Mean	Std. Error
$\varepsilon_{RC,G}$	−0.011	0.011	$\varepsilon_{ZI,G}$	0.191	0.070
$\varepsilon_{RC,I}$	−0.230	0.031	$\varepsilon_{ZK,G}$	−0.023	0.055
$\varepsilon_{RC,K}$	−0.122	0.030	$\varepsilon_{ZK,I}$	−0.048	0.128
$\varepsilon_{RC,pLP}$	0.133	0.002	$\varepsilon_{M,G}$	0.013	0.011
$\varepsilon_{RC,pLN}$	0.114	0.002	$\varepsilon_{M,I}$	−0.274	0.031
$\varepsilon_{RC,pM}$	0.752	0.005	$\varepsilon_{LN,G}$	−0.064	0.023
$\varepsilon_{RC,Y}$	0.710	0.014	$\varepsilon_{LN,I}$	−0.491	0.073
			$\varepsilon_{LP,G}$	−0.128	0.020
			$\varepsilon_{LP,I}$	0.171	0.065
			$\varepsilon_{MC,G}$	−0.00004	0.0003
			$\varepsilon_{MC,I}$	−0.00884	0.0129

evaluate the measures for the averaged data,[22] are reported in table 2.

The intrastate infrastructure benefit measure, $Z_I(\varepsilon_{RC,I})$, is broadly consistent in magnitude with results in much of the literature, and is statistically significant; these findings were robust across alternative specifications tried in preliminary empirical analysis. Our results thus support the notion, which the recent literature on the public capital hypothesis has drifted toward, that infrastructure effects are evident and significant but smaller than suggested by the original literature.

The results for G are less definitive. The sign of Z_G and thus $\varepsilon_{RC,G}$, a larger (in absolute value) $\varepsilon_{RC,I}$ estimate when G is included in the model (approximately −0.23 as opposed to −0.12), and the joint significance of the G parameters, imply that spatial spillovers confer complementary interstate infrastructure benefits that enhance intrastate benefits, although the $\varepsilon_{RC,G}$ estimate is not statistically significant. Note, however, that the standard error measure for $\varepsilon_{RC,G}$, computed at the mean values of the data, may underestimate its significance, as data variations are smoothed in the averaging process. $\varepsilon_{RC,G}$ also appears both larger (−0.03) and significant if weights from the end of the sample (1996) rather than an average are used to construct the G index, or if the AR(1) adjustment is omitted, possibly suggesting a time trend toward stronger G effects. And, as pointed out by an anonymous referee, some of the cost effects of spatial infrastructure spillovers may be muted empirically if the effects of public capital investment are captured in part by relative input price differences. Finally, the positive second-order elasticity $\varepsilon_{ZI,G}$, presented in table 2, supports the notion that I and G are complementary: infrastructure investment in neighboring states raises the value of intrastate public capital investment.

If G and the SAR [and AR(1)] adjustments are left out of the model, as in most of this literature, the shadow value of public infrastructure investment is approximately $Z_I = -0.3$. This is very similar to the estimate reported by Morrison and Schwartz (1996a,b), which is also based on a cost-function model but for an earlier time period and using a somewhat different functional form and data. This Z_I estimate corresponds to an $\varepsilon_{RC,I}$ elasticity of −0.15, which is also comparable to those found in other dual studies; Sturm et al. (1998) show that cost or profit models typically generate elasticities approximately half the size of Aschauer's (1989) estimate of 0.39. Further, although (the absolute value of) $\varepsilon_{RC,I}$ is not directly comparable to the production function elasticities from much of the existing literature, it is remarkably similar to Munnell's (1990) estimate, 0.15.

When our spatial (and temporal) adaptations are made, as in the table 1 estimates, the estimate of Z_I is closer to −0.4, and that of $\varepsilon_{RC,I}$ rises (in absolute value) to −0.23. If the I and G effects are combined, the total cost effect is −0.24. Our refinements thus increase the total measured infrastructure effect by more than 50% from the base case $\varepsilon_{RC,I} = -0.15$, although it remains in the vicinity of half the Aschauer estimate. Note also that the estimated shadow value of I, $Z_I = -0.39$, is greater (in absolute value) than that for K, $Z_K = -0.25$, consistent with Aschauer's (1989) original results.

The elasticity estimates for the 1980s and 1990s indicate strong upward time trends in $\varepsilon_{RC,I}$ and (especially) $\varepsilon_{RC,G}$. This tendency supports Aschauer's (2001) finding of an increase in public-infrastructure benefits from the 1970s to the 1980s, although the difference into the 1990s is even more striking. The $\varepsilon_{RC,G}$ patterns are also supportive of the suggestion that spillover effects are rising over time.[23]

Adjusting these elasticities to reflect the effects of I and G on total costs, by multiplying by the ratio RC/TC presented in table 1, makes them approximately 10% smaller. Further adjustment to accommodate utilization changes means multiplying by TC/TC^*, which is insignificantly different from 1. Thus, utilization variations do not seem important for the measurement and interpretation of intrastate public-infrastructure benefits for these data.[24] In turn, the ratio AC^*/MC implies significant (long-run) increasing

[22] This was done using the ANALYZ command in TSP, which applies the delta method by linearizing the elasticity functions around the estimated parameter values, and then using standard formulas for the variances and covariances of linear functions of random variables.

[23] If the stochastic adaptations are not made, particularly the AR(1) adaptation, then $\varepsilon_{RC,G}$ also appears much larger and more significant.

[24] This is consistent with the results of Nadiri and Mamuneas (1994). These estimates in fact suggest that manufacturing capital stocks are close to their long-run equilibrium levels on average, and vary little over time. This may be due to the largely cross-section rather than time series nature of the data, which might be expected to better represent the long run.

returns to scale, as often found in the public-infrastructure literature (Sturm et al., 1998). Thus, cost decreases from I or G investment that take growth into account, imputed by multiplying $\varepsilon_{RC,I}$ or $\varepsilon_{RC,G}$ by this ratio, are substantially greater (by a factor of approximately 1.6) than directly suggested by the cost elasticities. This is consistent with the higher primal than dual infrastructure benefit measures found in the literature (Sturm et al., 1998).

In sum, we find strongly significant cost effects of intrastate infrastructure investment, particularly in combination with the spatial linkages captured by the interstate G effects. These results differ from studies such as those of Holtz-Eakin (1994) and Hulten and Schwab (1991), who find little effect of own-state infrastructure investment when state differences and temporal dependence are accommodated. They also differ from the few studies that address interstate spillover issues, such as those of Holtz-Eakin and Schwartz (1995) and Boarnet (1998), where virtually no spillover effect was uncovered (and what was found appeared negative). Holtz-Eakin and Schwartz, however, estimated a production-function-based model in long-differenced form, which may oversmooth the patterns we are attempting to identify. And Boarnet interprets his results in terms of spatial mobility and the loss of productive factors to regions with higher infrastructure levels, which is more likely to be relevant for counties (as in his study) than for states.

In addition to the overall cost effects of I and G investment, it is illuminating to consider the input-specific effects. Insights into these patterns may be drawn from the output- and input-specific elasticities presented in table 2. The first-order input and output cost elasticities capture variable input cost shares $\varepsilon_{RC,pn}$ (with the M share on average above 75%) and scale economies $\varepsilon_{RC,Y}$ (increasing returns to scale are again implied by $\varepsilon_{RC,Y} < 1$). The second-order elasticities representing private input and output infrastructure effects reveal that K, M, and L^N are substitutable, and L^P complementary, with I. Intrastate public infrastructure investment also seems to have virtually no direct effect on marginal costs; $\varepsilon_{MC,I} < 0$, but it is small and statistically insignificant.

The estimated short-run substitutability of I with K is consistent with Morrison and Schwartz (1996b), who also found, however, that this tendency was "dampened by a long run tendency to move together." Such a broadly complementary long-term relationship has often been found in models that assume instantaneous adjustment of private capital stocks, such as Conrad and Seitz (1992), Deno (1988), and Lynde and Richmond (1992). Also, although I-K substitutability suggests that public capital investment depresses rather than stimulates private capital investment at existing output levels, output growth motivated by the cost-reducing impact of I increases could well counteract this effect, particularly in that output expansion tends to be capital-using (Morrison & Schwartz, 1996b).

The complementarity of L^P and I also deviates somewhat from the relationship usually found in the literature (although the magnitude of the average estimated effect is driven by large positive elasticities for states with very small L^P). These labor demand patterns imply indirect effects in the form of input productivity, as suggested by Pereira (2001). In particular, I-L^P complementarity suggests that L^P demand increases with I investment, but for given output levels this implies a reduction in (average) production-labor productivity, Y/L^P. Also, although I is substitutable with both L^N and M, the primary driving factor for reduced costs from I investment is materials savings, likely associated with transportation costs.

The G effects are somewhat different than those for I; although K and L^N still appear substitutable, L^P is also substitutable, and M (slightly) complementary, with G. Thus, higher G is associated with lower overall employment, perhaps due to a reduced labor force, consistent with Boarnet's (1998) suggestion that increased infrastructure in neighboring states may cause leaching of productive factors.

Finally, spatial variations in the (average) cost and input-specific elasticities by region, reported in table 3, indicate that intrastate public infrastructure investment effects are highest in the west;[25] $\varepsilon_{RC,I}$ is largest (in absolute value) in the Mountain and West North Central states, with the Pacific and West South Central states following. The smallest values are found in the east and south. This distinction does not correspond well to the usual division into the snowbelt and sunbelt states in the public-infrastructure literature, although many of the south central states might be thought of as the primary sunbelt states in terms of manufacturing activity. Thus these measures to a limited extent support the findings of Hulten and Schwab (1991) and Aschauer (2001) of a higher public-infrastructure effect in the snowbelt than in the sunbelt.

The regional implications are quite different for the spillover effect from G. In particular, some of the lowest (in absolute value) $\varepsilon_{RC,G}$ values are found in the Pacific region, for which the average is in fact very slightly positive. This could suggest that for a state such as California, which is both large and densely populated, interstate is not nearly as important as intrastate infrastructure investment. Some of the greatest effects again appear in the Mountain and West North Central regions, which tend to be sparsely populated; the full network of highway infrastructure in these areas

[25] The regional breakdowns are: Pacific (Washington, Oregon, California), Mountain (Arizona, Colorado, Idaho, Montana, New Mexico, Nevada, Utah, Wyoming), West North Central (Minnesota, Iowa, Missouri, North Dakota, South Dakota, Nebraska, Kansas), East North Central (Illinois, Indiana, Michigan, Ohio, Wisconsin), New England (Connecticut, Massachusetts, Maine, New Hampshire, Rhode Island, Vermont), Mid Atlantic (New York, New Jersey, Pennsylvania), South Atlantic (Delaware, Maryland, Virginia, West Virginia, North Carolina, South Carolina, Georgia, Florida), East South Central (Kentucky, Tennessee, Alabama, Mississippi), and West South Central (Arkansas, Louisiana, Oklahoma, Texas).

TABLE 3.—ELASTICITIES BY REGION

	Pacific	Mountain	West N. Central	East N. Central	New England	Mid Atlantic	South Atlantic	East S. Central	West S. Central
$\varepsilon_{RC,I}$	−0.217	−0.476	−0.292	−0.084	−0.159	−0.176	−0.139	−0.144	−0.190
$\varepsilon_{RC,G}$	0.021	−0.029	−0.019	0.0002	−0.008	−0.020	−0.008	−0.001	−0.011
$\varepsilon_{RC,K}$	−0.070	−0.121	−0.088	−0.149	−0.155	−0.105	−0.134	−0.113	−0.138
$\varepsilon_{RC,Y}$	0.705	0.693	0.696	0.711	0.697	0.746	0.725	0.677	0.748
$\varepsilon_{RC,t}$	−0.004	0.002	−0.002	−0.002	0.005	−0.004	−0.002	−0.002	−0.002
$\varepsilon_{RC,pLN}$	0.130	0.108	0.088	0.112	0.169	0.175	0.075	0.070	0.117
$\varepsilon_{RC,pLP}$	0.130	0.123	0.108	0.146	0.173	0.141	0.139	0.102	0.136
$\varepsilon_{RC,pM}$	0.741	0.764	0.809	0.743	0.651	0.683	0.791	0.831	0.745
$\varepsilon_{ZK,I}$	2.342	−0.185	−0.294	−0.478	−0.146	1.761	−0.301	−0.837	−0.409
$\varepsilon_{MC,I}$	−0.017	−0.004	−0.006	−0.014	−0.003	−0.021	−0.007	−0.012	−0.008
$\varepsilon_{LN,I}$	−0.342	−1.266	−0.704	−0.119	−0.177	−0.192	−0.329	−0.399	−0.295
$\varepsilon_{LP,I}$	−0.063	0.431	0.262	0.082	0.101	0.044	0.109	0.136	0.124
$\varepsilon_{M,I}$	−0.221	−0.556	−0.326	−0.112	−0.227	−0.219	−0.165	−0.158	−0.234
$\varepsilon_{ZI,G}$	0.413	0.084	0.118	0.365	0.080	0.364	0.149	0.306	0.149
$\varepsilon_{ZK,G}$	1.432	−0.088	−0.112	−0.202	−0.065	0.286	−0.114	−0.487	−0.122
$\varepsilon_{MC,G}$	−0.0002	−0.00002	−0.00002	−0.0001	−0.00002	−0.0001	−0.00003	−0.0001	−0.00003
$\varepsilon_{LN,G}$	0.008	−0.168	−0.101	−0.008	−0.027	−0.044	−0.055	−0.040	−0.041
$\varepsilon_{LP,G}$	−0.062	−0.280	−0.175	−0.046	−0.070	−0.118	−0.078	−0.102	−0.094
$\varepsilon_{M,G}$	0.034	0.020	0.009	0.010	0.012	0.006	0.009	0.013	0.008

seems to confer important productive contributions on manufacturing firms in such states.

IV. Concluding Remarks

In this paper we have reevaluated the public capital hypothesis for the U.S. manufacturing sector, for 1982–1996, in a cost-based framework with explicit recognition of inter- as well as intra-state public-infrastructure effects. We use two types of adaptations to incorporate interstate spatial spillovers into the analysis—allowing for spatial (in addition to temporal) autocorrelation in the stochastic structure, and including a spatial spillover index in the theoretical framework.

We find significant beneficial productive effects of intrastate public-infrastructure investment, which seem to be increasing over time, and which are augmented and enhanced by interstate cost effects. That is, spatial spillovers both indirectly and directly complement the cost-saving effects of within-state public infrastructure investment. Infrastructure investment in neighboring states raises the value of own-state public capital investment, as well as directly affecting manufacturing firms' costs.

Most of this value stem from materials cost savings, likely associated with transportation costs, although overall public-infrastructure–private-input substitution prevails. Regional variations are also evident, primarily between the east and west. The largest intrastate infrastructure effects appear in the west, and the smallest in the east and south, whereas the Pacific states benefit the least from neighboring states' infrastructure.

Adaptations of these infrastructure benefit measures to reflect capacity utilization variations have a negligible influence on the estimated cost effects. However, accommodating scale economies to make the measures more comparable to primal measures increases their estimated magnitudes toward those found in production-oriented models. This suggests that output growth motivated by the cost-depressing effect of infrastructure investment may stimulate capital investment and labor employment, even though overall short-run public-infrastructure–private-input substitutability is evident at existing output levels.

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DATA APPENDIX

Labor quantities: The number of workers engaged in production (L^P) at operating manufacturing establishments, and the number of full-time and part-time employees (*TOTAL*) on the payrolls of these manufacturing establishments, are from the U.S. Census Bureau's *Annual Survey of Manufactures* (ASM), *Geographic Area Statistics*. The number of nonproduction workers (L^N) is obtained as the difference between *TOTAL* and L^P.

Wage bills: The ASM reports wages paid to production workers and gross earnings of all employees on the payroll of operating manufacturing establishments. The wage bill for L^N is obtained by subtracting the wages paid to L^P from the gross earnings of all employees. The nonproduction wage is obtained by dividing the nonproduction wage bill by L^N. The production wage is obtained by dividing the production wage bill by L^P.

Public capital stock: Following Eberts, Park, and Dalenberg (1986), the perpetual inventory technique was applied to state-level data on public infrastructure investment to generate highway capital stock estimates. Discards were assumed to follow a truncated normal distribution, with the truncation occurring at one-half the average life and one and one-half times the average life. The Federal Highway Administration's composite price index was used to deflate the capital and maintenance outlay series.

Private capital stock: The perpetual inventory method was applied to data on state-level new capital expenditures from the ASM, with the initial capital stock (1982) values taken from Morrison and Schwartz (1996b). Depreciation rates for capital equipment are from the Bureau of Labor Statistics, Office of Productivity and Technology. The investment deflator was obtained from the Bureau of Labor Statistics and is its input price deflator for total manufacturing (SIC 20–39) capital services. The price of capital is obtained as $(i_t + d_t) \cdot q_{K,t}[1/(1 - taxrate_t)]$, where d_t is the depreciation rate, i_t is the Moody's Baa corporate bond rate (obtained from the Economic Report of the President), $q_{K,t}$ is the investment deflator, and $taxrate_t$ is the corporate tax rate (obtained from the Office of Multifactor Productivity, Bureau of Labor Statistics).

Materials: The ASM reports direct charges actually paid or payable for items consumed or put into production during the year. The quantity of materials (M) is obtained by deflating these charges by the ratio of nominal gross domestic product to real gross domestic product as reported on the Bureau of Economic Analysis Web site. This deflator is also used as the price of materials.

Output: Values of state-level shipments reported in the ASM were deflated by manufacturing gross state product deflators for each state (provided by DRI).

Spatial weights: Data on the value of goods shipped from state of origin to state of destination are from the 1997 and 1993 Commodity Flows Surveys, U.S. Bureau of Transportation Statistics. Data on the value of goods shipped from state of origin to state of destination for 1977 are imputed from data on state-to-state tonnage shipped from the Census Bureau's 1977 Census of Transportation Commodity Transportation Survey, Geographic Area Series. These values were imputed for each state by multiplying the state's 1992 value of shipment numbers by the ratio of its 1977 tonnage to its 1992 tonnage.

TABLE A1.—PARAMETER ESTIMATES, STANDARD ERRORS, t-STATISTICS, AND R^2'S

Parameter	Estimate	Std. Error	t-Stat.
α_{LNLP}	−9.85E+01	3.34E+02	−0.29
α_{LNM}	2.77E+03	7.17E+02	3.87
α_{LPM}	2.79E+03	6.22E+02	4.48
δ_{LNY}	4.10E−02	4.30E−03	9.52
δ_{LPY}	6.40E−02	3.98E−03	16.05
δ_{MY}	4.98E−01	9.76E−03	51.05
δ_{LNt}	3.54E+01	1.46E+01	2.42
δ_{LPt}	1.95E+01	1.44E+01	1.35
δ_{Mt}	3.07E+01	4.86E+01	0.63
δ_{LNI}	−4.06E−02	4.21E−02	−0.96
δ_{LPI}	8.48E−02	3.88E−02	2.18
δ_{MI}	−3.61E−01	7.87E−02	−4.58
δ_{LNG}	5.92E−03	9.90E−03	0.60
δ_{LPG}	−1.69E−02	8.97E−03	−1.88
δ_{MG}	4.21E−02	2.26E−02	1.87
δ_{LNK}	5.38E−02	2.63E−02	2.04
δ_{LPK}	−1.30E−01	2.27E−02	−5.74
δ_{MK}	−4.16E−01	6.88E−02	−6.05
δ_{YY}	1.72E−07	2.67E−08	6.45
δ_{II}	−6.98E−07	6.56E−07	−1.06
δ_{KK}	3.14E−07	3.17E−07	0.99
δ_{GG}	1.89E−07	4.27E−08	4.42
δ_{YG}	−4.27E−10	3.49E−09	−0.12
δ_{YK}	−9.18E−07	1.37E−07	−6.68
δ_{GK}	9.24E−07	1.91E−07	4.83
δ_{YI}	−1.10E−07	1.61E−07	−0.69
δ_{GI}	−1.73E−06	4.02E−07	−4.30
δ_{KI}	2.39E−06	6.83E−07	3.49

Parameter	Estimate	Std. Error	t-Stat.
δ_{Yt}	−1.67E−03	2.96E−04	−5.66
δ_{Gt}	−2.12E−03	6.69E−04	−3.18
δ_{It}	−3.83E−03	1.63E−03	−2.34
δ_{Kt}	6.51E−03	1.05E−03	6.21
ρ_s	1.92E−01	4.51E−02	4.25
ρ_θ	7.40E−01	1.36E−02	54.43
$\rho_{s,LN}$	1.52E−01	4.61E−02	3.29
$\rho_{\theta,LN}$	6.65E−01	1.64E−02	40.55
$\rho_{s,LP}$	3.55E−01	4.06E−02	8.76
$\rho_{\theta,LP}$	8.03E−01	1.29E−02	62.28
$\rho_{s,M}$	2.03E−01	4.52E−02	4.49
$\rho_{\theta,M}$	7.14E−01	1.30E−02	55.08

Number of observations: 672

Equation	R^2
RC	0.9993
L^N	0.9989
L^P	0.9994
M	0.9988