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by

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ABSTRACT

The size and significance of public infrastructure investment impacts on costs and productivity of private enterprise, and thus on economic health and growth, has proven nebulous to empirically substantiate. Various studies using alternative theoretical and econometric methodologies, and for different time periods, sectors, and countries, have tentatively established that such a productive impact exists and is statistically significant. It also seems smaller and more variable over time, space, and sector than was implied by initial studies on the "public capital hypothesis". One piece of the puzzle that has received little attention, however, is the role of spatial spillovers in driving infrastructure investment benefits. Such spillovers are not only conceptually important, but could also shed light on discrepancies between studies for different data, and particularly aggregation levels. In this study we apply a cost-based model to state-level U.S. manufacturing data, for capital, production and non-production labor, and materials inputs, and for the 1982-96 time period, in an attempt to untangle the private cost-saving contributions of inter- and intra-state public infrastructure investment. We carry out two kinds of spatial adaptations – a spatial autocorrelation adjustment and a spatial spillover theoretical modification – to the estimating system consisting of a Generalized Leontief cost function and input demand equations, to address this issue. We find that intra-state public infrastructure benefits appear larger in magnitude when inter-state spillovers are directly recognized, as well as being invariably statistically significant. Inter-state spillovers are also directly beneficial to manufacturing firms, although their contribution appears smaller in size when temporal serial correlation is recognized in addition to spatial correlation.

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Introduction

The size and significance of public infrastructure investment's impact on the economic performance of the private sector has been hotly debated at least since Aschauer's (1989) work in this area. Such early studies on the linkage between public infrastructure and growth identified a close correlation between reductions in investment levels (and thus stocks) for public capital in the early 1970's, and declining productivity of many developed countries. Most of the econometric investigations in the resulting literature on the "public capital hypothesis" have been aimed at quantitatively establishing the private impact of public capital investment on productivity and costs.

Summaries of the literature by Gramlich (1994), Sturm and De Haan (1995) and Sturm et al. (1998) suggest that many authors have found this productivity impact to be quite high. Aschauer's estimates suggested that public investment had a greater return to private sector economic performance than did private capital investment (Reich, 1991), while Deno (1988) estimated the impact to be even greater than that reported by Aschauer. Such findings suggested that policy inducements to augment public infrastructure capital would dramatically enhance U.S. productivity and competitiveness, implying in turn that policy measures should be taken to increase public infrastructure investment.

Subsequent studies in the literature on private benefits from public capital investment raised serious questions about the robustness of the results on which this story was based.[1] In particular, refinements to the econometric structure used (such as incorporation of state- and time-fixed effects) seemed to cause the important infrastructure impact on productivity and growth to virtually disappear (Holtz-Eakin, 1994, Hulten and Schwab, 1991, Garcia-Mila and McGuire, 1992).

Authors also began to relax restrictive assumptions in the theoretical framework by recognizing behavioral responses, and extending the representation of the technological base by allowing for various scale and homogeneity properties, and dynamics (Conrad and Seitz, 1994, Morrison and Schwartz, 1996 and Shah, 1992). Such dual cost-based formulations, by including interaction terms and thus input-substitution and scale economy responses to public capital investment, allowed consideration of infrastructure-to-capital and infrastructure-to-output relationships that are crucial for evaluating the potential for public capital investment to stimulate growth (Morrison and Schwartz, 1996b, Batina, 2001). These modifications to the underlying theoretical structure also tended to generate smaller but still statistically significant estimates of infrastructure impacts.

Further, questions were raised about aggregation, since the original studies in this literature were based on macro data. Many found that estimating the returns to a particular sector generated more plausible and interpretable results than taking a national perspective. In particular, much of the second wave of this literature (such as Hulten and Schwab, 1991, Shah, 1992, Nadiri and Manuneas, 1994, and Morrison and Schwartz, 1996a,b) focused on estimating returns to the manufacturing sector from public infrastructure investment, and Paul et al. (2001) analyzed infrastructure impacts for the agricultural sector. Others, such as Sturm (2001), who distinguished "sheltered" from "non-sheltered" sectors (where the latter includes both manufacturing and agriculture), compared returns for different sectors.[2]

Spatial disaggregation also reaped benefits in terms of interpretation, but reduced the estimated private sector benefits from public infrastructure investment. For example, studies that estimated state-specific impacts (such as Munnell, 1990, and Morrison and Schwartz, 1996a,b) obtained more justifiable estimates, in terms of magnitude, than those using aggregate national data, and yet most remained statistically significant. The size and significance also was found to differ regionally (Hulten and Schwab, 1991, Morrison and Schwartz, 1996a, Aschauer, 2001) as well as over time (Aschauer, 2001).

Other issues were also targeted, that seemed to be convoluting the interpretation of existing measures of public capital benefits, thus making consensus about their impacts elusive. In particular, the extent and direction of externalities associated with spillovers from infrastructure investment in geographically linked areas was questioned, in part because such externalities might be internalized at higher levels of aggregation.[3] Questions about the impact of temporal dependence, or serial correlation, on estimated infrastructure impacts were advanced. And queries about exogeneity versus endogeneity were raised, that cast doubt on the definitiveness of estimates especially from primal-based specifications.

In this study we provide a further investigation of the infrastructure question, focusing on the issue of spatial spillovers that seems a crucial component of the puzzle, and yet has received little attention in the literature. We use a recent and refined state-level data set for U.S. manufacturing, and a cost-based specification representing demand for two types of labor as well as capital and material inputs, to accommodate many questions raised in the literature in a consistent and comprehensive fashion. In particular, however, we recognize and measure the impacts of spatial spillovers across states to distinguish both intra- and inter-state impacts of public infrastructure investment, and their potential inter-dependency. We adapt both the stochastic structure (through spatial econometrics procedures) and the cost-based model (via a spatial externality or activity index) to recognize and measure the extent and significance of such spillovers. Their estimated impacts take the form of direct cost effects, as well as input-specific (substitution) consequences, which permits analysis of a broad range of potential cost structure impacts.

Our data set and theoretical framework limits the relevance of endogeneity issues, due to the sectoral estimation (manufacturing is a relatively small part of Gross State Product in most states) and the use of a cost-based model (where costs for observed levels of both output and infrastructure stocks are represented). We also, however, assess whether dealing with potential endogeneity more directly through the stochastic structure affects our results. We allow for temporal as well as spatial dependency, by including an adaptation for temporal serial correlation (AR1). We address issues about static as contrasted to dynamic behavior by comparing short- to long-run responses. And we evaluate time and regional variations in the public infrastructure impacts.

We find that inter-state public infrastructure capital investment generates a significantly positive contribution to U.S. manufacturing production, which is both enhanced and augmented by cross-state spillovers. Spatial adjustments increase the estimated impacts of within-state infrastructure investment, but significant between-state effects are also evident, so the combined impact becomes even greater. It in fact approaches that found by some for more aggregate data, depending on how the dual and primal measures are compared, possibly suggesting national-level internalization of inter-state impacts.

We also find increasing intra- and inter-state public capital impacts over time, that appear to coincide with a somewhat declining return to private capital investment. The estimated public investment benefits are further enhanced, in terms of implied output growth, by recognizing measured scale economies, although the impact of short run fixity is negligible. And taking potential endogeneity or temporal serial correlation (AR1) into account has little identifiable impact on the results for intra-state public investment, although the AR1 adaptation reduces the (still significant) measured impact of inter-state spillovers. The public infrastructure cost impacts also imply some private capital substitutability, but largely arise from materials substitution.

The Model

To facilitate analysis of the productive effects of public infrastructure benefits derived through cost-savings and thus enhanced competitiveness, our analysis is founded on a cost function specification, applied to state-level manufacturing industry data. A total cost function with some "inputs" associated with external forces is expressed in the general form $TC = VC(Y,\mathbf{p},\mathbf{x},\mathbf{r}) + \Sigma_k p_k x_k$, based on the restricted cost function $VC(\cdot)$ incorporating constraints from a vector of quasi-fixed inputs, **x**. The other arguments of the function are aggregate output, Y, a vector of J variable input prices, **p**, and a vector of exogenous or external factors shifting the production frontier, **r**.

For our purposes, the variable inputs represented in the **p** vector are non-production labor, NL, production labor, PL, and intermediate materials, M, with prices p_{NL}, p_{PL} and p_M. The private capital stock, K, is our only quasi-fixed input. The **r** vector includes the usual technical change (time trend) measure, t. Additional components of **r** stem from the private productive contribution of both public infrastructure in the state under consideration, I, and public infrastructure in geographically connected states, G. The I measure, from Bell and McGuire (1994), was constructed by applying standard perpetual inventory techniques to data on state-level public highway infrastructure investment.[4] And the externality index G was computed as a weighted sum of (relative) infrastructure stock in neighboring states,[5] where the weights are the value of goods shipped to each neighboring state, as a share of the value of goods shipped to all neighboring states.[6]

Including I in the cost function is analogous to the treatment in Morrison and Schwartz (1996a,b), and other cost-oriented studies such as Conrad and Seitz (1992), Lynde and Richmond (1992), and Nadiri and Mamuneas (1994). The incorporation of G, however, represents the additional spatial spillover impact within the theoretical framework. This spatial spillover adaptation, based on the computation and inclusion of an externality index, is similar to the approach used to represent supply- and demand-driven agglomeration effects by Bartlesman, Caballero and Lyons (1994), and Morrison and Siegel (1999).[7] This theoretical adaptation is distinguished from modifications to the stochastic structure to accommodate spatial linkages, which will also comprise an alternative model for our empirical specification.

One might think that such spillovers would generate positive externalities. For example having a neighboring state with an extensive highway network might provide benefits by facilitating transportation of materials inputs and produced output. However, inter-state spillovers could have no identifiable productive impact, as found by Holtz-Eakin and Schwartz (1995). Or infrastructure investment in a neighboring location may even draw production away, due to enhanced mobility of firms and productive factors, implying a negative externality (as found by Boarnet (1998) for California counties). Although one might think such location preference adaptations would be more likely for geographically close entities such as counties, rather than states, the sign as well as significance of the G effect is ultimately an empirical issue.

In some sense all the factors expressed in levels for this cost function – in the **r** or **x** vectors – can be thought of as generating externalities or spillovers, although the inter-state externalities embodied in G are the most explicit.[8] For G, the spillover is spatial; geographic proximity allows states to benefit from investment decisions on infrastructure, such as highways, in states that are close by. For I, the spillover involves a public good; public activities spill over, or provide externalities to, the private sector. For K, the spillover is temporal; stocks from the previous period affect potential cost minimization in the current period. Even t might be thought of as a "spillover", since the implied disembodied technical change is often characterized as "manna from heaven."

The contributions of these factors to production, and thus to input cost savings for a given amount of output, can be expressed in terms of their shadow values, $Z_G = \partial VC/\partial G$, $Z_I = \partial VC/\partial I$, $Z_K = \partial VC/\partial K$, and $Z_t = \partial VC/\partial t$. Such derivatives reflect the (marginal) cost-diminution impacts of changes in these shift factors, and thus will have negative values.[9] For example, Z_G indicates the extent of inter-state spillovers, in the sense of the cost impact for manufacturing firms in a particular state of a marginal increase in infrastructure investment in neighboring states. Z_I similarly represents the cost savings generated from intra-state infrastructure investment. Z_K is represents the shadow value of the short run quasi-fixed capital stock. And Z_t, usually expressed in the proportional or elasticity form $\varepsilon_{VC,t} = \partial \ln VC/\partial t$, is typically interpreted as cost-based disembodied technical change, or productivity, over time.

The cost or productivity contributions of changes in the levels of G, I, and K may also be expressed in elasticity form, as $\varepsilon_{VC,G} = \partial \ln VC/\partial \ln G = \partial VC/\partial G \cdot G/VC$, $\varepsilon_{VC,I} = \partial \ln VC/\partial \ln I$, and $\varepsilon_{VC,K} = \partial \ln VC/\partial \ln K$, to represent the proportional impact of changes in these factors on costs of production. These measures could alternatively be computed in terms of total costs. For most of these elasticities, since they are "gross" measures in the sense that the associated factor does not have a market price, the only adaptation between the total and variable cost measures is whether VC or TC is in the denominator. However, for K the total cost elasticity becomes $\varepsilon_{TC,K} = \partial \ln TC/\partial \ln K = (Z_K+p_K)\cdot K/TC$, which is a net measure; it reflects the marginal value of K net of its market price, p_K.

These (gross) cost elasticities are closely related (dual) to marginal products, or output elasticities, often computed to measure primal-oriented "returns" to productive factors. In particular, output elasticities such as $\varepsilon_{YI} = \partial \ln Y/\partial \ln I$ may be defined from the production function $Y(\mathbf{V},\mathbf{x},\mathbf{R})$, where $\mathbf{V}$ is the variable input vector corresponding to $\mathbf{p}$. Such measures have often been used in the existing literature to represent public infrastructure effects, and to compare, for example, the returns to private capital, $\varepsilon_{YK} = \partial \ln Y/\partial \ln K$, through evaluation of the $\varepsilon_{VC,I}$ and $\varepsilon_{VC,K}$ elasticities.

The distinction between factors included in the $\mathbf{x}$ (K) and $\mathbf{r}$ (G, I, t) vectors involves whether they are ultimately under control of the firms making production decisions, or are truly external. In the former case an optimality condition is implied, whereas this is not the case if the "input" is exogenous to the production process. In particular, for private capital, in the short run K is fixed and thus one would not expect $Z_K=p_K$, whereas in the long run there will be economic motivation to adjust the capital stock to the point where this equality holds – on the long run cost curve. This allows us to evaluate the current degree of subequilibrium for the K stock level through (positive or negative) deviation of Z_K/p_K from 1, or of $\varepsilon_{TC,K}$ from zero.[10]

By contrast, there is no (private) market price or optimal or equilibrium adjustment process implied for I, G, or t. G and t in particular are best interpreted as purely external forces. One would not think infrastructure investment in one state is determined by production from a particular sector in neighboring states. And time or overall technical developments in the economy certainly plod on without any specific contribution from individual firms, or even sectors within states.[11]

The situation for I is somewhat different. In a social context, one would think that if economic consequences for firms within a state derive from public infrastructure investment, there may be some socially "optimal" level of I that is determined by balancing these benefits, Z_I, by the associated social costs. It is thus a discretionary input in a broad sense. However, since manufacturing is a relatively small sector in most states, and in fact consumers likely benefit even more than firms from highways, only a small portion of these benefits are represented by our Z_I measures. So optimality is not well defined here, even if a social "price" could be computed (Morrison and Schwartz, 1996b). Thus, we will not pursue the question of I "optimality" here, but instead simply present measures of the contribution or value of I for this sector that indicate the size and significance of the gross public infrastructure benefit.[12]

The cost framework allows us not only to evaluate the 1st order or overall cost impacts of variations in productive factors – in particular I and G – but also 2nd order effects, which reflect input substitution and output valuation. That is, the first derivatives of the cost function represent shadow values for the productive factors expressed in levels, Z_I, Z_G, Z_K and Z_t, the marginal cost of output, $MC=\partial VC/\partial Y$, and input demands for the variable inputs (via Shephard's lemma), $v_q=\partial VC/\partial p_q$ (q=NL,PL,M). The MC and v_q measures in proportional or elasticity terms, $\varepsilon_{VC,Y} = \partial\ln VC/\partial\ln Y$ and $\varepsilon_{VC,Pq} = \partial\ln VC/\ln \partial p_q$ reflect (short run) scale economies for output, and cost shares for inputs. Each of these measures will be a function of all arguments of the cost function if the functional form assumed for $VC(\cdot)$ is flexible, or accommodates interactions among all its arguments.

Thus, for example, we can determine not only the overall cost-savings from additional investment in intra- and inter-state public infrastructure, through the shadow values Z_I and Z_G, but also their input-specific contributions through the input demand elasticities $\varepsilon_{vq,I} = \partial\ln v_q/\partial\ln I$ and $\varepsilon_{vq,G} = \partial\ln v_q/\partial\ln G$. We may also impute the associated impacts on marginal (output) cost, which indicate motivations for output growth, such as $\varepsilon_{MC,I} = \partial\ln MC/\partial\ln I$. In reverse – and equivalently due to Young's theorem – we could construct measures indicating the effect on Z_I and Z_G from changes in any argument of the function, such as $\varepsilon_{ZI,pq} = \partial\ln Z_I/\partial\ln p_q$, and $\varepsilon_{ZI,Y} = \partial\ln Z_I/\partial\ln Y$.

Similarly, we could compute the impact of I or G changes on their respective shadow values, or those for K and t, through elasticities such as $\varepsilon_{ZG,I} = \partial\ln Z_G/\partial\ln I$. For example, the short run substitutability between I or G and K may be imputed from $\varepsilon_{ZK,I} = \partial\ln Z_K/\partial\ln I$ and $\varepsilon_{ZK,G} = \partial\ln Z_K/\partial\ln G$ elasticities, which indicate that increasing I or G augments (diminishes) the demand for K if they are positive (negative), in turn suggesting a form of complementarity (substitability). This information could alternatively be derived from the $\varepsilon_{ZI,K} = \partial\ln Z_I/\partial\ln K$ and $\varepsilon_{ZI,K} = \partial\ln Z_I/\partial\ln K$ elasticities, which reveal how the shadow value of internal (to the state) or external public infrastructure increases with greater private capital stocks. These elasticities will be the same sign (although not magnitude in elasticity form) as $\varepsilon_{ZK,I}$ and $\varepsilon_{ZK,G}$. And if increases in I or G reduce (increase) the demand for v_q, so they are in some sense substitutes (complements), $\varepsilon_{vq,I}<0$ and $\varepsilon_{ZI,pq} = \partial \ln Z_I/\partial \ln p_q>0$, and analogously for G (the sign is reversed because Z_I is negative but v_q positive).

Using such measures we can therefore explore whether intra- or inter-state public infrastructure investment tends to enhance or reduce capital investment, employment of production and nonproduction labor, and intermediate materials use. These relationships have important implications for both productivity and growth. For example, growth theory suggests that the relationship of I to K (and in our scenario also of G to K) is important for ongoing growth stemming from public infrastructure investment (Batina, 2001). If such externalities stimulate private capital investment this will provide a stronger growth mechanism than if they act as substitutes.

These relationships among the private inputs and public capital also provide implications about input-specific productivity. For example, it has been hypothesized that labor productivity rises with greater public infrastructure investment (Pereira, 2001). In a cost function framework this implies that $\varepsilon_{NL,I}$ or $\varepsilon_{NL,G}$ is negative (for NL, and similarly for PL), since labor use must fall for a given output level to increase its productivity. Thus NL and I must in a sense be substitutes.

Finally, we need to recognize that these measures reflect short run cost responses, but for some applications or comparisons we may wish to explore the associated effects of short run rigidities, or output production adaptations, on infrastructure values. That is, although the focus on short run responsiveness for measurement of infrastructure effects was justified by Berndt and Hansson (1991), Shah (1992), and Morrison and Schwartz (1996a,b), it is useful to assess whether short run rigidities substantively limit input demand adjustment, and thus cost impacts. And inferring output enhancement from infrastructure investment, rather than just focusing on production costs for given output levels, make our measures more comparable to their primal counterparts, and provide growth implications.

First note that we have presented all our elasticity expressions in the context of variable costs, which precludes considering impacts on profitability that involve total costs. That is, our $\varepsilon_{VC,I} = \partial \ln VC/\partial \ln I = \partial VC/\partial I \cdot I/VC$ estimates represent private cost-savings from infrastructure investment as a proportion of variable rather than total costs. To instead reflect the proportion in terms of total costs, which may be more relevant depending on the application of the measure, we would compute $\varepsilon_{TC,I} = \partial \ln TC/\partial \ln I = \partial TC/\partial I \cdot I/TC$. This may be accomplished by constructing a VC/TC ratio to use as a multiplicative factor: $\varepsilon_{TC,I} = \varepsilon_{VC,I} \cdot (VC/TC)$. This will reduce the magnitude of the estimated infrastructure cost-elasticity, since TC>VC by construction.

Recognizing the fixed component of total costs, however, raises the question of whether fixities seriously constrain input, and thus cost, adaptations to changes in the availability of public infrastructure. That is, we must address the issue of subequilibrium, or non-optimal utilization of capital. If capital fixities preclude immediate adjustment to equilibrium K levels, the true economic or shadow value of capital, Z_K, is not equal to p_K. The deviation between Z_K and p_K represents the cost-effect of subequilibrium, and the extent of capital utilization, as well as the direction of K adjustment to its long run level.

Evaluating costs at the shadow rather than market value has been demonstrated to be important for appropriate measurement of cost effects and productivity, net of utilization issues, in studies such as Morrison (1985), and Berndt and Hansson (1992). Adaptation of public infrastructure benefit measures to accommodate utilization changes has also been central to studies such as Nadiri and Mamuneas (1994). To pursue this in our framework, we can use a shadow cost measure defined as $TC^{*}=VC(\cdot)-Z_{K}\cdot K$, which provides the basis for the cost-side capacity (in this case capital) utilization ratio TC^{*}/TC.[13]

If excess capacity exists, $TC^{*}/TC<1$, because the shadow value of capital is low. If overutilization prevails, $TC^{*}/TC>1$. Thus, to adapt for utilization fluctuations, the shadow cost measure becomes the appropriate denominator of the cost elasticity, rather than either variable or total costs. This implies another multiplicative adjustment factor, of the form $\varepsilon_{TC^{*},I} = \varepsilon_{TC,I}\cdot(TC/TC^{*})$. This measure represents the extent to which long run marginal costs differ from short run marginal costs, rather than average costs, as discussed by Morrison (1985). For example, if $p_{K}<-Z_{K}$ so $TC/TC^{*}<1$, and there is incentive for K investment, the implication is that movement to the long run will cause marginal costs to drop, because it will reduce the overutilization of capital.

Our final consideration, recognizing the role of scale economies, generates measures more analogous to those from primal models, accommodates the growth stimulus from lower costs, and supports the interpretation of the utilization adjustment in terms of marginal costs. This type of adaptation is typically attributed to Ohta (1975), who showed that the 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 imputed from the dual cost perspective as a combination of the cost-side disembodied technical change measure, $\varepsilon_{TC,t} = \partial \ln TC/\partial t$ and the cost-based measure of scale economics, $\varepsilon_{TC,Y} = \partial \ln TC/\partial \ln Y$: $\varepsilon_{Y,t} = -\varepsilon_{TC,t}/\varepsilon_{TC,Y}$.[14] Since $\varepsilon_{TC,Y}$ may be written as $\partial TC/\partial Y\cdot Y/TC = MC/AC$ (where MC is marginal and AC average cost), this is equivalent to redefining the denominator of $\varepsilon_{TC,t}$ as $MC\cdot Y$ (which we will call MCY), or multiplying it by $1/\varepsilon_{TC,Y}=TC/MCY$. Equivalent adaptations may be made for the I or G elasticities.

Also note that the scale economy elasticity $\varepsilon_{TC,Y}$, if measured within a short run model, represents the difference between average costs and *short run* marginal costs. To adapt this to reflect long run marginal costs, the numerator should instead be TC*, as discussed in Paul (1999). That is, a utilization-adjusted scale economy indicator, evaluated at current K and Y levels, may be constructed as $1/\varepsilon_{TC,Y}$=TC*/MCY.

In sum, adapting the $\varepsilon_{VC,I}$ (or other cost elasticity) measure for the difference between variable and total costs involves multiplying it by VC/TC. Accommodating utilization fluctuations requires further multiplication by TC/TC*. And recognizing long run scale economies (and thus lower costs when output is allowed to adapt) implies multiplying by TC*/MCY. This full set of adjustments can therefore be imputed by multiplying $\varepsilon_{VC,I}$ by VC/MCY.

Empirical Implementation and the Stochastic Structure

Empirical implementation of the model discussed above, to evaluate the extent and significance of intra- and inter-state public infrastructure investment impacts on costs and input demand in U.S. manufacturing, requires assumptions to be made about the functional forms of the cost function and of the stochastic structure.

The system of estimating equations for our model includes the variable cost function, VC(·), and input demand equations for the variable inputs, NL, PL, and M, derived from Shephard's lemma: $v_q=\partial VC/\partial p_q$ (q=NL,PL,M). The functional form assumed for the cost function, and thus implicitly for the variable input equations, is a generalized Leontief (GL) approximation used in Paul (2001a), where the factors expressed in levels are included in quadratic form. This function can be written as:

1) $VC(Y,K,\mathbf{p},\mathbf{r}) = \Sigma_q\Sigma_i\, \delta_{qi}\, p_q\, DUM_i + \Sigma_q\Sigma_b\, \alpha_{qb}\, p_q^{5}\, p_b^{.5} + \Sigma_q\, \delta_{qY}\, p_qY + \Sigma_q\, \delta_{qK}\, p_qK + \Sigma_q\Sigma_n\, \delta_{qn}\, p_q\, r_n + \Sigma_q p_q(\delta_{YY}\, Y^2 + \delta_{YK}\, K\cdot Y + \Sigma_n\, \delta_{nY}\, r_nY + \delta_{KK}\, K^2 + \Sigma_n\, \delta_{nK}\, r_nK + \Sigma_n\Sigma_m\, \delta_{nm}\, r_nr_m)$,

where q and b denote the variable inputs and m and n the components of the **r** vector, I, G, and t. This (flexible) functional form allows for a full set of cross-effects (including those for I and G), and scale economies, and maintains linear homogeneity in prices through the square-root form for the p_q terms, and the $\Sigma_q p_q$ multiplicative factor for the terms in levels.

Estimation of the four equation system comprised of (1) and the input demand equations may proceed by seemingly unrelated systems (SUR) estimation procedures, although to accommodate econometric issues such as possible heteroskedasticity, endogeneity, or autocorrelation, these procedures must be adapted. In particular, to recognize heteroskedasticity we can compute the standard errors in a robust-White form.[15] To deal with endogeneity issues, we could use three stage least squares (THSLS) to ascertain whether instrumenting the associated variables affects the results substantively, and how sensitive the estimates are to specification of the instruments. The primary adaptation in the context of our analysis, however, is for spatial autocorrelation.

Such a “spatial econometrics” approach, analogous to the more standard econometric model of temporally autocorrelated errors (such as a first order autoregressive or AR1 process), has been suggested by Kelejian and Robinson (1997). Spatial inter-connections in this context are defined via spatially “lagged” error terms representing linkages with neighboring states at one point in time; we will call such a model a spatial autogressive, or SAR model.

For our application, if there is only one adjoining state (j) whose infrastructure investment affects costs of production in the state under consideration (i), this adaptation is directly analogous to an AR1 adjustment. $VC_{i,t} = VC(\cdot)_{i,t} + u_{i,t}$, where $u_i = \rho_s u_{j,t} + \psi_{i,t}$, $-1<\rho_s<1$, and $u_{j,t}$ is the (unadjusted) error term for state j in year t; ρ_s is the spatial spillover measure (analogous to the AR1 parameter in a temporal autocorrelation model); and $\psi_{i,t}$ is a normally distributed error for $VC(\cdot)_{i,t}$ with mean zero and constant variance. Each of the input demand equations can be analogously written as $v_{q,i,t} = v(\cdot)_{q,i,t} + u_{q,i,t}$, where $u_{q,i,t} = \rho_{s,q} u_{q,j,t} + \psi_{q,i,t}$, $-1<\rho_{s,q}<1$, and $\psi_{q,i,t}$ is a normally distributed error for $v(\cdot)_{i,t}$ with mean zero and constant variance.

If multiple states' production or costs affect state i's costs, we need to accommodate the effect of a weighted average of these states' error terms on state i's error term. The cost function therefore becomes $VC_{i,t} = VC(\cdot)_{i,t} + u_{i,t}$, where $u_{i,t} = \rho_s \Sigma_j w_{i,j} u_{j,t} + \psi_{i,t}$, $-1<\rho_s<1$, and $\psi_{i,t} \sim N(0, \sigma^2)$. The input demand equations would be written as above, except now $u_{q,i,t} = \rho_{s,q} \Sigma_j w_{i,j} u_{q,j,t} + \psi_{q,i,t}$, where $-1<\rho_{s,q}<1$ and $\psi_{q,i,t} \sim N(0, \sigma_q^2)$.

We can then stack the observations for all states for each given year, and transform each of the four equations (VC, v_{NL}, v_{PL}, v_M) to obtain a four equation system where each equation has a normally distributed error term with mean zero and constant variance:

2) $$VC_t = \rho_s WVC_t + VC(\cdot)_t - \rho_s WVC(\cdot)_t + \psi_t$$

$$v_{q,t} = \rho_{s,q} Wv_{q,t} + v(\cdot)_{q,t} - \rho_{s,q} Wv(\cdot)_{q,t} + \psi_{q,t} ,$$

where (q=NL,PL,M) and W is a 48 by 48 matrix of weights. This system is what we refer to as our SAR specification. This extension to apply stochastic spatial econometric techniques to a system of cost and input demand equations is, to our knowledge, novel in the literature.

Defining the "connecting" states, and their weights, is key to implementing this approach. Consider the geographic neighbors to a particular state i. For our analysis we define the weight that neighboring state j has on state i ($w_{i,j}$) as the value of goods shipped from state i to neighboring state j, as a share of the value of goods shipped from state i to all of i's neighbors. These $w_{i,j}$ were used both for the spatial autocorrelation specification and to weight the sum of state j's relative infrastructure investment to compute G.[16]

Although our analysis here focuses on spatial dependencies, which implies a key role for the SAR adjustment, with or without the associated spillover variable G in the theoretical model, temporal dependence might also affect our results due to the panel nature of the data. Recognition of temporal dependency through temporal serial correlation has been suggested by some studies (such as Holtz-Eakin and Schwartz, 1995) to be essential for appropriately representing the size and significance of infrastructure effects. This further adaptation may be particularly important due to our reliance on panel data; if we recognize the potential for spatial linkages to affect the valuation of infrastructure investment, then it seems temporal connections should also be accommodated for appropriate assessment of I benefits.

We thus allowed for AR1 in addition to spatial linkages in the stochastic structure, by adding the time stationary AR1 process $\psi_t = \rho_\theta \psi_{t-1} + \varphi_t$ to the variable cost function in 2), where $-1<\rho_\theta<1$ and $\varphi_t \sim N(0, \sigma_\theta^2)$. Similarly, for each of the input demand equations in 2), we added the time stationary AR1 process $\psi_{t,q} = \rho_{\theta,q}\psi_{t-1,q} + \varphi_{t,q}$, where $-1<\rho_{\theta,q}<1$ and $\varphi_{t,q} \sim N(0, \sigma_{\theta q}^2)$. The state-by-time adjustment accomplished by appending this stochastic structure to the SAR model accommodates both spatial and temporal autocorrelation for our panel data, resulting in the system of estimating equations:

3) $VC_t= \rho_\theta VC_t + \rho_s WVC_t + VC(\cdot)_t - \rho_s WVC(\cdot)_t -\rho_\theta [\rho_s WVC_{t-1} + VC(\cdot)_{t-1} - \rho_s WVC(\cdot)_{t-1}] + \varphi_t$

$v_{q,t}=\rho_{\theta,q}v_{q,t} + \rho_{s,q}Wv_{q,t} + v(\cdot)_{q,t} - \rho_{s,q}Wv(\cdot)_{q,t} - \rho_{\theta,q} [\rho_{s,q}Wv_{q,t-1} + v(\cdot)_{q,t-1} - \rho_{s,q}Wv(\cdot)_{q,t-1}] +\varphi_{q,t}$

We refer to this system 3) as the SAR/AR1 specification.

A final econometric issue that should be considered is whether some endogeneity might be associated with I. Although the relatively small share of manufacturing in states' production suggests that this sector is unlikely to drive policy decisions, the endogeneity issue may be addressed econometrically by pursuing estimation by THSLS, to ascertain its possible impact on our results. As was suggested and popularized by Pindyck and Rotomberg (1983), we accomplished this by instrumenting the I level by various combinations of lagged values for I and the exogenous variables.[17] The results were not conclusive, since they exhibited great sensitivity to the choice of instruments, although the general pattern was that the $\varepsilon_{VC,I}$ estimate tended to fall but $\varepsilon_{VC,G}$ to rise (sometimes to implausibly high levels). We therefore retained SUR estimation for our final models.

Our exploration of intra- and inter-state infrastructure investment impacts for 1982-1996 is carried out by comparing a sequence of specifications, to identify variations in estimates resulting from differential treatments of spillovers, and of the error structure. Our base model (Base) includes I but not G as an argument of $VC(\cdot)$, with no SAR or AR1 adjustment. The SAR and combined SAR/AR1 adaptations to this model comprise our second and third specifications (Base/SAR and Base/SAR/AR1). The separate inclusion of G in the $VC(\cdot)$ function, the SAR adaptation to this model, and the adjustment to also allow for AR1 serially correlated errors, comprise our fourth to sixth specifications (G, G/SAR, and G/SAR/AR1). Parameter estimates for these models (without the dummy variables to keep the presentation manageable) are presented in Appendix Table A1.

The parameter estimates and t-statistics presented in Appendix Table A1 document a strong statistical significance of virtually all parameters of these complex models. The R^2s indicating the "fits" of the equations are, in fact, always 0.98 or above. Furthermore, all of the temporal autocorrelation and spatial autocorrelation parameter estimates are highly significant in all of the specifications in which they were incorporated. This suggests that our cost-specification with both time and space dimensions well represents the data.

The primary shadow values and elasticities computed from these parameter estimates are presented in Table 1 on average over the entire sample, and divided into the two decades covered by our data sample to identify time trends. The reported t-statistics were computed by evaluating the measures for the averaged data.

Overall, the size and significance of the measures for both intra- and inter-state infrastructure benefits, Z_I ($\varepsilon_{VC,I}$), and Z_G ($\varepsilon_{VC,G}$) are in a reasonable range that is broadly consistent with results in much of the literature, and are also invariably statistically significant. Our results thus clearly support the notion, which the recent literature seems to have drifted toward (if in a somewhat haphazard fashion), that infrastructure impacts are evident and significant, but are smaller than suggested by the original literature on the "public capital hypothesis". They also suggest not only significant own- or intra-state infrastructure benefits, but complementarity with inter-state infrastructure benefits, that enhance the own-benefits as well as being individually significant. To explore this further we will overview the primary results for our sequence of models.

First consider the Base case, as a comparison for the vast majority of the literature that precludes inter-state spillovers, including only intra-state effects. We find a shadow (nominal or dollar) value of public infrastructure investment, Z_I, of approximately -0.3. This is very similar to the results found by Morrison and Schwartz (1996a,b), which might be expected since both are based on a cost-approach, although the current study is for a later

Table 1: Public and Private Capital Shadow Values and Elasticities

Entire Sample

	Base	Base SAR	Base SAR/AR1	G in	G in SAR	G in SAR/AR1
Z_I	-0.3091	-0.3770	-0.3189	-0.3697	-0.5059	-0.3938
Z_G				-0.3222	-0.3050	-0.0678
Z_K	-0.3292	-0.2614	-0.2738	-0.3050	-0.2856	-0.2323
$\varepsilon_{VC,I}$	**-0.1518**	**-0.2009**	**-0.1617**	**-0.1972**	**-0.2938**	**-0.2337**
t stat	*-5.26*	*-7.36*	*-3.71*	*-6.55*	*-10.50*	*-4.65*
$\varepsilon_{VC,G}$				**-0.1629**	**-0.1524**	**-0.0332**
t stat				*-13.68*	*-14.37*	*-2.57*
$\varepsilon_{VC,K}$	**-0.1579**	**-0.1269**	**-0.1325**	**-0.1468**	**-0.1383**	**-0.1131**
t stat	*-8.23*	*-6.34*	*-4.34*	*-7.80*	*-7.25*	*-3.72*
VC/TC	0.8915	0.8915	0.8917	0.8915	0.8915	0.8917
TC/TC*	0.9703	0.9964	0.9913	0.9802	0.9882	1.0092
TC*/MCY	1.4208	1.5620	1.6582	1.3408	1.4174	1.5834
VC/MCY	1.2283	1.3864	1.4639	1.1690	1.2465	1.4218

80s

	Base	Base SAR	Base SAR/AR1	G in	G in SAR	G in SAR/AR1
Z_I	-0.2180	-0.2852	-0.2789	-0.2523	-0.3881	-0.3192
Z_G				-0.2891	-0.2787	-0.0423
Z_K	-0.3128	-0.2437	-0.2899	-0.2850	-0.2411	-0.2675
$\varepsilon_{VC,I}$	**-0.1123**	**-0.1647**	**-0.1532**	**-0.1442**	**-0.2471**	**-0.2066**
$\varepsilon_{VC,G}$				**-0.1571**	**-0.1496**	**-0.0226**
$\varepsilon_{VC,K}$	**-0.1575**	**-0.1243**	**-0.1472**	**-0.1440**	**-0.1233**	**-0.1359**
VC/TC	0.8867	0.8867	0.8865	0.8867	0.8867	0.8865
TC/TC*	0.9758	1.0042	0.9843	0.9876	1.0062	0.9944
TC*/MCY	1.4639	1.6047	1.7022	1.3964	1.4700	1.6549
VC/MCY	1.2658	1.4277	1.4838	1.2210	1.3095	1.4572

90s

	Base	Base SAR	Base SAR/AR1	G in	G in SAR	G in SAR/AR1
Z_I	-0.4132	-0.4819	-0.3588	-0.5040	-0.6406	-0.4684
Z_G				-0.3600	-0.3350	-0.0933
Z_K	-0.3481	-0.2816	-0.2577	-0.3280	-0.3365	-0.1971
$\varepsilon_{VC,I}$	**-0.1969**	**-0.2423**	**-0.1702**	**-0.2577**	**-0.3472**	**-0.2608**
$\varepsilon_{VC,G}$				**-0.1696**	**-0.1558**	**-0.0438**
$\varepsilon_{VC,K}$	**-0.1585**	**-0.1300**	**-0.1179**	**-0.1501**	**-0.1554**	**-0.0903**
VC/TC	0.8970	0.8970	0.8970	0.8970	0.8970	0.8970
TC/TC*	0.9640	0.9876	0.9982	0.9717	0.9676	1.0241
TC*/MCY	1.3717	1.5131	1.6143	1.2771	1.3572	1.5119
VC/MCY	1.1853	1.3392	1.4439	1.1096	1.1745	1.3864

time period with somewhat different data and functional form. The Z_I shadow value is also closely comparable to that for K, Z_K, which is slightly larger at -0.33.

The Z_I estimate corresponds to an $\varepsilon_{VC,I}$ elasticity (in proportional terms) of -0.152, with the $\varepsilon_{VC,K}$ measure again very similar.[18] Although (the negative of) this value is not directly comparable to the ε_{YI} elasticities reported in much of the existing literature, since it is a short run measure and does not incorporate scale economies in this form, it is remarkably similar to Munnell's (1990) estimate of 0.15. It is also far smaller than the original 0.39 estimate by Aschauer (1989). As documented in the survey by Sturm et al. (1998), who note that dual cost or profit models typically generate elasticities about half the size of Aschauer's, this measure is also in the same range as most other studies based on this type of methodology.

The second two panels of Table 1, which present estimates for the 1980s and 1990s, indicate a significantly upward time trend in the $\varepsilon_{VC,I}$ elasticity. In fact the measure for the 1990s is nearly twice that for the 1980s for the Base specification (although the difference is not as dramatic for some of the other specifications). This general tendency is consistent with Aschauer's (2001) findings of an upward trend in public infrastructure benefits between the 1970s and 1980s, although the difference into the 1990s is even more striking.

As outlined in the previous section, adaptations to these measures may be carried out to make them comparable to others in the literature based on alternative methodologies, particularly those founded on estimation of production functions. First, if adjusted to reflect the proportion in terms of total costs, the VC/TC ratio in Table 1 indicates that these elasticities would be approximately 10 percent smaller.[19]

Adapting to purge the impacts of utilization variations, through multiplication by TC/TC*=0.97, implies a 3 percent further drop in the $\varepsilon_{VC,I}$ estimate for this specification. But the deviation of the utilization ratio TC/TC* from 1 is insignificant (and the other specifications result in TC/TC* ratios even closer to 1), so utilization fluctuations do not seem central to measurement and interpretation of intra-state public infrastructure benefits for these data.[20] In fact, according to these estimates, capital stocks seem close to their long run equilibrium levels on average. This may be due to the largely cross-section nature of the data, which might be expected to better represent long run levels than time series data alone. The utilization measures also do not exhibit substantive time trends, so the implied utilization cost elasticity adaptations for the two decades are similar.

Finally, the TC*/MCY ratio implies significant (long run) increasing returns to scale, which is often found in this literature, as documented by Sturm et al. (1998). Thus, output increases or growth resulting from I investment (and neighboring states' I investment), imputed by multiplying $\varepsilon_{VC,I}$ (or $\varepsilon_{VC,G}$) by this ratio, would be substantially higher than suggested by the cost declines alone.

In sum, accommodating these various adjustments scales up the estimates of $\varepsilon_{VC,I}$ and $\varepsilon_{VC,K}$ by more than 20 percent. Most of this difference arises, however, from the scale economy adjustment, which reflects comparisons across states (the spatial dimension) as well as for a particular state over time, so care must be taken for appropriate interpretation of this measure. Note also that the impact of scale economies appears lower for the 1990s as compared to the 1980s, with a 27 percent adaptation implied for the 1980s (but applied to a smaller $\varepsilon_{VC,I}$), as compared to 18.5 percent in the 1990s. And that these adaptations, although not implying as large public infrastructure elasticities as those often found in the production function literature, push the estimates in that direction.

The second and third specifications (Base/SAR and Base/SAR/AR1) represent the adaptation of the stochastic structure to SAR, and then the addition of the AR1 adjustment. The spatial econometrics adaptation is statistically supported; the estimates of the spatial autocorrelation parameters for each equation are strongly significant (as can be seen in Table A1). And slight differences in both the magnitude and significance of Z_I and $\varepsilon_{VC,I}$ are evident for the SAR model; both rise (in absolute value), with the magnitude of $\varepsilon_{VC,I}$ increasing by about 30 percent, to -0.201. The corresponding $\varepsilon_{VC,K}$ estimate falls slightly in absolute value. Allowing also for serial correlation, however, through the AR1 adaptation, counteracts these changes, resulting in elasticity estimates close to those from the base specification. In particular, $\varepsilon_{VC,I}$ falls back to -0.162, with a slightly lower t-statistic but still strongly significant.

The adjustment ratios for these specifications are very similar to those for the base model, although even greater scale economies are implied with the AR1 model. Also, although the time trends are very similar for the SAR case, the AR1 adaptation somewhat smooths the time trends in the measures.

Incorporating G into the cost specification has a more noticeable effect, on balance. Z_G and thus $\varepsilon_{VC,G}$ are not only significantly positive on average, but the Z_I and $\varepsilon_{VC,I}$ measures increase (and those for K decrease slightly). In particular, for the model with G incorporated but no stochastic adaptations, $\varepsilon_{VC,I}$ rises to -0.197 and $\varepsilon_{VC,G}$ is estimated as -0.163. These measures suggest cross-state infrastructure complementarity, in the sense that the G-effects augment the measured I-effect. That is, when (positive) interactions among states’ infrastructure investments are recognized, the within- or intra-state infrastructure effect appears greater. Also, the sum of the I and G impacts reaches levels more closely approximating estimates generated with more aggregate data, in which the spillover effects would be internalized.

If both SAR and G are accommodated the $\varepsilon_{VC,I}$ value increases again quite substantively, to -0.294 and $\varepsilon_{VC,G}$ drops slightly, to -0.152. Further refinement to incorporate an AR1 stochastic structure counteracts the rise in the estimated I impact somewhat, but not to the level suggested by the base case; on average $\varepsilon_{VC,I} = -0.234$. The effect of recognizing AR1 is more dramatic for the $\varepsilon_{VC,G}$ measure; $\varepsilon_{VC,G}$ drops (in absolute value) substantively, to -0.033 (although it remains significant). This suggests that at least some of the apparent spillover effect may be indirectly tied to time trends. However, the positive externality from inter-state infrastructure investment still has a consequential estimated impact, with about a 0.04 percent reduction in production costs associated with a 1 percent increase in infrastructure investment in neighboring states.

Adaptations to all these models to adjust the elasticities to reflect total costs, utilization, and scale economies are very similar to those for the Base model, although the most general G/SAR/AR1 specification suggests more dramatic scale economies than the others. Time trends for the specifications with G included are also generally comparable to those for the Base model.

Both the signs and significance of the I and G cost-impacts distinguish the results for this sequence of models from those reported by authors such as Holtz-Eakin (1994) and Hulten and Schwab (1991), who find little impact from intra-state infrastructure investment. They also differ from the few studies that address inter-state spillover issues, including

Holtz-Eakin and Schwartz (1995) and Boarnet (1998), where virtually no spillover impact was uncovered, and what *was* evident appeared to be negative. These studies, and particularly Boarnet, however, interpret these results in the context of spatial mobility and the resulting loss of productive factors to regions with higher levels of infrastructure support. This is more likely to be relevant for counties, as in Boarnet, than at the state level of our analysis. Also, Holtz-Eakin and Schwartz estimated a production-oriented model in long-differenced form, which may over-smooth the patterns we are attempting to identify.

In addition to the direct cost impacts of I and G investment, it is illuminating to consider the input-specific effects of public investment on private decisions such as private capital investment and labor demand or employment. Some indication of these patterns is exhibited by the netput- (output- and input-) specific elasticities presented in Table 2. These measures are presented for the most general G/SAR/AR1 model. Due to some very small values of Z_G, however, the corresponding elasticities were widely variable. The seven sample points for which this resulted in large outliers were thus omitted from the sample before averaging the results. Although some of the G and K elasticity values still remain larger in magnitude than they would be if the estimates were more consistent across states, the signs of the elasticities are generally consistent with other specifications.[21]

First note from the additional 1st-order elasticities that not only the $\varepsilon_{VC,G}$ elasticities are on average lower for the specifications with AR1 incorporated, the $\varepsilon_{VC,Y}$ measures, which represent scale economies, are also significantly smaller (although all specifications imply increasing returns to scale). The implied rejection of constant returns to scale from $\varepsilon_{VC,Y}$ (short run *and* long run given the close approximation of the average TC*/TC ratio to 1) is consistent with that generally found in this literature. The VC elasticities with respect

Table 2: Netput-Specific Elasticities, G/SAR/AR1

$\varepsilon_{VC,I}$	-0.2351	$\varepsilon_{G,I}$	0.5640	$\varepsilon_{I,K}$	-0.2615
$\varepsilon_{VC,G}$	-0.0338	$\varepsilon_{K,I}$	-0.5432	$\varepsilon_{I,Y}$	0.0254
$\varepsilon_{VC,K}$	-0.1129	$\varepsilon_{MC,I}$	-0.0054	$\varepsilon_{I,NL}$	0.1790
$\varepsilon_{VC,Y}$	0.7133	$\varepsilon_{NL,I}$	-0.5152	$\varepsilon_{I,PL}$	-0.0828
$\varepsilon_{VC,t}$	-0.0001	$\varepsilon_{PL,I}$	0.1513	$\varepsilon_{I,M}$	0.9039
$\varepsilon_{VC,NL}$	0.1142	$\varepsilon_{M,I}$	-0.2741	$\varepsilon_{I,t}$	0.0221
$\varepsilon_{VC,PL}$	0.1330				
$\varepsilon_{VC,M}$	0.7526	$\varepsilon_{I,G}$	0.1342	$\varepsilon_{G,K}$	-0.5983
		$\varepsilon_{K,G}$	-0.3072	$\varepsilon_{G,Y}$	0.0015
		$\varepsilon_{MC,G}$	-0.0001	$\varepsilon_{G,NL}$	0.3787
		$\varepsilon_{NL,G}$	-0.1483	$\varepsilon_{G,PL}$	0.6328
		$\varepsilon_{PL,G}$	-0.1751	$\varepsilon_{G,M}$	-0.0114
		$\varepsilon_{M,G}$	0.0002	$\varepsilon_{G,t}$	0.0792

to the variable inputs, $\varepsilon_{VC,q}$, reflect their (variable cost) input shares, with the M share on average over 75 percent. And the $\varepsilon_{VC,t}$ elasticity, although negative on average, implying cost diminution (cost-side technical change) over time, is nearly negligible in magnitude, although statistically significant.

To pursue our exploration of public infrastructure effects further with the 2nd order elasticites, note that that the positive $\varepsilon_{I,G} = \partial Z_I/\partial G \cdot G/Z_I$ and $\varepsilon_{G,I} = \partial Z_G/\partial I \cdot I/Z_G$ (where Z_G, $Z_I<0$) elasticities support the notion that infrastructure in neighboring states raises the value of intra-state public capital investment; they are in some sense "complements". The large elasticity values for this specification, however, are to some extent driven by outliers, so the magnitude of this average measure is not very definitive.

For private inputs, our results show that K, M, and NL act as substitutes with I, whereas PL and I are complements. Symmetry is also maintained for these elasticities; $\varepsilon_{NL,I}$ and $\varepsilon_{I,NL}$ are, for example, consistent in sign, given that NL is positive and Z_I negative. Public infrastructure investment also seems to reduce the marginal cost of output (on average $\varepsilon_{MC,I}<0$, although it is small), providing a stimulus for growth. And $\varepsilon_{I,t}$ indicates that Z_I is increasing (in absolute value) over time, as found by our temporal comparision from Table 1.

The short run substitutable relationship 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". By contrast, a complementary relationship between K and I has often been found in models that assume immediate adjustment of private capital stocks, such as Conrad and Seitz (1992), Deno (1988), and Lynde and Richmond (1992). Note also that substitutability suggests investment in public infrastructure does not stimulate private capital investment at existing output levels, although output growth resulting from I investment will tend to counteract this, particularly since such growth tends to be capital-using (as shown by Morrison and Schwartz, 1996b).

The complementarity between PL and I also varies from the relationship usually found in the literature, although again the average is in this case to some extent driven by large positive elasticity values for states with very small PL. Although substitution of I with both NL and M variable inputs is evident, the primary driving factor for reduced costs from public infrastructure investment is clearly significant materials savings.

These variable input patterns imply "indirect impacts", as denoted by Pereira, in the context of input productivity patterns. In particular, complementarity of PL with I suggests that its marginal product, and therefore production labor demand and employment, increases with I investment. But for given output levels this implies a reduction in (average) labor productivity, Y/PL. Output growth arising from infrastructure investment will tend to counteract this to some extent, however, since output increases seem to be associated with smaller proportional employment increases, as found by Morrison and Schwartz (1996b).

The G-impacts are somewhat different than for I. Although K and NL also appear substitutable with G, PL now also seems substitutable and M very slightly complementary. Higher G seems to be associated with lower employment levels, perhaps due to a reduced labor force, which is consistent with Boarnet's (1998) suggestion that increased infrastructure in neighboring states may cause leaching of productive factors. Also, the impact of G on MC is even smaller than that for I.

The spatial variations in the cost and input-specific elasticities exhibited by the regional averages presented in Table 3 indicate that the impacts of intra-state public

Table 3: Elasticities by Region, G/SAR/AR1 specification

	Pacific	**Mountain**	**West N. Central**	**East N. Central**	**New England**	**Mid Atlantic**	**South Atlantic**	**East S. Central**	**West S. Central**
Z_I	-0.557	-0.383	-0.401	-0.350	-0.358	-0.450	-0.372	-0.401	-0.378
Z_G	-0.025	-0.088	-0.086	-0.032	-0.073	-0.069	-0.070	-0.049	-0.074
Z_K	-0.146	-0.213	-0.226	-0.323	-0.236	-0.217	-0.243	-0.210	-0.242
MC	0.482	0.474	0.481	0.486	0.470	0.478	0.475	0.468	0.476
$\varepsilon_{VC,I}$	**-0.214**	**-0.474**	**-0.296**	**-0.089**	**-0.158**	**-0.191**	**-0.142**	**-0.149**	**-0.197**
$\varepsilon_{VC,G}$	**0.005**	**-0.076**	**-0.047**	**-0.009**	**-0.029**	**-0.028**	**-0.025**	**-0.015**	**-0.027**
$\varepsilon_{VC,K}$	**-0.063**	**-0.107**	**-0.079**	**-0.147**	**-0.139**	**-0.106**	**-0.124**	**-0.105**	**-0.128**
$\varepsilon_{VC,Y}$	0.707	0.697	0.699	0.711	0.701	0.748	0.728	0.679	0.751
$\varepsilon_{VC,t}$	-0.004	0.003	-0.002	-0.002	0.005	-0.003	-0.001	-0.001	-0.001
$\varepsilon_{VC,NL}$	0.130	0.108	0.088	0.112	0.169	0.175	0.075	0.071	0.117
$\varepsilon_{VC,PL}$	0.130	0.123	0.109	0.146	0.174	0.141	0.139	0.102	0.136
$\varepsilon_{VC,M}$	0.740	0.763	0.805	0.743	0.656	0.683	0.790	0.830	0.747
$\varepsilon_{G,I}$	-0.634	0.257	0.443	-8.733	0.331	2.005	0.667	-3.319	0.989
$\varepsilon_{K,I}$	2.531	-0.200	-0.315	-0.443	-0.153	-1.964	-0.305	-0.832	-0.417
$\varepsilon_{MC,I}$	-0.011	-0.002	-0.004	-0.008	-0.002	-0.013	-0.005	-0.008	-0.005
$\varepsilon_{NL,I}$	-0.343	-1.288	-0.729	-0.136	-0.179	-0.221	-0.352	-0.433	-0.320
$\varepsilon_{PL,I}$	-0.061	0.406	0.234	0.065	0.097	0.002	0.094	0.103	0.098
$\varepsilon_{M,I}$	-0.218	-0.549	-0.324	-0.113	-0.224	-0.225	-0.165	-0.158	-0.235
$\varepsilon_{I,G}$	0.326	0.058	0.089	0.255	0.059	0.241	0.108	0.223	0.105
$\varepsilon_{K,G}$	4.895	-0.100	-0.145	-0.215	-0.078	-0.683	-0.132	-0.613	-0.135
$\varepsilon_{MC,G}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\varepsilon_{NL,G}$	-0.038	-0.364	-0.218	-0.037	-0.072	-0.060	-0.131	-0.119	-0.085
$\varepsilon_{PL,G}$	-0.089	-0.380	-0.250	-0.061	-0.102	-0.126	-0.110	-0.135	-0.124
$\varepsilon_{M,G}$	0.024	-0.006	-0.004	0.005	-0.001	-0.001	0.000	0.006	-0.001

infrastructure investment are highest in the West.[22] In particular, the $\varepsilon_{VC,I}$ elasticity is greatest in the Mountain and West North Central states, with the Pacific and West South Central states following. The smallest values are found toward the East and South – East North Central, South Atlantic, and East South Central. This does not easily correspond to the usual division into the “snowbelt” and “sunbelt” states in this 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 some extent support the findings of Hulten and Schwab (1991) and Aschauer (2001), that suggest a higher public infrastructure impact in the snowbelt than the sunbelt.

The implications are quite different for the impact of spillovers. In particular, some of the lowest $\varepsilon_{VC,G}$ values are found in the Pacific region and the average in fact is very slightly positive. This could suggest that for a state such as California, which is both large and relatively densely populated, spillovers are not nearly as important as intra-state investment in infrastructure. The next lowest tend to be in the East and Central regions – East North Central and East South Central. The largest impacts again arise in the Mountain and West North Central regions, which tend to be sparsely populated, so the full network of highway infrastructure in these regions is likely to be important productive contributors for manufacturing firms in these states.

Concluding Remarks

In this paper we have reevaluated the “public capital hypothesis” for the U.S. manufacturing sector, 1986-92, in a cost-based framework with explicit recognition of not only intra-state public infrastructure investment impacts, but also inter-state infrastructure spillovers. We use two types of adaptations to incorporate spatial spillovers into the analysis

– imposing a spatial autocorrelation stochastic structure, and including a spatial externality index in the theoretical framework. We also account for first order serial correlation within this spatial framework.

We find significant beneficial productive impacts for both intra- and inter-state public infrastructure investment, which have been increasing over time. Spillovers also seem to complement the productive impact of within-state public infrastrastructure investment, further enhancing their measured cost impact. Adaptations to reflect variations in capacity utilization due to short run rigidities have little impact on the estimates. However, accommodating scale economies to make the measures more comparable to primal measures increases their estimated magnitudes toward those found in production-oriented models.

Regional variations in these patterns are also evident. The largest intra-state infrastructure impacts are apparent in the West, and the smallest in the East/South states. By contrast, the Pacific states exhibit virtually no inter-state infrastructure impact, although the Mountain and West North Central regions still maintain high values, and the East/Central states also receive little benefits from public capital spillovers.

Overall, intra-state public infrastructure investment appears to substitute for materials inputs and private capital, and to some extent non-production labor. But the marginal cost impact of such investment provides a slight stimulus for output growth that could help to counteract these trends, and enhance private capital investment. Inter-state spillovers, by contrast, seem to increase marginal costs somewhat, and reduce employment (demand for both production and non-production labor, through substitutability), while again acting as a substitute for, or augmenting the input-specific productivity of, private capital and intermediate materials.

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Appendix A1: Parameter Estimates and t-statistics

	Base		**Base SAR**		**Base SAR/AR1**	
Parameter	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
$\alpha_{NL,PL}$	-4137.72	*-7.86*	-1107.28	*-2.02*	-106.38	*-0.30*
$\alpha_{NL,M}$	8670.41	*8.84*	2706.45	*2.44*	2719.21	*3.72*
$\alpha_{PL,M}$	12834.8	*15.52*	7215.83	*7.71*	2929.11	*4.39*
$\delta_{NL,Y}$	0.07	*14.85*	0.06	*11.72*	0.04	*9.32*
$\delta_{PL,Y}$	0.10	*23.22*	0.08	*18.07*	0.06	*14.82*
$\delta_{M,Y}$	0.56	*57.53*	0.50	*51.11*	0.50	*50.91*
$\delta_{NL,t}$	38.49	*4.59*	45.58	*4.80*	9.07	*0.63*
$\delta_{PL,t}$	38.05	*5.50*	48.72	*6.56*	-19.46	*-1.30*
$\delta_{M,t}$	26.39	*1.30*	119.36	*4.68*	18.05	*0.37*
$\delta_{NL,I}$	0.21	*7.37*	0.09	*3.59*	3.25E-03	*0.08*
$\delta_{PL,I}$	0.26	*9.63*	0.18	*7.51*	0.14	*3.56*
$\delta_{M,I}$	-0.52	*-10.19*	-0.52	*-11.35*	-0.31	*-3.94*
$\delta_{NL,K}$	0.08	*4.38*	0.11	*5.81*	0.05	*1.78*
$\delta_{PL,K}$	-0.06	*-3.29*	-0.02	*-1.05*	-0.10	*-4.33*
$\delta_{M,K}$	-0.50	*-12.41*	-0.44	*-11.57*	-0.42	*-6.26*
$\delta_{Y,Y}$	1.73E-07	*3.51*	8.59E-08	*2.06*	1.89E-07	*6.79*
$\delta_{I,I}$	4.91E-07	*1.00*	2.30E-06	*5.65*	-2.61E-06	*-4.44*
$\delta_{K,K}$	1.80E-06	*3.85*	-1.72E-07	*-0.45*	7.45E-07	*2.37*
$\delta_{Y,K}$	-7.48E-07	*-3.00*	2.98E-07	*1.48*	-6.53E-07	*-4.70*
$\delta_{Y,I}$	-8.95E-07	*-4.61*	-1.31E-06	*-7.81*	-4.99E-07	*-3.20*
$\delta_{K,I}$	-3.89E-07	*-0.54*	-1.50E-07	*-0.24*	1.38E-06	*2.01*
$\delta_{Y,t}$	-1.71E-03	*-5.74*	-1.63E-03	*-5.55*	-2.28E-03	*-7.57*
$\delta_{I,t}$	-6.32E-03	*-7.23*	-6.06E-03	*-7.80*	1.38E-03	*0.96*
$\delta_{K,t}$	1.31E-03	*1.64*	6.07E-04	*0.80*	4.69E-03	*4.71*
ρ_{s}			0.46	*23.13*	0.26	*11.37*
ρ_{θ}					0.74	*53.93*
$\rho_{s,NL}$			0.41	*16.38*	0.24	*8.50*
$\rho_{\theta,NL}$					0.65	*39.18*
$\rho_{s,PL}$			0.51	*21.07*	0.35	*12.05*
$\rho_{\theta,PL}$					0.80	*63.96*
$\rho_{s,M}$			0.47	*23.76*	0.26	*11.57*
$\rho_{\theta,M}$					0.72	*54.33*

Appendix A1 Continued: Parameter Estimates and t-statistics

	Base/G		**G/SAR**		**G/SAR/AR1**	
Parameter	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
$\alpha_{NL,PL}$	-3938.45	*-7.83*	-684.47	*-1.31*	-43.48	*-0.13*
$\alpha_{NL,M}$	8425.16	*8.74*	2312.04	*2.09*	2629.28	*3.66*
$\alpha_{PL,M}$	12484.50	*16.03*	6122.50	*6.85*	2795.88	*4.48*
$\delta_{NL,Y}$	0.08	*16.38*	0.07	*15.12*	0.04	*9.80*
$\delta_{PL,Y}$	0.11	*25.01*	0.10	*22.29*	0.07	*16.07*
$\delta_{M,Y}$	0.56	*59.26*	0.52	*53.78*	0.50	*49.77*
$\delta_{NL,t}$	42.06	*4.97*	44.74	*4.64*	34.03	*2.31*
$\delta_{PL,t}$	48.35	*7.07*	51.24	*6.98*	16.20	*1.12*
$\delta_{M,t}$	25.50	*1.24*	125.48	*4.76*	29.38	*0.59*
$\delta_{NL,I}$	0.18	*6.65*	0.04	*1.72*	-0.04	*-1.04*
$\delta_{PL,I}$	0.23	*8.79*	0.12	*5.30*	0.08	*2.11*
$\delta_{M,I}$	-0.54	*-10.68*	-0.61	*-13.33*	-0.36	*-4.61*
$\delta_{NL,K}$	0.14	*7.18*	0.16	*8.67*	0.06	*2.24*
$\delta_{PL,K}$	-3.63E-04	*-0.02*	0.03	*1.75*	-0.12	*-5.35*
$\delta_{M,K}$	-0.44	*-10.98*	-0.39	*-10.61*	-0.39	*-5.70*
$\delta_{Y,Y}$	1.58E-07	*3.31*	7.65E-08	*2.02*	1.66E-07	*6.20*
$\delta_{I,I}$	1.40E-06	*2.57*	2.79E-06	*6.32*	-1.13E-06	*-1.77*
$\delta_{K,K}$	-6.95E-08	*-0.15*	-1.63E-06	*-4.47*	2.39E-07	*0.75*
$\delta_{Y,K}$	-8.65E-07	*-3.64*	9.10E-08	*0.48*	-9.32E-07	*-6.72*
$\delta_{Y,I}$	-9.06E-07	*-4.54*	-1.33E-06	*-7.78*	-6.79E-08	*-0.42*
$\delta_{K,I}$	8.59E-08	*0.12*	1.08E-06	*1.90*	2.21E-06	*3.31*
$\delta_{Y,t}$	-7.93E-04	*-2.73*	-4.17E-04	*-1.47*	-1.71E-03	*-5.69*
$\delta_{I,t}$	-9.32E-03	*-9.83*	-8.18E-03	*-9.48*	-3.39E-03	*-2.09*
$\delta_{K,t}$	2.06E-03	*2.49*	-1.15E-03	*-1.54*	6.66E-03	*6.29*
ρ_{s}			0.48	*23.59*	0.26	*11.55*
ρ_{θ}					0.73	*52.79*
$\rho_{s,NL}$			0.41	*16.28*	0.24	*8.39*
$\rho_{\theta,NL}$					0.66	*39.34*
$\rho_{s,PL}$			0.54	*21.79*	0.36	*11.92*
$\rho_{\theta,PL}$					0.80	*61.66*
$\rho_{s,M}$			0.49	*24.39*	0.27	*11.71*
$\rho_{\theta,M}$					0.71	*53.56*
$\delta_{NL,G}$	-0.14	*-12.65*	-0.12	*-11.99*	-0.02	*-1.74*
$\delta_{PL,G}$	-0.17	*-15.59*	-0.15	*-15.67*	-0.04	*-3.54*
$\delta_{M,G}$	-0.17	*-8.88*	-0.18	*-10.74*	0.01	*0.64*
$\delta_{G,G}$	2.65E-07	*5.52*	3.59E-07	*9.43*	1.49E-07	*3.87*
$\delta_{Y,G}$	6.97E-08	*1.05*	-6.32E-10	*-0.51*	-7.73E-10	*-0.25*
$\delta_{G,K}$	9.90E-07	*5.11*	5.17E-07	*3.79*	9.63E-07	*5.21*
$\delta_{G,I}$	-4.73E-07	*-1.38*	-3.23E-07	*-1.05*	-1.26E-06	*-3.22*
$\delta_{G,t}$	1.10E-04	*0.21*	8.52E-04	*1.91*	-2.09E-03	*-3.26*

Data Appendix

Labor quantities: The number of workers engaged in production (PL) 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*. Total number of non-production workers (NL) are obtained as the difference between TOTAL and PL.

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

Public capital stock: Following Eberts, Park and Dalenberg (1986), the perpetual inventory technique was applied to state-level public infrastructure investment data 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 (1996). 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 their input price deflator for total manufacturing (SIC 20-39) capital services. The price of capital is obtained as $(i_t+d_t) \cdot q_{K,t}[1/(1\text{-taxrate}_t)]$, 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 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 website. This deflator is also used as the price of materials.

Output: Value of state-level shipments reported in the ASM were deflated by manufacturing Gross State Product deflators for each state (provided by Standard & Poor's DRI).

Spatial Weights: Value of goods shipped data from state of origin to state of destination are from the 1997 Commodity Flows Survey, U.S. Bureau of Transportation Statistics.

Footnotes

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

[2] Non-sheltered sectors are distinguished as those more open to global impacts.

[3] In particular, Holtz-Eakin and Schwartz (1995) consider inter-state 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.

[4] See the data appendix for details on the public capital stock construction.

[5] The stock levels are relative in the sense that if Nevada, for example, has 1/10 the manufacturing production of California, it is assumed to benefit only from this fraction of California's I stock. We used these relative stock levels because some states, Nevada and Vermont in particular, had huge G/VC ratios if the full I stock in the neighboring state was assumed to provide economic benefits.

[6] These values were for 1997, since no corresponding time series is available.

[7] Bartlesman, Caballero and Lyons, however, incorporated this index into a first order logarithmic production function in first differenced form, rather than a cost model.

[8] Further discussion of the representation and analysis of temporal, spatial, and supply- and demand-spillovers in more general form may be found in Paul (2001b).

[9] Note that K may be thought of as a shift factor as well as the more explicitly exogenous factors in the **r** vector, since it's changes toward the long run involve shifts in the short run cost curve along the long run cost curve.

[10] If this ratio significantly falls short of 1, for example, substantial excess capital exists, suggesting motivation for disinvestment, and the reverse is true for a value much exceeding 1.

[11] Although the literatures on endogenous growth and cost economy externalities suggests that economies arising from interactions among sectors may be important contributors to ongoing technological development and growth, these effects are unlikely to be directly correlated with a time trend, or substantive for a small sector of the economy.

[12] This information could potentially, however, be interpreted as a way to impute the social price justifying additional I investment.

[13] See Morrison (1985) for further elaboration of the construction and use of this measure.

[14] An extensive discussion of this and other manipulations of the cost as compared to primal-based measures, and short as compared to long run measures, is contained in Paul (1999).

[15] This was tried by computing robust-White standard errors, which only negligibly altered our results, except that for the G/SAR/AR1 specification the $\varepsilon_{VC,G}$ measure became only marginally significant, with the t-statistic falling slightly short of 2. Given the already complex stochastic specification of our model, however, with both SAR and AR1 incorporated, it is not obvious that this adaptation to the model remains relevant, so we retained the usual standard error computations.

[16] An alternative assumption about the weights, where all neighbors to a particular state received equal weight, was tried in preliminary investigation for the G/SAR/AR1 model. This assumption did not affect the model results substantively, except that the t statistic for the $\varepsilon_{VC,G}$ measure dropped further. This result is not surprising since such a simple specification of the weights does not really reflect the nature of the spatial interactions between manufacturing firms and infrastructure in neighboring states that we are attempting to capture.

[17] We also tried instrumenting G, with little difference in the results from those for I only.

[18] These elasticities are highlighted in the table because they are key estimates.

[19] The differences across specification arise because the first year of observations drop out for the AR1 specifications due to the time lags.

[20] This was also suggested by the results of Nadiri and Mamuneas (1994).

[21] The seven most dramatic outliers for these elasticities were omitted from the sample for the averages presented in Table 2.

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[22] The regional breakdowns are as follows: **Pacific** (Washington, Oregon, California), **Mountain** (Arizona, Colorado, Idaho, Montana, New Mexico, Nevada, Utah, Wyoming), **West N. Central** (Minnesota, Iowa, Missouri, North Dakota, South Dakota, Nebraska, Kansas), **East N. 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 S. Central** (Kentucky, Tennessee, Alabama, Mississippi), and **West S. Central** (Arkansas, Louisiana, Oklahoma, Texas).