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Capital Asset Value Impacts of Airports and Highways In the Presence of Higher Order Spatial Autocorrelation

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Abstract

The benefits and costs to private industry of investments in the transportation network, such as impacts on property values, are key to assessing the welfare implications of public transportation expenditures. In this paper we evaluate the capital asset value benefits from enhanced access to highways and airports for U.S. manufacturing firms, using a state-level cost function-based model that incorporates public transportation infrastructure stocks as "free inputs" and allows for higher order spatial autocorrelation. We find that short run costs in some geographic regions are significantly impacted by public highway or airport investment, and that capital asset values as well as input composition are significantly affected overall. Allowing also for associated output growth from infrastructure improvements implies both increased private capital investment and variable input demands.

Introduction

A major issue in the transportation economics literature is the effects of transportation network proximity on capital asset or property values. Economic theory would predict that both advantages of easy access to highways and airports, and disadvantages of noise and congestion, should be capitalized into capital asset values. This implies private financial benefits or costs (in terms of both individuals' residential and firms' capital structure values), and location and production choices, that depend on investment in and levels of public transportation infrastructure.

Much of the existing literature on these economic issues focuses on the private benefits and costs of either railroad, airport, or highway infrastructure, and targets residential rather than industrial values related to public infrastructure levels. It also tends to emphasize the impacts on property values in the context of prices for land or property rather than the productive (cost-savings) impacts of infrastructure for businesses, although such an inference is often implicit.

For example, Bowes and Ihlanfeldt (2001) and Brons (2003) consider the desirability of proximity to rail transit stations. Bowes and Ihlanfeldt show that railway accessibility reduces commuting costs and attracts new retail activity, in turn raising property values. However, they also find negative externalities associated with increased crime from easier access to neighborhoods; similarly, Brons finds a negative effect of railroad noise on property values. Tomkins et al. (1998) and Espey and Lopez (2000) consider the capitalization of airport noise into property values. Although Espey and Lopez identify a significant decrease in the prices of homes subject to greater noise levels,[1] Tomkins et al. find that the benefits of easy access to airports outweigh the costs of proximity. Martinez and Araya (2000) assess the impacts of highway projects on land use, and show that the benefits of enhanced transport systems tend to "percolate" into land rents (to a limited degree). This is consistent with Jacoby's (2000) finding that the value of farmland increases with road access to markets.[2] Although these studies do not directly address the benefits to firms from transport infrastructure, inferences about such values emerge from findings of enhanced accessibility and thus lower commuting costs for workers (and potentially shipping costs for products), and the resulting motivations for businesses as well as individuals to locate close to transport networks.

Some studies have more directly considered the impacts of public infrastructure investment on firms' decisions to locate near improvements, based on capital investments and property values. Weinberger (2002) examines the effects of highways on commercial property rents, and finds no advantages of locating near highways. Bruinsmfa et al. (1997) show that highway construction is positively related to corporate investments for firms in the Netherlands. Hou and Zhang (2001) suggest that better transportation infrastructure in Taiwanese provinces attracts more firms. Coughlin and Segev (2000) and Coughlin et al. (1991) similarly find positive impacts of higher transportation infrastructure levels in the U.S. on the number of foreign owned plants, and on the location of foreign direct investment across states, respectively.

These studies raise questions that have yet to be specifically addressed about the impacts of highway and airport infrastructure on the productive value of private capital

[1] They find a $2400 difference in the price of a home in Reno-Sparks Nevada, U.S., in areas where the noise level reaches at least 65 decibels.
[2] Note that all these existing studies focus on private benefits, although Willis, Garrod and Harvey (1998) find reduced social "amenity" benefits of wildlife and landscape preservation from building new roads.

(buildings/structures and land)[3] for businesses. In this study we focus on this question, and related issues about the cost, input demand, and growth effects of capital asset investment incentives from public transportation infrastructure for U.S. manufacturing.

We evaluate the impacts of highways and airport investment on the values of structural capital assets for manufacturing industries across states, based on a cost function production model adapted to incorporate airport and highway infrastructure levels as external shift factors, to allow for (up to third-order) spatial autocorrelation, and to represent profit-maximizing behavior of firms. We use this framework to estimate implicit (shadow) values of manufacturing buildings and structures, their dependence on airport and highway infrastructure levels, and the implications of these capital plant investment incentives for employment, intermediate materials demand, and capital equipment investment.

We find that higher order spatial autocorrelation (SAR) is supported by statistical tests, although comparable implications for our primary questions emerge from this preferred model and one estimated by seemingly unrelated regression procedures. Elasticity estimates from the SAR model suggest that own-state highway and airport infrastructure investments generate limited short run cost-saving benefits for manufacturing firms on average at the national level, although some geographic regions experience significant cost-savings. Also, airport and highway infrastructure investments significantly enhance capital asset values and affect variable input composition, although the demand effects contradict each other, thus muting the overall cost effect. The variable

[3] Although our data on capital structures and plant is not designed to include also land values, in many cases it is difficult to distinguish the two, particularly if, for example, the land is used for something like a parking lot that is considered a structural asset. Therefore, we interpret our results primarily in terms of the values of capital structures or plant, but some land assets are also included.

input impacts from highway expansion arise primarily from materials cost savings. Labor cost savings from airport expansion are partially counteracted by increased materials costs. If the resulting output growth motivations are taken into account, capital structure investment incentives implied by their higher shadow values at greater transportation infrastructure levels further stimulate capital equipment investment, and increase employment and materials use even more significantly.

The Theoretical Model

To model and measure the cost, capital asset (property) value, and implied input demand and output supply impacts of public airport and highway infrastructure investment, we specify and estimate a cost function model using state level data for the manufacturing sectors of the 48 continental United States from 1982 to 1996 (described in the Data Appendix). The state-level total cost function has the general form $TC = VC(Y,\mathbf{p},\mathbf{x},\mathbf{r}) + \Sigma_k p_k x_k$, where VC is own-state variable costs, Y is manufacturing output, **x** is a vector of quasi-fixed capital inputs (private machinery and equipment capital stock, K, and private buildings and structures capital stock, S, with market prices p_k, k=K,S), **p** is a vector of variable input prices (for non-production labor, L^N, production labor, L^P, and materials, M), and **r** is a vector of external shift variables. In addition to the standard time counter, t, the **r** components include the state's public airport capital (infrastructure) stock, A, and highway capital (infrastructure) stock, H, which are both assumed to be "free" inputs to manufacturing firms.[4]

The cost function represents optimizing behavior on the part of manufacturing firms. It thus allows us to characterize variable input demands and fixed input values, and their

[4] Cohen and Paul (2003a, 2003b) separately examine the direct and spillover cost impacts of additional airport infrastructure and additional highway infrastructure on firms costs and variable input demands.

variations in response to changes in public airport and highway infrastructure, through first- and second-order cost derivatives or elasticities.

That is, the functional form we use to represent the costs of manufacturing production is a second order approximation to the true underlying cost function, so first order relationships are dependent on all arguments of the cost function. Variable input demand behavior, embodied in the cost function by definition, is represented via Shephard's lemma by first derivatives of VC(·) with respect to the **p** vector components: $v_m(Y,\mathbf{p},\mathbf{x},\mathbf{r}) = \partial VC(Y,\mathbf{p},\mathbf{x},\mathbf{r})/\partial p_m$, $m=L^N,L^P,M$. Shadow (implicit) values of the quasi-fixed inputs and external factors are similarly represented by first derivatives with respect to the **x** and **r** vector components: $Z_k(Y,\mathbf{p},\mathbf{x},\mathbf{r}) = -\partial VC(Y,\mathbf{p},\mathbf{x},\mathbf{r})/\partial x_k$, k=K,S, and $Z_n(Y,\mathbf{p},\mathbf{x},\mathbf{r}) = -\partial VC(Y,\mathbf{p},\mathbf{x},\mathbf{r})/\partial r_n$, n=A,H,t (Lau, 1978).[5] Although the input demand equations are used as estimating equations, the shadow value equations are not because the left hand variables cannot be measured directly from the data; these equations are instead used to compute shadow value measures from the parameter estimates of the model. Such measures, and the second derivatives that further identify the relationships among input and output choices and the impacts of the external factors, provide the basis for our empirical investigation of cost and capital asset value impacts of public airport and highway investment.

More specifically, we assume the short run cost structure may be approximated by a fully flexible generalized Leontief (GL) variable cost function similar to that used by Cohen and Paul (2003a,b):

1) $VC_{i,t}(Y_{i,t}, K_{i,t}, S_{i,t}, \mathbf{p}_{i,t}, A_{i,t}, H_{i,t}, t) = \Sigma_m\Sigma_i\ \delta_{m,i}\ p_{m,i,t}\ F_i + \Sigma_l\Sigma_m\ \alpha_{lm}\ p_{l,i,t}^{.5}\ p_{m,i,t}^{.5}$

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[5] Note that Z_k and Z_n is here defined as positive values – e.g., increasing x_k reduces variable costs, due to input substitution, so $=-\partial VC/\partial x_k>0$. Although such a measure is often defined directly as the negative derivative, for our application it is more interpretable to define this shadow "value" as a positive number.

$+ \Sigma_m \delta_{mY} p_{m,i,t}Y_{i,t} + \Sigma_m \delta_{mK} p_{m,i,t}K_{i,t} + \Sigma_m \delta_{mS} p_{m,i,t}S_{i,t} + \Sigma_m \delta_{mA} p_{m,i,t}A_{i,t}$

$+ \Sigma_m \delta_{mH} p_{m,i,t}H_{i,t} + \Sigma_m\delta_{mt} p_{m,i,t} t + \Sigma_m p_{m,i,t}(\delta_{YY} Y_{i,t}^2 + \delta_{KK} K_{i,t}^2 + \delta_{YK} K_{i,t}Y_{i,t}$

$+ \delta_{SY} S_{i,t} Y_{i,t} + \delta_{SK} S_{i,t} K_{i,t} + \delta_{SA} S_{i,t} A_{i,t} + \delta_{St} S_{i,t} t + \delta_{SS} S_{i,t}^2 + \delta_{AY} A_{i,t} Y_{i,t}$

$+ \delta_{AK} A_{i,t} K_{i,t} + \delta_{At} A_{i,t} t + \delta_{AA} A_{i,t}^2 + \delta_{HH} H_{i,t}^2 + \delta_{tY} Y_{i,t} t + \delta_{AH} H_{i,t} A_{i,t} + \delta_{Ht} H_{i,t} t$

$+ \delta_{SH} H_{i,t}S_{i,t} + \delta_{HY} H_{i,t} Y_{i,t} + \delta_{HK} H_{i,t} K_{i,t} + \delta_{tK} K_{i,t} t + \delta_{tt} t^2)$,

where $l,m =(L^N,L^P,M)$, $l\neq m$; $i,j =(1,2,...,48)$; $t=(1982, 1983,..., 1996)$; and F_i represents a fixed effect (dummy) term for state i. Thus, for example, $S_{i,t}$ represents the private structures and buildings capital stock for state i at time t, and $A_{i,t}$ and $H_{i,t}$ the public airport and highway infrastructure capital stocks for state i at time t. (See the Data Appendix for elaboration of the data construction for these capital stocks).

Cost-minimizing variable input demands are embodied in this function by definition. These demand equations, derived from Shephard's lemma, $v_{m,i,t} = \partial VC_{i,t}/\partial p_{m,i,t}$ $(m=L^N,L^P,M)$, take the form:

2) $v_{m,i,t} (Y_{i,t}, K_{i,t}, S_{i,t}\ \mathbf{p_{i,t}}, A_{i,t}, H_{i,t}, t) = \Sigma_i \delta_{mi} F_i + \Sigma_l \alpha_{lm} p_{m,i,t}^{-.5} p_{l,i,t}^{.5} + \delta_{mY}Y_{i,t}$

$+ \delta_{mK} K_{i,t} + \delta_{mS} S_{i,t} + \delta_{mA} A_{i,t} + \delta_{mH} H_{i,t} + \delta_{mt} t + \delta_{YY} Y_{i,t}^2 + \delta_{KK} K_{i,t}^2 + \delta_{YK} K_{i,t} Y_{i,t}$

$+ \delta_{SY} S_{i,t} Y_{i,t} + \delta_{SK} S_{i,t} K_{i,t} + \delta_{SA} A_{i,t} S_{i,t} + \delta_{St} S_{i,t} t + \delta_{SS} S_{i,t}^2 + \delta_{AY} A_{i,t} Y_{i,t} + \delta_{AK} A_{i,t} K_{i,t}$

$+ \delta_{At} A_{i,t} t + \delta_{AA} A_{i,t}^2 + \delta_{tY} Y_{i,t} t + \delta_{AH} A_{i,t} H_{i,t} + \delta_{Ht} H_{i,t} t + \delta_{SH} H_{i,t} S_{i,t} + \delta_{HY} H_{i,t} Y_{i,t}$

$+ \delta_{HK} H_{i,t} K_{i,t} + \delta_{tK} K_{i,t} t + \delta_{tt} t^2$.

We also represent profit maximizing output choice and pricing through an expression equating marginal costs (MC) and revenues (MR), given the implied inverse output demand equation $p_Y=p_Y(Y)$: $MR = p_Y + \partial p_Y/\partial Y \bullet Y = MC = \partial TC/\partial Y= \partial VC/\partial Y$, or $p_Y = -\partial p_Y/\partial Y \bullet Y +$

$\partial VC/\partial Y$.[6] Assuming $\partial p_Y/\partial Y$ can be represented by the parameter λ_Y, implying linearity of $p_Y(Y)$,[7] and substituting for $\partial VC/\partial Y$ from (1), results in:

$$3)\quad p_{Y,i,t} = -\lambda_Y \bullet Y_{i,t} + MC_{i,t}$$

$$= -\lambda_Y \bullet Y_{i,t} + \Sigma_n \delta_{nY}\, p_{n,i,t} + \Sigma_n p_n (2\delta_{YY}\, Y_{i,t} + \delta_{YK}\, K_{i,t} + \delta_{SY}\, S_{i,t} + \delta_{AY}\, A_{i,t} + \delta_{HY}\, H_{i,t} + \delta_{tY}\, t).$$

(1)-(3) comprise our system of estimating equations representing minimized production costs and implied variable input demands and output supply (pricing), which we use to construct first and second order derivatives and associated elasticities to explore the impacts of public airport and highway infrastructure on private industry.

The Econometric Specification

It is common in the literature on the empirical implementation of cost functions to estimate such an equation system by appending to each equation a normally distributed error term with zero mean and constant variance – $u_{VC,i,t} \sim N(0, \sigma_{vc}^2)$, $u_{m,i,t} \sim N(0, \sigma_m^2)$ $u_{Y,i,t} \sim N(0, \sigma_Y^2)$ for equations (1)-(3) – and relying on seemingly unrelated regression procedures. We will call such a model our "SUR" econometric specification.

These procedures recognize the potential linkages among the error terms of the equations in the model, but do not take into account temporal and spatial interconnections, or autocorrelation. Although preliminary investigation of our data showed that recognizing temporal autocorrelation (an AR1 autoregressive structure) had

[6] If this profit maximization equation is not included in the model the estimates are more volatile across states, so some average cost elasticities violate regularity conditions. This approach also directly incorporates endogenous output choice, rather than assuming exogeneity of current output levels.

[7] The estimate of λ_Y thus represents the deviation between (average) output price and marginal revenue (so λ_Y would be zero with perfect competition), and provides information about the degree of imperfect competition of manufacturing firms. This adaptation also accommodates to some extent any endogeneity in the output price that may arise from the level of aggregation of the data.

a negligible effect on our estimates, as might be expected with state-level data the spatial dimension was found to be empirically important to accommodate.

Recognizing the possibility of spatial dependencies requires a spatial autoregressive or spatial autocorrelation framework; we will call this model our “SAR” econometric specification. Spatial econometrics methods (Anselin, 1988) are the spatial equivalent of a temporal autocorrelation adjustment; spatial linkages are accommodated in the stochastic structure via “lags” for geographic location (state) at any point in time. If there is only one adjoining state who’s “activity” levels affect that of the state under consideration, the SAR adaptation is directly analogous to an AR1 adjustment; the error terms for each equation are of the form $u_{i,t} = \rho u_{j,t} + \varepsilon_{i,t}$, where $u_{j,t}$ is the (unadjusted) error term for state j at time t, and $\varepsilon_{i,t}$ is a white-noise error. If multiple states’ activities affect state i’s costs, the error terms appended to equations (1)-(2) for estimation are instead:

4) $u_{VC,i,t} = \rho\Sigma_j w_{i,j} u_{VC,j,t} + \varepsilon_{VC,i,t}$, $u_{m,i,t} = \rho_m \Sigma_j w_{i,j} u_{m,j,t} + \varepsilon_{m,i,t}$,

respectively, where $w_{i,j}$ is the weight that state j has on state i’s error term u.

We assume that $w_{i,i} = 0$, $\varepsilon_{VC,i,t} \sim$ i.i.d.$(0, \sigma^2)$, $\varepsilon_{m,i,t} \sim$ i.i.d.$(0, \sigma_m^2)$, $\varepsilon_{VC,i,t}$ and each of the $\varepsilon_{m,i,t}$ are independent; and the elements of $\varepsilon_{VC,i,t}$, and $\varepsilon_{m,i,t}$ are independent. Further, assuming ω is a 48x48 matrix of weights at each given time t, we can define $W \equiv \omega \otimes I$, where W is a 720x720 matrix and I is a 15x15 identity matrix (since t goes from 1982 to 1996). Alternatively, we can write these error terms in matrix notation:

4’) $u_{VC} = \rho W u_{VC} + \varepsilon_{VC,}$ $u_m = \rho W u_m + \varepsilon_m$,

where u_{VC}, and u_m are each 720x1 vectors of residuals.

A crucial step in implementing such a spatial model is defining the weights that a group of “neighbors” (broadly defined) has on any particular state. Researchers often assume that all states sharing a common border with a particular state should receive equal weight, and all other states no weight. Others have allowed a broader range of states to impact a particular state’s error term by assigning weights that vary by the inverse of the distance between the center point of that state and that of other non-border states (Florax and Nijkamp, 2003). Although this approach may be appealing, it seems more desirable to conduct an econometric test to determine the appropriate “bands” of states to include as “neighbors,” rather than merely imposing that states’ relationships are based on their distance.

We thus propose an alternative approach that estimates separate spatial autocorrelation coefficients for multiple bands of neighbors. For example, in Figure 1, for the state of Nebraska, there is one band of neighbors that share a border with Nebraska shaded in magenta; a second band of states shaded in green which each share at least one border with the states in the first band; and a third band shaded in blue consisting of states that share a border with those in the second band.

Applying the Kelejian and Robinson (1992) spatial autocorrelation test, we can test econometrically how many bands are significant when constructing the weights for the spatial autocorrelation specification. The Kelejian and Robinson spatial autocorrelation test requires some *a priori* knowledge of which units may be spatially correlated, but not full knowledge of the weight matrix.[8] So, for instance, this test can be

[8] The version of the test that we employ is based on the assumption of homoskedastic error terms. We tried implementing the White “robust” estimation procedure in TSP, and since the signs and significance of the elasticities of interest were unchanged, we concluded that heteroskedasticity was not a problem in the current model.

applied to check for spatial correlation in the first band of neighbors, for all 48 states simultaneously. If the null hypothesis of no spatial autocorrelation is rejected, spatial correlation in the second bands for all states can be tested for. One can continue testing for such fanning out until the null hypothesis of no spatial autocorrelation cannot be rejected for a given band.

In the present context, the Kelejian and Robinson test yields evidence of first order SAR, as in equation (4'), for the L^N demand equation. There is, however, evidence of first and second order SAR for the VC and M demand equations, and of first, second, and third order SAR for the L^P demand equation. Thus, we allow the error terms for the VC, and M and L^P demand equations to take the form:

5) $u_{VC} = \rho_{1,VC}W_1u_{VC} + \rho_{2,VC}W_2u_{VC} + \varepsilon_{VC,}$

$u_M = \rho_{1,M}W_1u_M + \rho_{2,M}W_2u_M + \varepsilon_M,$

$u_{LP} = \rho_{1,LP}W_1u_{LP} + \rho_{2,LP}W_2u_{LP} + \rho_{3,LP}W_3u_{LP} + \varepsilon_{LP,}$

where $W_1 \equiv \omega_1 \otimes I$, ω_1 is a 48x48 matrix of neighbors with each element taking the value of $1/n_1$ if the corresponding state borders state i and 0 otherwise, and n_1 is the number of states sharing common borders with state i for each year; $W_2 \equiv \omega_2 \otimes I$, ω_2 is a 48x48 matrix with each element taking the value of $1/n_2$ if the corresponding state borders a neighbor of state i and 0 otherwise, and n_2 is the number of states sharing common borders with the neighbors of state i; and $W_3 \equiv \omega_3 \otimes I$, ω_3 is a 48x48 matrix with each element taking the value of $1/n_3$ if the corresponding state borders a neighbor of a neighbor of state i and 0 otherwise, and n_3 is the number of states sharing common borders with the neighbors to the neighbors of the particular state (with states that were considered neighbors to state i in ω_1 excluded from ω_3).

To estimate the spatial autocorrelation coefficients we use the Generalized Moments (GM) approach outlined by Kelejian and Prucha (1999), and applied to problems with higher order spatial autocorrelation by Bell and Bockstael (2000). When there is only one set of neighbors (such as our L^N demand equation), the three moments of interest are:

6.1) $E[(1/NT)\ \varepsilon_m'\varepsilon_m] = \sigma_m^2$

$E[(1/NT)\ \varepsilon_m'W_1'W_1\varepsilon_m] = \sigma_m^2(NT)^{-1}Tr(W_1'W_1)$

$E[(1/NT)\ \varepsilon_m'W_1'\varepsilon_m] = 0,$

where here m=VC,L^N,L^P,M.

When second order spatial autocorrelation is apparent there are six moments of interest – the three outlined above, plus:

6.2) $E[(1/NT)\ \varepsilon_m'W_2'W_2\varepsilon_m] = \sigma_m^2(NT)^{-1}Tr(W_2'W_2)$

$E[(1/NT)\ \varepsilon_m'W_1'W_2\varepsilon_m] = \sigma_m^2(NT)^{-1}Tr(W_1'W_2)$

$E[(1/NT)\ \varepsilon_m'W_2'\varepsilon_m] = 0,$

for m=VC,L^P,M.

Finally, where third order spatial autocorrelation is evident, the following four moments are added to those in (6.1) and (6.2):

6.3) $E[(1/NT)\ \varepsilon_m'W_3'W_3\varepsilon_m] = \sigma_m^2(NT)^{-1}Tr(W_3'W_3)$

$E[(1/NT)\ \varepsilon_m' W_1' W_3 \varepsilon_m] = \sigma_m^2 (NT)^{-1} Tr(W_1' W_3)$

$E[(1/NT)\ \varepsilon_m' W_2' W_3 \varepsilon_m] = \sigma_m^2 (NT)^{-1} Tr(W_2' W_3)$

$E[(1/NT)\ \varepsilon_m' W_3' \varepsilon_m] = 0,$

For $m=L^P$.

For illustration purposes, consider the case where $m=L^P$. Substituting for ε_{LP} in (6.1)-6.3) by inverting the corresponding expression in (5), namely, $\varepsilon_{LP} = u_{LP} - \rho_{1,LP} W_1 u_{LP} - \rho_{2,LP} W_2 u_{LP} - \rho_{3,LP} W_3 u_{LP}$, and in turn replacing u_{LP} with its fitted value from the initial parameter estimates of the L^P demand equation (estimated together with the VC, L^N , and M equations by SUR), we end up with 10 nonlinear equations, each as a function of $\rho_{1,LP}$, $\rho_{2,LP}$, $\rho_{3,LP}$, and σ_{LP}^2. By performing nonlinear least squares on the observations in these equations, we obtain parameter estimates for $\rho_{1,LP}$, $\rho_{2,LP}$, $\rho_{3,LP}$, and σ_{LP}^2. Finally, we take the original L^P equation and do a spatial Cochrane-Orcutt transformation based on these parameter estimates. We repeat this process for each of the equations in the model (recognizing the different spatial lag lengths for the other equations), and estimate the transformed system for VC, L^N, L^P and M using SUR. This is equivalent to performing Feasible Generalized Least Squares with the GM approach on the estimating system consisting of the variable cost and three input demand equations.

For our application all of the spatial ρ coefficients for the VC and input demand equations are positive, and for the equations with more than one band of neighbors they decrease as the neighbor bands disperse outward. For the L^P equation, for example, $\rho_{1,LP} = 0.5293$, $\rho_{2,LP} = 0.4117$, and $\rho_{3,LP} = 0.0578$. This is intuitively appealing, since it implies that the error terms of states that are in "bands" of neighbors further away from a particular state have a diminishing impact on the particular state's error term.[9]

Measurement of Airport and Highway Investment Impacts

Shadow values of the quasi-fixed inputs S and K in our cost function-based model are measured as derivatives or elasticities with respect to these **x** vector components: $Z_k=-\partial VC/\partial x_k$ or $\varepsilon_{VC,k}=-\partial \ln VC/\partial \ln x_k$, k=K,S (Morrison, 1985). The cost-impacts of the external factors A and H can also be computed as shadow values, analogously to the usual specification of technical change as a shift in the cost function associated with a change in technology (or time, t): $Z_n=-\partial VC/\partial r_n$ or $\varepsilon_{VC,n}=-\partial \ln VC/\partial \ln r_n$, n=A,H (Morrison and Siegel, 1997). Note also that such elasticities can be added to impute combined effects, similarly to the summation of output elasticities to represent the effect of multiple input changes for a production function specification (Cohen and Paul, 2003b).

In addition to the overall cost impacts represented by first derivatives, the underlying input and output relationships may be assessed by computing second order measures. In particular, the dependence of the variable input demands or shadow valuations of x_k or r_n on the arguments of the cost function – such as the components of the **r** vector – are captured as second derivatives of VC(·): e.g., $\partial v_m/\partial r_n =\partial^2 VC/\partial p_m \partial r_n$, $\partial Z_k/\partial r_n =\partial^2 VC/\partial x_k \partial r_n$. Thus, we can decompose, say, the overall cost effect of a change or difference in r_n, into its input-specific components, based on the input demand elasticities $\varepsilon_{vm,rn} = \partial \ln v_m/\partial \ln r_n$. Similarly, $\varepsilon_{Zk,rn} = \partial \ln Z_k/\partial \ln r_n$ represents the impact on the shadow value of quasi-fixed input k on the "public

[9] Note that with the Generalized Moments approach we cannot test for significance of the spatial autocorrelation coefficients, since this technique does not invoke the normality assumption for the error terms. But even without such error term assumptions we are able to perform the Kelejian and Robinson (1992) test for spatial autocorrelation, and this provides us with information on the appropriate spatial autocorrelation lag length. Also, for computational simplicity we stopped extending the lag length for the

good"[10] r_n, and $\varepsilon_{ZA,H} = \partial \ln Z_A / \partial \ln H$ reflects the dependence of airport values to the manufacturing sector on the supporting highway network, or interactions between A and H.

For this study we are particularly interested in the effects of airports and highways (A,H) on the shadow value (implicit valuation) of building and structures capital (Z_S). We can characterize these impacts on the property values of manufacturing firms through the shadow value derivatives $\partial Z_S/\partial A$, $\partial Z_S/\partial H$, or their corresponding (proportional) elasticities $\varepsilon_{ZS,A}=\partial \ln Z_S/\partial \ln A$, $\varepsilon_{ZS,H}=\partial \ln Z_S/\partial \ln H$. Such measures will be positive (Z_S rises with additional A or H, or $\varepsilon_{ZS,n}>0$, n=A,H) if firms incur capital asset value benefits from additional transport infrastructure, or proximity to airports and highways.

That is, if a production location becomes more desirable to firms due to cost savings from easier shipping of inputs and outputs between the marketplace and the production facility from the expansion of A or H infrastructure, $\varepsilon_{ZS,n}>0$. Increases in A or H could alternatively, however, lower the shadow values of buildings and structures, due to the noise and traffic congestion often associated with proximity to highways and airports. If, for example, additional congestion increases the travel time for firms' input and output shipments, so particular site becomes a less desirable production location, $\varepsilon_{ZS,n}<0$. Whether positive or negative, one would expect the change in a location's desirability to become capitalized into property values.[11] Computing and evaluating these elasticities, therefore, yields key empirical information about the overall impacts of improvements in highway and airport infrastructure on the value of firms' capital assets.

L^P equation at 3 neighbors, although it would have been possible (but somewhat more complex) to test for 4th order spatial autocorrelation.

[10] Note that highway and airport infrastructure would not be considered a "pure" public good, but instead a "congestable" public good due to the failure to satisfy the "nonrival" assumption required for a good to be considered a "pure" public good.

In turn, increases (decreases) in Z_S imply investment incentives for firms to expand (downsize) their capital structures or plant. The subsequent pressures on demands for other inputs depend on their relationship with S. We can evaluate these effects on both variable inputs and private capital equipment through measures such as $\varepsilon_{vm,S} = \partial \ln v_m / \partial \ln S$, which represents the impact on the demand for variable input m, and $\varepsilon_{Zk,S} = \partial \ln Z_k / \partial \ln S$, which captures the impact on the shadow value of capital equipment, of a change in S.

These measures provide useful insights about the substitutability or complementarity of S with other inputs, and thus the direction of change in input use when external forces increase the productive value of private capital structures. But these cost function measures are based on given output and private capital equipment (K) levels, whereas incentives for firms to expand (higher Z_S and thus S investment) would naturally involve also increased output production and likely additional equipment investment. It is possible, however, to evaluate the combined impacts of these sequential forces similarly to the construction of long run input demand elasticities from the cost function literature (Berndt and Morrison, 1981).

For example, given that optimal output supply is implicitly represented by equation (3), this expression can be inverted to impute the associated profit maximizing $Y^*(p_Y,\mathbf{p},\mathbf{x},\mathbf{r})$ levels from the parameter estimates of the model. The impacts of enhanced investment incentives for S (from A or H investment) on the demand for v_m, allowing for profit maximizing Y changes, can thus be represented by $\varepsilon^*_{vm,S} = S/v_m \bullet (\partial v_m/\partial S + \partial v_m/\partial Y \bullet \partial Y^*/\partial S)$. A similar measure may be computed to capture the effect of S changes on the shadow value of K; $\varepsilon^*_{ZK,S} = S/Z_K \bullet (\partial Z_K/\partial S + \partial Z_K/\partial Y \bullet \partial Y^*/\partial S)$.

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[11] Baumol and Oates (1988) describe similar situations where externalities become capitalized into residential property that is located near a production facility that generates pollution, for instance.

These measures are still based on the given capital equipment (K) level. However, long run adjustment allowing for K changes may be inferred by recognizing that in equilibrium $p_K=Z_K$, where p_K is the market price (user cost) of K. If we set these values equal we can solve (given the analytical expression for Z_K) for the resulting long run level of K, K* (Morrison, 1985). We can then further expand our equations representing v_m responses to S changes to $\varepsilon^{**}_{vm,S} = S/v_m \bullet (\partial v_m/\partial S + \partial v_m/\partial Y \bullet \partial Y^*/\partial S + \partial v_m/\partial K \bullet \partial K^*/\partial S)$, as well as computing $\varepsilon^{**}_{K^*,S} = S/K^* \bullet (\partial K^*/\partial S + \partial K^*/\partial Y \bullet \partial Y^*/\partial S)$.

The estimated signs, magnitudes, and significance of the range of measures overviewed in this section provide a broad base for evaluation of the cost and property value impacts of expansions in airport and highway infrastructure, and the resulting effects of private capital (Z_S) investment incentives. In the next section we present and discuss such estimates for our SUR and SAR models of the cost structure.

Estimation and Results

Our SUR and SAR models of the cost, input demand, and output pricing relationships (1)-(3) were estimated using PC-TSP. Note that most of the parameter estimates presented for these models in Appendix Table A1 (state dummies are omitted to limit the length of the table) are statistically significant, and the R-squared values for equations (1) and (2) exceed 0.99. The estimates themselves, however, for this flexible functional form with many parameters and interactions, provide little interpretive power. To evaluate their implications further we must use them to compute the derivatives and elasticities overviewed above.

The cost effects of the private and public capital stocks S, K, A, H, are represented by the shadow values Z_S, Z_K, Z_A, Z_H,[12] and associated shadow value elasticities $\varepsilon_{VC,S}$, $\varepsilon_{VC,K}$,

[12] These elasticities are evaluated at the mean of the data for the entire sample. The standard errors are calculated with the ANALYZ command in TSP, which applies the delta method by linearizing the

$\varepsilon_{VC,A}$, $\varepsilon_{VC,H}$, reported in Table 1 on average across all states.[13] Consider first the SUR estimates. They indicate that additional amounts of each of these private and public capital stocks generate significant variable input cost-savings benefits. In particular, $\varepsilon_{VC,H} = \partial \ln VC/\partial \ln H$ and $\varepsilon_{VC,A} = \partial \ln VC/\partial \ln A$ are both positive and statistically significant, so additional highway or airport infrastructure in a state appreciably lowers own-state manufacturing costs. $\varepsilon_{VC,S} = \partial \ln VC/\partial \ln S$ is also significantly positive, so investment in buildings and structures by manufacturing firms leads to lower variable costs for a given amount of output.

For the SAR model, which is supported statistically over the SUR specification by the Kelejian and Robinson tests, the overall $\varepsilon_{VC,H}$ and $\varepsilon_{VC,A}$ estimates both become statistically insignificant (with t-statistics of 1.42 and 1.69). This result is driven by a lower (but more plausible) magnitude of the elasticities; the standard errors are in fact slightly smaller than those for the SUR model.

The differences in the overall SAR and SUR results could suggest that the SUR model includes some spurious correlation that yields a significant overall $\varepsilon_{VC,H}$ estimate. Location related measurement errors, such as state level data that are averaged over different size states, might also have an erroneous impact if spatial linkages are not accommodated.[14] Disparities between state boundaries and the locations at which decisions are made by firms may also be veiled by the SUR estimates. That is, it may be important to recognize spatial

elasticity functions around the estimated parameter values, and then uses standard formulas for the variances and covariances of linear functions of random variables.

[13] These estimates were computed by averaging the data and then computing the estimates for the averaged data. Although not separately reported since they are not a focus of the analysis, estimated average (short run) returns to scale from these estimates, $\varepsilon_{VC,Y}=\partial \ln VC/\partial \ln Y=1.185$ (st. error .006) suggests significant scale economies for these data, and estimated technical change, $\varepsilon_{VC,t}=\partial \ln VC/\partial t=-0.007$ (st. error=.001) shows statistically significant but slight cost savings over time.

autocorrelation because some manufacturing firms may not be confined to the boundaries of the states in which their inputs are employed.

More generally, the less significant estimated infrastructure impacts when SAR is accommodated is consistent with the Holtz-Eakin (1994) conclusion that adaptation of a model of highway infrastructure impacts to incorporate a more sophisticated stochastic specification (in his case a temporal autoregressive specification and spatial fixed and random effects) causes the overall public capital impact to become insignificant.

However, as shown in Table 2, both $\varepsilon_{VC,H}$ and $\varepsilon_{VC,A}$ are significant for some geographic regions ($\varepsilon_{VC,H}$ is significant for the Pacific and E.N. Central regions, while $\varepsilon_{VC,A}$ is significant for the Mountain and W.N. Central regions).[15] The counteracting geographic differences evident in Table 2 likely contribute to the insignificant $\varepsilon_{VC,A}$ and $\varepsilon_{VC,H}$ estimates at the national level.

In addition, the input-specific impacts of H and A, and especially the impact on the shadow values of structures, or property values, are more significant for the SAR than the SUR specification. However they often conflict, suggesting that input composition is significantly affected. That is, the $\varepsilon_{vm,rn}$ estimates in Table 1 provide insights about supporting and counteracting input effects underlying the overall cost impacts of A and H. All the input-specific elasticities with respect to A are statistically significant in the SAR (but not the SUR) model. But for airports they imply increases in materials costs with higher A

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[14] Bell and Bockstael (2000) note for their SAR application that spatially correlated errors may be present due to "Census data that are averaged over a larger area in rural block groups than in urban ones."
[15] 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).

levels, that combat the labor-cost-savings reflected by $\varepsilon_{LN,A}$ and $\varepsilon_{LP,A}$. The reverse is true for highways; more H is associated with materials savings, which are to some extent counteracted by greater L_N and especially L_P demand, although the M effect in this case dominates. These elasticity patterns suggest that freight transport is more heavily affected by highway transport systems, and worker transport by air networks, consistent with the traditional focus on materials in the highway, and labor in the airport, infrastructure literature.

The significance patterns of the A and H elasticities may also involve interactions between A and H. That is, our treatment evaluates the impact of, say, increased A given existing H levels, by contrast to studies that investigate airport expansion without directly considering the corresponding "support" of the highway infrastructure system. However, one might conjecture that airport expansion leads to intermodal highway congestion, so additional highway infrastructure may be necessary to counter resulting travel time delays (Cohen, 1997). This seems consistent with the strongly positive $\varepsilon_{M,A}$ elasticity, suggesting that M costs, which would be the most heavily affected by highway congestion, increase with airport expansion. We can more directly assess the effect of additional highway stocks on the value of airport infrastructure (or vice versa), via the second-order cross-elasticity $\varepsilon_{ZA,H} = \partial \ln Z_A / \partial \ln H$, which we find is positive but insignificant (particularly for the SAR model).[16] We can also evaluate whether increased A in *conjunction* with increased H generate positive cost savings by summing the corresponding elasticities and re-evaluating their joint significance. The resulting elasticity, $\varepsilon_{VC,PUB} = \varepsilon_{VC,A} + \varepsilon_{VC,H}$, where "PUB" denotes expansions in both

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[16] Τηε χονϖερσε μεασυρε, $\varepsilon_{ZH,A}$, shows how additional airport infrastructure affects the implicit value of additional highways; since it is symmetric by Young's theorem it also is positive but insignicant.

type of public capital stock, is statistically significant even for the SAR model, suggesting that combined increases in A and H do have a significant cost effect.[17]

In turn, to target our primary question about property (private capital) values, we can use the second order or cross-elasticities $\varepsilon_{Zk,rn}$ in Table 3 to examine how additional airport or highway infrastructure stocks impact Z_S. For both the SUR and SAR models we find $\varepsilon_{ZS,A} = \partial \ln Z_S/\partial \ln A$ and $\varepsilon_{ZS,H} = \partial \ln Z_S/\partial \ln H$ to be positive, indicating that additional airports or highways in a particular state enhance the value to manufacturing firms of buildings and structures in that state. This suggests that the positive value of greater proximity to the transportation network outweighs the potential drawbacks of noise and traffic congestion. In fact, the SUR $\varepsilon_{ZS,H}$ estimate of 0.989 implies that additional highway infrastructure leads to a nearly one for one increase in the buildings and structures shadow value; better highways become capitalized into commercial or industrial property (capital asset) shadow values. The SAR estimate of $\varepsilon_{ZS,H} = 0.680$ is perhaps more plausible; it suggests that a one percent increase in the highway stock leads to about a 0.7 percent increase in the (shadow) value of buildings and structures, or property value. These measures are also both statistically significant for the SAR model, although $\varepsilon_{ZS,A}$ is insignificant for the SUR specification.

These estimates suggest also that additional airport or highway infrastructure provides incentives for manufacturing firms to invest in buildings and structures; their productive value is higher on the margin. The impacts of such investment on firms' demands for other inputs may be evaluated using the cross-elasticity estimates with respect to S, $\varepsilon_{Zk,S}$ and $\varepsilon_{vm,S}$, in Table 3. $\varepsilon_{ZK,S} = \partial \ln Z_K/\partial \ln S$ is strongly positive and significant, so more buildings and structures cause the value of machinery and equipment to rise. Thus, S and K are

[17] This combined impact elasticity is barely insignificant in the SAR model.

complements, suggesting that forces that generate incentives for S investment also motivate K investment. By contrast, $\varepsilon_{LP,S}$, and $\varepsilon_{M,S}$ are negative for both models (although the SAR estimate of $\varepsilon_{LP,S}$ is statistically insignificant), and $\varepsilon_{LN,S}$ is ambiguous but appears positive from the SAR measure. This indicates substitutability between private capital and intermediate materials, and a propensity toward substitutability at least with L_P. Additional S investment in response to its increased valuation from H expansion thus tends to reduce variable input demand.

As discussed in the previous section, however, these measures are based on constant output and capital equipment levels. But if input cost declines and property investment incentives increase desired output levels, as one would expect, the growth effect could well counteract the substitution effect. The final two sets of elasticities in Table 3 document that this is indeed the case, and that the "profit maxizing" and "long run" results are nearly equivalent for the two specifications. The significantly positive $\varepsilon^*_{ZK,S}$ and $\varepsilon^*_{vm,S}$ measures show that when output expansion is allowed for the enhanced K value (Z_K) from S investment drops slightly, while the demands for variable inputs rise even more substantially than the S change. When adjustment to long run capital equipment levels is inferred the implications remain similar; K increases by about half the percentage that S has increased, and demands for the other inputs vary little from their short run profit maximizing levels, with L_P and M falling and L_N rising somewhat (as would be expected from capital-skilled labor complementarity, Morrison and Berndt 1981).

Concluding Remarks

In this paper we use a cost function model to evaluate the impacts on manufacturing industry costs, and particularly capital asset values, of state-level airport and highway infrastructure investment. To further interpret these overall measures, we also examine the underlying input- and output-specific effects of such public investment.

The overall results for our "base" (SUR) and higher-order spatial autocorrelation (SAR) model are similar, although the SAR estimated cost-impacts of airport and highway expansion are less, and the property-value impacts more, statistically significant at the national level. That is, for this model we find an insignificant decrease in costs overall but a significant increase in the value of buildings and structures (property values) for manufacturing firms in response to higher levels of public highway or airport infrastructure.

The individual responses of variable input costs to both airport and highway expansion are also significant but contradictory; increased material use counters decreased labor expenses associated with greater airport infrastructure levels, and the reverse is true for highways. In addition, some regions have significant and some insignificant cost effects. These input-specific and regional variations thus contribute to the overall insignificance of the SAR cost elasticities.

We also find that increased incentives for investment in capital structures resulting from their higher marginal valuations motivate additional investment in capital equipment (structures and equipment are complements), but reduce demands for variable inputs (structures are substitutable with materials and production labor) at existing output production levels. However, output expansion motivated by higher capital asset property values and corresponding investment in buildings and structures support even greater than proportional (to S) increases in demand for both production and non-production labor, as well as materials.

References

Baumol, W.J., and W.E. Oates. 1988. *The Theory of Environmental Policy*. Cambridge University Press.

Baumol, W.J., J.C. Panzar, and R.D. Willig. 1982. *Contestable Markets and the Theory of Industry Structure*. New York: Harcourt Brace Jovanovich.

Berndt, Ernst R., and Catherine J. Morrison. 1981. "Short Run Labor Productivity in a Dynamic Model." *Journal of Econometrics*. 16:339-365.

Bell, Kathleen P. and Nancy E. Bockstael. 2000. "Applying the Generalized-Moments Estimation Approach to Spatial Problems Involving Microlevel Data." *The Review of Economics and Statistics*. 82(1). February:72-82.

Bowes, D.R. and K.R. Ihlanfeldt. 2001. "Identifying the Impacts of Rail Transit Stations on Residential Property Values." *Journal of Urban Economics*. 50(1):1-25.

Brons, Martijn. 2003. "Railroad Noise: Economic Valuation and Policy." *Transportation Research: Part D: Transport and Environment*. 8(3):169-84.

Brunisma, Frank R., Sytze A. Rienstra and Piet Rietveld. 1997. "Economic Impacts of the Construction of a Transport Corridor: A Multi-level and Multi-approach Case Study for the Construction of the A1 Highway in the Netherlands." *Regional Studies*. 31(4): 391-402.

Cohen, Jeffrey P. and Catherine J. Morrison Paul. 2003a. "Airport Infrastructure Spillovers in a Network System." *Journal of Urban Economics,* 54(3):459-473.

Cohen, Jeffrey P. and Catherine Morrison Paul. 2003b. "Public Infrastructure Investment, Inter-State Spatial Spillovers, and Manufacturing Costs." Forthcoming in the *Review of Economics and Statistics*.

Cohen, Jeffrey P. and Cletus C. Coughlin. 2003. "Congestion at Airports: The Economics of Airport Expansions." Federal Reserve Bank of St. Louis *Review* 85:9-25.

Cohen, Jeffrey P. 1997. "Some Issues in Benefit Cost Analysis for Airport Development." *Transportation Research Record*. 1567:1-7.

Coughlin, Cletus C. and Eran Segev. 2000. "Location Determinants of New Foreign-Owned Manufacturing Plants." *Journal of Regional Science*. 40(2):323-51.

Coughlin, Cletus C., Joseph V. Terza, and Vachira Arromdee. 1991. "State Characteristics and the Location of Foreign Direct Investment within the United States." *Review of Economics and Statistics*. 73(4):675-83.

Eberts, R., C. S. Park and D. Dalenberg. 1986. "Public Infrastructure Data Development for the NSF Project." Manuscript.

Espey, M. and Lopez, H. 2000. "The Impact of Airport Noise and Proximity on Residential Property Values." *Growth and Change*. 31(3):408-19.

Florax, R. And P. Nijkamp. 2003. "Misspecification in Linear Spatial Regression Models." Tinbergen Institute Discussion Paper.

Holtz-Eakin, D. 1994. "Public-Sector Capital and the Productivity Puzzle." *The Review of Economics and Statistics*. 76(1):12-21.

Hou, Jack W. And Kevin H. Zhang. 2001. "A Location Analysis of Taiwanese Manufacturing Branch-Plants in Mainland China." *International Journal of Business*, 6(2):53-66.

Jacoby, Hanan. 2000. "Access to Markets and the Benefits of Rural Roads." *Economic Journal*. 110(465):713-37.

Kelejian, H. and I. R. Prucha. 1999. "A Generalized Moments Estimator for the Autoregressive Parameter in a Spatial Model." *International Economic Review*. 40(2):509-533.

Kelejian, H. And D. Robinson. 1992. "Spatial Autocorrelation: A New Computationally Simple Test With an Application to Per Capita County Police Expenditures." *Regional Science and Urban Economics*, 22:317-331.

Lau, Lawrence J. 1978. "Applications of Profit Functions." in *Production Economics: a Dual Approach to Theory and Applications*. (Melvyn A. Fuss and Daniel L. McFadden, eds.), Vol. 1, North-Holland Publishing Co., Amsterdam:133-216.

Martinez, Francisco and Claudio Araya. 2000. "Transport and Land-Use Benefits under Location Externalities." *Environment and Planning A*. 32(9):1611-24.

Morrison, Catherine J. 1985. "Primal and Dual Measures of Economic Capacity Utilization: An Application to Productivity Measurement in the US Automobile Industry." *Journal of Business and Economic Statistics*. 3(4):312-324

Morrison, Catherine J., and Donald Siegel. 1997. "External Capital Factors and Increasing Returns in US Manufacturing." *Review of Economics and Statistics*. 79:647-655.

Tomkins, J., N. Topham, J. Twomey and R. Ward. 1998. "Noise versus Access: The Impact of an Airport in an Urban Property Market." *Urban Studies*. 35(2):243-258.

Weinberger, R. 2000. "Commercial Rents and Transportation Improvements: The Case of Santa Clara County's Light Rail." Lincoln Institute of Land Policy Working Paper.

Willis, K.G., G.D. Garrod and D.R. Harvey. 1998. "A review of cost-benefit analysis as applied to the evaluation of new road proposals in the U.K." *Transportation Research Part D: Transport and Environment*. 3(3):141-156.

Data Appendix : The following data are utilized in this study:

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*. Total number of non-production workers (L^N) for each state is obtained as the difference between TOTAL and L^P for each state.

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 L^N is obtained by subtracting the wages paid to L^P from the gross earnings of all employees. Non-production wage is obtained by dividing the non-production wage bill by L^N. Production wage is obtained by dividing the production wage bill by L^P.

Private capital stocks: The perpetual inventory method is applied to ASM data on annual state level capital expenditures separately for the equipment category and the structures category, to generate, respectively, capital stocks for machinery and equipment (K) and buildings and structures (S). The initial buildings and structures capital stock and machinery and equipment capital stock values are taken from the "Beginning of Year" capital stock data in the 1982 Economic Census of Manufactures, Geographic Area Series. Depreciation rates and investment deflators for each type of capital are from the Bureau of Labor Statistics, Office of Productivity and Technology.

Airports capital stocks: The perpetual inventory method was applied to data on state level air transportation capital outlay (which includes construction, land and existing structures, and equipment), from the Census Bureau's "Government Finances" (various years). The sources of these funds include intergovernmental grants (such as Airport Improvement Program funds) and bond revenues.[18] The initial capital stock (1982) values for each state were taken as the average of air transportation capital outlays for 1977

[18] See Cohen and Coughlin (2003) for a discussion of airport financing.

through 1981 times the estimated average airports service life of 25 years (provided by Airports Council International). The annual depreciation rate of .04 was taken as the inverse of the average airports service life. The investment deflator was from the 2000 Economic Report of the President, Table B-7, for "Government consumption expenditures and gross investment, state and local."

Highway capital stocks: The perpetual inventory technique is applied to state-level public infrastructure investment data to generate highway capital stock estimates. Following Eberts, Park and Dalenberg (1986), discards are 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 is used to deflate the capital and maintenance outlay series.

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 website. This deflator is also used as the price of materials.

Output: Value of state-level shipments reported in the ASM are deflated by manufacturing Gross State Product (GSP) deflators for each state (provided by DRI). These state-level deflators are also used for output prices.

Table 1: Shadow values, and cost, input demand, and shadow value elasticities

Measure	*SUR Estimates* **Estimate**	St. Error	*t-statistic*	*SAR Estimates* **Estimate**	St. Error	*t-statistic*
Z_A	**1.476**	0.314	*4.70*	**0.470**	0.278	*1.69*
Z_H	**0.322**	0.075	*4.31*	**0.102**	0.071	*1.42*
Z_S	**1.196**	0.116	*10.28*	**0.886**	0.116	*7.64*
Z_K	**0.357**	0.056	*6.43*	**0.282**	0.053	*5.28*
$\varepsilon_{VC,A}$	**0.040**	0.009	*4.70*	**0.013**	0.008	*1.69*
$\varepsilon_{VC,H}$	**0.119**	0.028	*4.31*	**0.038**	0.026	*1.42*
$\varepsilon_{VC,PUB}$	**0.160**	0.028	*5.75*	**0.051**	0.026	*1.93*
$\varepsilon_{VC,S}$	**0.157**	0.015	*10.28*	**0.116**	0.015	*7.64*
$\varepsilon_{VC,K}$	**0.122**	0.019	*6.43*	**0.096**	0.018	*5.28*
$\varepsilon_{LN,A}$	**-0.122**	0.022	*-5.44*	**-0.074**	0.019	*-3.83*
$\varepsilon_{LP,A}$	**-0.144**	0.021	*-6.83*	**-0.109**	0.018	*-6.08*
$\varepsilon_{M,A}$	**-0.008**	0.009	*-0.95*	**0.015**	0.008	*1.90*
$\varepsilon_{LN,H}$	**-0.031**	0.072	*-0.43*	**0.334**	0.065	*5.10*
$\varepsilon_{LP,H}$	**0.247**	0.068	*3.64*	**0.523**	0.060	*8.74*
$\varepsilon_{M,H}$	**-0.200**	0.028	*-7.16*	**-0.201**	0.027	*-7.33*
$\varepsilon_{ZA,H}$	**0.437**	0.271	*1.61*	**0.009**	0.733	*0.01*
$\varepsilon_{ZH,A}$	**0.143**	0.088	*1.61*	**0.003**	0.233	*0.01*

Table 2 - Regional Elasticities (SAR)

	Pacific		Mountain		W.N. Central		E.N. Central		New England	
Measure	**Estimate**	*t-statistic*	**Estimate**	*t-statistic*	**Estimate**	*t-statistic*	**Estimate**	*t-statistic*	**Estimate**	*t-statistic*
Z_A	**0.49**	*1.65*	**0.89**	*2.99*	**1.05**	*3.00*	**-0.47**	*-1.52*	**1.04**	*3.05*
Z_H	**0.18**	*2.48*	**0.02**	*0.26*	**0.03**	*0.33*	**0.31**	*4.85*	**0.13**	*1.55*
Z_S	**0.56**	*4.73*	**1.14**	*8.33*	**0.84**	*6.50*	**0.44**	*3.71*	**0.74**	*5.38*
Z_K	**0.21**	*3.02*	**0.40**	*6.26*	**0.44**	*7.11*	**0.03**	*0.48*	**0.48**	*8.01*
$\varepsilon_{VC,A}$	**0.01**	*1.65*	**0.10**	*2.99*	**0.03**	*3.00*	**-0.01**	*-1.52*	**0.01**	*3.05*
$\varepsilon_{VC,H}$	**0.06**	*2.48*	**0.02**	*0.26*	**0.01**	*0.33*	**0.08**	*4.85*	**0.05**	*1.55*
$\varepsilon_{VC,PUB}$	**0.07**	*3.10*	**0.12**	*1.68*	**0.04**	*1.09*	**0.07**	*4.43*	**0.06**	*1.97*
$\varepsilon_{VC,S}$	**0.08**	*4.73*	**0.17**	*8.33*	**0.09**	*6.50*	**0.05**	*3.71*	**0.11**	*5.38*
$\varepsilon_{VC,K}$	**0.06**	*3.02*	**0.18**	*6.26*	**0.11**	*7.11*	**0.01**	*0.48*	**0.18**	*8.01*
$\varepsilon_{LN,A}$	**-0.05**	*-3.71*	**-0.39**	*-4.88*	**-0.13**	*-4.65*	**-0.01**	*-0.41*	**-0.03**	*-4.79*
$\varepsilon_{LP,A}$	**-0.11**	*-5.75*	**-0.62**	*-7.09*	**-0.17**	*-6.44*	**-0.02**	*-2.14*	**-0.05**	*-6.61*
$\varepsilon_{M,A}$	**0.01**	*1.84*	**0.04**	*1.23*	**0.01**	*0.91*	**0.02**	*3.37*	**0.00**	*0.87*
$\varepsilon_{LN,H}$	**0.20**	*4.04*	**0.84**	*5.29*	**0.62**	*5.30*	**0.10**	*2.41*	**0.19**	*3.94*
$\varepsilon_{LP,H}$	**0.46**	*7.51*	**1.45**	*8.38*	**0.88**	*8.37*	**0.21**	*6.28*	**0.37**	*6.74*
$\varepsilon_{M,H}$	**-0.21**	*-7.79*	**-0.43**	*-6.67*	**-0.23**	*-6.68*	**-0.16**	*-8.84*	**-0.24**	*-7.18*
$\varepsilon_{ZA,H}$	**0.02**	*0.01*	**0.00**	*0.01*	**0.00**	*0.01*	**0.01**	*0.01*	**0.00**	*-0.01*
$\varepsilon_{ZH,A}$	**0.00**	*0.01*	**0.00**	*0.01*	**0.01**	*0.01*	**0.02**	*0.01*	**0.00**	*0.01*

Table 2 - Regional Elasticities (SAR, continued)

	Mid Atlantic		E.S. Central		W.S. Central		S. Atlantic	
Measure	**Estimate**	*t-statistic*	**Estimate**	*t-statistic*	**Estimate**	*t-statistic*	**Estimate**	*t-statistic*
Z_A	**0.02**	*0.06*	**0.26**	*0.86*	**-0.21**	*-0.82*	**0.30**	*1.22*
Z_H	**0.04**	*0.47*	**0.10**	*1.42*	**0.12**	*1.90*	**0.08**	*1.15*
Z_S	**0.86**	*6.51*	**0.96**	*8.04*	**1.12**	*9.90*	**1.04**	*8.88*
Z_K	**0.14**	*1.99*	**0.27**	*5.64*	**0.09**	*1.81*	**0.22**	*4.02*
$\varepsilon_{VC,A}$	**0.00**	*0.06*	**0.01**	*0.86*	**-0.01**	*-0.82*	**0.01**	*1.22*
$\varepsilon_{VC,H}$	**0.02**	*0.47*	**0.04**	*1.42*	**0.04**	*1.90*	**0.03**	*1.15*
$\varepsilon_{VC,PUB}$	**0.02**	*0.53*	**0.04**	*1.64*	**0.04**	*1.59*	**0.05**	*1.58*
$\varepsilon_{VC,S}$	**0.13**	*6.51*	**0.12**	*8.04*	**0.15**	*9.90*	**0.13**	*8.88*
$\varepsilon_{VC,K}$	**0.05**	*1.99*	**0.11**	*5.64*	**0.03**	*1.81*	**0.08**	*4.02*
$\varepsilon_{LN,A}$	**-0.02**	*-1.75*	**-0.07**	*-2.87*	**-0.05**	*-1.54*	**-0.11**	*-3.65*
$\varepsilon_{LP,A}$	**-0.06**	*-3.24*	**-0.07**	*-4.83*	**-0.10**	*-3.82*	**-0.14**	*-6.23*
$\varepsilon_{M,A}$	**0.02**	*2.42*	**0.01**	*2.20*	**0.02**	*3.09*	**0.03**	*2.22*
$\varepsilon_{LN,H}$	**0.32**	*5.09*	**0.56**	*5.15*	**0.46**	*5.34*	**0.44**	*5.58*
$\varepsilon_{LP,H}$	**0.61**	*7.75*	**0.50**	*8.75*	**0.70**	*9.57*	**0.55**	*9.39*
$\varepsilon_{M,H}$	**-0.23**	*-6.54*	**-0.19**	*-7.30*	**-0.17**	*-7.63*	**-0.21**	*-7.20*
$\varepsilon_{ZA,H}$	**0.01**	*0.01*	**0.17**	*0.01*	**0.02**	*0.01*	**-0.02**	*-0.01*
$\varepsilon_{ZH,A}$	**0.00**	*0.01*	**0.00**	*0.01*	**0.01**	*0.01*	**0.00**	*0.01*

Table 3: Z_S or "property value" and S-investment elasticities

	SUR Estimates			*SAR Estimates*		
Measure	**Estimate**	St. Error	*t-statistic*	**Estimate**	St. Error	*t-statistic*
$\varepsilon_{ZS,A}$	**0.072**	0.060	*1.20*	**0.331**	0.072	*4.61*
$\varepsilon_{ZS,H}$	**0.989**	0.147	*6.75*	**0.680**	0.176	*3.87*
$\varepsilon_{ZK,S}$	**1.016**	0.175	*5.82*	**1.189**	0.211	*5.64*
$\varepsilon_{LN,S}$	**-0.036**	0.039	*-0.92*	**0.065**	0.036	*1.81*
$\varepsilon_{LP,S}$	**-0.168**	0.036	*-4.62*	**-0.027**	0.035	*-0.78*
$\varepsilon_{M,S}$	**-0.175**	0.017	*-10.39*	**-0.163**	0.017	*-9.67*
$\varepsilon^*_{ZK,S}$	**0.892**	0.211	*4.22*	**0.887**	0.241	*3.68*
$\varepsilon^*_{LN,S}$	**1.495**	0.202	*7.39*	**1.266**	0.166	*7.63*
$\varepsilon^*_{LP,S}$	**1.816**	0.253	*7.18*	**1.543**	0.204	*7.55*
$\varepsilon^*_{M,S}$	**1.516**	0.206	*7.35*	**1.405**	0.194	*7.23*
$\varepsilon^{**}_{K*,S}$	**0.583**	0.091	*6.44*	**0.474**	0.082	*5.76*
$\varepsilon^{**}_{LN,S}$	**1.510**	0.194	*7.77*	**1.323**	0.155	*8.51*
$\varepsilon^{**}_{LP,S}$	**1.652**	0.254	*6.52*	**1.477**	0.201	*7.34*
$\varepsilon^{**}_{M,S}$	**1.372**	0.211	*6.50*	**1.299**	0.197	*6.60*

Appendix Table A1 - Parameter Estimates

SUR Estimates

Parameter	**Estimate**	Std. Error	*t-stat*
$\alpha_{LN,LP}$	**-1916.100**	621.770	*-3.08*
$\alpha_{LN,M}$	**3913.500**	1164.520	*3.36*
$\alpha_{LP,M}$	**8243.270**	1045.300	*7.89*
$\delta_{LN,H}$	**-0.037**	0.047	*-0.78*
$\delta_{LP,H}$	**0.085**	0.045	*1.87*
$\delta_{M,H}$	**-0.502**	0.075	*-6.68*
$\delta_{LN,Y}$	**0.201**	0.004	*45.16*
$\delta_{LP,Y}$	**0.234**	0.004	*59.70*
$\delta_{M,Y}$	**0.776**	0.007	*111.46*
$\delta_{LN,t}$	**-5.082**	10.375	*-0.49*
$\delta_{LP,t}$	**-8.534**	9.111	*-0.94*
$\delta_{M,t}$	**-19.386**	21.150	*-0.92*
$\delta_{LN,S}$	**-0.108**	0.086	*-1.26*
$\delta_{LP,S}$	**-0.271**	0.084	*-3.22*
$\delta_{M,S}$	**-1.250**	0.135	*-9.24*
$\delta_{LN,A}$	**-1.105**	0.178	*-6.20*
$\delta_{LP,A}$	**-1.228**	0.171	*-7.17*
$\delta_{M,A}$	**-0.640**	0.301	*-2.13*
$\delta_{LN,K}$	**-0.122**	0.036	*-3.43*
$\delta_{LP,K}$	**-0.204**	0.034	*-5.98*
$\delta_{M,K}$	**-0.489**	0.067	*-7.32*
$\delta_{H,H}$	**6.04E-06**	1.34E-06	*4.50*
$\delta_{Y,Y}$	**-6.60E-07**	3.62E-08	*-18.24*
$\delta_{S,S}$	**2.87E-05**	6.49E-06	*4.42*
$\delta_{K,K}$	**5.14E-06**	1.06E-06	*4.85*
$\delta_{A,A}$	**1.27E-04**	3.20E-05	*3.96*
$\delta_{H,Y}$	**-1.27E-06**	1.93E-07	*-6.55*
$\delta_{H,A}$	**-1.70E-05**	1.06E-05	*-1.61*
$\delta_{H,K}$	**6.83E-06**	1.92E-06	*3.55*
$\delta_{Y,A}$	**1.58E-06**	1.08E-06	*1.46*

SAR Estimates

Parameter	**Estimate**	Std. Error	*t-stat*
$\alpha_{LN,LP}$	**-2472.1**	412.3	*-6.00*
$\alpha_{LN,M}$	**4300.4**	908.5	*4.73*
$\alpha_{LP,M}$	**6629.2**	701.9	*9.45*
$\delta_{LN,H}$	**0.166**	0.043	*3.86*
$\delta_{LP,H}$	**0.248**	0.041	*6.06*
$\delta_{M,H}$	**-0.462**	0.073	*-6.36*
$\delta_{LN,Y}$	**0.179**	0.004	*39.80*
$\delta_{LP,Y}$	**0.209**	0.004	*49.58*
$\delta_{M,Y}$	**0.805**	0.007	*110.43*
$\delta_{LN,t}$	**17.991**	8.757	*2.05*
$\delta_{LP,t}$	**31.352**	6.855	*4.57*
$\delta_{M,t}$	**36.985**	15.498	*2.39*
$\delta_{LN,S}$	**0.155**	0.081	*1.92*
$\delta_{LP,S}$	**0.039**	0.079	*0.49*
$\delta_{M,S}$	**-1.029**	0.132	*-7.77*
$\delta_{LN,A}$	**-0.783**	0.159	*-4.94*
$\delta_{LP,A}$	**-0.989**	0.150	*-6.58*
$\delta_{M,A}$	**0.138**	0.271	*0.51*
$\delta_{LN,K}$	**-0.105**	0.033	*-3.24*
$\delta_{LP,K}$	**-0.176**	0.031	*-5.62*
$\delta_{M,K}$	**-0.469**	0.063	*-7.45*
$\delta_{H,H}$	**5.09E-06**	1.23E-06	*4.13*
$\delta_{Y,Y}$	**-5.97E-07**	3.58E-08	*-16.69*
$\delta_{S,S}$	**2.27E-05**	6.10E-06	*3.72*
$\delta_{K,K}$	**5.77E-06**	9.81E-07	*5.89*
$\delta_{A,A}$	**6.75E-05**	2.80E-05	*2.41*
$\delta_{H,Y}$	**-8.72E-07**	1.58E-07	*-5.50*
$\delta_{H,A}$	**-1.14E-07**	9.41E-06	*-0.01*
$\delta_{H,K}$	**-6.29E-07**	1.75E-06	*-0.36*
$\delta_{Y,A}$	**-5.52E-07**	1.55E-07	*-3.55*

$\delta_{Y,K}$	**2.04E-07**	2.20E-07	*0.92*
$\delta_{A,K}$	**2.19E-05**	1.23E-05	*1.78*
$\delta_{H,S}$	**-3.09E-05**	4.58E-06	*-6.75*
$\delta_{Y,S}$	**7.97E-06**	5.89E-07	*13.53*
$\delta_{A,S}$	**-3.04E-05**	2.53E-05	*-1.20*
$\delta_{K,S}$	**-2.78E-05**	4.77E-06	*-5.82*
$\delta_{H,t}$	**8.80E-04**	1.26E-03	*0.70*
$\delta_{Y,t}$	**-3.99E-03**	2.26E-04	*-17.64*
$\delta_{A,t}$	**1.36E-02**	5.15E-03	*2.64*
$\delta_{S,t}$	**1.96E-02**	4.58E-03	*4.27*
$\delta_{K,t}$	**-9.35E-04**	1.61E-03	*-0.58*
λ_Y	**-2.03E-06**	5.32E-08	*-38.13*

$\delta_{Y,K}$	**4.39E-07**	2.16E-07	*2.03*
$\delta_{A,K}$	**5.79E-05**	1.12E-05	*5.16*
$\delta_{H,S}$	**-1.62E-05**	4.19E-06	*-3.87*
$\delta_{Y,S}$	**6.82E-06**	5.78E-07	*11.81*
$\delta_{A,S}$	**-1.07E-04**	2.32E-05	*-4.61*
$\delta_{K,S}$	**-2.51E-05**	4.44E-06	*-5.64*
$\delta_{H,t}$	**-2.99E-03**	1.11E-03	*-2.70*
$\delta_{Y,t}$	**-3.79E-03**	2.28E-04	*-16.62*
$\delta_{A,t}$	**-1.65E-03**	4.33E-03	*-0.38*
$\delta_{S,t}$	**-2.56E-03**	4.49E-03	*-0.57*
$\delta_{K,t}$	**3.52E-03**	1.54E-03	*2.28*
λ_Y	**-1.75E-06**	5.66E-08	*-31.01*
$\rho_{1,VC}$	**0.301**		
$\rho_{2,VC}$	**0.092**		
$\rho_{1,LN}$	**0.224**		
$\rho_{1,LP}$	**0.529**		
$\rho_{2,LP}$	**0.412**		
$\rho_{3,LP}$	**0.058**		
$\rho_{1,M}$	**0.392**		
$\rho_{2,M}$	**0.005**		

R^2

VC	0.998
L^N	0.995
L^P	0.994
M	0.996
p_Y	0.489

R^2

VC	0.998
L^N	0.995
L^P	0.995
M	0.997
p_Y	0.500

Figure 1