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Airport Infrastructure Spillovers in a Network System

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Abstract

Airports in the U.S. air transport network have become increasingly congested, leading to delays for business travelers and freight shipments. Since disruptions in one part of the network exacerbate problems throughout the system, airport infrastructure expansions to enhance air traffic flows confer travel-time savings and reliability benefits, and thus increased worker productivity and shipping efficiency for manufacturing firms. We evaluate such spillovers, and find that higher own-state airport infrastructure implies lower manufacturing costs from both labor- and materials-savings. Airport expansion in connected states has a comparable effect for states with hub airports, and an even greater impact for other states.

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Introduction

Since federal air deregulation, the U.S. air transport system has evolved into a highly interdependent network where passengers and freight are transported through “large hubs”, from remote “spokes” or other large hubs, on the way to their final destinations (Morrison and Winston [20], Baily [3], Brueckner, Dyer, and Spiller [6], Brueckner and Spiller[5]). However, in recent years many airports – particularly large hubs – have become congested, leading to frequent delays for business travelers and disruptions of freight shipments (Cohen and Coughlin [9]). In response, major expansion projects have been undertaken by many airports to reduce congestion, improve amenities, and generally enhance air travel flow. Security and safety concerns arising from recent terrorist events temporarily reduced congestion, but raised additional issues of reliability and safety. Expenditures to deal with these issues have also affected the travel experiences of business passengers, and the maintenance of travel service flows for both people and goods.[1]

A recent article by the Associated Press [2] stressed that interruptions of air travel services are a broad ranging, or “coast-to-coast” problem. It documented that: “More than one-quarter of flights into 11 of the nation’s busiest airports were at least 15 minutes late during the first five months of the year.” More recently, after a security breach at the Atlanta airport, the *Atlanta Journal and Constitution* (November 17, 2001) reported that “Hundreds of flights around the country were canceled or delayed… (and) dozens of planes heading to Atlanta were diverted to other airports.” These and many similar scenarios have underscored that congestion or security issues, combined with the hub and spoke structure of the network, can cause delays and disruptions to spill over across airports. Through these interdependencies, airport infrastructure choices in one state will have impacts on the flow of travelers and freight throughout the system.

The network structure of the U.S. air transport system makes these issues well suited for evaluation using a production model that allows for externalities or spillovers. For this study we incorporate spatial external effects in a cost function-based framework, to analyze cost or productivity spillovers from state airport infrastructure. The model represents the cost-impacts of higher airport infrastructure levels on state-level manufacturing industries, allowing for capital rigidities, profit maximization, and imperfect competition.

We accommodate two forms of spatial linkages through our structural and stochastic model specifications. First, we adapt the cost function to recognize that airport infrastructure stocks may play the role of "free inputs" for manufacturing firms – that is, that airport expansions in own and other states, which reduce congestion constraints in the airport network, directly generate industry cost savings. Second, we check the robustness of our findings by adapting the stochastic specification to accommodate a spatial autoregressive structure, representing interdependencies of states with their airport network "neighbors". We also take into account differences among states with and without large hubs, since one might expect greater travel-time savings to accrue to industry employees in states with large hubs, but the story might be quite different for other states.

Our empirical results reveal substantive impacts from air transport network linkages, and support our treatment of spatial interdependencies. We define a "large hub state" as a state that has at least one large hub located within its borders, and a "large hub" (hereafter referred to inter-changeably as "hub") as an airport with at least 1 percent of the country's enplanements of passengers (U.S. Department of Transportation [21]), rather than explicitly a hub in the "hub and spoke" network. We find that hub airport expansion has a significant direct cost savings effect on own-state manufacturing production, and a roughly equal indirect cost-effect on manufacturing industries in other states. These cost savings arise from both greater productivity of non-production workers (who are likely to travel on business), and, to a lesser extent, reduced materials expenditures (e.g., from lower transport costs or improved inventory management). Further, incentives for private capital investment, and thus resulting growth of manufacturing industries, are implied by increased private capital shadow values from airport infrastructure expansion.

Cost savings are also associated with own-state airport investment in states without large hubs, but the effect is smaller. These cost effects again primarily result from non-production worker cost reductions, although the impacts on production worker and materials demands are also statistically significant. Cost savings accruing in one state from other states' airport stocks are also relatively large for states without large hubs. This may suggest that high congestion in passengers' destination states relative to their origin states implies greater cost-effects from other- than own-state airport expansion.

The Motivation, Model and Measures for our Analysis

The Issue and Literature

A delay resulting from congestion or security problems at one node in the U.S. air transportation network often results in delays throughout the system. An increase in airport infrastructure stocks that reduces congestion may thus be expected to confer productivity spillover benefits upon firms. Such effects may take the form of reduced travel-time and frustration for business employees who frequently travel, and enhanced efficiency and reliability of freight shipments, that result in production cost savings. Time savings for leisure travelers could even improve productivity, since individuals will be more rested and productive upon their return to work if they do not encounter severe air traffic problems.

In a network system, travel time- and thus manufacturing cost-savings from airport infrastructure investment involve productivity externalities or spillovers. That is, airport improvements to limit congestion in one hub state could result in interstate as well as in-state productivity spillovers, lowering manufacturing costs for firms in states connected through the airport network. An analysis of state-level manufacturing industry cost structure that recognizes external impacts from enhanced own- and connected-state airport infrastructure (and thus services) can provide insights about such cost effects.[2]

Studies in the literature on public infrastructure productivity effects, which primarily focuses on highways, have generally been based on (first-order Cobb-Douglas) production function models representing only technological relationships.[3] These studies represent the effects of highway infrastructure expenditures as shifts in private firms' technological structure from this investment. However, a cost-based optimization framework provides additional key insights about productivity patterns because it can directly capture cost-impacts, and indirectly represent implied input demand responses, from public infrastructure investment. Morrison and Schwartz [19], for example, use a cost function model to characterize cost effects from and substitution patterns among both internal and external productive factors, including highway infrastructure investment.

A cost-based framework is particularly applicable to analysis of airport infrastructure impacts and interdependencies if the spatial or network dimension is explicitly recognized.

This can be pursued both by incorporating variables into the structural model to capture spatial interdependencies, and by applying spatial econometrics methods.[4] For example, in the early literature on spatial econometrics, Case, Rosen, and Hines [8] examined how a given state's expenditures on public investments are affected by (a weighted average of) other states' public spending patterns.[5] Brueckner [7] and Cohen [10] similarly tested for interdependencies in growth control choices for California cities, and in states' airport spending choices, respectively. Although the estimating models in such studies are not embedded in an optimizing framework, these methods can be applied to a cost-based model to analyze cost and input demand effects from airport network infrastructure investment, similarly to Cohen and Paul's [11] treatment of highway infrastructure interdependencies.

To represent cross-state cost-impacts from airport improvements, we also recognize that spatial interdependencies do not necessarily involve sharing a geographic border; the notion of "neighbors" is different in this context than that in the highway infrastructure literature. That is, airport linkages have a network rather than a geographical dimension. Two states that share a common border are likely to have less connection with each other than two distant states that have a substantial number of air passenger trips between them. The linkage involves the number of person trips between a particular state and other states in the airport network web.

Finally, the literature on highway infrastructure impacts focuses primarily on the shipment of goods between states, and thus on transport costs. However, it might be expected that for the airport network the labor component is more relevant – that cost effects arise primarily from enhanced worker mobility and thus productivity. We therefore focus here on the labor cost impacts of airport expansion.

The Empirical Model

Our model is based on a cost function for manufacturing production, incorporating spatial inter-relationships through external shift factors reflecting the dependence of industrial productivity on own- and connected-state airport infrastructure investment.[6] The model is estimated using state level data for the manufacturing sectors of the 48 continental United States from 1982 to 1996 (described in the Data Appendix).

Total costs (TC) are represented by TC = $VC(Y,\mathbf{p},K,\mathbf{r}) + p_k K$, where VC(•) is a variable cost function, Y is state-level manufacturing output, **p** is a vector of variable input prices (here non-production labor, L^N, production labor L^P, and materials, M), K is quasi-fixed private capital, p_k is the price of private capital, and **r** is a vector of external shift variables. For our purposes, the components of **r** include not only a standard time counter, t, but also the own-state airport infrastructure stock, I, and (a weighted average of) other hub states' airport infrastructure stocks, G. As described in the data appendix, I is measured by applying the perpetual inventory method to state level airport capital expenditures data, for construction, land, structures, and equipment. G is constructed as a weighted average of airport infrastructure stocks in other states.

I and G are thus "free inputs" to manufacturing firms' production processes in own- and neighboring- or connected-states, in the sense that they represent the productive and thus cost impacts of improved air transport services, but are not internally chosen (and paid for) inputs. They are external factors that act as shift variables for manufacturing firms, where I reflects within-state impacts and G captures spatial interdependencies across states.

Constructing the G measure (as well as implementing the spatial autocorrelation robustness check) requires carefully specifying the spatial weights, $w_{i,j}$, that represent the form of spatial linkages. We postulate that the importance of other states' airports depends on the extent of interaction – the use of other-state airports by passengers originating from a particular state. Thus, a destination state with a large number of person-trips between it and the origin-state receives greater weight than a destination-state with fewer person-trips.

The data on air passenger trips, from the 1995 American Travel Survey (Bureau of Transportation Statistics), do not include intermediate stopovers at hub airports in trip counts because if "more than one place was visited on the same trip, the place which was the farthest point from the origin was considered the destination of the trip."[7] Thus, we are unable to capture the actual hubbing phenomenon practiced by many U.S. airlines with these data. We are also unable to distinguish between business and non-business (leisure) travelers, which could also have been informative since our primary focus is travel time savings for business travelers (as noted by an anonymous referee), because the survey does not break down passenger trips into these categories at the state level. However, it seems reasonable to postulate that even leisure travelers return to work more rested, and thus are more productive, if their travel experience is smooth due to improved airports.

As an alternative to person-trips, the weight structure could potentially be based on air cargo shipments, as firms may prefer to locate close to airports to minimize transport costs from shipping goods to and from airports.[8] However, the Commodity Flows survey does not report state to state air shipments for most states, and we are unaware of an alternative source for such data. Our choice of passenger trip weights is also consistent with our primary focus on productivity spillovers from air passenger travel time savings.

We therefore specify the weight that state j has on state i as:[9]

4) $$w_{i,j} = a_{i,j} / \Sigma_j a_{i,j} \quad ,$$

where $a_{i,j}$ represents the number of air passenger trips originating in state i with destination in state j. We then combine these weights with information on differences in the relative sizes of state-level economic activity (measured by Gross State Product, GSP) to construct G as:

5) $G_{i,t} \equiv \Sigma_j \; w_{i,j} \; I_{j,t} \bullet [GSP_{i,t}/GSP_{j,t}]$,

where $GSP_{i,t}$ represents the Gross State Product of state i in year t.

The GSP multiplicative factor reflects the relatively large effect that airport infrastructure stocks in state j, which shares a large amount of inbound passenger movement originating in state i, will have on state i's manufacturing costs. Also, a state with a high level of economic activity, such as Illinois (IL), presumably constitutes a large portion of G (and thus external impacts) for a relatively small state such as Rhode Island (RI). Thus, by multiplying IL's airport infrastructure stock by GSP_{RI}/GSP_{IL} when constructing G for RI, we essentially neutralize the size effects through multiplication by a relatively small number.

Further, we assume the short run cost structure may be approximated by a Generalized Leontief (GL) variable cost function similar to that used by Cohen and Paul [11]. The GL form is desirable for our purposes because it is flexible, and incorporates optimizing behavior on the part of manufacturing firms, thus allowing us to represent firms' behavior in response to changes in airport infrastructure through first- and second-order cost elasticities. That is, the direct cost effects of changes or differences in arguments of the VC(•) function such as I and G can be represented as first derivatives, or in percentage terms as first order cost elasticities. Given that input demand behavior is embodied in the specification of the cost function, input demand or substitution responses to changes in I and

G can in turn be characterized as second order derivatives of the function, or in percentage terms as second order elasticities (as elaborated below).

In addition, to represent spatial interdependencies within the stochastic structure, we can allow for the possibility that shocks to states' error terms spill over to other states. This leads to spatial autoregressive errors or spatial autocorrelation, as developed by Anselin [1], Kelejian and Robinson [18], and Kelejian and Prucha [17]. We will call the model allowing for this type of error structure our spatial autoregressive (SAR) model, as contrasted to our Base case for which the estimating equations are each assumed to have an independently, identically distributed error term with zero mean and constant variance.

Our Base model is thus formalized as:

$$1)\quad VC_{i,t}(Y_{i,t}, K_{i,t}, \mathbf{p_{i,t}}, I_{i,t}, G_{i,t}, t) = \Sigma_n\Sigma_i\, \delta_{n,i}\, p_{n,i,t}\, DUM_i + \Sigma_n\Sigma_m\, \alpha_{nm}\, p_{n,i,t}^{\ .5}\, p_{m,i,t}^{\ .5}$$
$$+ \Sigma_n\, \delta_{nY}\, p_{n,i,t}Y_{i,t} + \Sigma_n\, \delta_{nK}\, p_{n,i,t}K_{i,t} + \Sigma_n\, \delta_{nI}\, p_{n,i,t}I_{i,t} + \Sigma_n\, \delta_{nG}\, p_{n,i,t}G_{i,t} + \Sigma_n\delta_{nt}\, p_{n,i,t}\, t$$
$$+ \Sigma_n\, p_{n,i,t}(\delta_{YY}\, Y_{i,t}^2 + \delta_{KK}\, K_{i,t}^2 + \delta_{YK}\, K_{i,t}Y_{i,t} + \delta_{IY}\, I_{i,t}\, Y_{i,t} + \delta_{IK}\, I_{i,t}\, K_{i,t} + \delta_{IG}\, I_{i,t}\, G_{i,t}$$
$$+ \delta_{It}\, I_{i,t}\, t + \delta_{II}\, I_{i,t}^2 + \delta_{GY}\, G_{i,t}\, Y_{i,t} + \delta_{GK}\, G_{i,t}\, K_{i,t} + \delta_{Gt}\, G_{i,t}\, t + \delta_{GG}\, G_{i,t}^2 + \delta_{tY}\, Y_{i,t}\, t$$
$$+ \delta_{tK}\, K_{i,t}\, t + \delta_{tt}\, t^2) + u_{i,t}\ ,$$

where $u_{i,t}$ is an independently, identically distributed error term with zero mean and constant variance, n,m =L^N,L^P,M, i,j =1,2,...,48, t=1982, 1983,..., 1996, and DUM_i represents a dummy variable for state i. Given constraints on adjustment of private capital in U.S. manufacturing (as suggested by Cohen and Paul [11]), this function represents short run cost minimizing behavior.[10,11] For estimation purposes, this primary estimating equation is augmented by behavioral equations representing input demands and output supply.

The (variable) input demand equations are derived from Shephard's lemma, $v_{n,i,t}=\partial VC_{i,t}/\partial p_{n,i,t}$ ($n=L^N,L^P,M$), and so take the form:

$$2)\quad v_{n,i,t}\,(Y_{i,t}, K_{i,t}, \mathbf{p_{i,t}}, I_{i,t}, G_{i,t}, t) = \partial VC_{i,t}/\partial p_{n,i,t} = \Sigma_i\, \delta_{ni}\, DUM_i + \Sigma_m\, \alpha_{nm}\, p_{n,i,t}^{\;-.5}\, p_{m,i,t}^{\;.5} + \delta_{nY}\, Y_{i,t}$$
$$+ \delta_{nK}\, K_{i,t} + \delta_{nI}\, I_{i,t} + \delta_{nG}\, G_{i,t} + \delta_{YY}\, Y_{i,t}^{\;2} + \delta_{KK}\, K_{i,t}^{\;2} + \delta_{YK}\, K_{i,t}\, Y_{i,t} + \delta_{iY}\, I_{i,t}\, Y_{i,t} + \delta_{IK}\, I_{i,t}\, K_{i,t}$$
$$+ \delta_{IG}\, I_{i,t}\, G_{i,t} + \delta_{It}\, I_{i,t}\, t + \delta_{II}\, I_{i,t}^{\;2} + \delta_{GY}\, G_{i,t}\, Y_{i,t} + \delta_{GK}\, G_{i,t}\, K_{i,t} + \delta_{Gt}\, G_{i,t}\, t + \delta_{GG}\, G_{i,t}^{\;2} + \delta_{tY}\, Y_{i,t}\, t$$
$$+ \delta_{tY}\, Y_{i,t}\, t + \delta_{tK}\, K_{i,t}\, t + \delta_{tt}\, t^2 + u_{n,i,t}\,,$$

where $u_{n,i,t}$ is again an independently, identically distributed error term. [12]

Output choice is represented in terms of pricing behavior as a profit maximizing decision allowing for imperfect competition, using the standard output supply expression equating marginal costs (MC) and revenues (MR): $MR = p_Y + \partial p_Y/\partial Y \bullet Y = MC = \partial TC/\partial Y= \partial VC/\partial Y$, or $p_Y = -\partial p_Y/\partial Y \bullet Y + \partial VC/\partial Y$. Substituting for $\partial VC/\partial Y$, and assuming that $\partial p_Y/\partial Y$ can be represented by the parameter λ_Y (which implies linearity of the output demand function),[13] results in the final estimating equation:

$$3)\quad p_{Y,i,t} = -\lambda_Y \bullet Y_{i,t} + MC_{i,t} = -\lambda_Y \bullet Y_{i,t} + \Sigma_n \delta_{nY}\, p_{n,i,t} + \Sigma_n p_n (2\delta_{YY}\, Y_{i,t} + \delta_{YK}\, K_{i,t} + \Sigma_n \delta_{nY}\, r_{n,i,t}\,)$$
$$+ u_{Y,i,t}\ .$$

The estimate of λ_Y, which represents the deviation between (average) output price and marginal revenue (and so would be zero with perfect competition), thus provides information about the degree of imperfect competition of manufacturing firms.[14]

Measures of Cost Effects and their Components

To evaluate own- and neighboring-state productive spillovers from transport network investments on state-level manufacturing industries, we represent the cost effects of these external factors as shadow values. These shadow values are measured as first derivatives, or first order elasticities, of the cost function. They thus yield insights about the implicit value to firms, in terms of production cost reductions, of additional airport infrastructure.

For example, our scenario suggests that the cost-based shadow value of G, $Z_G = \partial VC/\partial G$, or its proportional equivalent in elasticity form, $\varepsilon_{VC,G} = \partial \ln VC/\partial \ln G$, will be (significantly) negative for states with strong interdependencies within the network. This cost savings measure represents decreased congestion (or increased reliability or other amenities) from airport expansions in linked hubs that enhance air traffic flows and thus the transport of business travelers. Analogous measures may be constructed for other components of the **r** vector. In particular, we may compute shadow values and cost elasticities for own-state airport infrastructure stocks: $Z_I = \partial VC/\partial I$ and $\varepsilon_{VC,I} = \partial \ln VC/\partial \ln I$.[15] Similarly, we can represent the shadow value of (quasi-fixed) private capital input through $Z_K = \partial VC/\partial K$ or $\varepsilon_{VC,K} = \partial \ln VC/\partial \ln K$ measures.

In addition, since optimal input demands are embodied in the cost function through Shephard's lemma ($v_n=\partial VC/\partial p_n$), input-specific adaptations to G and I changes may be represented by derivatives and elasticities of the v_n functions, which are second derivatives or second order elasticities of the cost function. For example, to determine the (percentage or proportional) impact of a change or difference in linked-hub transport infrastructure, G, on L^N demand, we can compute the elasticity $\varepsilon_{LN,G} = \partial \ln L^N/\partial \ln G = (\partial L^N/\partial G) \bullet G/L^N = (\partial^2 VC/\partial p_{LN}\partial G) \bullet G/L^N$. The impacts of G changes on the shadow value of K, indicating long run incentives to expand or contract the capital stock for efficient production, may similarly be computed as $\varepsilon_{ZK,G} = \partial \ln Z_K/\partial \ln G = \partial Z_K/\partial G \bullet G/Z_K = (\partial^2 VC/\partial K\partial G) \bullet G/Z_K$.

If all variable input-specific impacts (for L^N,L^P,M) are the same, the $\varepsilon_{vn,G}$ elasticities will be equal to the overall cost elasticity $\varepsilon_{VC,G}$. If they differ, however (in magnitude or even sign), the effects of G (or similarly other external factors) are considered “biased.” Thus, for this example, G investment is absolutely L^N-saving (it increases the marginal product of L_N, so less L_N is needed) if $\varepsilon_{LN,G}$ is negative, and relatively L^N-saving if it is also larger (in absolute value) than $\varepsilon_{VC,G}$.

Note also that from Young’s theorem (symmetry of second-order derivatives of the cost function) $\varepsilon_{LN,G}$ will be equivalent to (but have a somewhat different interpretation than) the elasticity $\varepsilon_{ZG,pLN} = \partial \ln Z_G/\partial \ln p_{LN} = (\partial Z_G/\partial p_{LN})\bullet p_{LN}/Z_G = (\partial^2 VC/\partial G\partial p_{LN})\bullet p_{LN}/Z_G$. If $\varepsilon_{ZG,pLN}$ is negative, for example, the shadow value of G is greater at higher p_{LN} levels, implying larger cost saving benefits from reducing L^N.

Finally, we can represent interactions among the external variables as second-order elasticities. Since the shadow values of the **r** components take the form of first derivatives, the cross-effect of, say, G and I, may be expressed as $\varepsilon_{ZG,I} = \partial \ln Z_G/\partial \ln I = \partial Z_G/\partial I\bullet I/Z_G = (\partial^2 VC/\partial G\partial I)\bullet I/Z_G$. This reflects the impact of an expanded hub in the own-state on the cost savings associated with additional airport infrastructure investment in connected states, or the “substitutability” or “complementarity” of I and G.

Estimation Results

Airport Network Effects

We estimated the system of equations represented by (1), (2), and (3) by multivariate regression methods, using PC-TSP. We also checked the robustness of our Base model results for the presence of spatial autocorrelation by estimating a SAR model (with the error structure described in endnote 8), using the Generalized Moments techniques outlined by Kelejian and Prucha [17]. This did not alter the substantive results of our analysis.[16]

The parameter estimates for the Base model are presented in Appendix Table A1 (excluding the state dummy parameter estimates for ease of presentation).[17] The close "fits" for the equations, represented by R^2s of 0.993 or higher for the cost equation and all three of the input demand equations, indicate a close characterization of the state-level manufacturing cost structure for our data sample. The individual parameter estimates are also largely statistically significant, although with this flexible functional form most of the parameter estimates are not intuitively very interpretable. The significance of the cost effects or elasticity (shadow value) estimates depends on combinations of coefficients, each with their own standard error.[18]

Since large hub airports tend to be particularly congested (Cohen and Coughlin [9]), one might expect both the own- and other-state impacts of airport infrastructure to be different for manufacturing firms in states with large hubs than in states with no large hub airports. That is, at the margin, additional airport infrastructure may generate greater travel time savings in a state with more congested airports. Manufacturing firms in a state without a large hub, such as Connecticut, may thus face different cost impacts from airport expansions in it own as compared to connected states than firms in a state such as Illinois. In order to evaluate the empirical evidence of such differences across states with different air traffic volumes, we present the results separately for two sub-samples of states – with and without large hubs.

The elasticities reported in Table 1 are averages (means) of the estimates computed for each observation in the sample under consideration. The associated t-statistics are based on evaluation of the elasticities at the mean values of the data. These measures document a wide variety of cost impacts and interactions associated with airport expansions.

First, for states with large hubs, the average own-state effect of airport infrastructure investment – reflected by $\varepsilon_{VC,I}$ – is negative and significant at about -0.113. This estimate implies that, on average, a 1 percent increase in airport infrastructure stocks in a state with at least one large hub airport corresponds to a 0.113 percent fall in manufacturing costs within that state. The cost-effects of airport development in other states, measured by $\varepsilon_{VC,G}$ = –0.116, are similar; this result suggests that manufacturing costs in large hub states fall by 0.116 percent in response to a 1 percent increase in airport infrastructure stocks in other states. The similarity of the average $\varepsilon_{VC,I}$ and $\varepsilon_{VC,G}$ magnitudes for these states indicates that, since an airline passenger must travel through both an origin and a destination airport, improvements to congested destination airports yield comparable travel time savings (and in turn, manufacturing cost reductions) to improvements in congested origin airports.

The interpretation of the cost-effects of G and I in terms of travel-time and transport reliability for business travelers and freight is supported by the second order elasticities. The large (average) negative value and significance of the mean $\varepsilon_{LN,G}$ elasticity for states with hub airports indicate that increased airport stocks in other hub states results in non-production labor-saving (lowers non-production labor manufacturing industry demand) in the own state, which in turn implies an increased marginal product (or "effective labor input") for these workers. The negative $\varepsilon_{LP,G}$ elasticity suggests a similar pattern for production workers. Also, $\varepsilon_{LN,I}$ is the same sign as $\varepsilon_{LN,G}$, and significant (but smaller), which implies that benefits to firms from increased L^N marginal productivity are driven more by expansion of other states' airports, and enhanced traffic flows in and out of those states, than by merely expanding own-state airports. The story for freight is reversed in terms of magnitudes, but the average input demand elasticities $\varepsilon_{M,G}$ = -0.039 and $\varepsilon_{M,I}$ = -0.132 are still negative and significant. Although freight transport is facilitated by both own-state and connected states' airport expansion, it appears more affected by own-state investment.

Overall, these negative input demand elasticity estimates may be interpreted as increasing productivity of manufacturing workers who save traveling time (and, to a lesser extent, materials that are shipped with less disruption or more reliability), from both own- and neighboring-state airport improvements. Input-composition biases – different impacts on different inputs – from these public infrastructure shift factors are also evident from the different sizes of the input demand elasticities $\varepsilon_{vn,I}$ and $\varepsilon_{vn,G}$.

Recall also that an alternative perspective may be attributed to these measures, since elasticities such as $\varepsilon_{LN,G}$ and $\varepsilon_{ZG,pLN}$ must be symmetric by Young's theorem.[19] For example, $\varepsilon_{ZG,pLN}$ is positive and significant in both subsamples, implying that when the wages for non-production workers increase, the values to own-state manufacturing firms of additional airport investment in other hub states rise.[20] This is the converse of the $\varepsilon_{LN,G}$ interpretation. Finally, the positive sign and significance of $\varepsilon_{ZK,I}$ suggests that the shadow value of private capital rises with increases in public airport infrastructure, implying long run growth incentives that are consistent with overall lower production costs, although this is not true for other-state airport investment ($\varepsilon_{ZK,G}$ is positive but statistically insignificant).

In turn, for states with no major hubs, $\varepsilon_{VC,I}$ and $\varepsilon_{VC,G}$ are on average significantly negative, but $\varepsilon_{VC,G}$ is more than three times as large in magnitude as $\varepsilon_{VC,I}$. The greater deviation between the own- and connected-state network effects may be due to airports in states without large hubs being less congested, so there are fewer gains to expanding these airports. However, expansion of other airports generates benefits because any trip involves movement between at least two airports. Also, the cross-effects $\varepsilon_{ZG,I}$ and $\varepsilon_{ZI,G}$ are negative and significant, implying substitutability between I and G; increases in I (G) reduce Z_G (Z_I).

For input-specific effects, on average $\varepsilon_{LN,I}$ and $\varepsilon_{LN,G}$ are both negative and significant for the non-hub- as well as the hub-state subsamples. This indicates again that larger own- or connected-state airport stocks are associated with labor-saving and higher marginal productivity – that is, with travel-time savings and thus productivity gains for business travelers. Similar impacts are evident for production workers from the $\varepsilon_{LP,I}$ and $\varepsilon_{LP,G}$ estimates. The average $\varepsilon_{M,I}$ and $\varepsilon_{M,G}$ elasticities are also negative and significant for the non-hub states; the cost saving effects from greater I or G investment involves lower M costs for a given amount of output. Also, the $\varepsilon_{ZK,I}$, $\varepsilon_{ZK,G}$ elasticities show that private capital investment incentives are enhanced by both I and G investment, although the impact of own-state airport investment is smaller than for the hub states.

Concluding Remarks

In this study we have estimated a generalized Leontief cost function model incorporating measures of air transport infrastructure stocks, combined with input demand and output pricing equations, to compute elasticities representing the web of interactions among U.S. air transport network components and manufacturing industry costs. Our results document substantive impacts of own-state airport infrastructure on manufacturing industry costs and productivity. They also show that the impact of this “free input” on manufacturing firms is greatly enhanced by spillovers within the air transport network across states.

We find that manufacturing costs are lower in hub-states with greater own-state airport infrastructure stocks, implying cost saving benefits from airport improvements.

These savings are due to increased effectiveness (marginal products) of non-production workers, production workers and materials, from the enhanced traffic flow and reliability of the transport network. In large hub states, airport expansion in linked states appears to have a comparable cost impact on manufacturing firms to own-state airport investment. This impact, again driven by labor and materials savings from augmented input effectiveness, implies a key transport network externality that should be taken into account when developing policy to boost air traffic system efficiency. For states without hubs, own-state airport investment is also cost saving, primarily due to enhanced business travel for non-production workers, although its impact is smaller and there is a much stronger impact of investment in linked hub-states.

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Table 1 - Base Elasticities

	States with large hubs			***States with no large hubs***	
	Mean	*t-statistics*		*Mean*	*t-statistics*
$\varepsilon_{VC,I}$	**-0.113**	*-7.56*	$\varepsilon_{VC,I}$	**-0.056**	*-5.30*
$\varepsilon_{VC,G}$	**-0.116**	*-7.82*	$\varepsilon_{VC,G}$	**-0.188**	*-12.11*
$\varepsilon_{VC,K}$	**-0.327**	*-18.96*	$\varepsilon_{VC,K}$	**-0.382**	*-18.87*
$\varepsilon_{VC,Y}$	**1.149**	*152.58*	$\varepsilon_{VC,Y}$	**1.262**	*243.53*
$\varepsilon_{VC,T}$	**-0.012**	*-25.33*	$\varepsilon_{VC,T}$	**-0.018**	*-17.24*
$\varepsilon_{VC,pLN}$	**0.138**	*106.16*	$\varepsilon_{VC,pLN}$	**0.084**	*83.02*
$\varepsilon_{VC,pLP}$	**0.138**	*96.23*	$\varepsilon_{VC,pLP}$	**0.118**	*120.84*
$\varepsilon_{VC,pM}$	**0.738**	*394.38*	$\varepsilon_{VC,pM}$	**0.785**	*222.28*
$\varepsilon_{ZG.I}$	**-0.406**	*-3.45*	$\varepsilon_{ZG.I}$	**-0.086**	*-4.22*
$\varepsilon_{ZK,I}$	**0.606**	*7.04*	$\varepsilon_{ZK,I}$	**0.062**	*6.67*
$\varepsilon_{LN,I}$	**-0.074**	*-3.31*	$\varepsilon_{LN,I}$	**-0.095**	*-2.12*
$\varepsilon_{LP,I}$	**-0.079**	*-3.64*	$\varepsilon_{LP,I}$	**-0.065**	*-2.27*
$\varepsilon_{M,I}$	**-0.132**	*-6.62*	$\varepsilon_{M,I}$	**-0.053**	*-6.08*
$\varepsilon_{ZI,G}$	**-1.388**	*-3.38*	$\varepsilon_{ZI,G}$	**-0.441**	*-3.78*
$\varepsilon_{ZK,G}$	**0.183**	*1.46*	$\varepsilon_{ZK,G}$	**0.021**	*1.48*
$\varepsilon_{LN,G}$	**-0.220**	*-5.76*	$\varepsilon_{LN,G}$	**-0.675**	*-9.86*
$\varepsilon_{LP,G}$	**-0.440**	*-12.20*	$\varepsilon_{LP,G}$	**-0.721**	*-16.04*
$\varepsilon_{M,G}$	**-0.039**	*-2.30*	$\varepsilon_{M,G}$	**-0.069**	*-4.43*
$\varepsilon_{ZI,K}$	**1.631**	*4.79*	$\varepsilon_{ZI,K}$	**0.584**	*4.37*
$\varepsilon_{ZI,pLN}$	**0.086**	*3.85*	$\varepsilon_{ZI,pLN}$	**0.116**	*2.81*
$\varepsilon_{ZI,pLP}$	**0.108**	*4.57*	$\varepsilon_{ZI,pLP}$	**0.129**	*3.21*
$\varepsilon_{ZI,pM}$	**0.807**	*10.64*	$\varepsilon_{ZI,pM}$	**0.755**	*8.25*
$\varepsilon_{ZI,T}$	**-0.029**	*-3.84*	$\varepsilon_{ZI,T}$	**-0.026**	*-3.05*
$\varepsilon_{ZG,K}$	**-0.028**	*1.45*	$\varepsilon_{ZG,K}$	**0.039**	*1.46*
$\varepsilon_{ZG,pLN}$	**0.257**	*6.29*	$\varepsilon_{ZG,pLN}$	**0.272**	*11.31*
$\varepsilon_{ZG,pLP}$	**0.475**	*9.75*	$\varepsilon_{ZG,pLP}$	**0.444**	*15.99*
$\varepsilon_{ZG,pM}$	**0.268**	*2.90*	$\varepsilon_{ZG,pM}$	**0.284**	*5.84*
$\varepsilon_{ZG,T}$	**0.015**	*2.98*	$\varepsilon_{ZG,T}$	**0.012**	*3.16*

Appendix Table A1 - Parameters, t-statistics, and R-Squareds

Base Model

Parameter	Estimate	t-statistic	Parameter	Estimate	t-statistic
$\alpha_{LN,LP}$	**-1780.120**	-2.861	$\delta_{K,I}$	**-4.353E-05**	-7.183
$\alpha_{LN,M}$	**4245.060**	3.652	$\delta_{Y,T}$	**-0.003**	-13.393
$\alpha_{LP,M}$	**8699.620**	8.202	$\delta_{G,T}$	**-0.011**	-3.140
$\delta_{LN,Y}$	**0.196**	44.027	$\delta_{I,T}$	**0.019**	4.095
$\delta_{LP,Y}$	**0.244**	63.163	$\delta_{K,T}$	**0.001**	1.077
$\delta_{M,Y}$	**0.743**	97.694	λ_{Y}	**-1.668E-06**	-31.749
$\delta_{LN,T}$	**7.166**	0.793			
$\delta_{LP,T}$	**13.411**	1.729			
$\delta_{M,T}$	**-99.021**	-4.457			
$\delta_{LN,I}$	**-0.354**	-2.054			
$\delta_{LP,I}$	**-0.364**	-2.171	Equation	R-Squared	
$\delta_{M,I}$	**-1.659**	-5.937	VCOST	0.998	
$\delta_{LN,G}$	**-0.858**	-9.690	L^{N}	0.995	
$\delta_{LP,G}$	**-1.278**	-15.434	L^{P}	0.993	
$\delta_{M,G}$	**-0.817**	-4.571	M	0.996	
$\delta_{LN,K}$	**0.009**	0.436	P_{Y}	0.484	
$\delta_{LP,K}$	**-0.124**	-6.210			
$\delta_{M,K}$	**-0.972**	-25.173	No. of observations: 720		
$\delta_{Y,Y}$	**-4.413E-07**	-10.672			
$\delta_{I,I}$	**5.552E-05**	2.448			
$\delta_{K,K}$	**2.619E-06**	5.255			
$\delta_{G,G}$	**1.731E-06**	0.300			
$\delta_{Y,G}$	**2.348E-06**	4.494			
$\delta_{Y,K}$	**2.887E-07**	1.312			
$\delta_{G,K}$	**-3.226E-06**	-1.478			
$\delta_{Y,I}$	**-4.942E-07**	-0.528			
$\delta_{G,I}$	**1.707E-04**	4.561			

Data Appendix

Labor quantities: The number of workers engaged in production (L^P) at operating manufacturing establishments and the number of full-time and part-time employees (TOTAL) on the payrolls of operating 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) are obtained as the difference between TOTAL and L^P.

Wage bills: The ASM reports wages paid to production workers and gross earnings of all employees on the payroll of operating manufacturing establishments. 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.

Airports capital stock: 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.[21] The initial capital stock (1982) values for each state were taken as the average of air transportation capital outlays for 1977 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."

Private capital stock: the private capital stock data were constructed for each state using the perpetual inventory method on state level new capital expenditures data 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 $(i_t + d_t)q_{K,t}[1/(1\text{-}taxrate_t)]$, 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 shipments reported in the ASM were deflated by manufacturing Gross State Product deflators for each state (provided by DRI).

[1] See Coughlin, Cohen and Khan [13] for a detailed discussion of the economics of aviation security.

[2] Haughwout [15] notes that difficulties can arise when using state level data for infrastructure studies. We carry out our analysis at the state level at least in part due to the availability of production data at the state level (including capital stock data, which the above mentioned study does not incorporate). Although it is possible to consider a more disaggregated sample of airports, since expenditure data are available for individual airports, it is not possible to consistently partition the production data. In addition, our data on person-trips are at the state level – from state of origin to state of destination.

[3] See, for example Holtz-Eakin and Schwartz [16], Kelejian and Robinson [18], and Boarnet [4].

[4] This distinction is similar to representing temporal dependencies by including (lags in) fixed inputs and time trends into the theoretical model used for empirical implementation, versus incorporating an autoregressive structure in the stochastic model.

[5] They find a positive effect on own-states' choices of "neighboring" states expenditure patterns, including those for highways

[6] We also check the robustness of our findings for the presence of spatial autocorrelation.

[7] This definition is provided in "Appendix B: Definitions of Subject Characteristics" of the Survey. The data were provided by the Bureau of Transportation Statistics.

[8] This was suggested by an anonymous referee.

[9] This is similar to Cohen and Paul's [11] treatment of highway interdependencies.

[10] Note, however, that we could potentially represent long run behavior by solving for the implied level of K associated with the steady state equilibrium condition $p_K = -\partial VC/\partial K$, where p_K is the market price of K and $= -\partial VC/\partial K = Z_K K$ is the shadow value of K.

[11] This model representing short run cost minimizing behavior of firms is built upon the assumption of exogenous factor prices. Note that even though Haughwout [15] assumes general equilibrium in his analysis of the effects of public infrastructure, such a general equilibrium approach would not be appropriate for our short run model that uses annual data. Furthermore, we are looking at the manufacturing sector only, which represents a small component of U.S. production, so our assumption of factor price exogeneity seems justifiable.

[12] For the SAR model the error specification for the variable cost function becomes $VC_{i,t} = VC(\bullet)_{i,t} + u_{i,t}$, where $u_{i,t} = \rho_s \Sigma_j w_{i,j} u_{j,t} + \phi_{i,t}$, $-1<\rho_s<1$, $w_{i,i} = 0$, $\phi_{i,t}$ is independently, identically distributed with zero mean and constant variance, and $w_{i,j}$ is the weight that state j has on state i's error term. This expression represents the error term for a particular observation (state-year combination) as a random component, $\phi_{i,t}$, plus a component capturing a weighted average of other states' error terms that spill over to the state under consideration. The input equations also specified for estimation are analogously adapted to allow for errors of the form $u_{n,i,t} = \rho_{s,n} \Sigma_j w_{i,j} u_{n,j,t} + \phi_{n,i,t}$, where $-1<\rho_{s,n}<1$, $\phi_{n,i,t}$ is independently, identically distributed with zero mean and

constant variance, and n=L^N,L^P,M. The error term for each input demand equation thus has its own random component, and the spatial component consists of a weighted average of the error terms for input n for all other states.

[13] This is consistent with a linear demand curve.

[14] This adaptation also accommodates to some extent any endogeneity in the output price that may arise from the level of aggregation of the data.

[15] In our discussion of results below we will emphasize the proportional elasticity measures, both because their interpretation is more clear (like any other elasticity they are unit-less), and because their sign and statistical significance is equivalent to those for the shadow value.

[16] In particular, we found that the signs and significance of $\varepsilon_{VC,I}$ and $\varepsilon_{VC,G}$ in both sub-samples were unchanged. We thus chose to focus on the Base model results.

[17] Based on the suggestion of an anonymous referee, we also tried adding state and year fixed effects to the pricing equation (3). These fixed effects caused the G and I cost elasticities to become unstable, and for that reason, we decided to omit these fixed effects from our estimation.

[18] It is worth noting, however, that the λ_Y parameter estimate is very small but highly significant. Due to this significance, plus the impact on other elasticities' significance when the imperfect competition adaptation was omitted (implying joint significance), we included equation (3) in the estimating model even though it is not the focus of our analysis.

[19] The symmetry of the second order derivatives does not mean that the elasticities are necessarily equivalent in magnitude or significance ($\varepsilon_{LN,I}$ is insignificant but $\varepsilon_{I,LN}$ is significant), because the shadow value elasticities are evaluated at the fitted shadow values, and thus depend on coefficients and standard errors embodied in these estimates as well as the derivatives themselves.

[20] Note that this interpretation requires recognizing that $Z_G<0$.

[21] See Cohen and Coughlin [9] for a discussion of airport financing.