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Authors
Cohen, Jeffrey P.
Morrison Paul, Catherine J.

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Department of Agricultural and Resource Economics
University of California Davis

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by Jeffrey P. Cohen and Catherine J. Morrison Paul

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ABSTRACT

In this paper we postulate, measure, and evaluate the importance of cost-impacts from spatial and industrial spillovers for analysis of economic performance. To accomplish this, we incorporate measures of "activity levels" of related states and industries in a cost function model, and estimate their associated thick market and agglomeration effects in terms of shadow values and elasticities. We focus on the food processing sector, the proximity of own-industry activity in neighboring states, and the supply- and demand- side "drivers", associated with urbanization and localization economies (represented by the GSP and agricultural intensity in the own and neighboring states). We find significant cost-savings benefits to a states' food processing sector of being close to other food manufacturing centers (high levels of food processing activity in neighboring states). We also find it beneficial to be in a state with high purchasing power (demand), and to have neighboring states that are agriculture-based (supply). However, it also seems costly to actually be located in a heavily agricultural or rural state, possibly due to diseconomies from "thin markets" associated with infrastructure support and labor markets.

The authors are Assistant Professor of Economics, Barney School of Business, University of Hartford and Professor, Department of Agricultural and Resource Economics, University of California, Davis, and member of the Giannini Foundation.

Introduction

It seems increasingly clear that, especially in our "new era" of modern production systems, interconnections between productive entities are substantive and expanding. These interconnections have various dimensions – in particular spatial and industrial (thick markets, and supply and demand agglomeration effects). They also likely have important productivity implications, that may be driving observed trends toward urbanization and industrial concentration, and horizontal and vertical consolidation and integration. Understanding these productive inter-dependencies, and their potential to motivate various types of conglomeration, requires modeling and measuring their existence and impacts. However, productivity studies are typically based on models that preclude recognition of connections or externalities among economic entities, and resulting spillovers affecting economic performance through cost economies.

In this paper we overview and implement a conceptual basis for including various types of spillovers in cost and productivity analysis, following the development in Paul (2001). This treatment allows for temporal, spatial, and industrial linkages, through input quasi-fixities, geographic proximity, and horizontal and vertical spillovers among own and supplier/demander economic sectors. Such spillovers are accommodated in the analysis through adjustments to the structural model (shadow values from external effects) and the stochastic structure (temporal and spatial autoregressive structures).

The resulting model allows us to characterize and measure the potential for short run quasi-fixities to keep costs higher than if long run adjustment were possible, implying economies of flexibility. It also permits us to represent and quantify spatial connections that result in thick market and agglomeration economies associated with concentrations of own-industry establishments in neighboring states, and with production levels of suppliers and demanders in own and neighboring states.

Thick market economies may result from external knowledge spillovers, or "geographic concentrations of knowledge", which imply that locating close to like or related enterprises "enhances the generation of innovation and yields higher rates of technological advance and economic growth" (Feldman, 1999). Agglomeration impacts from demanding and supplying sectors may also take the form of urbanization and localization economies associated with distance. For these and other potential forms of spatial and industrial spillovers, as Feldman puts it, location involves "a geographic unit over which interaction and communication is facilitated,… and economic activity is enhanced." Either economies or diseconomies may, however, arise from these externalities due to potentially counteracting economic forces associated with urbanization and density, and with "ruralization" or "thin markets", that might generate benefits for producers in the state, but could also impose costs.

For our empirical representation and measurement of these spillovers we use a cost function framework including activity measures for spatially and industrially linked sectors. We target the U.S. food system and its sectoral layers, with a focus on the food manufacturing industry. We base our analysis on panel data for food processing (manufacturing) output production and input use (capital, non-production and production labor, and intermediate materials), and agricultural and overall (gross state product, GSP) production levels, for each of the 48 contiguous states from 1986-96.

Our model recognizes spatial connections within this industry, as well as externalities from the proximity of the supply of primary agricultural materials, and consumers' demand for food products. To accommodate these temporal, spatial, and industrial linkages we allow for capital quasi-fixity, and include measures of neighboring state's food processing levels, and own- and (weighted) neighboring-state's agricultural and total production levels, as cost function arguments. We also take into account state size to recognize the potential for internalizing such benefits in relatively large states.

Although we find little evidence of temporal connections in our largely cross-sectional dataset (48 states, 3 sectors and 11 years), we find significant cost-saving benefits from locating in a region that is relatively food-processing intensive (neighboring states have high levels of food manufacturing activity). And we find evidence that it is cost-saving to locate in a high-demand area (urbanization economies), and *close* to agricultural markets (with neighboring states having high agricultural production – localization economies). By contrast, we find that locating directly *in* a state with a high agricultural output level is costly for producers, suggesting that there are diseconomies associated with rural states, or "thin market" effects possibly resulting from lower infrastructure levels or limited labor markets.

These measured economies (cost-saving benefits) and diseconomies (increased costs) associated with spatial and industrial spillovers also imply interactions among them and with input demands. When we consider the implied substitutability or complementarity among external and internal production factors underlying the cost patterns, we find limited linkages among the external effects. We also find that observed cost patterns are primarily driven by materials demand, with capital and particularly labor demand responses varying more broadly, depending on the external factor affecting the system. So input composition as well as costs are impacted by spillovers.

Representing the Cost Structure and External Spillover Effects

Modeling and measuring the factors affecting economic performance is typically based on specifying and estimating a production or cost function relationship, since performance is fundamentally based on the output producible from a given amount of inputs, or the costs of a given level of output. The cost function represents optimization (input demand) behavior in addition to the technological relationships embodied in the production function, and so becomes a function of the prices of productive (choice or internal) inputs rather than their levels. Otherwise it is a function of the same factors that appear as arguments of the production function. In particular, if externalities have a productive impact they will affect the cost relationship, and thus economic performance, through cost economies or diseconomies.

More specifically, technically efficient production processes can be represented by a production function of the form Y(**X,T**), where Y is (aggregate) output, **X** is a vector of inputs, and **T** is a vector of external factors determining the existing technological and environmental base underlying the production structure. The least cost way to produce a given amount of output may in turn be characterized by a cost function of the form TC(Y), or, more fully, TC(Y,**p**,**K,T**) = VC(Y,**p**,**K,T**) + $\Sigma_k p_k K_k$, where TC is total input cost, VC is variable input cost, **p** is a vector of observed prices of the **X** inputs that are variable, **K** is a vector of levels of **X** inputs that are not immediately adjustable (quasi-fixed), and p_k is the market price of K_k. Various exogenous or external factors, including the input fixities (temporal linkages) and spatial and industrial spillovers (thick market or agglomeration effects) representing inter-dependencies across time, space, and sector, focused on in Paul (2001), may be components of the **K** and **T** vectors.

The cost function representing the minimization of input costs, $TC=\Sigma_b p_b X_b$, subject to the production function, $Y(\mathbf{X,T})$, can be graphed as the short run cost curve $TC(Y;\mathbf{p},\mathbf{K,T})$. Constraints on **K** adjustment cause a difference between short and long run cost curves, so **K** adjustment implies cost savings (economies) from moving to or toward long run from short run costs. If the **K** factors are instead choice variables in the time frame represented by the data, $TC(Y;\mathbf{p},\mathbf{T})$ characterizes the long run cost curve. Changes in the (external) components of the **T** vector also generate cost economies if they trigger a downward shift of the cost curve (lower unit costs for a given amount of output), or diseconomies if they involve an upward shift. And the optimization process imbedded in the cost function implicitly captures the input demand changes, or the substitutability among internal and external productive factors, associated with shifts in the cost curve(s). Modeling and measuring this full set of cost- and cross-effects therefore provides a rich basis for analyzing internal and external cost drivers, and cost and economic performance patterns.

Questions about the productive impact of any recognized cost determinant may be addressed in terms optimizing responses for the internal (adjustable) factors, or shadow values for the quasi-fixed or external factors, resulting from changes in the arguments of the cost function. For example, the total cost impact of a change in the price of a variable input is, by Shephard's lemma, the demanded input level; $\partial TC/\partial p_b=X_b$, or $\varepsilon_{TC,pb} = \partial \ln TC/\partial \ln p_b=X_b p_b/TC=S_b$ in proportional terms (where S_b is the cost share of the input, and $\varepsilon_{TC,pb}$ denotes the total cost elasticity with respect to a change in input price p_b).

The shadow values of output or inputs expressed in terms of levels in the TC function may similarly be computed as first order derivatives. For example,

$\partial TC/\partial Y=MC$ or $\varepsilon_{TC,Y} = \partial \ln TC/\partial \ln Y = MC\bullet Y/TC$, where MC (marginal cost) is essentially the shadow value of Y, and the cost elasticity $\varepsilon_{TC,Y}$ reflects scale economies. And the net shadow value of the kth quasi-fixed factor K_k, expressed as $\partial TC/\partial K_k=Z_k+p_k$ or $\varepsilon_{TC,Kk} = \partial \ln TC/\partial \ln K_k = (Z_k+p_k)K_k/TC$, where $Z_k=\partial VC/\partial K_k$ is the shadow value of K_k, captures the extent of subequilibrium for K_k. [1]

More to the point for our current application, shadow values and corresponding elasticities (proportional impacts) may also be computed for the external shift factors contained in the **T** vector. That is, they can be measured as $\partial TC/\partial T_m=Z_m$, or $\varepsilon_{TC,Tm} = \partial \ln TC/\partial \ln T_m = Z_mT_m/TC$, if T_m is a quantitative variable, and $\varepsilon_{TC,Tm} = \partial \ln TC/\partial T_m = Z_m/TC$ if T_m is a time counter or qualitative variable.

The most common of such measures, representing temporal cost trends for a given entity (such as firm, industry, or nation), is typically expressed as the elasticity of TC with respect to a time counter t: $\varepsilon_{TC,t} = \partial \ln TC/\partial t$. Or if time dummies rather than a time trend are included in the T vector, the shift associated with a particular time period, t_1, may be measured as $\varepsilon_{TC,t1} = \partial \ln TC/\partial t_1$. In this case, for comparison purposes, one time period must provide the basis for analysis – say t_0 – so these time derivatives represent the cost difference compared to t_0.

Measuring the cost impacts resulting from changes in the various arguments of the cost function – or "sourcing" the drivers of cost patterns – may be accomplished parametrically by empirically estimating the cost function and directly taking these derivatives. However, if the only shift factor in **T** is the time trend t, as is typical for

[1] The shadow values for internal outputs and inputs have optimization implications, since $MC=p_Y$ and $Z_k=p_k$ (where p_Y is the market price of Y) if the Y and K_k markets are perfectly competitive, and if Y and K_k are at their profit-maximizing levels. However, this optimization is not *a priori* imposed on the model.

production analysis, the "technical change" measure $\varepsilon_{TC,t}$ in a sense becomes a residual measure, even though it is estimated parametrically.[2] The impacts of any cost factors not taken into account as arguments of the estimated function (normally only aggregate output, and capital, labor, and materials input prices) cannot be identified, and thus are imbedded in the measures of contributions of the recognized factors – $\varepsilon_{TC,t}$ as well as $\varepsilon_{TC,pb}$ and $\varepsilon_{TC,Y}$ (and $\varepsilon_{TC,Kk}$ if potential quasi-fixity is recognized). In particular, if other cost determinants or shifters such as fixities, or thick market or agglomeration effects, are ignored in the computation of these elasticities, the elasticity estimates will erroneously embody these effects, so their cost impacts cannot be separately identified.

That is, temporal spillovers from input quasi-fixities may generate such interpretation difficulties if not taken into consideration, because they cause short run costs to be higher than may be attained in the long run. If the distinction between short and long run behavior is relevant (affects observed costs), and this is not accommodated in the cost function specification, this is likely to result in erroneous cost and substitution elasticity estimates. Such temporal linkages might also affect the appropriate stochastic structure, implying that an autoregressive process (such as AR1) might be empirically justified for estimation of the cost relationship.

Spatial and industrial externalities or spillovers that cause cost economies (diseconomies) that could differ over time and location, and have varying output- and input-specific components, may also convolute standard elasticity measures if not recognized. If such impacts are likely to be substantive, measures representing these

[2] That is, rather than explicitly as a residual, as for the Solow residual which is commonly recognized to be a residual "measure of our ignorance".

spillovers should be incorporated as components of the **T** vector, to facilitate identifying the associated cost economies and underlying production relationships.

Spatial connections within and across sectors may arise due to information diffusion, interaction and communication, innovation, intellectual capital, and quality or ideas embodied in goods that cause geographic and industry inter-dependencies. For example, Krugman (1991), and David and Rosenbloom (1990) emphasize that the generation of innovation, which in turn fuels productivity and growth, may be enhanced by location. Zucker and Darby (1998) focus on knowledge embodied in individuals, and the importance of localized intellectual capital. And Coe and Helpman (1995) stress the transmission of ideas through trade, or demand of products embodying ideas or innovations, which may have a spatial dimension.

Thick-market effects in the food processing industry might well stem from knowledge spillovers or interdependencies that motivate like firms to conglomerate in a particular geographic location. If so, it will be informative to incorporate a measure of own-industry production levels in neighboring localities, or states, as a **T** component in our cost function specification.[3] Alternatively – or in combination – such spatial linkages may be accommodated similarly to the AR1 stochastic specification used to capture temporal inter-dependencies, through a spatial autoregressive model, as proposed in the recent spatial econometrics literature.[4]

In addition to this purely spatial dimension of thick markets linkages, agglomeration effects might arise from proximity to supplying or demanding sectors, both in the own- and neighboring-states, implying an industrial or sectoral dimension.

[3] For our analysis, we weight these activity measures by land mass to recognize that such spillovers will be less important for a large than a small state.

Including measures of such vertically linked sectors' "activity levels" in the **T** vector, which is similar in spirit to Bartlesman, Caballero and Lyons (1994) and Morrison and Siegel (1999), can represent such inter-dependencies. The activity measures may be expressed in terms of input or output levels of the direct supplying/demanding sectors, or weighted averages of a variety of sectors.

These externalities may also be interpreted as urbanization and localization economies. If firms in a particular sector find it advantageous to locate close to an area of high population density and buying power, associated with greater demand for the final product or perhaps infrastructure availability, one might characterize this as urbanization economies. If it is cost-saving to locate close to suppliers, this might be thought of as localization economies.[5] Thus, in the food processing context developed here, urbanization economies may arise from high potential food demand levels in a state or its close neighbors, represented by concentrations of total production (GSP) and thus purchasing power. And localization economies may be generated from high agricultural intensity in a state or surrounding areas, and the resulting proximity/availability of primary agricultural materials.

To model and measure such external cost impacts, we incorporate temporal and spatial spillovers from own-, supplying- and demanding- sectors, in both own- and neighboring-states, in our specification of food processing industry costs. In the next section we further develop such a framework for empirical implementation.

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[4] This will be elaborated further below. See, for example, Kelejian and Prucha, and Bell and Bockstael.
[5] These distinctions are common in the Urban Economics literature, as developed and overviewed by Hoover, 1948, and O'Sullivan, 2000.

Empirical Implementation of a Cost Model with Spatial and Industrial Spillovers

As alluded to above, accommodating temporal, spatial, and industrial linkages in a cost-based model may be accomplished by directly representing the driving forces as factors in the cost (and thus implicitly production) function, or by recognizing them in the stochastic specification. To move toward an implementable model, however, we need to be more specific about what form these adaptations to the standard model might take.

The most common example of this is in the temporal dimension, where cost linkages between time periods are due to input stock durability and quasi-fixity. Incorporating temporal dependence in the structural model is often accomplished by representing **K** – usually assumed to be capital, K – as a fixed input vector that is not optimized over in the short run. If K is the one quasi-fixed variable, the productive contribution of K may be expressed in terms of its shadow value, Z_K, and the deviation from long run equilibrium captured by the difference between Z_K and p_K. A more explicitly dynamic model may alternatively be developed by incorporating an indicator of adjustment costs, usually represented by the investment level $\Delta K=K_t-K_{t-1}$, as in Morrison (1985), which implicitly brings lagged variables into the cost representation.

Another way time-dependence may be recognized is to allow for autoregressive errors in the stochastic structure, which again in effect brings lagged variables into the estimating function. In such a case $TC = TC(\bullet) + u_t$ and $u_t = \rho u_{t-1} + \varepsilon_t$ (where ρ is the cost function-specific AR(1) parameter, and ε_t is the random or white noise period t estimation error for TC), so substituting $u_{t-1} =TC_{t-1}- TC(\bullet)_{t-1}$ incorporates lagged values of all variables into the equation to be estimated.[6]

[6] This adjustment may be written in matrix form for an equation system, as in Berndt (1991).

In preliminary empirical investigation for our application, we found that allowing for the temporal dimension was not empirically relevant for our primarily cross-sectional dataset. That is, shadow values for capital were not significantly different than the corresponding market prices, and appending an AR1 process did not impact the results substantively. So the primary emphasis in the empirical development and estimation below is on the spatial and industry dimensions.

It remains important to recognize the temporal dimension, however, both to establish its impact empirically, and to motivate the symmetry of the temporal and spatial dimensions. One way to allow for spatial linkages is through adaptation of the stochastic structure, similarly to the standard adjustment for temporal autocorrelation. Such models, as developed by Kelejian and Prucha (1999) and Bell and Bockstael (2000), provide the basis for the spatial econometrics literature. Spatial inter-connections are in this context defined via lags for geographical location (say, state) at any one point in time. If there is only one adjoining state who's production, cost, or other "activity" levels might affect that of the state under consideration, this adaptation is directly analogous to the AR(1) adjustment. $TC_{i,t} = TC(\bullet)_{i,t} + u_{i,t}$, where $u_{i,t} = \rho u_{j,t} + \varepsilon_{i,t}$; and $u_{j,t}$ is the (unadjusted) error term for state j at time t, (rather than for time period t-1), and $\varepsilon_{i,t}$ is a white-noise error.

If multiple states' production or costs affect state i's costs, the error structure for state i at time t becomes $u_{i,t} = \rho\Sigma_j w_{i,j}u_{j,t} + \varepsilon_{i,t}$. Substituting, and writing this in matrix notation, yields $TC = TC(\bullet) + \rho Wu_t + \varepsilon_t$, where W is a weighting matrix and u_t is a vector of time-t error terms for each state that has a cost effect on state i. So Wu_t reflects a weighted sum of the $u_{j,t}$ from $TC(\bullet)$ estimation for other states (assuming $w_{i,j} = 0$).

Defining the "connecting" states, and their weights, then becomes important (and somewhat arbitrary, as for any lag-type structure imposed on a model). For example, the inter-related states might be those that have a common boundary, and their weights the amounts of state-produced commodities that cross state lines.[7]

A spatial externality index might also directly be included as an independent variable in the cost function, to represent the dependence of costs in state i on activity in geographically connected areas. Such an externality index may be defined as the weighted sum of all state j's activities (a_j = production, input use, or costs) related to that of state i, $\Sigma_{j\neq i}w_{i,j}a_{j,O}=WA_O=A^W{}_O$, so TC=TC(Y,**p**,t,$A^W{}_O$). Establishing the cost benefit of adjoining states' activity thus involves measuring the shadow value $Z_{AO}=\partial TC/\partial A^W{}_O$.

"Related to" in this case implies being in the same ("own", denoted by subscript O) industry, but in neighboring states, implying thick market impacts with only a spatial dimension. However, it could also, or alternatively, involve being suppliers or demanders for the industry, implying agglomeration effects that reflect the broader notion of externality or spillover effects from the activity of (vertically) linked sectors.

This was the motivation for including weighted sums of "aggregate activity", based on the share of materials received by or supplied to other industries, in a 1st-order model of aggregate national U.S. manufacturing production by Bartlesmen, Caballero and Lyons (1994). In their study measures of the externalities $\Sigma_j w_{i,j}a_{j,d} = A^W{}_d$ (in our notation), where j now denotes industry and d denotes demanding (D) or supplying (S) sector, were imbedded into a first-differenced log-linear production function relationship to identify their productive impact. Morrison and Siegel (1999) incorporated analogous

[7] Such linkages or spillovers might also be characterized for nations, according to their trade balances.

measures into a cost function model of the form $TC = TC(Y,\mathbf{p},t,A^W_D,A^W_S)$, where t, A^W_D, and A^W_S are the components of the **T** vector. In this context, quantifying the impacts of supply- and demand-agglomeration spillovers involves establishing the magnitude and significance of the shadow values $Z_{AWD}=\partial TC/\partial A^W_D$, $Z_{AwS}=\partial TC/\partial A^W_S$.

In this study we have used a combination of these spatial and industrial spillover notions to empirically capture a web of thick market and agglomeration, or urbanization and localization economies, across states for the U.S. food manufacturing industry. To accomplish this, we need to more explicitly define A^W_O, A^W_D, and A^W_S.

The "activity" variables a_j underlying the spillover variable A^W_O are defined in terms of production levels in the own (food processing) industry in neighboring states. The weights w_{ij} that are used to obtain the weighted average give all states neighboring state i equal weight, and all other states zero weight. This weight structure was also used to incorporate a spatial autocorrelation adjustment.[8]

The supply- and demand- agglomeration effects might be expected to stem from own-state suppliers and demanders, and so our primary agglomeration measures were defined as (unweighted) measures of own-state agricultural production and GSP, A_S and A_D.[9] This is similar to the use by Bernstein (1998) of an unweighted sum of R&D capital stocks from related industries to capture R&D spillovers. We also, however, allowed for industry layer linkages in neighboring states, by defining additional A^W_S and A^W_D measures as weighted sums of agricultural production and GSP activity levels in states

[8] Both these adjustments are often made in this literature, which has primarily focused on linkages of government expenditures across states. So, for example as in Case et al., W becomes a weighting matrix for u_t in the stochastic specification, and for other states' expenditures, E_t, in the estimating model.
[9] Lagged values were alternatively tried in order to accommodate possible endogeneity or overlap between the sectors, but this had very little impact on the results.

with joint borders, based on the weights w_{ij} used for constructing A^W_O. The agglomeration spillovers variables were normalized by the size of the state, in terms of land mass, to recognize that it is the intensity or density of supplier and demander production levels that drives urbanization and localization economies.

Although in preliminary empirical investigation we found temporal adaptations allowing for K fixity not to be empirically supported, A^W_O, A_S, A_D, and A^W_S were significant cost-determinants for state-level food manufacturing industries. Our final estimation model was therefore based on a cost function of the form $TC(Y,p_N,p_P,p_M,p_K,t, \mathbf{D_S},A^W_O,A_D,A_S,A^W_S)$, where Y is own-state output from the food manufacturing sector, N,P,K and M denote non-production labor, production labor, capital, and intermediate materials inputs, t is a time counter, $\mathbf{D_S}$ is a vector of state dummy variables, and A^W_O, A^W_S, A_D, A_S, represent the (weighted) activity levels of neighboring states in the same and the agricultural sector, own-state demanders, and own-state suppliers.

The cost function is assumed to have the flexible generalized Leontief form:

$$1)\quad TC(Y,p_N,p_P,p_M,p_K,t,\mathbf{D_S},A^W_O,A_D,A_S,A^W_S) = \Sigma_b\Sigma_S\, \delta_{bS}\, p_b\, D_S + \Sigma_b\Sigma_q\, \alpha_{bq}\, p_b^{.5}\, p_q^{.5}$$
$$+ \Sigma_q\, \delta_{bY}\, p_b Y + \Sigma_b\Sigma_n\, \delta_{bn}\, p_b\, T_n + \Sigma_b p_b(\delta_{YY}\, Y^2 + \Sigma_n\, \delta_{nY}\, T_n Y + \Sigma_n\Sigma_m\, \delta_{nm}\, T_n T_m)\ ,$$

where b,q denote the variables inputs N, P, M, K, and m,n denote the external shift factors A^W_O,A_D,A_S,A^W_S, and the trend term t. This total cost function by definition embodies optimal input demand for N, P, M, K, given Y and **T**, so Shephard's lemma may be used to formalize the demand equations:

$$2)\quad X_b = \partial TC/\partial p_b = \Sigma_b\, \Sigma_S\, \delta_{bS}\, D_S + \Sigma_q\, \alpha_{qb}\, p_q^{.5}/p_b^{.5} + \delta_{bY}\, Y + \Sigma_n\, \delta_{bn}\, T_n + \delta_{YY}\, Y^2$$
$$+ \Sigma_n\, \delta_{nY}\, T_n Y + \Sigma_n\Sigma_m\, \delta_{nm}\, T_n T_m\ .$$

Similarly, the shadow values for the arguments of the function expressed in levels – Y, and T_m – may be expressed as:

3) $Z_Y = MC = \partial TC/\partial Y = \Sigma_q \delta_{bY} p_b + \Sigma_b p_b(2 \bullet \delta_{YY} Y + \Sigma_n \delta_{nY} T_n)$,

where MC is the marginal cost of Y, and

4) $Z_m = \partial TC/\partial T_m = \Sigma_b \delta_{bm} p_b + \Sigma_b p_b(\delta_{mY} Y + \Sigma_n \delta_{nm} T_n)$.

Although the system of equations represented by (1) and (2) comprise the estimation model (since MC and Z_m are not observable and thus require imputation from the cost function estimation), the full set of equations (1)-(4) provide the basis for our measures representing the production structure. In particular, they allow us to estimate the cost-, output value-, and input demand-specific impacts of the spillover factors contained in the **T** vector. They also permit estimation of other cost and substitution measures characterizing production processes and behavior, such as scale economies and their input-specific components, and input demand substitution patterns.

In particular, we have already seen that the total cost function can be used to estimate a range of 1st-order elasticities representing equations (2)-(4) as $\varepsilon_{TC,pb}$, $\varepsilon_{TC,Y}$, $\varepsilon_{TC,Tm}$, and $\varepsilon_{TC,t}$, from the corresponding derivatives in terms of levels X_b, MC, Z_m, and Z_t. These elasticities represent the cost impacts of changes in input prices,output levels, spillovers and temporal/spatial patterns.

Since the flexible functional form used for estimation embodies a full range of cross-effects among the arguments of the cost function, second order derivatives and elasticities may also be computed to represent the interactions among these production determinants. For example, the impacts of changes in external factors (or other arguments of the function such as p_b and t) on marginal as contrasted to total costs may be computed as $\varepsilon_{MC,Tm} = \partial \ln MC/\partial \ln T_m$. Similarly, input demand substitution patterns can be represented by $\varepsilon_{Xb,Tm} = \partial \ln X_b/\partial \ln T_m$, for an external factor, or $\varepsilon_{Xb,pq} = \partial \ln X_b /\partial \ln p_q$ for a (more standard) demand response to an input price change. In turn, the dependence of shadow values for components of **T** on any production cost determinant may be computed, e.g. for a change in output levels, as: $\varepsilon_{Zm,Y} = \partial \ln Z_m /\partial \ln Y$.

The broad range of production cost determinants incorporated in our cost function specification allow many such relationships to be estimated and assessed, to gain insights about internal and external cost impacts and drivers. In the next section we overview our estimates of these measures, which provide evidence about cost patterns and spillover impacts for the U.S. food processing sector on average across states from 1986 to 1996.

Estimation and Results

The system of equations represented by (1) and (2) above was estimated using PC-TSP systems estimation procedures (SUR) for the food processing sectors of the 48 contiguous states (data summary statistics are reported in Appendix Table A1; more details on the data construction are in Cohen and Paul, 2001). Allowing for heteroskedasticity by computing standard errors using robust-White methods made no substantive difference to the results. Incorporating an AR1 process also had virtually no impact on the measured indicators, even though all ρs (except for the K equation) were significant. This result, combined with the evidence that K could justifiably be considered variable for these data, indicates that little information is gained from the temporal dimension for this application. The AR1 adaptation was therefore dropped from the final specification (and K considered a choice variable)

By contrast, the spatial dimension appears a key component of cost performance. A spatial autocorrelation adaptation analogous to that described above for the TC equation was made for each (cost and input demand) equation in the system, leading to differerent ρs for each equation. These estimates were primarily statistically significant, as were the cost impacts from the spatial and industrial spillovers variables included in the final model. So these aspects of the model were retained for the final empirical results (although the SAR adaptation had little impact on the measures' magnitudes).

The estimated coefficients for the model are presented in Appendix Table A2, with t-statistics in italics. The state dummy variables are omitted to keep the table manageable, but were primarily statistically significant. The t-statistics for the remaining coefficients indicate much statistical significance, although the cross- or interaction-terms for the external effects are largely insignificant. Omitting these terms, however, did not affect the results substantively, and indicated some joint significance. The model was thus left fully flexible, so the significance of the complete range of elasticities, each based on a combination of coefficients and their standard errors, could be examined. The R^2s (all greater than 0.99) also indicate a very close fit for the equations as a system.

The shadow value and elasticity estimates indicating the total and marginal cost-effects of changes in the external or spillover effects, and other arguments of the cost function, are presented in Table 1. These and all other measures are computed as (unweighted) averages of the measures across all states, and reported with their standard deviations, and maximum and minimum state values. The standard errors were computed by evaluating the elasticities at the mean values of all the variables in the model; these estimates and the associated P-values indicate the statistical significance of the measures.

The shadow values themselves are not very interpretable, since they are expressed in levels rather than proportions and thus depend on the units of measurement. Note, however, that on average these measures are significantly negative (implying cost-savings) for all external factors except A_S – own-state agricultural (supplier) production – for which the measure is significantly positive. This initially surprising result, indicating that food processing production costs are higher in heavily agricultural states, was very robust across alternative specifications. This was the motivation for our inclusion in the final model of the neighboring states' weighted agricultural production measure, $A^W{}_S$, which by contrast indicates benefits of proximity to agricultural producers.

Overall, these measures clearly indicate economies associated with thick markets from own-industry conglomeration. This is implied not only by the significantly negative (cost-saving) value of Z_{AWO}, based on the extent of food processing activity in neighboring states, but also by the value of Z_Y, through its implications for scale economies. That is, the average value of $\varepsilon_{TC,Y} = \partial \ln TC/\partial \ln Y$ is significantly less than one, suggesting that greater output may be obtained with a less than proportional increase in costs. With our largely cross-sectional dataset, this indicates not only that expansion of the food processing sector in a given state implies lower average production costs, but also that states with higher Y levels have lower unit costs of production, given all other cost determinants represented in the function.

In terms of demand- and supply-side agglomeration economies, the measures in Table 1 suggest some contribution of urbanization economies or demand-drivers on costs (Z_{AD} has both positive and negative values, although it is primarily negative). And we find localization economies or supply-side cost effects associated with proximity to agricultural producers, *but* diseconomies associated with what might be called "thin markets" from being actually located in too rural a state (measured in terms of agricultural intensity – agricultural production per square mile). The corresponding elasticity (proportional) measures indicate that the strongest cost-saving impact on average is that of neighboring agricultural (supply) producers, although there is a wide range of measured benefits depending on the state under consideration.

If one thinks of the combination of external effects analogously to a combination of the production of different outputs, one might adapt the idea of a multiple-output measure of scale economies to this problem to aggregate these effects. In particular, as developed by Baumol, Panzar and Willig (1982), multiple output scale economy measure may simply be computed as the sum of the corresponding cost elasticities with respect to output. Such a measure for R outputs, Y_r, would be $\varepsilon_{TCY} = (\Sigma_r \partial TC/\partial Y_r \bullet Y_r)/TC = \Sigma_r MC_r \bullet Y_r/TC = \Sigma_r \varepsilon_{TCYr}$, and indicates the combined cost impact if all outputs increased by 1 percent rather than if only one output changed.

If one makes a similar argument for the external effects, on average the supply-side agglomeration effect from neighboring states, $\varepsilon_{TC,AWS}$, alone outweighs that from the own state, $\varepsilon_{TC,AS}$, implying an overall cost-saving benefit from agricultural supply sector externalities. If the other measures are added, the total is even more negative, and indicates that on average if all spillover factors were 1 percent higher, nearly a 0.9 percent drop in costs would be implied.[10]

[10] This experiment is not fully justifiable, however, at least on average, since each of these measures is evaluated for a particular state and time based on actual levels of external factors. Since the measures vary widely by observation, a simple average and sum is only broadly indicative of the actual aggregate effects.

Our last observations for the total cost elasticities are for the $\varepsilon_{TC,t}$ measure, representing the time trend in food processing costs, and the $\varepsilon_{TC,pb}$ elasticities, indicating the input shares for this industry. The average $\varepsilon_{TC,t}$ measure suggests that costs are increasing over time, which is contrary to the usual interpretation of this elasticity as a technical change indicator. However, there are a number of reasons we might think that costs in this sector are rising for a given amount of measured input, including increased food processing, quality, and diversity demanded by consumers.

In terms of input shares, we can see that intermediate materials are an even greater proportion of total costs than in other manufacturing industries, which might be expected for food; $\varepsilon_{TC,pM}$=0.82 (82 percent) on average. Also, the share of production workers exceeds that for non-production workers, at 0.07 versus 0.05, and the capital is closer to the labor share than for aggregate manufacturing, at more than 8 percent.

The marginal cost elasticities also provide some insights about cost patterns, since they indicate the difference between incremental cost effects (the MC elasticities) and total or average cost effects (the TC elasticities). Note in particular that increases in both own- and supplying-industry production in neighboring states decrease marginal as well as average costs, but they reduce marginal costs by a smaller proportion than on average. And the supply and demand own-state effects are reversed in terms of the marginals; greater potential demand in the state implies higher marginal costs on average, and more agricultural intensity, or "rurality", implies lower marginal costs. Therefore it seems these factors act more as fixed than marginal effects. Marginal costs also may be increasing over time, but not significantly either statistically or in terms of magnitude. And intermediate materials seem to be a much larger share of marginal than total costs, at

91 instead of 82 percent. This is associated with increases in labor and capital costs that are only half, and less than one-third, respectively, the implied average increases required to accommodate higher output levels. This again suggests these inputs may be more associated with the existing cost base than adjusted fully on the margin.

The results discussed so far, representing cost patterns, and in particular the cost effects of spatial and industry spillovers, are the primary focus of this study. However, it is also informative to explore the underlying 2^{nd} order effects, or the input demand and shadow value patterns associated with changes in the economic environment.

Input demand elasticities, on average across all states, are presented in Table 2. First note that all own-elasticities (such as $\varepsilon_{N,pN}$ for non-production labor) are negative and statistically significant, implying appropriate (in terms of theory) demand responses to input price changes. Production labor seems to adjust the most in response to a change in its price, and intermediate materials the least.

All other input response patterns indicate substitutability across factors. Although we will not explore these measures in depth, some of these patterns are particularly interesting, such as the large increase in K in response to a rise in p_P. It appears that increases in the price of production labor induce mechanization; or that in states where production labor is the most expensive one would find the most capital-intensive food manufacturing processes. It also seems that materials use adapts little in response to changes in the prices of other inputs, although again the relationship with P is the strongest (and that with p_K is both small and statistically insignificant). If the price of production workers increases, more intermediate materials are used, perhaps indicating that less care is taken to screen the incoming agricultural products so quality is maintained by having higher throughput and likely more waste.

The other standard measures from this type of cost function analysis are the $\varepsilon_{Xb,Y}$ and $\varepsilon_{Xb,t}$ elasticities. The output elasticities indicate that output augmentation is supported primarily by increases in materials use – which is consistent with the implications from the marginal cost elasticities.[11] By contrast, higher output levels seem to be associated with a very small increase in the capital stock. The t elasticities indicate a fall in the use of non-production workers over time (but not significant), and only a small increase in capital on average, although P and M demand seems on average to be rising (significantly) by 5-6 percent per year for a given amount of output production. This again could be consistent with more greater demand for more processed and higher quality final food products, including increasing packaging.

The elasticities of input use with respect to changes or differences in the external factors – the input-specific impacts of spillovers – indicate very different effects across inputs. For example, the cost-saving impact of having higher levels of food processing activities in neighboring states seems to stem primarily from lower production worker and materials use; it actually implies a greater contribution of non-production workers, although the change in both types of labor is statistically insignificant. The higher costs associated with in-state agricultural production also appear to be primarily associated with greater M use, and to a somewhat smaller extent production worker levels. This may suggest that food processing establishments requiring higher levels of agricultural or other materials, and more production workers, are more likely to locate in rural areas. In

[11] These are, of course, directly related since they are inverse 2nd order elasticities; $\varepsilon_{MC,pM}$ is based on the $\partial^2TC/\partial Y\partial p_M$ derivative, and $\varepsilon_{M,Y}$ is based on $\partial^2TC/\partial p_M\partial Y$.

reverse, the cost-savings benefits implied by having neighboring states with high agricultural intensity is driven by lower materials use, as well as some reduction in K, but is associated with greater labor demand. This perhaps indicates that firms with more labor but less agricultural materials requirements benefit from being close, but not directly associated with, suppliers. And urbanization economies, or the benefits of being close to greater demand, are associated with lower levels of all inputs.

Finally, let us move to the elasticities for the shadow values of the external effects, presented in Table 4. Note first that from a glance at the P-values we can see that there is less significance (a value over .05 implies a statistically insignificant estimate) of these elasticities than others. The significance levels in fact indicate few cross-effects for, and especially across, the external factors. This is particularly true for the Z_{AWS} elasticities, which are all insignificant except $\varepsilon_{ZAWS,pM}$ and $\varepsilon_{ZAWS,pK}$. This implies that an increase in p_M significantly increases the value of having proximity to agricultural production, and that this is true also, but to a lesser extent, for p_K. Note also that the only spillover shadow value that does not increase (in absolute value) significantly with an increase in p_K is Z_{AWO}, and all increase significantly with p_M.

Additional insights may be gained from the Y and t elasticity measures in this Table. It seems that high levels of food processing output stem from greater thick market values associated with proximity to other food processing activity, and to neighboring state's agricultural activity, as exhibited by the $\varepsilon_{ZAWO,Y}$ and $\varepsilon_{ZAWS,Y}$ elasticities (although neither are statistically significant). The $\varepsilon_{ZAS,Y}$ estimate may be similarly interpreted, even though it is the opposite sign, since the sign of Z_{AS} is itself reversed. By contrast, states with higher levels of food processing activity seem to reap less benefits from being close to areas with greater purchasing power, or demand.

For the temporal dimension, both the demand-side agglomeration and thick-market- impacts seem to have provided increasing cost-savings benefits over the time frame of our analysis. Whereas the disadvantages of being in a rural area also seem to be growing, and the cost-savings from being close to suppliers to be falling. This suggests that over time the "draw" of both urbanization economies and own-industry thick market effects is pushing the balance toward a spatial divergence of the food processing industry and high agricultural intensity areas.

Concluding Remarks:

In this paper we have estimated and evaluated evidence of spatial and industrial spillover effects across states in the U.S. food system. Our focus is on state-level food manufacturing activity, with thick market effects arising from neighboring states' food processing levels, and supply- and demand-agglomeration effects stemming from proximity to high purchasing power areas (based on GSP), and to high agricultural-intensity in both the own and neighboring states.

We find statistically significant cost impacts of all these spillover effects, although the supply-effect is a combination of benefits from having neighboring states with high agricultural levels, and costs of having high agricultural intensity in the own state. This latter result might be interpreted as a "thin markets" effect arising from the disadvantages of being in too rural an area, such as low infrastructure levels (e.g. telecommunications), and limited labor and capital pools or markets.

Increasing returns to scale, or to being in a state with a higher level of food processing activity, and greater processing costs over time, possibly due to increasing levels of processing, quality, and differentiation of food products, are also evident. And we find differences between total and marginal cost effects that imply a greater proportion of materials costs at the margin than for other inputs, and that both in-state supply and demand cost impacts seem to have more a fixed effects than marginal nature.

Although these external effects are the focus of our analysis, assessment of second-order relationships underlying these cost effects indicates that the specification is generating reasonable (in terms of theory and intuition) representations of production patterns. These elasticities also imply little impact of cross-effects among the external factors, but a significant degree of differentiation among input responses to changes in not only the spillover measures, but also to output, time, and input price changes.

Overall, our results seem not only to be plausible, but to provide provocative indications that empirically recognizing spillovers across space and sector generates meaningful insights about cost and performance patterns. The typical focus of production and performance analysis on substitution and temporal patterns is not sufficient to represent the spatial linkages, and the thick-market and agglomeration effects, that seem from observed increases in spatial conglomeration and vertical and horizontal integration and consolidation to be increasingly important performance drivers in most industries in our “new era”.

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Table 1: Shadow Values and Total and Marginal Cost Elasticities

measure	*estimate*	*st. dev.*	*min*	*max*	*st. error*	*P-value*
Z_{AWO}	**-0.0884**	0.035	-0.2459	-0.0444	0.028	[.002]
Z_{AS}	**0.0159**	0.002	0.0101	0.0204	0.002	[.000]
Z_{AWS}	**-0.0103**	0.001	-0.0148	-0.0082	0.002	[.000]
Z_{AD}	**-0.00013**	0.00005	-0.00021	0.00004	0.00003	[.000]
Z_{Y}=MC	**0.5034**	0.035	0.4005	0.6316	0.014	[.000]
$\varepsilon_{TC,AWO}$	**-0.3607**	0.492	-2.9159	-0.0106	0.042	[.002]
$\varepsilon_{TC,AS}$	**0.3574**	0.438	0.0338	2.6909	0.022	[.000]
$\varepsilon_{TC,AWS}$	**-0.7032**	1.584	-10.8947	-0.0041	0.031	[.000]
$\varepsilon_{TC,AD}$	**-0.1889**	0.413	-3.0656	0.0281	0.000	[.000]
$\varepsilon_{TC,Y}$	**0.7401**	0.109	0.5664	2.0287	0.020	[.000]
$\varepsilon_{TC,t}$	**0.0493**	0.069	0.0027	0.3961	0.001	[.000]
$\varepsilon_{TC,pN}$	**0.0468**	0.023	-0.1897	0.1535	0.001	[.000]
$\varepsilon_{TC,pP}$	**0.0743**	0.022	-0.0839	0.2177	0.002	[.000]
$\varepsilon_{TC,pM}$	**0.8218**	0.264	-1.4864	2.6222	0.004	[.000]
$\varepsilon_{TC,pK}$	**0.0828**	0.029	0.0050	0.3135	0.001	[.000]
$\varepsilon_{MC,AWO}$	**-0.0169**	0.008	-0.0447	-0.0014	0.011	[.132]
$\varepsilon_{MC,AS}$	**-0.0091**	0.008	-0.0497	-0.0003	0.006	[.148]
$\varepsilon_{MC,AWS}$	**-0.0180**	0.026	-0.2096	-0.0006	0.010	[.073]
$\varepsilon_{MC,AD}$	**0.0302**	0.043	0.0006	0.2201	0.005	[.000]
$\varepsilon_{MC,Y}$	**-0.0164**	0.017	-0.1034	-0.0005	0.005	[.001]
$\varepsilon_{MC,t}$	**0.0002**	0.000	0.0001	0.0002	0.000	[.589]
$\varepsilon_{MC,pN}$	**0.0267**	0.013	-0.0101	0.0699	0.003	[.000]
$\varepsilon_{MC,pP}$	**0.0491**	0.014	0.0126	0.1122	0.003	[.000]
$\varepsilon_{MC,pM}$	**0.9077**	0.030	0.8094	0.9890	0.006	[.000]
$\varepsilon_{MC,pK}$	**0.0166**	0.004	0.0062	0.0281	0.003	[.000]

Table 2: Input Demand Elasticities

measure	*estimate*	*st. dev.*	*min*	*max*	*st. error*	*P-value*
$\varepsilon_{N,AWO}$	**0.0119**	1.204	-6.2360	7.4567	0.086	[.057]
$\varepsilon_{N,AS}$	**0.1500**	0.823	-5.3413	3.7905	0.054	[.055]
$\varepsilon_{N,AWS}$	**0.1969**	0.733	-2.3611	5.4745	0.079	[.988]
$\varepsilon_{N,AD}$	**-0.2599**	1.294	-7.9681	7.4958	0.091	[.000]
$\varepsilon_{N,Y}$	**0.4604**	0.293	-0.2326	2.5414	0.051	[.000]
$\varepsilon_{N,t}$	**-0.0195**	0.106	-0.8333	0.4647	0.003	[.917]
$\varepsilon_{N,pN}$	**-0.8287**	2.257	-25.5648	-0.0276	0.035	[.000]
$\varepsilon_{N,pP}$	**0.1051**	0.279	0.0036	3.2112	0.034	[.506]
$\varepsilon_{N,pM}$	**0.6246**	1.707	0.0207	19.2012	0.055	[.015]
$\varepsilon_{N,pK}$	**0.0989**	0.271	0.0032	3.1523	0.037	[.566]
$\varepsilon_{P,AWO}$	**-0.3815**	0.945	-8.2194	1.6036	0.051	[.000]
$\varepsilon_{P,AS}$	**0.2378**	0.305	-0.6405	1.4410	0.033	[.000]
$\varepsilon_{P,AWS}$	**0.1451**	0.701	-1.1478	6.9444	0.049	[.830]
$\varepsilon_{P,AD}$	**-0.2255**	0.670	-2.7411	5.1160	0.054	[.000]
$\varepsilon_{P,Y}$	**0.5111**	0.172	0.1011	1.4253	0.031	[.000]
$\varepsilon_{P,t}$	**0.0509**	0.079	-0.0136	0.5795	0.002	[.000]
$\varepsilon_{P,pN}$	**0.0597**	0.101	0.0023	0.6530	0.020	[.506]
$\varepsilon_{P,pP}$	**-1.3494**	2.252	-15.6851	-0.0499	0.039	[.000]
$\varepsilon_{P,pM}$	**0.8223**	1.371	0.0301	9.4779	0.045	[.000]
$\varepsilon_{P,pK}$	**0.4674**	0.781	0.0170	5.5853	0.035	[.003]
$\varepsilon_{M,AWO}$	**-0.4270**	0.677	-5.2538	-0.0088	0.051	[.010]
$\varepsilon_{M,AS}$	**0.4055**	0.540	0.0375	3.4959	0.025	[.000]
$\varepsilon_{M,AWS}$	**-0.8997**	2.057	-15.9322	-0.0041	0.036	[.000]
$\varepsilon_{M,AD}$	**-0.1941**	0.579	-5.2257	-0.0042	0.024	[.003]
$\varepsilon_{M,Y}$	**0.8468**	0.151	0.5748	2.7800	0.024	[.000]
$\varepsilon_{M,t}$	**0.0586**	0.088	0.0027	0.5975	0.001	[.000]
$\varepsilon_{M,pN}$	**0.0306**	0.048	0.0013	0.3677	0.003	[.015]
$\varepsilon_{M,pP}$	**0.0724**	0.111	0.0031	0.6765	0.004	[.000]
$\varepsilon_{M,pM}$	**-0.1043**	0.160	-1.0059	-0.0045	0.006	[.000]
$\varepsilon_{M,pK}$	**0.0012**	0.002	0.0000	0.0126	0.003	[.934]
$\varepsilon_{K,AWO}$	**-0.0166**	0.275	-1.6464	0.9247	0.039	[.477]
$\varepsilon_{K,AS}$	**0.1910**	0.217	0.0168	1.1077	0.026	[.000]
$\varepsilon_{K,AWS}$	**-0.3419**	0.846	-4.6405	-0.0027	0.037	[.020]
$\varepsilon_{K,AD}$	**-0.2346**	0.594	-4.1273	0.0061	0.026	[.000]
$\varepsilon_{K,Y}$	**0.1618**	0.062	0.0459	0.4073	0.025	[.000]
$\varepsilon_{K,t}$	**0.0182**	0.022	-0.0004	0.1039	0.001	[.000]
$\varepsilon_{K,pN}$	**0.0453**	0.061	0.0021	0.2764	0.020	[.566]
$\varepsilon_{K,pP}$	**0.3860**	0.528	0.0184	2.6201	0.032	[.003]
$\varepsilon_{K,pM}$	**0.0112**	0.015	0.0005	0.0664	0.033	[.934]
$\varepsilon_{K,pK}$	**-0.4425**	0.604	-2.9336	-0.0211	0.034	[.001]

Table 3: Shadow Value Elasticities

measure	*estimate*	*st. dev.*	*min*	*max*	*st. error*	*P-value*
$\varepsilon_{ZAWO,Y}$	**0.0917**	0.077	0.0025	0.3183	0.071	[.180]
$\varepsilon_{ZAWO,t}$	**0.0081**	0.002	0.0029	0.0138	0.004	[.062]
$\varepsilon_{ZAWO,AWO}$	**-0.2293**	0.140	-0.6438	-0.0195	0.150	[.183]
$\varepsilon_{ZAWO,AS}$	**0.0712**	0.052	0.0039	0.2742	0.084	[.407]
$\varepsilon_{ZAWO,AWS}$	**-0.0425**	0.049	-0.3980	-0.0016	0.046	[.350]
$\varepsilon_{ZAWO,AD}$	**0.1791**	0.187	0.0059	0.7600	0.086	[.005]
$\varepsilon_{ZAWO,pN}$	**0.0266**	0.076	-0.1385	0.2097	0.033	[.104]
$\varepsilon_{ZAWO,pP}$	**0.0935**	0.062	-0.0399	0.2767	0.042	[.007]
$\varepsilon_{ZAWO,pM}$	**0.8717**	0.161	0.4991	1.2186	0.068	[.000]
$\varepsilon_{ZAWO,pK}$	**0.0082**	0.024	-0.0469	0.0638	0.023	[.459]
$\varepsilon_{ZAS,Y}$	**-0.0386**	0.041	-0.2509	-0.0010	0.026	[.157]
$\varepsilon_{ZAS,t}$	**0.0120**	0.001	0.0097	0.0169	0.002	[.000]
$\varepsilon_{ZAS,AWO}$	**-0.0519**	0.026	-0.1350	-0.0039	0.059	[.392]
$\varepsilon_{ZAS,AS}$	**-0.0151**	0.013	-0.0890	-0.0005	0.039	[.711]
$\varepsilon_{ZAS,AWS}$	**-0.0176**	0.028	-0.2118	-0.0005	0.022	[.458]
$\varepsilon_{ZAS,AD}$	**-7.65805D-09**	8.17740D-10	-1.08155D-08	-6.20376D-09	0.023	[.104]
$\varepsilon_{ZAS,pN}$	**0.0227**	0.029	-0.0820	0.1047	0.013	[.054]
$\varepsilon_{ZAS,pP}$	**0.0514**	0.027	-0.0565	0.1089	0.013	[.000]
$\varepsilon_{ZAS,pM}$	**0.8855**	0.061	0.7710	1.1240	0.025	[.000]
$\varepsilon_{ZAS,pK}$	**0.1486**	0.020	0.0536	0.1810	0.011	[.000]
$\varepsilon_{ZAWS,Y}$	**0.0699**	0.063	0.0022	0.3297	0.042	[.079]
$\varepsilon_{ZAWS,t}$	**-0.0022**	0.000	-0.0032	-0.0016	0.002	[.346]
$\varepsilon_{ZAWS,AWO}$	**-0.0315**	0.015	-0.0722	-0.0029	0.033	[.338]
$\varepsilon_{ZAWS,AS}$	**0.0160**	0.012	0.0006	0.0777	0.022	[.458]
$\varepsilon_{ZAWS,AWS}$	**0.0094**	0.013	0.0003	0.0930	0.016	[.563]
$\varepsilon_{ZAWS,AD}$	**-3.91817D-09**	4.14711D-10	-5.50797D-09	-2.75844D-09	0.018	[.303]
$\varepsilon_{ZAWS,pN}$	**-0.0023**	0.022	-0.0494	0.0877	0.019	[.988]
$\varepsilon_{ZAWS,pP}$	**0.0022**	0.023	-0.0540	0.0889	0.020	[.828]
$\varepsilon_{ZAWS,pM}$	**0.9613**	0.049	0.7712	1.0708	0.038	[.000]
$\varepsilon_{ZAWS,pK}$	**0.1423**	0.016	0.1076	0.2090	0.015	[.011]
$\varepsilon_{ZAD,Y}$	**-0.2330**	2.003	-26.8285	13.0939	0.062	[.000]
$\varepsilon_{ZAD,t}$	**0.0144**	0.060	-0.2579	1.0428	0.003	[.002]
$\varepsilon_{ZAD,AWO}$	**0.5607**	2.824	-12.4289	48.6829	0.089	[.000]
$\varepsilon_{ZAD,AS}$	**0.1005**	0.529	-2.3856	9.1937	0.042	[.117]
$\varepsilon_{ZAD,AWS}$	**-0.1017**	0.692	-12.1336	3.0770	0.034	[.325]
$\varepsilon_{ZAD,AD}$	**-0.9343**	7.743	-135.4718	35.7245	0.034	[.000]
$\varepsilon_{ZAD,pN}$	**0.0855**	0.859	-14.5232	4.1201	0.040	[.000]
$\varepsilon_{ZAD,pP}$	**0.1343**	0.681	-11.4265	3.1244	0.041	[.000]
$\varepsilon_{ZAD,pM}$	**0.6870**	1.530	-6.2679	26.6105	0.088	[.000]
$\varepsilon_{ZAD,pK}$	**0.0933**	0.014	0.0234	0.3393	0.022	[.000]

Appendix Table A1: Summary Statistics

	Mean	St. Deviation	Min	Max
TC	6233.09	6154.53	164.41	37095.11
Y	9176.72	9232.43	226.38	52671.01
N	306.38	320.59	2.35	1902.40
P	513.17	529.92	10.25	3037.49
M	5334.15	5245.19	120.79	29481.90
K	1855.53	1913.74	79.77	10154.70
p_N	0.8742	0.1392	0.4240	1.7177
p_P	0.8835	0.1038	0.6189	1.3730
p_M	0.9382	0.0447	0.8501	1.0000
p_K	0.2721	0.0073	0.2573	0.2825
A^W_O	9278.65	4362.12	766.16	21481.21
A_D	4840202.93	7408846.59	100511.10	3.85144D+07
A_S	70610.29	54263.11	2612.98	324824.44
A^W_S	106906.93	144625.77	3668.58	1054409.75

A_D, A_S, and A^W_S are normalized by land area, in terms of million square miles.

Appendix Table A2: Coefficient Estimates (dummies omitted, t statistics in italics)

$\alpha_{N,L}$	**1.39E+01**	*0.67*
$\alpha_{N,M}$	**7.89E+01**	*2.42*
$\alpha_{N,K}$	**2.32E+01**	*0.57*
$\alpha_{P,M}$	**1.85E+02**	*4.12*
$\alpha_{P,K}$	**1.95E+02**	*3.00*
$\alpha_{K,M}$	**5.56E+00**	*0.08*
$\delta_{N,Y}$	**2.03E-02**	*6.25*
$\delta_{P,Y}$	**3.28E-02**	*10.01*
$\delta_{M,Y}$	**4.91E-01**	*34.81*
$\delta_{K,Y}$	**3.55E-02**	*6.14*
$\delta_{N,t}$	**-1.71E+00**	*-1.45*
$\delta_{P,t}$	**6.19E+00**	*5.24*
$\delta_{M,t}$	**7.34E+01**	*9.32*
$\delta_{K,t}$	**8.38E+00**	*3.37*
$\delta_{N,WS}$	**1.31E-04**	*0.48*
$\delta_{P,WS}$	**7.72E-05**	*0.27*
$\delta_{M,WS}$	**-1.04E-02**	*-5.69*
$\delta_{K,WS}$	**-1.35E-03**	*-2.06*
$\delta_{N,WO}$	**7.97E-04**	*0.14*
$\delta_{P,WO}$	**-5.17E-03**	*-0.90*
$\delta_{M,WO}$	**-7.03E-02**	*-2.36*
$\delta_{K,WO}$	**7.08E-04**	*0.08*
$\delta_{N,S}$	**8.94E-04**	*1.99*
$\delta_{P,S}$	**1.41E-03**	*3.11*
$\delta_{M,S}$	**1.54E-02**	*7.91*
$\delta_{K,S}$	**2.84E-03**	*3.64*
$\delta_{N,D}$	**-2.24E-05**	*-3.26*
$\delta_{P,D}$	**-2.75E-05**	*-4.04*
$\delta_{M,D}$	**-7.59E-05**	*-2.91*
$\delta_{K,D}$	**-4.32E-05**	*-4.14*
$\delta_{Y,Y}$	**-1.49E-07**	*-3.34*

$\delta_{WS,WS}$	**-1.51E-10**	*-0.59*
$\delta_{S,S}$	**-5.44E-10**	*-0.37*
$\delta_{WO,WO}$	**3.19E-07**	*1.44*
$\delta_{D,D}$	**7.30E-13**	*6.66*
$\delta_{D,Y}$	**1.10E-09**	*7.32*
$\delta_{D,WO}$	**-1.48E-09**	*-6.37*
$\delta_{D,S}$	**-4.07E-11**	*-1.64*
$\delta_{Y,WO}$	**-3.07E-07**	*-1.50*
$\delta_{Y,S}$	**-2.15E-08**	*-1.44*
$\delta_{Y,D}$	**-2.94E-08**	*-0.86*
$\delta_{D,WS}$	**1.35E-11**	*1.03*
$\delta_{Y,WS}$	**-2.83E-08**	*-1.80*
$\delta_{WO,WS}$	**1.18E-08**	*0.96*
$\delta_{S,WS}$	**-8.08E-10**	*-0.75*
$\delta_{D,t}$	**-4.06E-07**	*-4.79*
$\delta_{Y,t}$	**2.86E-05**	*0.54*
$\delta_{WO,t}$	**-2.18E-04**	*-2.37*
$\delta_{WS,t}$	**7.75E-06**	*0.95*
$\delta_{S,t}$	**6.37E-05**	*6.03*
ρ	**0.369797**	*9.50*
ρ_{LD}	**0.39307**	*7.73*
ρ_{L}	**0.280306**	*5.45*
ρ_{M}	**0.375107**	*9.47*
ρ_{K}	**6.66E-04**	*0.98*

R^2s	TC	***0.9940***
	LD	***0.9939***
	L	***0.9973***
	M	***0.9916***
	K	***0.9971***