Preliminary, May 2002 (empecrev5.doc)

Spatial and Supply/Demand Agglomeration Economies: State- and Industry-Linkages in the U.S. Food System

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ABSTRACT

Cost-impacts of spatial and industrial spillovers on economic performance are evaluated by incorporating activity level measures for nearby states and related industries into a cost function model. We focus on localization and urbanization economies for state level food processing industries, from activity levels of similar industries in neighboring states, agricultural input suppliers, and final product demand. We find significant cost-savings from proximity to other food manufacturing centers, and areas with high purchasing power. Cost savings from locating near an agricultural area are also evident, although it seems costly to be located within a rural agricultural state, implying thin market diseconomies. Marginal production costs instead appear higher in more urban, and lower in more rural, areas. These spillover patterns also have input composition implications; materials demand responses are the most closely tracked by the agglomeration cost effects, and capital and labor impacts vary.

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Introduction

It is increasingly clear that interconnections among productive entities are substantive, and expanding as we move into a new era of modern production systems. These inter-dependencies have various dimensions, such as spatial and industrial agglomeration effects. They also have important technological and market structure implications; cost economies from such linkages may be driving trends toward urbanization and industrial concentration, and horizontal and vertical consolidation and integration. Understanding the extent and consequences of these productive inter-dependencies requires modeling and measuring their impacts. However, conventional production structure analyses are based on models that do not recognize connections or externalities among economic entities, and resulting spillovers affecting economic performance.

In this paper we overview and implement a framework for including spillovers in cost and productivity analysis. Our treatment allows for temporal, spatial, and industrial spillovers, through input quasi-fixities, geographic proximity, and horizontal and vertical linkages among own-industry establishments, and suppliers and customers. In particular, the model facilitates characterizing and measuring input rigidities that cause higher short than long run costs, implying economies of flexibility, and spatial and sectoral inter-dependencies underlying thick market or agglomeration cost economies.

As recognized by Hall (1989), production is more efficient, or cost effective, when it is concentrated over space as well as time. Such thick market effects or agglomeration economies, that imply aggregate increasing returns (Hall, 1991), may result from external knowledge spillovers that cause spatial density to "enhance the generation of innovation and yield higher rates of technological advance and economic growth" (Feldman, 1999). Similarly, urbanization and localization economies associated with distance may take the form of cost effects from demanding and supplying sectors. For these and other types of spatial and industrial spillovers, location involves "a geographic unit over which interaction and communication is facilitated,… and economic activity is enhanced" (Feldman). Diseconomies could also arise from counteracting external costs associated with density and urbanization, or with "ruralization" – thin market effects from lack of markets in regions of sparse economic activity.

We represent and measure such spillovers using a cost function framework, including activity measures for spatially and industrially linked sectors. Our empirical analysis is based on panel data for the food processing (manufacturing) industry, for the 48 contiguous U.S. states from 1986-96. Our model recognizes temporal and spatial inter-dependencies within the industry, and externalities from the proximity of supplying and demanding sectors. To accommodate these linkages we include measures of capital constraints, neighboring states' food processing levels, and own- and (weighted) neighboring states' agricultural and total production levels, as cost function arguments. This allows us to compute the cost effects of such factors in terms of shadow values. We also adapt the stochastic structure to represent temporal and spatial autoregressive patterns, and control for state size to recognize the greater potential for internalizing such benefits in relatively large states.

We find evidence of spatial but not temporal spillovers; cost-saving benefits are achieved from locating in a relatively food processing-intensive region (where neighboring states exhibit high levels of food manufacturing activity). Cost economies are also associated with locating in high-demand areas (urbanization economies), and *close* to rural areas. By contrast, locating directly *in* an agricultural-intensive state appears costly for producers, suggesting diseconomies associated with rural areas (thin market effects from limited infrastructure support or input markets). We also find that the supply and demand own-state effects are reversed in terms of marginal costs, implying different fixed as compared to incremental cost patterns.

These thick market economies and diseconomies also have cross effects; input composition as well as overall costs is affected by spatial and industrial spillovers. Consideration of the substitutability or complementarity of production factors reveals weak linkages among the external effects. Observed cost patterns associated with external forces seem primarily related to materials demand, with more varied responses across driving factors emerging for capital and particularly labor demand.

Representing the Cost Structure and External Spillover Effects

Modeling and measuring the factors affecting economic performance typically involves specifying and estimating a production or cost function relationship, since performance is fundamentally based on the output producible from a given amount of inputs (primal), or the costs of a given level of output (dual). A 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 an impact on production, they will also affect the cost relationship, through cost economies.

More specifically, technically efficient production processes are often 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 underlying the existing technological and environmental base, or production structure. The least cost way to produce a given output level 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**) + $\Sigma_r p_r K_r$, where TC is total input cost, VC is variable input cost, **p** is a vector of observed prices of the variable **X** inputs, **K** is a vector of levels of the quasi-fixed **X** inputs, and p_r is the market price of the rth quasi-fixed input. Various exogenous or external factors, including input fixities (temporal linkages) and spatial and industrial spillovers (thick market or agglomeration effects), representing inter-dependencies across time, space, and sector, may be captured as components of the **K** and **T** vectors.

The cost function representing variable input cost minimization subject to the production function Y(**X,T**), can be written as the short run cost curve TC(Y;**p**,**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 the long from the short run. If the **K** factors are instead choice variables in the time frame represented by the data, TC(Y;**p**,**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, 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 such cost curve shifts. Modeling and measuring this full set of cost- and cross-effects therefore provides a rich basis for analyzing internal and external cost drivers, and resulting cost and economic performance patterns.

Questions about the productive impact of any recognized cost determinant may be addressed in terms of optimizing responses for the internal (variable) factors, or shadow values for the quasi-fixed or external factors. For example, the total cost impact of a change in the price of a variable input reproduces, by Shephard's lemma, optimal input demand; $\partial TC/\partial p_k=X_k$. This measure becomes $\varepsilon_{TC,pk} = \partial \ln TC/\partial \ln p_k=X_k p_k/TC=S_k$ in proportional terms, where S_k is the cost share of the jth variable input, and $\varepsilon_{TC,pk}$ denotes the total cost elasticity with respect to a change in input price p_k. The shadow values of output or inputs expressed as levels in the cost function may analogously be computed as first order derivatives. For example, $\partial TC/\partial Y=MC$, or $\varepsilon_{TC,Y} = \partial \ln TC/\partial \ln Y = MC\cdot Y/TC$, where MC (marginal cost) is the shadow value of Y, and the cost elasticity $\varepsilon_{TC,Y}$ reflects scale economies. Similarly, the net shadow value of the jth quasi-fixed factor K_r, expressed as $\partial TC/\partial K_r=Z_r+p_r$ or $\varepsilon_{TC,Kr} = \partial \ln TC/\partial \ln K_r = (Z_r+p_r)K_r/TC$, where $Z_r=\partial VC/\partial K_r$ is the shadow value of K_r, captures the extent of subequilibrium for K_r.[1]

More to the point for our application, shadow values and corresponding elasticities or proportional impacts may also be computed for the external shift factors in **T**. They can be measured as $\partial TC/\partial T_m=Z_m$, or $\varepsilon_{TC,Tm} = \partial \ln TC/\partial \ln T_m = Z_m T_m/TC$, 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, is typically expressed as the elasticity of TC with respect to a time counter t: $\varepsilon_{TC,t}$

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

= ∂ln TC/∂t. Or, if time dummies rather than a time trend are included in the **T** vector, the shift for a particular time period, t_1, may be measured as $\varepsilon_{TC,t1} = \partial \ln TC/\partial t_1$.[2]

Measuring the cost impacts 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 function and directly taking such derivatives. However, if the only shift factor in **T** is the time trend t, as is typical for production analysis, the "technical change" measure $\varepsilon_{TC,t}$ essentially becomes a residual, even if it is estimated parametrically.[3] The impacts of any cost factors not taken into account as arguments of the function (such as input rigidities or agglomeration effects) cannot be identified; they are imbedded in the measured contributions of the recognized factors – $\varepsilon_{TC,t}$ as well as $\varepsilon_{TC,pk}$, and $\varepsilon_{TC,Y}$ (and $\varepsilon_{TC,Kr}$ if quasi-fixity is recognized).

That is, temporal spillovers from input rigidities may generate such problems if short run costs are higher than may be attained in the long run. If the distinction between short and long run behavior is relevant (affects costs), and this is not captured in the cost function specification, the effects of the underlying fixities will erroneously be embodied in the elasticity estimates. Temporal linkages might also affect the appropriate stochastic structure, so allowing for an autoregressive process in the stochastic specification may be necessary for justifiable estimation of the cost relationship.

Similar problems arise if spatial and industrial spillovers (that differ over time and location, and across outputs and inputs) exist but are not recognized.[4] If such impacts

[2] 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.
[3] That is, rather than explicitly as a residual, as for the Solow residual which is commonly recognized to be a "measure of our ignorance".
[4] Note that estimating elasticities based on Shephard's lemma many also be misleading if wedges between measured and true economic values of the factors arise from technical and allocative inefficiency that might

may be substantive, measures representing these externalities should be incorporated as components of the **T** vector, to facilitate identifying their associated cost economies. Adaptations of the stochastic structure to recognize these inter-dependencies may also be required to generate valid estimates.

Such spillovers may arise from various driving forces. Hall and Ciccone (1996) argue that thick markets – aggregate increasing returns or economies associated with spatial or industrial density – could emerge from local geographical externalities or the diversity of local intermediate services. Krugman (1991) and David and Rosenbloom (1990) emphasize that spatial inter-dependencies within and across sectors can enhance productivity through innovation generation or information diffusion. Zucker and Darby stress that synergies from human (knowledge) interactions and communication imply thick market effects associated with localized intellectual capital. And Coe and Helpman (1995) underscore the potential for spatial connections from the transmission of quality or ideas embodied in goods through trade to generate agglomeration economies.

Thick market effects might well stem from such knowledge spillovers or interdependencies in the food processing industry, and thus motivate similar firms to concentrate in a particular geographic location. If so, we can gain insights about the existence and extent of resulting cost economies by incorporating a measure of own-industry production levels in neighboring localities (states) as a **T** component in our cost function specification.[5] Such spatial (horizontal) linkages may also be accommodated in

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be attributable to specific factors generating this measured inefficiency, as recognized by Atkinson and Halvorsen (1990), Sickes and Streitwieser (1998), and Kumbhakar (2001), among others.

[5] 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.

the stochastic structure, similarly to an autoregressive specification used to capture temporal inter-dependencies.[6]

In addition to this spatial thick market dimension, agglomeration effects might arise from proximity to supplying (agricultural producers) or demanding (consumers) sectors (in both own- and neighboring-states). Including measures of these vertically linked sectors' activity levels in the **T** vector, expressed in terms of input or output levels of the suppliers or demanders, allows us to represent these inter-dependencies.[7]

Such sectoral externalities may be interpreted as urbanization and localization economies. If firms find it advantageous to locate close to an area of high population density and buying power, implying perhaps greater final product demand or infrastructure support, this may be referred to as urbanization economies. If it is cost-saving to locate close to suppliers, this may be thought of as localization economies.[8] In the food processing context, urbanization economies may be associated with high potential food demand levels (purchasing power) within a state or from its close neighbors, represented by concentrations of total production (GSP). Localization economies may be generated from high agricultural intensity in a state or its surrounding areas, and the resulting proximity or availability of primary agricultural materials.

Empirical Implementation of a Cost Model with Spatial and Industrial Spillovers

Accommodating temporal, spatial, and industrial linkages in a cost-based model may thus be accomplished by including production activity levels in linked time periods, areas, or sectors, as cost function arguments, and/or by recognizing them in the stochastic

[6] As elaborated further below, this has been proposed in the spatial econometrics literature by, for example, Anselin (1988), Kelejian and Prucha (1999), and Bell and Bockstael (2000).
[7] This is similar in spirit to Bartlesman, Caballero and Lyons (1994) and Paul and Siegel (1999).

specification. To move toward an implementable model, however, we need to be more specific about these adaptations to the conventional framework.

The most familiar of such adaptations is for the temporal dimension, where cost linkages between time periods are due to input stock durability and associated quasi-fixity. Incorporating temporal dependence in the structural model may be accomplished by representing existing stock factors, **K**, as a fixed input vector that is not optimized over in the short run. If the capital stock K is the one quasi-fixed factor, its productive contribution may be expressed in terms of its shadow value, Z_K, and the deviation of short from long run equilibrium captured by the difference between Z_K and p_K.[9] Time-dependence may also be recognized by allowing for autoregressive errors in the stochastic structure. For an AR(1) specification, for example, $TC_t = TC(\cdot)_t + u_t$ and $u_t = \rho_\tau u_{t-1} + \varepsilon_t$ (where ρ_τ is the cost function-specific AR(1) parameter, ε_t is the white noise period t estimation error for TC, and $u_{t-1} = TC_{t-1} - TC(\cdot)_{t-1}$) so substitution for u_t results in an estimating equation with an appropriate random error term.[10]

In our preliminary empirical investigation, we found that allowing for the temporal dimension was not empirically relevant for our data; K shadow values and market prices were not significantly different, and appending an AR(1) process did not substantively affect the results. This is perhaps a result of the greater spatial (states) than temporal (years) dimension of our data. It is also consistent with the findings of Goodwin and Brester (1995), Morrison (1997), and Arnade and Gopinath (1998), that

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[8] These distinctions are common in the Urban Economics literature, as developed and overviewed by Hoover, 1948, and O'Sullivan, 2000.
[9] 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.
[10] This adjustment may be written in matrix form for an equation system, as in Berndt (1991).

adjustment of capital is relatively rapid in this industry, and that this flexibility is increasing. The primary emphasis in the empirical development and estimation below is thus on the spatial and industry dimensions, although it is useful to recognize the symmetry of the temporal and spatial model adaptations.

That is, a spatial externality index representing the dependence of costs in state i on own-industry activity in geographically connected areas may be incorporated as an argument of the cost function, analogously to the inclusion of quasi-fixed input levels to represent temporal inter-dependencies.[11] Such an 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 $TC=TC(Y,\mathbf{p},t,A^W_O)$. 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 (or "own", denoted by subscript O) industry, but in neighboring states, implying thick market effects with only a spatial dimension. However, connections could also, or alternatively, arise from spillovers or agglomeration effects associated with the activity of vertically linked sectors, as in Bartlesman, Caballero and Lyons (1994).

Bartlesman et al. recognized productive impacts from weighted sums of "aggregate activity", based on the share of materials received by or supplied to other industries, in a first-order model of aggregate U.S. manufacturing. 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

[11] Both these (structural and stochastic model) adjustments are made in the spatial econometrics 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 other states' expenditures, E_t, in the estimating model, as well as for u_t in the stochastic specification.

production function relationship to identify their performance impact. Paul and Siegel (1999) incorporated analogous 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). Quantifying the impacts of supply- and demand-agglomeration spillovers in this context involves establishing the magnitude and significance of the shadow values $Z_{AWD}=\partial TC/\partial A^W{}_D$ and $Z_{AwS}=\partial TC/\partial A^W{}_S$.

In addition, spatial linkages may be accommodated through adaptation of the stochastic structure, similarly to that for temporal autocorrelation, to allow for spatial autoregressive (SAR) errors (as developed in the spatial econometrics literature by Anselin, 1988, and others).[12] In this context, spatial inter-connections are defined via lags for geographical location at any one point in time.

This is analogous to a standard AR(1) adjustment if only one state's activity level affects the state under consideration (state i); $TC_{i,t} = TC(\cdot)_{i,t} + u_{i,t}$, where $u_{i,t} = \rho_s u_{j,t} + \varepsilon_{i,t}$, $u_{j,t}$ is the (unadjusted) error term for state j at time t, and $\varepsilon_{i,t}$ is a white-noise error. If, however, multiple states have productive interdependencies, the error structure for state i at time t becomes $u_{i,t} = \rho_s \Sigma_j w_{i,j} u_{j,t} + \varepsilon_{i,t}$, or $u_t = \rho_s W u_t + \varepsilon_t$ in matrix notation, 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. Substituting this expression into the cost equation yields $TC_t = TC(\cdot)_t + \rho_s W u_t + \varepsilon_t$, where Wu_t is a weighted sum of the $u_{j,t}$ from $TC(\cdot)$ estimation for other states (assuming $w_{i,i} = 0$), which can be rewritten as $TC_t = TC(\cdot)_t + \rho_s TC_t - \rho_s WTC(\cdot)_t + \varepsilon_t$.

[12] Kelejian and Prucha (1999) develop a generalized moments technique for estimating the spatial autocorrelation coefficient, and show that the resulting estimate is consistent. But, to our knowledge, the theory behind this technique has not been developed for estimation of a system of cost and input demand equations, so we chose to follow the more direct estimation technique outlined in the text.

Determining the "connecting" states and defining appropriate weights thus become important issues for implementation of the model.

In this study we allow for a combination of spatial and industrial spillovers to empirically capture a web of thick market and agglomeration, or urbanization and localization, economies across states for the U.S. food processing industry. We define the activity variables a_j underlying the spillover factor A^W_O as production levels in the own (food processing) industry in neighboring states. The weights w_{ij} used for the weighted average, as well as the spatial autocorrelation adjustment, give all states bordering state i equal weight, and all other states zero weight.[13] Our primary sectoral spillover measures, (unweighted) measures of own-state agricultural production and GSP, A_S and A_D, represent within-state supply- and demand- agglomeration effects.[14] We also allow for supply-side sectoral inter-dependencies from neighboring states, through a weighted sum of agricultural production in states with joint borders, A^W_S (based on the weights w_{ij} used for constructing A^W_O). The spillovers variables were normalized by state size, 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.

[13] Other weighting structures could alternatively be specified. For example, although the common approach in the spatial econometrics literature of including all other states as "neighbors" does not seem relevant here, one could postulate that the connection between neighboring states depends on something more than just having a border. For example, it could depend on the amount of "trade" between the states. We tested such an alternative model, where the impact of neighbors are weighted by the value of shipments of goods between neighboring states (data from the 1992 Commodity Flows Survey, Bureau of Transportation Statistics), and found our simpler specification to be preferred. More specifically, Case, Rosen and Hines suggested a procedure whereby a new weight W is constructed as a further-weighted average of two potential weights, $W = aW_1 + (1-a)W_2$, where W_1 and W_2 are the 2 different candidates for weights, and indicate that the likelihoods of the models as "a" ranges from 0 to 1 may be compared as a test of the relevant weight specification. We compared the likelihoods for cases where a=0 and a=1, and found that the likelihood drops to –15522 from -14270.9 when the trade weights are used.

[14] 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.

Our final estimation model is 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 are 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, reflect (weighted) activity levels of neighboring states in the same and the agricultural sector, and within-state demanders and suppliers.

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

$$1)\quad TC(Y,p_N,p_P,p_M,p_K,t,\mathbf{D_S},A^W{}_O,A_D,A_S,A^W{}_S) = \Sigma_k\Sigma_i\ \delta_{ki}\ p_k\ D_i + \Sigma_k\Sigma_l\ \alpha_{kl}\ p_k{}^{.5}\ p_l{}^{.5}$$

$$+ \Sigma_k\ \delta_{kY}\ p_kY + \Sigma_k\Sigma_n\ \delta_{kn}\ p_k\ T_n + \Sigma_k p_k(\delta_{YY}\ Y^2 + \Sigma_n\ \delta_{nY}\ T_nY + \Sigma_n\Sigma_m\ \delta_{nm}\ T_nT_m)\ ,$$

where i denotes state, k,l the variables inputs N, P, M, K, and m,n the external shift factors or **T** components $A^W{}_O$, $A^W{}_S$, A_D, A_S, and 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:

$$2)\quad X_k\ =\ \partial TC/\partial p_k = \Sigma_i\ \delta_{ki}\ D_i + \Sigma_l\ \alpha_{kl}\ p_l{}^{.5}/p_k{}^{.5} + \delta_{kY}\ Y + \Sigma_n\ \delta_{kn}\ T_n + \delta_{YY}\ Y^2$$

$$+ \Sigma_n\ \delta_{nY}\ T_nY + \Sigma_n\Sigma_m\ \delta_{nm}\ T_nT_m\ .$$

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

$$3)\quad Z_Y = MC = \partial TC/\partial Y = \Sigma_k\ \delta_{kY}\ p_k + \Sigma_k p_k(2\delta_{YY}\ Y + \Sigma_n\ \delta_{nY}\ T_n),$$

where MC is the marginal cost of Y, and

$$4)\quad Z_m = \partial TC/\partial T_m = \Sigma_k\ \delta_{km}\ p_k + \Sigma_k p_k(\delta_{mY}\ Y + \Sigma_n\ \delta_{nm}\ T_n)\ .$$

The system of equations (1) and (2), adapted to incorporate a spatial autoregressive stochastic structure, comprise the estimation model (because MC and Z_m are not observable). Equations (1)-(4), however, provide the basis for constructing our measures of the production structure. They allow us to estimate the cost, output value, and input demand-specific impacts of the spillover factors in **T**. They also permit estimation of other measures characterizing production processes and behavior, such as scale economies and their input-specific components, and input substitution patterns.

More specifically, we have seen that the TC(·) function can be used to estimate first-order elasticities from the derivatives in (2)-(4), as $\varepsilon_{TC,pk}$, $\varepsilon_{TC,Y}$, $\varepsilon_{TC,Tm}$, and $\varepsilon_{TC,t}$. These elasticities represent cost impacts of changes in input prices, output levels, spillovers and temporal or spatial factors. Since the flexible functional form used for estimation embodies a full range of cross-effects among the arguments of the function, second order derivatives and elasticities may also be computed to represent interactions among the cost drivers. For example, the impacts of changes in an external factor (or other cost determinant such as p_k or t) on marginal costs may be computed as $\varepsilon_{MC,Tm} = \partial \ln MC/\partial \ln T_m$. Similarly, input demand responses to a change in T_m are captured by $\varepsilon_{Xk,Tm} = \partial \ln X_k/\partial \ln T_m$. In reverse, the dependence of the shadow value of T_m on any cost function argument, such as Y, may be computed as: $\varepsilon_{Zm,Y} = \partial \ln Z_m /\partial \ln Y$.

Estimation and Results

The broad range of production cost determinants incorporated in our cost function specification allows a variety of such relationships to be estimated and assessed. Our estimates of these measures provide insights about cost patterns and spillover impacts for the U.S. food processing sector, on average across states from 1986 to 1996.

Our system of equations comprised of (1) and (2) was estimated by PC-TSP using seemingly unrelated systems procedures, for the food processing industries of the 48 contiguous states (an overview of data construction procedures and data summary statistics are presented in Appendix A). Allowing for heteroskedasticity, by using robust-White methods to compute the standard errors, made no substantive difference to the results. Incorporating an AR(1) process in the TC equation and each of the input demand equations also had a negligible impact on the measured indicators, even though all ρ_τ estimates (except for the K equation) were statistically significant. These adaptations were thus omitted in the final specification.

By contrast, spatial and sectoral linkages seem to be key cost drivers. A SAR adjustment, as described above for TC($\cdot$), was made for each equation in the estimating system, leading to separate spatial autocorrelation parameters for each cost and input demand equation. The resulting ρ_s estimates were statistically significant (again except for the K equation), and the adaptation had some impact on the elasticity measures (although not substantively in terms of overall patterns). The shadow values of the included spatial and industrial spillover variables were also significant. These aspects of the model were thus retained for the final reported specification.

The estimated coefficients for the model are presented in Appendix Table A2 (with t-statistics in italics). The state dummy parameters are omitted to keep the table manageable, but were primarily significant. The t-statistics for the remaining coefficients indicate overall statistical significance, although the cross-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.

Our shadow value and elasticity estimates, capturing the total and marginal cost-effects of changes in the spillover factors and other arguments of the cost function, are provided in Table 1. These and all other reported estimates are computed as (unweighted) averages of the measures across all states, and presented 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.

The shadow values themselves are not very interpretable, since they are expressed in levels and thus depend on the units of measurement. Note, however, that on average the estimated spillover effects 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. The latter initially surprising result, indicating that food processing production costs are higher in heavily agricultural states, was quite robust across alternative specifications. It is also consistent with the fact that state governments increasingly promote food manufacturing activity "as an economic development strategy designed to counteract effects of rural population decline and job losses" (Goetz, 1997), implying subsidies for such activity in otherwise less profitable areas. This evidence also provided the motivation for our inclusion in the model of $A^W{}_S$, the measure of neighboring states' weighted agricultural production, which by contrast indicates cost-saving benefits of *proximity* to agricultural producers.

Overall, these measures document state-level cost economies associated with thick markets from own-industry agglomeration, as suggested by Goetz (1997). 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. The average value of $\varepsilon_{TC,Y} = Z_Y Y/TC = \partial \ln TC/\partial \ln Y$ falls significantly short of one, suggesting that more output may be obtained with a less than proportionate cost increase (as also found by Morrison, 1997).[15] These external and internal economies thus have synergistic effects,[16] consistent with Gopinath and Vasavada's (1999) suggestion of significant intra-industry spillovers from industry level R&D in this sector, and and Paul and Siegel's (1999) finding that such impacts are augmented by knowledge capital effects from human and high-tech capital.

The reported measures also provide evidence of demand- and supply-side agglomeration economies. Demand-side or urbanization economies are implied by the primarily negative Z_{AD} values. Supply-side or localization economies are associated with agricultural intensity in neighboring states, since $Z_{AWS}<0$ (for all states), but "thin market" diseconomies arise from locating in too rural a state (in terms of agricultural production per square mile): $Z_{AS}>0$. The corresponding elasticity measures show that the strongest cost-saving impact is that from proximity to agricultural producers (from $\varepsilon_{TC,AWS}$), although the measured benefits vary widely across states.

If this combination of external effects is interpreted analogously to a combination of the production of a variety of outputs, the idea of a multi-output scale economy measure may be adapted to aggregate these effects. As developed by Baumol, Panzar and Willig (1982), a 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

[15] If one divides the sample into the earlier and later part of the sample (1986-90 versus 1991-96) to identify trends, these economies also seem to be increasing, even though this is a short time series. The average $\varepsilon_{TC,Y}$ of 0.74 drops from 0.78 to 0.70 between these two time periods. This is the only substantive change in the Y, **T**, and K elasticities, although some evidence of varying average cost shares for the variable inputs is evident, with that for N dropping, and P and M increasing

S outputs, Y_s, $\varepsilon_{TCY} = (\Sigma_s \partial TC/\partial Y_s \cdot Y_s)/TC = \Sigma_s MC_s \cdot Y_s/TC = \Sigma_s \varepsilon_{TCYr}$, indicates the cost impact if all rather than just one output increased by 1 percent.

If the external effects are treated similarly, on average the supply-side agglomeration effects from neighboring states, $\varepsilon_{TC,AWS}$, outweigh that from the own state, $\varepsilon_{TC,AS}$, implying an overall cost-saving benefit from agricultural supply sector externalities. Adding the other measures results in an even larger (in absolute value) effect, indicating that nearly 0.9 percent lower costs are implied if on average all spillover factors are 1 percent higher.[17]

The final total cost elasticities to consider are the $\varepsilon_{TC,t}$ measures, representing the time trend in food processing costs, and the $\varepsilon_{TC,pk}$ measures, reflecting the input shares. The average $\varepsilon_{TC,t}$ value suggests increasing costs over time, which is contrary to its usual interpretation as a technical change indicator. However, costs in this sector might well be rising due to increasing food processing, quality, and diversity demanded by consumers. The input elasticities show that intermediate materials comprise a 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 (0.07 versus 0.05), and the capital share is higher and labor share lower than in aggregate manufacturing (about 0.08 and 0.12 on average).

The marginal cost elasticities also provide insights about cost patterns; they represent incremental cost effects, versus the total or average cost effects captured by the

[16] Since our dataset has a spatial as well as temporal dimension, this indicates both that expansion of a state's food processing industry implies lower average production costs, and that states with higher Y levels have lower unit costs of production (given all other cost determinants represented in the function).
[17] 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.

TC elasticities. The MC and TC elasticities in Table 1 indicate that increases in own- and supplying-industry production in neighboring states cause marginal as well as average (total, given output) costs to fall, but that marginal costs drop by a smaller proportion; e.g., $0 < \varepsilon_{TC,AWO} < \varepsilon_{MC,AWO}$. By contrast, the supply and demand average and marginal own-state effects are reversed in sign ($\varepsilon_{MC,AS} < 0 < \varepsilon_{TC,AS}$ and $\varepsilon_{MC,AD} > 0 > \varepsilon_{TC,AD}$); greater potential demand in the state implies higher marginal costs on average, and more agricultural intensity, or "rurality", implies lower marginal costs. These spillover factors thus seem to act more as fixed than incremental effects. Marginal costs also appear to be increasing over time, but not significantly (either statistically or in terms of magnitude). And intermediate materials are a much larger share of marginal than total costs, at 91 percent, whereas marginal increases in labor and capital costs to accommodate greater production are only half, and less than one-third, the corresponding average increases.

The results discussed so far, representing cost patterns, and in particular cost effects of spatial and industry spillovers, are our primary focus. However, it is also informative to explore their underlying second order implications – the associated input demand and shadow value patterns.

The input demand elasticities 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 theoretically appropriate demand responses to input price changes. Production labor appears to adjust the most in response to a change in its price, and intermediate materials the least.

The remaining input price elasticities indicate that substitutability prevails across factors, consistent with Huang (1991) and Goodwin and Brester (1995). Although we will not explore these patterns in depth, some are particularly striking, such as large K responses (as in Morrison, 1997) – especially to p_P. Higher production labor prices appear to induce mechanization; or areas where production labor wages are low attract less capital-intensive food manufacturing processes or industries. Materials use instead adapts little to changes in the prices of other inputs, although its demand response to p_P is the strongest, and to p_K the weakest. When production worker wages are high, more intermediate materials are used, perhaps indicating that less time is taken to screen incoming agricultural products, resulting in more waste.

Input-specific scale and time elasticities, $\varepsilon_{Xk,Y}$ and $\varepsilon_{Xk,t}$, are also presented in Table 2. The Y elasticities indicate that output augmentation is supported primarily by increased materials use, which is consistent with the implications from the marginal cost elasticities.[18] By contrast, larger output levels seem to be associated with only slightly higher capital stocks. The t elasticities indicate a fall in the use of non-production workers over time (but not significantly), and only a small increase in capital. But P and M demands for a given output level seem to be rising (significantly) by 5-6 percent per year on average, which could be associated with expanded demands for more processed and higher quality final food products, including increased packaging.

The input demand elasticities with respect to the external factors indicate widely varying input-specific spillover impacts. The cost-saving impact of own-industry thick markets is related primarily to lower M and P use; more food processing activity in neighboring states actually implies higher N levels (although changes in both types of labor are statistically insignificant). Costs associated with greater in-state agricultural

[18] 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 $\partial^2TC/\partial p_M\partial Y$.

intensity are also primarily related to M (and to some extent P) use. This may suggest that food processing establishments requiring higher levels of agricultural or other materials, and production workers, are more likely to locate in rural areas. Cost savings of having neighboring agricultural states are also driven by materials use (and some reduction in K), but imply greater labor demand. This perhaps indicates that firms requiring more labor but less agricultural materials benefit from proximity, but not close connections, to suppliers. And urbanization economies, or the benefits of nearness to demand concentrations, are associated with lower levels of all inputs.

Finally, it is useful to consider elasticities of the spillover shadow values, presented in Table 3. Note first that the low overall statistical significance levels for these elasticities, and especially for cross-effects between external factors. In particular, the Z_{AWS} elasticities are all insignificant except $\varepsilon_{ZAWS,pM}$ and $\varepsilon_{ZAWS,pK}$. This implies that a rise in p_M (and to a lesser extent p_K) increases the value of proximity to agricultural production. Note also that the only spillover shadow value that does not increase (in absolute value) significantly with p_K is Z_{AWO}, and all increase significantly with p_M.

Additional insights may be gained from the Y and t elasticities in this Table. Higher levels of food processing production weakly imply greater value associated with closeness to other food processing activity, and to neighboring state's agricultural activity, as exhibited by the $\varepsilon_{ZAWO,Y}$ and $\varepsilon_{ZAWS,Y}$ elasticities (but they are not statistically significant). $\varepsilon_{ZAS,Y}$ may be similarly interpreted, although it is the opposite sign (since the sign of Z_{AS} is reversed). By contrast, states with greater food processing intensity reap less benefits from proximity to areas with higher demand concentrations.

In the temporal dimension, cost savings benefits from both demand-side agglomeration and own-industry thick market impacts have increased over the time frame of our analysis. The disadvantages of being in a rural area also are rising, and the cost-savings from proximity to suppliers falling. This suggests that over time the "draws" of urbanization economies and thick market effects are motivating food processing industries to move away from rural or agricultural areas.

Concluding Remarks:

In this paper we have estimated and assessed spatial and industrial spillover effects in the U.S. food system. Our focus is on state-level food processing production, with thick market effects from neighboring states' own-industry activity levels, and supply- and demand-agglomeration effects from proximity to high food demand concentrations and agricultural-intensity, both within and across states.

We find statistically significant cost impacts of these spillover effects, although the supplier-effect is a combination of benefits from having neighboring states with high agricultural levels, and costs of 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. roads or 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 apparent differences between total and marginal cost effects imply that there is a greater proportion of materials than other input costs at the margin, and that within-state supply and demand cost impacts have more a fixed effects than incremental nature.

Measured second-order relationships underlying these cost effects indicate that the specification is generating (theoretically and conceptually) reasonable representations of production processes. The elasticities also reveal negligible cross-effects among the spillover factors, but clear differentiation among input responses to variations in spillovers, as well as different output levels, input prices, and time period.

Our results thus provide provocative evidence about the insights that may be gained from incorporating spatial and sectoral spillovers in production analyses; such factors seem to be key economic performance determinants, although they are not allowed for in conventional production models.

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Appendix A: The Data

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

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

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

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

Materials: The ASM reports direct charges actually paid or payable for items consumed or put into production during the year. The quantity of materials is obtained by deflating these charges by the ratio of nominal Gross Domestic Product to real Gross Domestic Product as reported on the Bureau of Economic Analysis website. This deflator is also used as the price of materials.

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

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

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 (t statistics in italics)

$\alpha_{N,L}$	**1.39E+01**	*0.67*	$\delta_{WS,WS}$	**-1.51E-10**	*-0.59*
$\alpha_{N,M}$	**7.89E+01**	*2.42*	$\delta_{S,S}$	**-5.44E-10**	*-0.37*
$\alpha_{N,K}$	**2.32E+01**	*0.57*	$\delta_{WO,WO}$	**3.19E-07**	*1.44*
$\alpha_{P,M}$	**1.85E+02**	*4.12*	$\delta_{D,D}$	**7.30E-13**	*6.66*
$\alpha_{P,K}$	**1.95E+02**	*3.00*	$\delta_{D,Y}$	**1.10E-09**	*7.32*
$\alpha_{K,M}$	**5.56E+00**	*0.08*	$\delta_{D,WO}$	**-1.48E-09**	*-6.37*
$\delta_{N,Y}$	**2.03E-02**	*6.25*	$\delta_{D,S}$	**-4.07E-11**	*-1.64*
$\delta_{P,Y}$	**3.28E-02**	*10.01*	$\delta_{Y,WO}$	**-3.07E-07**	*-1.50*
$\delta_{M,Y}$	**4.91E-01**	*34.81*	$\delta_{Y,S}$	**-2.15E-08**	*-1.44*
$\delta_{K,Y}$	**3.55E-02**	*6.14*	$\delta_{Y,D}$	**-2.94E-08**	*-0.86*
$\delta_{N,t}$	**-1.71E+00**	*-1.45*	$\delta_{D,WS}$	**1.35E-11**	*1.03*
$\delta_{P,t}$	**6.19E+00**	*5.24*	$\delta_{Y,WS}$	**-2.83E-08**	*-1.80*
$\delta_{M,t}$	**7.34E+01**	*9.32*	$\delta_{WO,WS}$	**1.18E-08**	*0.96*
$\delta_{K,t}$	**8.38E+00**	*3.37*	$\delta_{S,WS}$	**-8.08E-10**	*-0.75*
$\delta_{N,WS}$	**1.31E-04**	*0.48*	$\delta_{D,t}$	**-4.06E-07**	*-4.79*
$\delta_{P,WS}$	**7.72E-05**	*0.27*	$\delta_{Y,t}$	**2.86E-05**	*0.54*
$\delta_{M,WS}$	**-1.04E-02**	*-5.69*	$\delta_{WO,t}$	**-2.18E-04**	*-2.37*
$\delta_{K,WS}$	**-1.35E-03**	*-2.06*	$\delta_{WS,t}$	**7.75E-06**	*0.95*
$\delta_{N,WO}$	**7.97E-04**	*0.14*	$\delta_{S,t}$	**6.37E-05**	*6.03*
$\delta_{P,WO}$	**-5.17E-03**	*-0.90*	ρ	**0.369797**	*9.50*
$\delta_{M,WO}$	**-7.03E-02**	*-2.36*	ρ_N	**0.39307**	*7.73*
$\delta_{K,WO}$	**7.08E-04**	*0.08*	ρ_P	**0.280306**	*5.45*
$\delta_{N,S}$	**8.94E-04**	*1.99*	ρ_M	**0.375107**	*9.47*
$\delta_{P,S}$	**1.41E-03**	*3.11*	ρ_K	**6.66E-04**	*0.98*
$\delta_{M,S}$	**1.54E-02**	*7.91*			
$\delta_{K,S}$	**2.84E-03**	*3.64*	R^2s	TC	***0.9940***
$\delta_{N,D}$	**-2.24E-05**	*-3.26*		N	***0.9939***
$\delta_{P,D}$	**-2.75E-05**	*-4.04*		P	***0.9973***
$\delta_{M,D}$	**-7.59E-05**	*-2.91*		M	***0.9916***
$\delta_{K,D}$	**-4.32E-05**	*-4.14*		K	***0.9971***
$\delta_{Y,Y}$	**-1.49E-07**	*-3.34*			

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	-0.246	-0.044	0.028	[.002]
Z_{AS}	**0.0159**	0.002	0.010	0.020	0.002	[.000]
Z_{AWS}	**-0.0103**	0.001	-0.015	-0.008	0.002	[.000]
Z_{AD}	**-0.00013**	0.00005	0.000	0.000	0.00003	[.000]
Z_{Y}=MC	**0.5034**	0.035	0.400	0.632	0.014	[.000]
$\varepsilon_{TC,AWO}$	**-0.3607**	0.492	-2.916	-0.011	0.042	[.002]
$\varepsilon_{TC,AS}$	**0.3574**	0.438	0.034	2.691	0.022	[.000]
$\varepsilon_{TC,AWS}$	**-0.7032**	1.584	-10.895	-0.004	0.031	[.000]
$\varepsilon_{TC,AD}$	**-0.1889**	0.413	-3.066	0.028	0.000	[.000]
$\varepsilon_{TC,Y}$	**0.7401**	0.109	0.566	2.029	0.020	[.000]
$\varepsilon_{TC,t}$	**0.0493**	0.069	0.003	0.396	0.001	[.000]
$\varepsilon_{TC,pN}$	**0.0468**	0.023	-0.190	0.154	0.001	[.000]
$\varepsilon_{TC,pP}$	**0.0743**	0.022	-0.084	0.218	0.002	[.000]
$\varepsilon_{TC,pM}$	**0.8218**	0.264	-1.486	2.622	0.004	[.000]
$\varepsilon_{TC,pK}$	**0.0828**	0.029	0.005	0.313	0.001	[.000]
$\varepsilon_{MC,AWO}$	**-0.0169**	0.008	-0.045	-0.001	0.011	[.132]
$\varepsilon_{MC,AS}$	**-0.0091**	0.008	-0.050	0.000	0.006	[.148]
$\varepsilon_{MC,AWS}$	**-0.0180**	0.026	-0.210	-0.001	0.010	[.073]
$\varepsilon_{MC,AD}$	**0.0302**	0.043	0.001	0.220	0.005	[.000]
$\varepsilon_{MC,Y}$	**-0.0164**	0.017	-0.103	0.000	0.005	[.001]
$\varepsilon_{MC,t}$	**0.0002**	0.000	0.000	0.000	0.000	[.589]
$\varepsilon_{MC,pN}$	**0.0267**	0.013	-0.010	0.070	0.003	[.000]
$\varepsilon_{MC,pP}$	**0.0491**	0.014	0.013	0.112	0.003	[.000]
$\varepsilon_{MC,pM}$	**0.9077**	0.030	0.809	0.989	0.006	[.000]
$\varepsilon_{MC,pK}$	**0.0166**	0.004	0.006	0.028	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	-6.236	7.457	0.086	[.057]
$\varepsilon_{N,AS}$	**0.1500**	0.823	-5.341	3.790	0.054	[.055]
$\varepsilon_{N,AWS}$	**0.1969**	0.733	-2.361	5.475	0.079	[.988]
$\varepsilon_{N,AD}$	**-0.2599**	1.294	-7.968	7.496	0.091	[.000]
$\varepsilon_{N,Y}$	**0.4604**	0.293	-0.233	2.541	0.051	[.000]
$\varepsilon_{N,t}$	**-0.0195**	0.106	-0.833	0.465	0.003	[.917]
$\varepsilon_{N,pN}$	**-0.8287**	2.257	-25.565	-0.028	0.035	[.000]
$\varepsilon_{N,pP}$	**0.1051**	0.279	0.004	3.211	0.034	[.506]
$\varepsilon_{N,pM}$	**0.6246**	1.707	0.021	19.201	0.055	[.015]
$\varepsilon_{N,pK}$	**0.0989**	0.271	0.003	3.152	0.037	[.566]
$\varepsilon_{P,AWO}$	**-0.3815**	0.945	-8.219	1.604	0.051	[.000]
$\varepsilon_{P,AS}$	**0.2378**	0.305	-0.640	1.441	0.033	[.000]
$\varepsilon_{P,AWS}$	**0.1451**	0.701	-1.148	6.944	0.049	[.830]
$\varepsilon_{P,AD}$	**-0.2255**	0.670	-2.741	5.116	0.054	[.000]
$\varepsilon_{P,Y}$	**0.5111**	0.172	0.101	1.425	0.031	[.000]
$\varepsilon_{P,t}$	**0.0509**	0.079	-0.014	0.579	0.002	[.000]
$\varepsilon_{P,pN}$	**0.0597**	0.101	0.002	0.653	0.020	[.506]
$\varepsilon_{P,pP}$	**-1.3494**	2.252	-15.685	-0.050	0.039	[.000]
$\varepsilon_{P,pM}$	**0.8223**	1.371	0.030	9.478	0.045	[.000]
$\varepsilon_{P,pK}$	**0.4674**	0.781	0.017	5.585	0.035	[.003]
$\varepsilon_{M,AWO}$	**-0.4270**	0.677	-5.254	-0.009	0.051	[.010]
$\varepsilon_{M,AS}$	**0.4055**	0.540	0.038	3.496	0.025	[.000]
$\varepsilon_{M,AWS}$	**-0.8997**	2.057	-15.932	-0.004	0.036	[.000]
$\varepsilon_{M,AD}$	**-0.1941**	0.579	-5.226	-0.004	0.024	[.003]
$\varepsilon_{M,Y}$	**0.8468**	0.151	0.575	2.780	0.024	[.000]
$\varepsilon_{M,t}$	**0.0586**	0.088	0.003	0.598	0.001	[.000]
$\varepsilon_{M,pN}$	**0.0306**	0.048	0.001	0.368	0.003	[.015]
$\varepsilon_{M,pP}$	**0.0724**	0.111	0.003	0.677	0.004	[.000]
$\varepsilon_{M,pM}$	**-0.1043**	0.160	-1.006	-0.005	0.006	[.000]
$\varepsilon_{M,pK}$	**0.0012**	0.002	0.000	0.013	0.003	[.934]
$\varepsilon_{K,AWO}$	**-0.0166**	0.275	-1.646	0.925	0.039	[.477]
$\varepsilon_{K,AS}$	**0.1910**	0.217	0.017	1.108	0.026	[.000]
$\varepsilon_{K,AWS}$	**-0.3419**	0.846	-4.641	-0.003	0.037	[.020]
$\varepsilon_{K,AD}$	**-0.2346**	0.594	-4.127	0.006	0.026	[.000]
$\varepsilon_{K,Y}$	**0.1618**	0.062	0.046	0.407	0.025	[.000]
$\varepsilon_{K,t}$	**0.0182**	0.022	0.000	0.104	0.001	[.000]
$\varepsilon_{K,pN}$	**0.0453**	0.061	0.002	0.276	0.020	[.566]
$\varepsilon_{K,pP}$	**0.3860**	0.528	0.018	2.620	0.032	[.003]
$\varepsilon_{K,pM}$	**0.0112**	0.015	0.001	0.066	0.033	[.934]
$\varepsilon_{K,pK}$	**-0.4425**	0.604	-2.934	-0.021	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	0.002	0.318	0.071	[.180]
$\varepsilon_{ZAWO,t}$	**0.0081**	0.002	0.003	0.014	0.004	[.062]
$\varepsilon_{ZAWO,AWO}$	**-0.2293**	0.140	-0.644	-0.020	0.150	[.183]
$\varepsilon_{ZAWO,AS}$	**0.0712**	0.052	0.004	0.274	0.084	[.407]
$\varepsilon_{ZAWO,AWS}$	**-0.0425**	0.049	-0.398	-0.002	0.046	[.350]
$\varepsilon_{ZAWO,AD}$	**0.1791**	0.187	0.006	0.760	0.086	[.005]
$\varepsilon_{ZAWO,pN}$	**0.0266**	0.076	-0.138	0.210	0.033	[.104]
$\varepsilon_{ZAWO,pP}$	**0.0935**	0.062	-0.040	0.277	0.042	[.007]
$\varepsilon_{ZAWO,pM}$	**0.8717**	0.161	0.499	1.219	0.068	[.000]
$\varepsilon_{ZAWO,pK}$	**0.0082**	0.024	-0.047	0.064	0.023	[.459]
$\varepsilon_{ZAS,Y}$	**-0.0386**	0.041	-0.251	-0.001	0.026	[.157]
$\varepsilon_{ZAS,t}$	**0.0120**	0.001	0.010	0.017	0.002	[.000]
$\varepsilon_{ZAS,AWO}$	**-0.0519**	0.026	-0.135	-0.004	0.059	[.392]
$\varepsilon_{ZAS,AS}$	**-0.0151**	0.013	-0.089	0.000	0.039	[.711]
$\varepsilon_{ZAS,AWS}$	**-0.0176**	0.028	-0.212	0.000	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	-0.082	0.105	0.013	[.054]
$\varepsilon_{ZAS,pP}$	**0.0514**	0.027	-0.057	0.109	0.013	[.000]
$\varepsilon_{ZAS,pM}$	**0.8855**	0.061	0.771	1.124	0.025	[.000]
$\varepsilon_{ZAS,pK}$	**0.1486**	0.020	0.054	0.181	0.011	[.000]
$\varepsilon_{ZAWS,Y}$	**0.0699**	0.063	0.002	0.330	0.042	[.079]
$\varepsilon_{ZAWS,t}$	**-0.0022**	0.000	-0.003	-0.002	0.002	[.346]
$\varepsilon_{ZAWS,AWO}$	**-0.0315**	0.015	-0.072	-0.003	0.033	[.338]
$\varepsilon_{ZAWS,AS}$	**0.0160**	0.012	0.001	0.078	0.022	[.458]
$\varepsilon_{ZAWS,AWS}$	**0.0094**	0.013	0.000	0.093	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	-0.049	0.088	0.019	[.988]
$\varepsilon_{ZAWS,pP}$	**0.0022**	0.023	-0.054	0.089	0.020	[.828]
$\varepsilon_{ZAWS,pM}$	**0.9613**	0.049	0.771	1.071	0.038	[.000]
$\varepsilon_{ZAWS,pK}$	**0.1423**	0.016	0.108	0.209	0.015	[.011]
$\varepsilon_{ZAD,Y}$	**-0.2330**	2.003	-26.828	13.094	0.062	[.000]
$\varepsilon_{ZAD,t}$	**0.0144**	0.060	-0.258	1.043	0.003	[.002]
$\varepsilon_{ZAD,AWO}$	**0.5607**	2.824	-12.429	48.683	0.089	[.000]
$\varepsilon_{ZAD,AS}$	**0.1005**	0.529	-2.386	9.194	0.042	[.117]
$\varepsilon_{ZAD,AWS}$	**-0.1017**	0.692	-12.134	3.077	0.034	[.325]
$\varepsilon_{ZAD,AD}$	**-0.9343**	7.743	-135.472	35.724	0.034	[.000]
$\varepsilon_{ZAD,pN}$	**0.0855**	0.859	-14.523	4.120	0.040	[.000]
$\varepsilon_{ZAD,pP}$	**0.1343**	0.681	-11.426	3.124	0.041	[.000]
$\varepsilon_{ZAD,pM}$	**0.6870**	1.530	-6.268	26.610	0.088	[.000]
$\varepsilon_{ZAD,pK}$	**0.0933**	0.014	0.023	0.339	0.022	[.000]