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# Agglomeration Economies and Industry Location Decisions: The Impacts of Vertical and Horizontal Spillovers

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*ABSTRACT*

Economic analysis of production processes and performance typically neglects consideration of spatial and industry inter-dependencies that may affect economic performance, although there is increasing theoretical recognition that such linkages may be both substantive and expanding. In particular, thick market or agglomeration effects may arise due to knowledge or other types of spillovers associated with own-industry (horizontal), and supply-side or demand-driven (vertical), externalities. In this paper we provide a conceptual and empirical framework for measuring and evaluating such spillovers, which allows us both to quantify their cost-effects, and to evaluate their contribution to location decisions. We focus on the U.S. food manufacturing sector, and the spillovers that may occur across states within the sector and from agricultural production (supply) and consumer buying power (demand). And we find substantive total and marginal cost-impacts in both spatial and industry dimensions, which appear to be motivating forces for regional concentration patterns of the U.S. food manufacturing industries.

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## Introduction

Although there has recently been increased focus in the economics literature on spatial location or "economic geography" (Krugman, 1991a,b), the literature on the effects of agglomeration externalities on location decisions and associated economic performance remains sparse. In particular, little attention has been paid – especially in the empirical context – to the competing effects of different types of spatial and industrial agglomeration effects on the connection between economic performance and optimal location of firms and industries.

There are clear indications, however, both anecdotally and theoretically, that there is an important spatial dimension to firms' decisions and resulting performance. Locating a firm in an area where other similar types of firms, or suppliers/demanders, are in close proximity, seems to have a clear economic motivation in terms of enhanced productivity (reduced costs). The implied agglomeration externalities or economies across firms in an industry or sector may be due to various forces, including a conglomeration of specialized inputs, and informational or knowledge spillovers.

In the industry or sectoral dimension, agglomeration economies that work through layers of a system – via geographic linkages to suppliers and demanders – may motivate the increasing vertical coordination or integration observed in many industries. However, forces counteracting these spatial or industry external cost economies might also exist. For example, congestion or greater input competition in high-density areas could cause producers in an industry, and/or their suppliers, to locate in more rural areas.

In this context, we attempt in this study to shed new light on the question posed by Krugman (1991a): "Why and when does manufacturing becomes concentrated in a few regions…". We address this question for the U.S. food system, from the perspective of the overall food manufacturing or processing industry. This is obviously a crucial sector, which plays a key role not only in producing perhaps the most essential consumption commodity, but also in demanding inputs from the agricultural sector – a foundation of all economies. It is thus fundamentally connected both with primary agricultural production, which tends to be in rural areas, and consumption demand, which is concentrated in more urban areas. The food manufacturing industries are also important in terms of magnitudes; the food and fiber industries as a whole employed almost 23 million people, and contributed almost $998 billion (more than 13 percent) to U.S. GDP in 1996 (Lipton *et al*, 1998). This sector thus seems a particularly important example of the combination of spatial and industrial linkages we wish to explore.

Our treatment of spillovers is similar to the recognition of external as well as internal contributors to scale economies that has recently been stressed in various literatures, such as the "new" growth and trade literatures. Spatial or sectoral inter-dependencies can be thought of as external economies of scale in the sense that they augment (or counteract) internal scale economies by acting as shift factors, which affect the cost-output relationship and thus economic performance and competitiveness. Since both positive and negative external spillovers – or thick and thin market effects – might exist, however, the combined impacts of these shift factors on economic performance (costs) and location are not *a priori* obvious. Empirical investigation is thus required to quantify and analyze the impacts and patterns of spatial and industrial spillovers.

Using state-level data for the U.S. food manufacturing industry, and associated supplying and demanding sectors, we construct a cost-based model to identify thick or thin market effects. We evaluate their contribution to productive performance in terms of production costs, and motivations for location decisions. In particular, we examine the productive spillovers for state-level food processing industries from own-industry activity in neighboring states, and from inter-dependencies with suppliers (primary agricultural production, or the activity level of a crucial supplying sector) and demanders (consumer demand, proxied by overall economic activity in the state).

These spatial and industrial agglomeration effects are measured via shadow value elasticities representing cost effects from the proximity of own-industry production, own-state and neighboring state's agricultural production, and overall production density (gross state product, GSP). Such indicators allow us to represent both benefits and costs of industrial proximity, which may result from thick market agglomeration effects, or insufficient density to facilitate economical food manufacturing production, respectively.

We find substantive variations between total and marginal cost-economies or shadow values, as well as significant regional differences in all these measures. State-level food manufacturing industries appear to reap significant total cost-saving benefits from locating close to own-industry markets as well as suppliers and demanders (thick-market or agglomeration effects), but high agricultural intensity within the state under consideration seems to augments production costs (thin market effects). By contrast, marginal costs are greater in areas of high consumer demand, perhaps due to congestion or quality impacts, whereas they are lower in rural areas.

In turn, geographic concentration patterns in this industry seem to have clear cost-based motivations. Food processing is less concentrated than agriculture in rural states, but still more concentrated in these regions than is total productive activity (GSP). Measures of the average and marginal cost-benefits from internal and external scale economies confirm that the observed density of the food processing industry in regions (states) such as Pacific (CA), East North Central, Mid-Atlantic (NY, PA), and West South Central (TX), are consistent with lower marginal costs from such economies in these areas.  Because marginal costs motivate behavior – in this context location choices – there seems a clear convergence of, and thus explanation for, observed geographical densities in this sector from a combination of marginal spillover cost effects, although average cost patterns are less consistent.

**The Conceptual and Theoretical Context of the Analysis**

Marshall recognized the importance of external geographical economies to firms' performance and thus decisions in the mid 1800s.  These ideas stimulated a broad traditional literature on the impacts of agglomeration externalities, as represented by Hoover (1948).  However, such productive linkages, externalities, or spillovers still receive little attention in the mainstream economics literature.  In fact, Krugman (1991a) asserted that it "seems fair to say that the study of economic geography plays at best a marginal role in economic theory."

Although the recognition of the spatial dimension has recently increased, this crucial dimension of economic behavior needs much more attention and exploration.  In particular, empirical investigation of external costs and benefits from various types of spatial and industrial thick or thin market effects seems crucially important for measuring and understanding firms' or industries' performance patterns and their location decisions.

It is clear that there are important economic motivations for population and production to cluster in a few relatively dense areas (Krugman, 1991a,b).  Some of the advantages of clustering stem from transportation costs.[1] Others emerge from various types of thick market effects such as the availability of skilled labor or other specialized inputs for firms, and knowledge or informational spillovers across own- and associated industrial sectors.[2] There may also, however, be counteracting stimuli for moving away from densely populated centers, due to competition for inputs (especially land), or "thin market" effects in more rural areas that may be linked to distance, such as lack of telecommunications or limited communications or transportation infrastructure.

The balancing of positive and negative external factors may be particularly striking in industries where the primary inputs for production are located in rural areas, and yet the main demanders of the products are in more urban centers, such as those in the food manufacturing/processing sector. This sector also has a key role in the economy due to its (vertically) central location in the food system between the fundamental primary agricultural sector and the purchasers of a crucial consumption commodity. It thus seems a particularly interesting target for an analysis of thick and thin, and spatial and industrial, spillover effects, and resulting performance and location decisions.

Various thick market or agglomeration effects that have impacts on firms' costs, and thus on economic performance, might be summarized as spatial and industrial inter-dependencies of both own-industry firms, and supplying or demanding sectors. These forces are similar to agglomeration impacts, in the form of localization and urbanization economies, which provide an important basis of the urban/regional economics literature. They may also be thought of as associated with "activity levels" of related sectors.

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[1] About 4 percent of the U.S. food dollar, or $22.3 billion in total in 1996, was spent for transportation.

[2] They might also take the form of either (or both) technological and pecuniary economies, although to the extent that the latter are reflected in price variables in a cost analysis the former become the primary target of analysis of spillover effects.

These inter-dependencies have a fundamental spatial dimension, in the sense that formalizing their cost or productivity impacts requires measuring linkages to own or neighboring locations – states for our application. An industry dimension is also relevant, however, since urbanization economies largely stem from (consumer) demand spillovers, and the density of (intermediate) inputs implies supply-side spillovers from lower vertical levels of the sector – or of the "food chain" for our application.

Such agglomeration effects are in some sense external to firms' decision making, although in a full long run context – at least implicitly – they are the basis for localization choices or changes. Our goal is therefore to identify agglomeration effects from various spillover factors, through their measured external cost impacts, given existing industry concentration patterns. We then evaluate to what extent these are consistent with observed location choices of food processing firms, by characterizing optimal localization decisions on the margin. That is, we measure the benefits (costs) of thick (thin) market effects for existing firms, and then to use these patterns to examine their implications for optimal, cost effective, or "productive" locational choices.

The impacts of such spillovers may be expressed in the context of increasing returns, like in the "New Growth" literature (Romer 1986), and to a more limited extent in the "New Trade" (Krugman, 1991a,b), and the cost and productivity literatures (Paul 1999, Morrison and Siegel 1999). The external nature of these factors is recognized by representing their productivity impacts in terms of shifts of the production or cost function. As (overall) production expands over time, the firm not only moves down its existing cost curve due to internal scale economies, but experiences downward shifts in the curve due to agglomeration effects (external cost economies) associated with augmented production in its own and neighboring states and industries. A positive (negative) shift factor thus enhances internal scale economies.

We can formalize these relationships through a production function for the food processing industry of a particular state, of the form $Y_O = Y_O(\mathbf{X},t, \mathbf{D_S},\mathbf{E}) = Y_O(N,P,M,K,t,\mathbf{D_S},Y_N,A_O,A_N,G_O)$, where $Y_O$ is food processing output in the own (O) state, and $\mathbf{X}$ is a vector of (internally demanded) inputs: nonproduction labor, N, production labor, P, intermediate materials, M, and capital, K. t and $\mathbf{D_S}$ represent variations over time and space: the trend term t represents shifts in the production frontier over time due to technical change, and the vector of state-level dummy variables or fixed effects $\mathbf{D_S}$ represents cost variations across states not explained by other arguments of the function. And $\mathbf{E}$ is a vector of external or agglomeration factors, including the extent of food processing production in neighboring states, $Y_N$, agricultural output in the own and neighboring states, $A_O$ and $A_N$, and total production in the own state, $G_O$.

If we wish to focus on production costs instead of technological relationships, we can more directly represent the costs and benefits of agglomeration factors through a cost function. This requires assuming cost minimizing behavior, where firms choose internal input demand levels – here N, P, M, K – given their market prices, the production function (or technology), and the levels of external factors. This results in the dual total cost function $TC(Y_O,p_N,p_P,p_M,p_K,t,Y_N,A_O,A_N,G_O,G_N)$.[3]

[3] Note that in much of the current production/cost literature short run fixities of factors such as capital are often recognized. In preliminary investigation with our data, however, we found little evidence of short run rigidities. In particular, we found that imposing Shephard's lemma with respect to K, which implies that K is a variable input, did not change our results substantively; its shadow value and market prices were insignificantly different. This seems consistent with the fact that our panel data are more cross-sectional than time-series in nature, so the temporal dimension or short run rigidities are unlikely to play a large role.

Although the roles of **X**, t and even $\mathbf{D_S}$ (for panel data) in the production and thus cost function are standard, and therefore require little further discussion, those of the components of the **E** vector need additional elaboration. First, the mechanism underlying agglomeration economies is often stated in general terms as: "by locating close to one another, firms can produce at a lower cost" (O'Sullivan, 2000). This suggests that there are some types of information or knowledge spillovers, or other unmeasured factors, that cause thick markets in terms of own-industry production to enhance productivity. This is represented by $Y_N$.[4] The roles of supply-side agglomeration factors – largely benefits from the proximity of, and thus interactions with, materials input producers (since much of M for the food processing sector is agricultural products) – are represented by $A_O$ and $A_N$.[5] And the impact of own-state demand density is represented by $G_O$, measured as gross state product (GSP), indicating the extent of the local market for food products.

More specifically, this treatment is related to the notion of "agglomerative economies in production" in the form of localization and urban economies in the regional economics literature, as overviewed in O'Sullivan (2000). Localization economies are attributed to three principal causes – "scale economies in the production of intermediate inputs, labor-market pooling, and knowledge spillovers" – and occur "if the production costs of firms in a particular industry decrease as the total output of the industry increases". The scale economies associated with expansion of the industry in the own state are captured as the own scale effect, represented by the proportional impact of $Y_O$ on TC. The other identified drivers for agglomeration economies, both in general and

[4] The production measures for neighboring states are weighted sums of production in all states with a common boundary, as discussed in the data appendix.

specific terms, relate to the inclusion of the $Y_N$, $A_O$ and $A_N$ agglomeration factors in our framework.

Thick market effects from localization of labor (or other specialized input) markets, and knowledge or informational spillovers, are captured by the cost-impacts of food processing production levels in neighboring states, represented by the level of $Y_N$ and its changes or spatial differences. For example, labor market pooling for food processing firms may well exist, particularly if the products being produced are seasonal. Also, as equipment for such firms is becoming increasingly specialized, clustering of production around equipment suppliers, or secondary equipment markets, may generate cost-benefits. Less well-defined inputs, such as specialized banking services and product distribution networks, or even expert information on food markets provided by government and university extension services, may also be relatively localized. These mechanisms are in turn related to the notion of information spillovers and the diffusion of technology, which may be expected to stimulate own-industry production clustering.

In turn, location spillovers associated with intermediate input markets are represented through the measures of agricultural output in the own and neighboring states, $A_O$ and $A_N$. These supply impacts implicitly represent the impact of transportation costs, as well as other factors associated with the "closeness" of agricultural markets or rural areas. As noted by O'Sullivan, if transportation costs are high, the proximity of input markets may have an important cost-savings impact on production. However, in our treatment transport costs for the inputs – a pecuniary economy – will be at least to some extent captured in the price of the materials input, M. Thus, the primary forces

[5] Although one might think that one measure indicating the effect of producing close to primary agricultural producers would suffice here, this distinction is retained because it became clear in preliminary

reflected in the cost-benefits of higher $A_O$ or $A_N$ will be factors indirectly related to transportation costs, such as the perishable and fragile nature of most agricultural products, or other technological benefits of having agricultural markets close by.

For example, as processed food products change in quality, and increase in differentiation, being physically close to the agricultural markets to monitor the primary product growing process in some form may be important. In addition, although demand for food products is relatively stable, supply of agricultural products is not, which suggests that direct connection with the primary agricultural producers may help to smooth the availability of agricultural materials over supply fluctuations.

Note also that the rural nature of highly agricultural states may impose rather than relieve production costs for processing plants, if, say, fewer services such as telecommunications are available in these states. It is also likely that the labor pool will be more limited, and perhaps less educated, in more rural regions. There may thus be a balance between higher and lower rurality for the costs and thus location of food manufacturing operations.

Urbanization economies instead arise from the demand side. Again, as for the agricultural inputs, some indication of the impacts of urbanization that may affect costs will appear in the price data for our model. For example, input competition, which will increase the cost of producing closer to urban centers, will be to some extent captured in measured input prices. Such factors could also be reflected in cost differentials embodied in the state-level fixed effects $D_S$, which accommodates any "unexplained" positive or negative own-state impacts. Other agglomeration economies associated with increased urbanization or higher product demand levels are measured as the cost effects of higher

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empirical investigation that $A_O$ and $A_N$ had very different and contradictory impacts.

own-state GSP, $G_O$. Urbanization economies are implied if costs are lower in more dense production/population areas.

As noted by O'Sullivan, such economies "result from the scale of the entire urban economy, not simply the scale of a particular industry." They are often thought to be associated with input (N,P,K) market impacts, although for food processing this is not as likely to be a major factor, since agricultural materials are the primary input for many food manufacturing industries. Knowledge spillovers and innovation may also be enhanced by being in a more urban area, but again, for this industry, there is no obvious reason to think this mechanism will be strong. By contrast, demand effects will clearly be operative in this industry, although competing forces may cause such externalities to be either positive or negative. For example, scale economies in production generated by proximity to a higher demand area may permit cost savings. However, it may also be that more processed, high quality, or differentiated products may be demanded in more urban areas, which will increase the costs of producing the measured output.

The distinctions between the own, supply-side and demand-side agglomeration effects made here are also similar to those in other literatures. In particular, they are related to macro- and production-oriented studies such as those by Bartlesman, Caballero and Lyons (1994), and Morrison and Siegel (1999), in which "activity levels" of suppliers and demanders generate agglomeration externalities. In these studies, externalities arising through various types of knowledge spillovers, which may feed through labor, capital, R&D, or other markets, are summarized in the activity variables.[6] But such studies focus only on the industrial, rather than spatial, dimension.

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[6] This provides the basis for much of the development of the recent "new growth theory", or the endogenous growth literature, much of which is well summarized in Barro and Sala-i-Martin (1995).

Our treatment may therefore be thought of as an attempt to quantify a combination of spatial and industrial agglomeration effects. As discussed in Paul (2001), these dimensions are fundamentally connected. However, distinguishing them in terms of own- and supplying- or demanding-industry, and own- and neighboring-state production, facilitates representing and analyzing not only the relative magnitudes of the associated spillovers, but also the extent to which positive agglomeration externalities might be counteracted by contradictory forces. For example we can identify the advantages of locating near primary agricultural markets, and yet the disadvantages of being in a highly rural state, away from dense demand centers.

Evaluating these impacts requires measuring both the cost-effects or shadow values of the external factors, and the fixed effects associated with state characteristics not captured in other aspects of the model. We will elaborate on these measures, after developing their underlying estimation model, in the next section.

**Model Implementation and Measures of Agglomeration Effects**

For empirical implementation of our model a functional form must be specified, appropriate data identified, estimating equations constructed, and measures of cost determinants computed. We assume the functional form can be approximated by a fully flexible generalized Leontief (GL) function, of the form:

1) $TC(Y_O,D_S,p_N,p_P,p_M,p_K,t,Y_N,A_O,A_N,G_O,G_N) = \Sigma_q\Sigma_S\, \delta_{qS}\, p_q\, D_S + \Sigma_q\Sigma_b\, \alpha_{qb}\, p_q^{\,.5}\, p_b^{\,.5} + \Sigma_q\, \delta_{qYO}\, p_qY_O + \Sigma_q\Sigma_n\, \delta_{qn}\, p_q\, r_n + \Sigma_q p_q(\delta_{YOYO}\, Y_O^2 + \Sigma_n\, \delta_{nY}\, r_nY + \Sigma_n\Sigma_m\, \delta_{nm}\, r_nr_m)$ ,

Where q,b denote the variables inputs in the **X** vector (N, P, M, K), and m,n denote the external shift factors in the **E** vector ($Y_N$,$A_O$,$A_N$,$G_O$,$G_N$) as well as the trend term t.[7] This function by definition represents the costs of production associated with optimal input demand for N, P, M, and K, given **E**, t. Thus, Shephard's lemma may be used to formalize the implied input demand equations as:

$$2)\quad X_q = \partial TC/\partial p_q = \Sigma_S\, \delta_{qS}\, D_S + \Sigma_b\, \alpha_{qb}\, p_b^{.5}/p_q^{.5} + \delta_{qYO}\, Y_O + \Sigma_n\, \delta_{qn}\, r_n + \delta_{YOYO}\, Y_O^2 + \Sigma_n\, \delta_{nYO}\, r_n Y_O + \Sigma_n \Sigma_m\, \delta_{nm}\, r_n r_m\ .$$

The system of equations for the four variable input equations represented by (2), plus the cost function (1), comprise the system of estimating equations, which was estimated by seemingly unrelated systems estimation methods.[8]

Since the model directly represents cost-minimizing input demand behavior, the patterns of spillover effects on both costs and input use from the proximity of own-industry, supply-side, and demand-side activity may be estimated. The existence and form of these agglomeration or thick markets effects are measured via cost elasticities, based on cost-side shadow values. That is, the external cost-effects of the thick-market variables in **E**, and the unspecified state-level impacts represented by the fixed effects $D_S$, may be expressed as (proportional) shadow values. These measures can be used to summarize a range of individual and combined external, and residual spatial, cost effects.

The cost-effect on an own-state food processing industry from higher levels of food processing production in neighboring states is reflected by the derivative (shadow

[7] 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 associated agglomeration economies.

value) $\partial TC/\partial Y_N$, or its proportional impact by the associated shadow value elasticity $\varepsilon_{TC,YN} = \partial \ln TC/\partial \ln Y_N$.[9] This is similar to the more familiar representation of scale economies within the own state by the cost-output elasticity $\varepsilon_{TC,YO} = \partial TC/\partial Y_O \cdot Y_O/TC = MC_{YO}/AC_{YO} = \partial \ln TC/\partial \ln Y_O$.[10] The $\varepsilon_{TC,YN}$ and $\varepsilon_{TC,YO}$ elasticities therefore represent external and internal cost economies associated with own-industry production. If higher levels of $Y_N$ yield cost-savings for firms in the own-state, the $\varepsilon_{TC,YN}$ measure will be negative, and indicate the proportion by which both average and total costs fall (since $Y_O$ is held constant by construction): $\varepsilon_{AC,YN}=\varepsilon_{TC,YN}$. By contrast, $\varepsilon_{TC,YO}$ represents the proportional change in total input costs when own-output expands, and therefore indicates scale economies if it falls short of 1. The implied average cost change may therefore be imputed as $\varepsilon_{AC,YO}=\varepsilon_{TC,YO}-1$.

Thus, the total reduction in average costs associated with 1% higher levels (across time or space) of both $Y_N$ and $Y_O$, which implies both a shift in and movement along the cost curve due to external localization and internal scale economies, may be computed as the sum of $\varepsilon_{AC,YN}$ and $\varepsilon_{AC,YO}$. This is similar to the measurement of scale economies for a multiple-output production process (as developed by Baumol, Panzar and Willig, 1982) as the sum of the corresponding cost elasticities with respect to the various outputs. Such a multi-output (internal) scale economy measure for R outputs, $Y_r$, $\varepsilon_{TCY}$=

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[8] Since such a complex model is typically quite sensitive to alternative specifications of instruments (see Cohen and Paul, 2001), SUR estimation methods were retained for the final model

[9] Since this represents a shift in the cost function, and thus the change in the cost/output ratio $TC/Y_O$, it is dual to the more commonly discussed notion of a production function effect, which may be thought of as a change in $Y/\mathbf{X}$ (where TC is the cost of X at given input prices).

[10] These types of elasticities implicitly capture the range of input use changes resulting from the thick market effects, through their overall cost impact. The input-specific impacts may also be evaluated, through second order derivatives from the input demand functions. That is, since $X_q = \partial TC/\partial p_q$, the impact of a change in, say, $Y_N$, on $X_q$ demand, is reflected in the second-order cost elasticity $\partial^2 TC/\partial p_q \partial Y_N = \partial X_q/\partial Y_N$, which can be rewritten in elasticity form as $\partial \ln X_q/\partial \ln Y_N = \varepsilon_{Xq,YN}$. Although these elasticities are

$(\Sigma_r \partial TC/\partial Y_r \cdot Y_r)/TC = \Sigma_r MC_r \cdot Y_r/TC = \Sigma_r \varepsilon_{TCYr}$, indicates the combined (total) cost impact if all outputs were 1 percent larger, rather than if only one output level increased. It is straightforward to make an analogous argument for adding the total (average) internal and external cost economies represented by $\varepsilon_{TC,YO}$ and $\varepsilon_{TC,YN}$ ($\varepsilon_{AC,YO}$ and $\varepsilon_{AC,YN}$).

In turn, one may append to this own-industry cost economy measure the external effects from other **E** factors and $D_S$. That is, the contribution to average costs – or cost economies – in any particular location from a combination of internal and external cost effects, may be imputed as a sum of the measured cost elasticities evaluated at existing levels of **Y** ($Y_O$,$Y_N$), **A** ($A_O$,$A_N$), and G ($G_O$).

To examine the impacts of supply- and demand-side spillover or agglomeration factors, for example, we may compute the (total and average) shadow value elasticities $\varepsilon_{TC,AO} = \partial \ln TC/\partial \ln A_O = \varepsilon_{AC,AO}$, and $\varepsilon_{TC,AN} = \partial \ln TC/\partial \ln A_N = \varepsilon_{AC,AN}$, representing supply-side agglomeration economies, and $\varepsilon_{TC,GO} = \partial \ln TC/\partial \ln G_O = \varepsilon_{AC,GO}$, capturing demand-side agglomeration or urbanization economies. These elasticities, which individually provide estimates of the separate cost economies derived from the agglomeration factors, can also be combined to impute their balance in terms of overall cost effects from spillovers in the industry dimension.

Finally, the state-level fixed effect may be computed as $\partial TC/\partial D_S$, or the proportional cost-saving from being in state S as $\varepsilon_{TC,DS} = \partial \ln TC/\partial D_S$. This measure, representing the unexplained relative cost differential for the state S industry, may in turn be added to the other spillover cost effects to indicate the total cost economies or

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not considered in the empirical results section below since a full analysis of substitution patterns is beyond the scope of this paper, they are summarized on average in Cohen and Paul (2001b).

diseconomies gained from locating in a particular state or region, from a combination of internal, external, and residual, cost effects.

More formally, to evaluate the combined (average) cost impacts of the full range of these cost economies, one may construct the combined measure $\varepsilon_{AC,IEF} = \varepsilon_{AC,I} + \varepsilon_{AC,E} + \varepsilon_{AC,F}$, where $\varepsilon_{AC,I} = \varepsilon_{AC,YO} = \partial \ln AC_O/\partial \ln Y_O = \varepsilon_{TC,YO} - 1$ captures internal (average) cost economies, $\varepsilon_{AC,E} = \varepsilon_{AC,YN} + \varepsilon_{AC,AO} + \varepsilon_{AC,AN} + \varepsilon_{AC,GO} = \varepsilon_{TC,YN} + \varepsilon_{TC,AO} + \varepsilon_{TC,AN} + \varepsilon_{TC,GO}$ represents a combination of external cost economies from own, supplying, and demanding-sector spillover or agglomeration factors, and $\varepsilon_{AC,F} = \varepsilon_{AC,DS} = \varepsilon_{TC,DS}$ reflects residual fixed effects.

Note that both positive (thick market) and negative (thin market) externalities may be evident, and reflected by negative and positive (average) cost elasticities, respectively. If there are such conflicting forces, a balance across the associated localization and urbanization externalities is implied, that pulls firms in different directions. That is, there are counteracting implicit cost and benefits associated with locational choices. The combined measures provide information about the dominating forces in this balance, and so, along with the individual measures, facilitate our exploration of spillover cost effects, and their impact on localization decisions.[11]

One way to summarize our evidence of cost-effects or economies – and associated locational motivations – from spatial and industrial spillovers is simply to peruse, and compare across time and space, the patterns of individual and combined costs and benefits captured by the shadow value elasticities. These measures will be dependent on the existing concentration patterns of food processing firms, since the shadow values are

[11] We could potentially also consider state-level information, but tabling the results then quickly becomes beyond the scope of one paper. Regional and state-level patterns are, however, very consistent.

implicit valuations given the existing distribution of firms. However, to focus on the location implications, we wish to directly evaluate the concentration and location of food processing industries, their supplying and demanding sectors, and the implied (marginal) motivations for location decisions or changes by food processing firms. In particular, it may be useful to represent existing concentration patterns, and compare them to spatial patterns of the average (or total) and corresponding marginal cost savings associated with internal and external productive factors.

More specifically, although average cost elasticities indicate unit cost savings obtained by the existing firms/industry in a particular state, examination of the spillover motivations for making location decisions – which are based on marginal net benefits – requires evaluation of the marginal cost effects from the spillover factors. Measures of these cost-saving benefits may be obtained through second-order relationships associated with the marginal cost (MC) of own-industry and -state (internal) production, $MC_O=\partial TC/\partial Y_O$. For example, the contribution of higher $Y_N$ levels to $MC_O$, or the marginal cost impact of proximity to own-industry enterprises, can be computed as $\varepsilon_{MC,YN} = \partial \ln MC_O/\partial \ln Y_N = \partial^2 TC/\partial Y_O \partial Y_N \cdot (Y_N/MC)$. Similarly, $\varepsilon_{MC,AO} = \partial \ln MC_O/\partial \ln A_O$, $\varepsilon_{MC,AN} = \partial \ln MC_O/\partial \ln A_N$, and $\varepsilon_{MC,GO} = \partial \ln MC_O/\partial \ln G_O$.[12] A combination of these state-level spillover effects' contributions to marginal costs may therefore be expressed in terms of a sum of the individual effects, similarly to the combination of average cost elasticities.[13]

[12] Note that there is no marginal cost elasticity associated with the $\mathbf{D}_S$ since they are fixed effects, and therefore do not have interaction terms with cost function arguments other than the input prices.
[13] Since internal scale economies may be measured as a marginal-to-average cost ratio, these measures could also be used directly to impute the effect of external factors on measured internal cost economies.

Further insights about concentration and location may thus be obtained by investigating where $Y_O$, $A_O$, and $G_O$ are concentrated, and comparing these patterns to the location motivations implied by the marginal cost elasticities for the internal scale and external spillover factors. To pursue this, we can summarize our data on own- and associated-industry concentration along the lines of Krugman (1991b), who constructed a "locational Gini coefficient" as a measure of industrial concentration by comparing the concentration of a specific manufacturing industry to that for overall manufacturing. A similar mechanism may be used to evaluate to what extent concentration patterns are consistent with observed internal and external cost savings or economies.

Since our focus is on the food processing industry, an exercise similar to that underlying Krugman's locational Gini curve might be carried out to compare the concentration of $Y_O$ with that of overall production, $G_O$. We may also, however, compare $Y_O$ with $A_O$, and $G_O$ with $A_O$, to consider a broader range of concentration patterns for the overall food system.

Pursuing this involves computing (a) a region or state's share of GNP (the total GSP of states in the region as compared to the sum of all state's GSP), and (b) the corresponding share of production in the food processing industry (total $Y_O$ in the region compared to national $Y_O$). The ratios of the regions' shares of $Y_O$ to their share of GNP ($S_{YO}=Y_O/\Sigma_S Y_O$ and $S_{GO}=G_O/\Sigma_S G_O=G_O/GNP$) are then computed, the regions ranked in descending order according to this ratio, and the shares cumulated from the top to bottom of the ranking. The regions' relative $Y_O$-$G_O$ cumulative shares are then graphed in terms of a Gini-type curve. Similar exercises may be carried out to compare the balance of agricultural ($A_O$) to overall production ($G_O$) density, or of $Y_O$ to $A_O$ density.

Further discussion of such measurement tools will be deferred until we present the resulting graphs in the next section, which facilitates their interpretation. But it is worth noting here that such a $Y_O$-$G_O$ comparison, for example, uses $G_O$ as a base; it represents how concentrated $Y_O$ production is *relative* to $G_O$. The measures and diagram indicate whether the states with, say, 10% of $G_O$, have more than 10% of food processing. But since they are ranked in terms of the $S_{YO}/S_{GO}$ ratio – firms with the highest $S_{YO}/S_{GO}$ ratio appear first on the graph – the measure is always relative to the denominator (here $G_O$), rather than absolute.

Finally, we can use a similar mechanism (again discussed more in the next section when the results are presented since perusal of the resulting graphs helps motivate their use), to compare the convergence, or "tracking" of $Y_O$ location relative to the average and marginal spillover cost effects. For example, one might think that external economy motivations for location choices imply that the state with the greatest marginal cost benefits from external effects should attract the greatest observed $Y_O$ production. To evaluate these patterns, we will use a Gini-type comparison of the state-share of (average or marginal) cost benefits from internal, external, and fixed effects to its share of $Y_O$. Although the computation of the $Y_O$ share is standard, the notion of the cost economy share requires some further elaboration.

For example, consider the contribution to food processing cost economies or savings from the proximity of agricultural (supply) production in neighboring states, $\varepsilon_{AC,YN} = \varepsilon_{TC,YN} = \partial \ln TC/\partial \ln Y_N = \partial TC/\partial Y_N \cdot Y_N/TC$. In some sense this represents the "share" of $Y_N$-related cost effects in total costs; it indicates the cost-contribution of $Y_N$, in terms of levels or dollars – $\partial TC/\partial Y_N \cdot Y_N$ – as a proportion of TC. Total U.S. cost savings from the proximity of $Y_N$ may therefore be computed as the sum of the numerators of these measures across states, $\Sigma_S\ \partial TC/\partial Y_N \cdot Y_N$. The share of overall cost savings for a particular state is thus simply $S_{TC,N} = (\partial TC/\partial Y_N \cdot Y_N)/\ (\Sigma_S \partial TC/\partial Y_N \cdot Y_N)$. This share may be compared with $S_{YO}$ for that state to assess whether states with high $Y_O$ levels exhibit correspondingly high cost economies derived from the external factor $Y_N$.

A summary measure reflecting a combination of internal, external, and residual cost economies may similarly be computed based on $\varepsilon_{AC,IEF}$, say, rather than $\varepsilon_{AC,YN}$, to represent the driving forces for location decisions from overall cost economies. And such comparisons can also be carried out based on the marginal cost elasticities, which drive choices and thus might be expected to more closely reflect observed behavior.

**Empirical Results**

Estimation of the system of cost and input demand equations represented by (1) and (2), for the food processing sectors of the 48 contiguous states,[14] was carried out by seemingly unrelated regressions procedures using PC-TSP. This resulted in the coefficient estimates presented in Appendix Table A1 (with t statistics in italics, and where coefficients on the dummy variables are omitted to keep the table manageable, although they were primarily statistically significant). Various adaptations to the model were tried in preliminary empirical investigation to identify patterns in the data, and to determine the robustness of the results. The final model is therefore representative of strong patterns emerging from a broad exploration of the data.

Allowing for heteroskedasticity by computing standard errors using robust-White methods made no substantive difference to the results. Incorporating an AR(1)

[14] Further information on the data construction is presented in the Data Appendix.

autoregressive process also had virtually no impact on the measured indicators, even though all $\rho$s (except for the K equation) were statistically significant. This result, combined with evidence that K could justifiably be considered variable for these data,[15] indicates that little information is gained from the temporal dimension for this application. The AR(1) adaptation was therefore omitted from the final specification.

By contrast, the spatial dimension appears to be a key component of cost performance, not only in terms of the structural model (significant shadow value elasticities for spatial linkages, as elaborated below), but also in terms of the stochastic specification. That is, using spatial econometrics techniques to accommodate spatial autocorrelation was clearly statistically supported.

Such methods, as developed by Kelejian and Prucha (1999) and Bell and Bockstael (2000), recognize spatial linkages in the stochastic structure via lags for geographical location (say, state) at any one point in time. If there is only one adjoining state who's "activity" levels affect that of the state under consideration, this adaptation is directly analogous to an AR(1) adjustment: $TC_{i,t} = TC(\cdot)_{i,t} + u_{i,t}$, where $u_{i,t} = \rho u_{j,t} + \varepsilon_{i,t}$, $u_{j,t}$ is the (unadjusted) error term for state j at time t, and $\varepsilon_{i,t}$ is a white-noise error. If 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 $TC = TC(\cdot) + \rho Wu_t + \varepsilon_t$, 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 $TC(\cdot)$ estimation for other states (assuming $w_{i,i} = 0$).

[15] Models representing K as a quasi-fixed input for these data suggested that its shadow value was insignificantly different from its measured market price, so specifying it as a variable input whose demand is appropriately represented by Shephard's lemma seemed justified. This is likely due to the greater cross-section than temporal dimension in the data, with 48 states but only 11 years.

For our application we defined the inter-related states as those with a common boundary, and $w_{i,j}$ to give all neighboring states equal weight, and all other states zero weight. Such a SAR (spatial autoregressive) adaptation was carried out for each (cost and input demand) equation in the system, with different $\rho$ coefficients for each equation. These estimates were primarily statistically significant, as can be seen in Table A1, so this adaptation was retained although the SAR adaptation had limited impact on the elasticity measures' magnitudes.

The t-statistics for the remaining coefficients presented in Table A1 also indicate much statistical significance, except for the cross- or interaction-terms for the external effects, which are largely insignificant. Omitting these terms, however, did not affect the results substantively, and indicated some joint significance, so the model was left fully flexible for completeness. The $R^2$s (all greater than 0.99) also indicate a very close fit for the equations as a system.

Total (average), and marginal shadow value elasticities, representing the extent of agglomeration economies, are reported on average across the full sample, and for the two decades covered by our data (the 80s and 90s), in Table 1. The reported mean estimate (Mean Est) values are constructed by computing the indicators for each observation and then averaging across the sample. The standard deviation (Std Dev) is based on this distribution of estimated elasticities. The t-statistics (t stat) for these measures were computed by evaluating the elasticities (which comprise a combination of data, coefficient estimates, and their standard errors) at the mean value of the data, and then generating the statistics from the resulting coefficient estimates and standard errors.

First note that all the estimated total (average) cost elasticities are very statistically significant.[16] They are also primarily negative, indicating cost-savings from higher levels of the associated scale or agglomeration factors. This is not true, however, for either $\varepsilon_{TC,YN}$ or $\varepsilon_{TC,t}$. The positive – and very robust – measures for $\varepsilon_{TC,YN}$ initially prompted the inclusion of $A_O$ as well as $A_N$ in our model. As we explored why estimated $\varepsilon_{TC,YN}$ might be positive, it became evident that although being in a state with a high level of agricultural production seems to enhance costs of production, being in close proximity to a heavily agricultural/rural state appears cost-saving. This suggests some form of thin market effect, possibly due to limited labor/capital markets in highly rural states, or lower levels of infrastructure support (such as telecommunications). It thus implies "ruralization diseconomies", similar to the "urbanization economies" often alluded to or found in the urban economics literature.

The time-trend evidence from $\varepsilon_{TC,t}$ initially appears to indicate technological regression, if it is interpreted, as is typical, as a technical change indicator. Note, however, that even though measured parametrically, this is in essence a residual measure representing any time trend in costs not explained by other arguments of the function. It thus is likely that this measure represents demand impacts not otherwise represented, that are determinants of observed production trends in this industry. In particular, this upward cost trend could reflect the rapidly increasing demand for more processed and diverse, and higher quality, food products, particularly since the time dimension seems otherwise a limited driving force for this short time frame data panel.

[16] t statistics are not reported for the $\varepsilon_{AC,YO}$ elasticity ,since it is computed simply as $\varepsilon_{TC,YO}$-1, or for the $\varepsilon_{TC,DS}$ elasticity since the significance differs across state and washes out in the average data, but it is almost invariably significant across states.

All other external measures – associated with localization economies (proximity to own-industry production), $\varepsilon_{TC,YO}$ or $\varepsilon_{AC,YO}$, supply-side agglomeration economies from neighboring states, $\varepsilon_{TC,AN}$, and urbanization economies (proximity to high demand or buying power), $\varepsilon_{TC,GO}$ – clearly indicate significant cost-economies on average across the U.S., as found by Cohen and Paul (2001b). In sum, the costs associated with high $A_O$ in the own-state are on average outweighed by cost-savings associated with $A_N$, and further cost benefits from other external effects substantively dominate any external costs ($\varepsilon_{TCYN}+\varepsilon_{TC,AO}+\varepsilon_{TC,AN}+\varepsilon_{TC,GO} \approx -0.9$, an overall cost decline).

The marginal cost elasticities, by contrast, suggest that higher levels of all externalities except $G_O$ imply lower marginal costs, and thus likely motivate location decisions; the supply and demand own-state effects are reversed in terms of the marginals. Since greater potential demand in the state implies higher marginal costs on average, and more agricultural intensity, or "rurality", implies lower marginal costs, this may suggest that these factors act more as fixed than marginal effects.

It also seems that both own- and supplying-industry production in neighboring states ($Y_N$, $A_N$) decrease marginal as well as average costs, but reduce marginal costs by a smaller proportion than on average. And the change in marginal cost over time appears positive, but is not significant either statistically or in terms of magnitude. However, although only the $Y_O$ and $G_O$ elasticities are statistically significant on average for the full (country) sample, the significance of the elasticities varies somewhat across the individual regions, and the MC impacts overall seem substantive.

Finally, when compared for the 1980s and 1990s few of these measures appear to have varied very much (at least statistically significantly). This might be expected due to the dominance in these data of the spatial as compared to temporal variations and patterns. However, it does seem that more internal- or own-industry and -state ($Y_O$) scale economies, and less demand ($G_O$) economies are evident later in the sample period.

More variation is apparent from the elasticities summarized across regions, as reported in Table 2. For example, the food processing industries of the New England region, which have the smallest food manufacturing share of all regions, also exhibit the second smallest internal scale economies, and the largest own-industry localization economies. This region also has the greatest diseconomies from own-state agricultural production, and economies from neighboring state agricultural (supply) and overall (demand) production.

These patterns seem potentially due to the small size of the states in this region. However, the agglomeration factors were normalized by the size of the state to recognize the importance of density rather than absolute levels for spillover effects, and the $Y_O$ per land mass in this region is lower than for many states – particularly those in the South Atlantic region, such as DE. The results may more likely be related to the proximity to the second largest, and clearly most dense ($Y_O$ per land mass) Mid-Atlantic region.

A similar mechanism seems to be at work in the Mountain region, which surrounds the highest – Pacific (dominated by CA) – food-processing share region. This small (in terms of both overall-production- and food-processing-intensity) region exhibits large cost impacts from neighboring states, with the largest (in absolute value) $\varepsilon_{TC,YN}$ and third largest $\varepsilon_{TC,AN}$ elasticities. It also has the only negative fixed-cost-effect (indicating the lowest unit costs net of all explanatory variables for food processing industries in the

U.S.), but the highest increase in costs of production over time, as well as the second highest $TC/Y_O$ ratio.

The only states that exceed this overall average cost ratio on average are those in the traditionally agricultural W.N. Central region, although they also exhibit the highest internal scale economies. And they display some of the lowest localization or own-industry agglomeration economies ($Y_N$), and the smallest urbanization ($G_O$) economies.

The Pacific region exhibits the lowest localization economies and external supply agglomeration economies (from $A_N$), and nearly the smallest diseconomies from own-state agricultural production ($A_O$). Average costs are also quite low. This may imply that external economies from own- and related-industry agglomeration effects are internalized in this large and heavily agricultural as well as food manufacturing-intensive region.

The E.N. Central region – the second largest food processing region (on average across states), and comprising much of the traditional dairy and related industries – also has a very low average production cost. It does not, however seem to gain a significant amount from agglomeration effects, although it has one of the lowest diseconomies from own-state agricultural production. These states, like those in the Pacific region, also exhibit some of the smallest economies from neighboring states production ($Y_N$ and $A_N$).

The Mid-Atlantic region, which has the third highest state-share of food processing activity (dominated by NY and PA) displays a similarly low level of diseconomies from own-state agricultural production, and the lowest overall average cost ($TC/Y_O$). But it otherwise has few obvious locational driving forces on average, with the least own-industry cost (or scale) economies of any region, and a relatively large residual cost diseconomy measure ($\varepsilon_{TC,DS}$). Note also that $\varepsilon_{MC,YO}$, indicating the reduction in marginal costs when own-industry scale expands, is second only to the Pacific region in magnitude. But this is counteracted, as in the Pacific region, by marginal (MC) diseconomies associated with higher urbanization levels ($G_O$), perhaps indicating congestion or greater demand for high-quality or processed products associated with the high $G_O$ levels in these regions.

To move to the implications of these measures for location and concentration, we can first consider the concentration patterns for $Y_O$ as compared to $G_O$ and $A_O$. The Gini curves for these experiments, for the last year of our sample, 1996, are presented in Figure 1 (1a,b,c), and the underlying data, in terms of shares and rankings, are reported in Table 3. Although the curves are based on state level data, and information in the Table is summarized by region, the states grouped quite closely to the regional breakdowns so the regional rankings are strongly representative of the overall state ranking.

Note from the $Y_O$-$G_O$ diagram, Figure 1a, that the food processing industries are substantively more concentrated than overall production, represented by GSP. For example, ranking from the highest to lowest $S_{YO}/S_{GO}$ ratio, we find that 40 percent of $Y_O$ output is found in regions with only 20 percent of total production (aggregate GSP, or GNP). The highest $S_{YO}/S_{GO}$ levels by far are found in the W.N. Central region, with E.N. Central and E.S. Central at about half this level. Pacific, with the highest $Y_O$ levels, falls in the middle due to its correspondingly high $G_O$ level, and the Mid-Atlantic region is second-to-last in terms of this ratio, for the same reason.

Figure 1b shows, however, that agricultural production is even more concentrated relative to $G_O$; regions with only 20 percent of total $G_O$ have over 50 percent of total $A_O$. And about 90 percent of agricultural output is in states with only 60 percent of the GNP.

In particular, we find a 5-to-1 ratio of $A_O$ to $G_O$ for the W.N. Central region, which drops to 1.5, 1.4, and 1.3 for the Mountain, E.S. Central, and W.S. Central regions.

This conclusion is supported by the comparison of $Y_O$ to $A_O$ production in Figure 1c. The curve by definition falls above the 45-degree line (unless the distributions are exactly equal, in which case it will coincide with the line), since concentration of the industry on the vertical axis is expressed relative to that on the horizontal axis, with the ratios in descending order. But this diagram, in combination with Table 3, documents that approximately the same order of regions is retained for this comparison. So the highest levels of agricultural activity are clearly in states with correspondingly high food processing intensity, even though agricultural production is more concentrated than $Y_O$.

In particular, from Figure 1c it is apparent that states with 10 percent of $Y_O$ output produce about 25 percent of total $A_O$. The deviation of the Gini curve from the 45 line is, in fact, very similar to that for the $Y_O$ to $G_O$ comparison, but is much smaller than that for $A_O$ to $G_O$. Table 3 also shows that the Mountain states rise to the first in this ranking; they exhibit even higher $S_{AO}/S_{YO}$ than $S_{AO}/S_{GO}$ ratios, although this is largely due to low $Y_O$ and $G_O$ levels in these states rather than to high $A_O$ levels. The Central states clearly dominate in terms of not only the $A_O/G_O$ but also the $A_O/Y_O$ ratios, with Pacific falling next in line due to the size of its $S_{YO}$, even though it also has the highest $S_{AO}$.

Finally, consider the implications from Figures 2a,b,c and d, and Table 4. The $S_{AC,IEF}$ and $S_{MC,IEF}$ measures (abbreviated to $S_A$ and $S_M$ in some cases to fit on the tables), represent the regional share of $\varepsilon_{AC,IEF} \cdot TC$ and $\varepsilon_{MC,IEF} \cdot TC$, or the aggregate average and marginal cost savings from a combination of all internal, external, and residual cost economies, respectively. These values, expressed in terms of dollar levels rather than proportions through the multiplication of the elasticities by TC, may be compared to the corresponding shares of $Y_O$ to see to what extent food processing industry concentration is consistent with, or "tracks", measured cost economies. That is, since we are analyzing food manufacturing location decisions, and we would expect that states with high shares of marginal cost savings from overall cost economies would also have relatively high shares of food manufacturing output, comparing these share ratios illustrates the extent to which these patterns are consistent.

The measures presented in Table 4 indicate discrepancies between the distribution of the average cost measures and the regions with the highest food processing activity or density. Consider, for example, the $\varepsilon_{AC,IEF\text{-}YO}$ comparison for 1986. It is evident that the W.S. Central (dominated by TX, a heavily food-processing intensive state), Pacific (dominated by CA), and Mid Atlantic (NY, PA) states have very low average cost-savings ($S_A$) shares from expansion relative to their $Y_O$ shares. This implies that the total contribution of the internal, external, and residual economies to these states are relatively lower – in proportional or share terms – than are observed production levels. Or that the concentration of food processing activity in these states is greater than might be "explained" by lower average costs in these regions due to these cost economy factors, so average cost savings from the cost economies are more spread out geographically, or less concentrated, relative to production.

This could at least partly be driven by state industry size – that is, the high absolute amounts of $Y_O$ produced in these regions. For example, these average cost ratios more closely track a land-mass normalized $Y_O$ measure, which places some of the S. Atlantic states (particularly DE) at the top of a ranking of states in terms of food processing density rather than just levels. Note, for example, that the highest $S_{AC,IEF}$ level appears in the E.N. Central region; it is the relatively high corresponding $S_{YO}$ that pushes it down on the rankings.

There is also a time dimension to these patterns, although the concentration evidence from the $Y_O$, $G_O$, and $A_O$ Ginis is consistent over the sample period. E.g., although the Pacific region remains the second lowest in terms of the $S_A/S_{YO}$ ratio, its $S_{AC,IEF}$ share rises from 11.7 to 17.5 percent. It maintains its place in the $S_A/S_{YO}$ rankings due to the corresponding rise in $S_{YO}$ from 20.6 to 21.5 percent. Overall, the states that have experienced the greatest increases in $S_{AC,IEF}$ on balance also have the highest and increasing share of $Y_O$, $S_{YO}$, although they still have low $S_A/S_{YO}$ ratios in absolute terms.

These patterns are evident from the 1986 and 1996 Gini curves for the $S_A/S_{YO}$ comparison, in Figures 2a and 2b. The interpretation of such a diagram can loosely be based on concentration, like the Krugman locational Ginis on which it is modeled. However, it may also be thought of simply as a useful mechanism to summarize the industry- and cost economy- location information contained in Table 4.

In particular, the diagram for 1986 shows a heavy concentration of states at the bottom of the curve with very little $Y_O$ share, although a relatively large share of $S_{AC,IEF}$. In fact, states with only 35 percent of $Y_O$ production have twice that – 70 percent – of the unit-cost savings from combined cost economies. By 1996, $Y_O$ production seems to more closely follow or track unit cost savings, since the curve is closer to the 45-degree line, although it is even more concentrated at the very low end where states have very small $Y_O$ shares relative to measured average cost economies.

The marginal cost economy measures, however, tell a different story. This suggests that internal scale economies, which involve a MC-AC comparison, are an important piece of the puzzle. It may also imply that states exhibiting particularly high $Y_O$ levels have already internalized – and perhaps even to some extent "used up" – these economies, through expansion of the industry.[17]

From Table 4 it is clear that the states with the highest shares of $Y_O$ production, in particular the Pacific (CA) and E.N. Central regions, exhibit by far the highest shares of marginal cost savings from internal, external, and residual cost economies. In fact, the Pacific region alone, with approximately 20 percent of $Y_O$, has about 40 percent of the measured marginal cost savings. These patterns changed less over time than those for average costs, although the $\varepsilon_{MC,IEF}$ (*and* $S_{YO}$) shares for the Mid Atlantic fell significantly from 1986 to 1996 (with the W.S. Central states taking up much of the slack).

These patterns are reflected in Gini curves (Figures 2c,d) which look much different than those for average cost economies, with most of the states congregated at the top of the curve, and the large states, led by CA, spread out over the low range (with high $S_{YO}$ , $S_{MC,IEF}$ *and* $S_M/S_{YO}$ levels). That is, high values of the share of marginal cost savings from cost economies are accompanied by high values of the own state output share. There also seems to be a tendency for the curve to move toward the 45-degree line over time, implying more consistency between marginal cost savings and $Y_O$ output levels. But overall the heavy concentration of $S_{MC,IEF}$ in a few regions seems not only to be consistent with high concentration levels of $Y_O$, but even to imply more concentration in these areas is likely to be supported on the margin due to cost economies.

[17] A similar divergence was found when we compared $AC=TC/Y_O$ and $MC=\partial MC/\partial Y_O$ measures to the $Y_O$ distribution. This supports the idea that the marginal measures have the most impact on location decisions.

**Concluding Remarks**

In sum, our analysis of internal, external, and residual or fixed effect cost economies across U.S. states for the food manufacturing industries, and the resulting implications for location and concentration, suggest that such cost economies not only are substantive, but provide important motivations on the margin for location decisions.

The evidence from total and average cost economies, which are usually focused on as shadow values of external effects, vary from marginal cost impacts. We find significant (total and average) cost economies associated with own-production, own-industry thick market effects, neighboring state supply-sector agglomeration effects, and own-state demand drivers, but high costs of locating in a heavily agricultural state. However, marginal cost economies from spillovers differ from their average cost counterparts. High production density (urbanization) appears to drive higher marginal costs, possibly due to congestion, and high agricultural density implies lower marginal costs. And these measures vary significantly by region.

When these spatial patterns are compared to observed state-level concentration levels for the food processing and agricultural sectors, we find that food processing sector concentration is lower than that for agriculture, and greater than overall production, but that regional concentration patterns are quite consistent. Location decisions also seem well "explained" by a combination of internal, external, and residual marginal cost economies, in particular for the Pacific (CA), Central, and Mid Atlantic (NY,PA) states. They are less consistent with average cost saving patterns, which might be expected since marginal benefits drive decision-making, although these indicators also seem to be converging to more closely reflect location concentrations.

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**Data Appendix**

Annual state-level data for 1986 through 1996 were used in this study.

Labor quantities: The number of workers engaged in production (PL) at operating food 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 in the food and kindred products industry and gross earnings of all employees on the payroll of operating food and kindred products establishments. Wage bill for NL is obtained by subtracting the wages paid to PL from the gross earnings of all food and kindred products 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.

Private capital stock: The perpetual inventory method was applied to data on state level new capital expenditures for the food and kindred products industry from the ASM, with the initial capital stock (1986) calculated by multiplying the average of the first three years of data for each state by the inverse of the depreciation rate. Annual depreciation rates for capital equipment are assumed to be 10 percent. The investment deflator, from the Office of Productivity and Technology of the Bureau of Labor Statistics, is their national capital price deflator for all assets for total manufacturing. The price of capital is obtained as $(i_t+d_t) \cdot q_{K,t}[1/(1-taxrate_t)]$, where $d_t$ is the depreciation rate, $i_t$ the Moody's Baa corporate bond rate (obtained from the Economic Report of the President), $q_{K,t}$ the investment deflator, and $taxrate_t$ the corporate tax rate (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 a national materials deflator for agriculture provided by the Economic Research Service, USDA. This deflator is also used as the price of materials.

Output: Value of state-level food manufacturing shipments reported in the ASM were deflated by the ratio of nominal to real GSP for food and kindred products. Nominal and real GSP data for food and kindred products were obtained from the BEA website.

Agricultural industry output: state level data were obtained from the Economic Research Service, USDA.

Total Gross State Product: State-level data were obtained from the BEA website.

State Land Area: Data were obtained online from:

http://ddi.digital.net/~sjoiner/city/CapitalCities.htm

Data were missing from the ASM for several states for various variables in various years. These food manufacturing data points were interpolated as follows:

$F_i = (F_{US} / T_{US})*(T_i)$

Where $F_i$ represents state i's food manufacturing variable,
$T_i$ represents state i's total manufacturing variable,
$T_{US}$ represents U.S. total for the total manufacturing variable,
$F_{US}$ represents U.S. total for the food manufacturing variable.

These states, years, and missing variables were:

FL 1986: all employees, production workers, cost of materials, value of shipments, new capital expenditures.

GA 1986: all employees, production workers, cost of materials, value of shipments, new capital expenditures.

ID 1986: all employees, production workers, cost of materials, value of shipments, new capital expenditures.

MI 1987, 1988, 1989, 1990, 1991: new capital expenditures only.

WY 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1993, 1994: all employees, production workers, cost of materials, value of shipments, new capital expenditures.

WY 1992, 1996: new capital expenditures only.

***Table 1, Total and Marginal Cost Elasticities***
*(average measures, overall and by time period)*

| | **Entire Time Period** | | | **80s** | | **90s** | |
|---|---|---|---|---|---|---|---|
| *Measure* | *Mean Est* | *Std Dev* | *t stat* | *Mean Est* | *Std Dev* | *Mean Est* | *Std Dev* |
| $\varepsilon_{TC,YO}$ | **0.7401** | 0.109 | *36.910* | **0.7873** | 0.093 | **0.7131** | 0.109 |
| $\varepsilon_{AC,YO}$ | **-0.2599** | 0.109 | | **-0.2127** | 0.093 | **-0.2869** | 0.109 |
| $\varepsilon_{TC,YN}$ | **-0.3607** | 0.492 | *-3.091* | **-0.3764** | 0.526 | **-0.3518** | 0.473 |
| $\varepsilon_{TC,AO}$ | **0.3574** | 0.438 | *8.345* | **0.3435** | 0.419 | **0.3654** | 0.450 |
| $\varepsilon_{TC,AN}$ | **-0.7032** | 1.584 | *-5.682* | **-0.7077** | 1.515 | **-0.7007** | 1.624 |
| $\varepsilon_{TC,GO}$ | **-0.1889** | 0.413 | *-4.525* | **-0.1817** | 0.387 | **-0.1929** | 0.427 |
| $\varepsilon_{TC,DS}$ | **0.4821** | 1.810 | | **0.5088** | 1.713 | **0.4669** | 1.865 |
| $\varepsilon_{TC,t}$ | **0.0493** | 0.069 | *10.519* | **0.0525** | 0.073 | **0.0474** | 0.067 |
| | | | | | | | |
| $\varepsilon_{MC,YO}$ | **-0.0164** | 0.017 | *-3.347* | **-0.0154** | 0.016 | **-0.0169** | 0.018 |
| $\varepsilon_{MC,YN}$ | **-0.0169** | 0.008 | *-1.507* | **-0.0159** | 0.008 | **-0.0175** | 0.009 |
| $\varepsilon_{MC,AO}$ | **-0.0091** | 0.008 | *-1.446* | **-0.0081** | 0.006 | **-0.0098** | 0.008 |
| $\varepsilon_{MC,AN}$ | **-0.0180** | 0.026 | *-1.790* | **-0.0162** | | **-0.0191** | 0.028 |
| $\varepsilon_{MC,GO}$ | **0.0302** | 0.043 | *6.941* | **0.0269** | 0.039 | **0.0320** | 0.046 |
| $\varepsilon_{MC,t}$ | **0.0002** | 0.000 | *0.540* | **0.0002** | 0.000 | **0.0002** | 0.000 |
| | | | | | | | |
| TC | **6233.091** | 6154.525 | | **5550.616** | 5414.638 | **6623.076** | 6515.532 |
| $Y_O$ | **9176.721** | 9232.434 | | **9053.672** | 9120.884 | **9247.035** | 9308.380 |
| $TC/Y_O$ | **0.690** | 0.081 | | **0.624** | 0.056 | **0.727** | 0.068 |

***Table 2, Total and Marginal Cost Elasticities, Regions***

| | **_Region 1, Pacific_** (CA,OR,WA) | | **_Region 2 , Mountain_** (AZ,CO,ID,MT,NM,NV, UT, WY) | | **_Region 3, W.N. Central_** (IA,KS,MN,MO,ND) NE,SD) | | **_Region 4, E. N. Central_** (IL,IN,MI,OH,WI) | |
|---|---|---|---|---|---|---|---|---|
| *Measure* | *Mean Est* | *Std Dev* | *Mean Est* | *Std Dev* | *Mean Est* | *Std Dev* | *Mean Est* | *Std Dev* |
| $\varepsilon_{TC,YO}$ | **0.7349** | 0.073 | **0.7215** | 0.080 | **0.6857** | 0.167 | **0.7419** | 0.080 |
| $\varepsilon_{AC,YO}$ | **-0.2651** | 0.073 | **-0.2785** | 0.080 | **-0.3143** | 0.167 | **-0.2581** | 0.080 |
| $\varepsilon_{TC,YN}$ | **-0.1063** | 0.103 | **-0.7110** | 0.756 | **-0.1677** | 0.146 | **-0.1210** | 0.042 |
| $\varepsilon_{TC,AO}$ | **0.1181** | 0.050 | **0.3114** | 0.234 | **0.3400** | 0.302 | **0.1662** | 0.084 |
| $\varepsilon_{TC,AN}$ | **-0.0916** | 0.084 | **-0.6291** | 0.622 | **-0.2421** | 0.264 | **-0.1223** | 0.052 |
| $\varepsilon_{TC,GO}$ | **-0.0250** | 0.021 | **-0.0750** | 0.065 | **-0.0198** | 0.010 | **-0.0549** | 0.028 |
| $\varepsilon_{TC,DS}$ | **0.1589** | 0.082 | **-0.4546** | 0.982 | **0.0387** | 0.279 | **0.2305** | 0.063 |
| $\varepsilon_{TC,t}$ | **0.0128** | 0.008 | **0.1274** | 0.110 | **0.0265** | 0.031 | **0.0082** | 0.003 |
| | | | | | | | | |
| $\varepsilon_{MC,YO}$ | **-0.0374** | 0.037 | **-0.0042** | 0.004 | **-0.0200** | 0.012 | **-0.0335** | 0.013 |
| $\varepsilon_{MC,YN}$ | **-0.0134** | 0.010 | **-0.0121** | 0.008 | **-0.0193** | 0.006 | **-0.0287** | 0.007 |
| $\varepsilon_{MC,AO}$ | **-0.0090** | 0.005 | **-0.0022** | 0.002 | **-0.0136** | 0.008 | **-0.0159** | 0.005 |
| $\varepsilon_{MC,AN}$ | **-0.0066** | 0.004 | **-0.0059** | 0.002 | **-0.0147** | 0.004 | **-0.0205** | 0.005 |
| $\varepsilon_{MC,GO}$ | **0.0191** | 0.015 | **0.0027** | 0.002 | **0.0060** | 0.004 | **0.0302** | 0.011 |
| $\varepsilon_{MC,t}$ | **0.0002** | 9.52707D-06 | **0.0002** | 0.000 | **0.0002** | 9.75992D-06 | **0.0002** | 8.82995D-06 |
| | | | | | | | | |
| TC | **13464.963** | 12684.445 | **1683.722** | 1736.110 | **7888.612** | 4688.448 | **12076.535** | 4727.155 |
| $Y_O$ | **20432.753** | 19579.757 | **2366.889** | 2386.690 | **10869.124** | 6326.128 | **18348.419** | 7006.685 |
| $TC/Y_O$ | **0.678** | 0.075 | **0.710** | 0.082 | **0.729** | 0.092 | **0.659** | 0.068 |

| Measure | Region 5, New Englan(CT,MA,ME,NH,RI,VT | | Region 6, Mid Atlantic (NJ,NY,PA) | | Region 7, E. S. Central (AL,KY,MS,TN) | | Region 8, W. S. Central (AR,LA,OK,TX) | | Region 9, S. Atlantic (DE,FL,GA,MD,NC) SC,VA,WV) | |
|---|---|---|---|---|---|---|---|---|---|---|
| *Measure* | *Mean Est* | *Std Dev* | *Mean Est* | *Std Dev* | *Mean Est* | *Std Dev* | *Mean Est* | *Std Dev* | *Mean Est* | *Std Dev* |
| $\varepsilon_{TC,YO}$ | **0.8192** | 0.115 | **0.8224** | 0.087 | **0.7130** | 0.076 | **0.7195** | 0.073 | **0.7407** | 0.080 |
| $\varepsilon_{AC,YO}$ | **-0.1808** | 0.115 | **-0.1776** | 0.087 | **-0.2870** | 0.076 | **-0.2805** | 0.073 | **-0.2593** | 0.080 |
| $\varepsilon_{TC,YN}$ | **-0.7075** | 0.627 | **-0.2114** | 0.219 | **-0.1652** | 0.052 | **-0.1757** | 0.118 | **-0.4109** | 0.443 |
| $\varepsilon_{TC,AO}$ | **0.7531** | 0.532 | **0.1151** | 0.056 | **0.2411** | 0.104 | **0.2080** | 0.133 | **0.5550** | 0.743 |
| $\varepsilon_{TC,AN}$ | **-2.1019** | 2.853 | **-0.2012** | 0.291 | **-0.1815** | 0.056 | **-0.2272** | 0.169 | **-1.4114** | 2.394 |
| $\varepsilon_{TC,GO}$ | **-0.8214** | 0.825 | **-0.0659** | 0.104 | **-0.0630** | 0.021 | **-0.0533** | 0.043 | **-0.2983** | 0.337 |
| $\varepsilon_{TC,DS}$ | **2.0663** | 3.991 | **0.4889** | 0.545 | **0.1644** | 0.092 | **0.2702** | 0.166 | **1.1594** | 1.786 |
| $\varepsilon_{TC,t}$ | **0.0961** | 0.054 | **0.0070** | 0.003 | **0.0185** | 0.005 | **0.0184** | 0.012 | **0.0420** | 0.048 |
| | | | | | | | | | | |
| $\varepsilon_{MC,YO}$ | **-0.0030** | 0.003 | **-0.0270** | 0.010 | **-0.0123** | 0.004 | **-0.0205** | 0.018 | **-0.0130** | 0.009 |
| $\varepsilon_{MC,YN}$ | **-0.0077** | 0.004 | **-0.0171** | 0.003 | **-0.0191** | 0.004 | **-0.0187** | 0.006 | **-0.0185** | 0.005 |
| $\varepsilon_{MC,AO}$ | **-0.0046** | 0.002 | **-0.0094** | 0.002 | **-0.0082** | 0.002 | **-0.0073** | 0.003 | **-0.0128** | 0.011 |
| $\varepsilon_{MC,AN}$ | **-0.0216** | 0.017 | **-0.0197** | 0.021 | **-0.0138** | 0.003 | **-0.0134** | 0.008 | **-0.0370** | 0.056 |
| $\varepsilon_{MC,GO}$ | **0.0765** | 0.066 | **0.1043** | 0.065 | **0.0127** | 0.005 | **0.0098** | 0.004 | **0.0392** | 0.031 |
| $\varepsilon_{MC,t}$ | **0.0002** | 0.000 | **0.0002** | 0.000 | **0.0002** | 0.000 | **0.0002** | 0.000 | **0.0002** | 0.000 |
| | | | | | | | | | | |
| TC | **1274.144** | 1245.583 | **10436.152** | 3426.879 | **4812.432** | 1609.389 | **7888.283** | 6672.266 | **4995.569** | 3364.689 |
| $Y_O$ | **1885.697** | 1763.598 | **16029.826** | 5139.440 | **6889.446** | 2516.020 | **11451.982** | 9775.019 | **7456.739** | 4971.662 |
| $TC/Y_O$ | **0.673** | 0.086 | **0.656** | 0.064 | **0.707** | 0.083 | **0.689** | 0.066 | **0.676** | 0.069 |

*Table 3: Gini Location Concentration Data, $Y_O$, $G_O$, and $A_O$*

***$Y_O$-$G_O$ comparison***

| 1996 | $S_{YO}$ | $S_{GO}$ | $S_{YO}/S_{GO}$ |
|---|---|---|---|
| **W.N. Central** | 0.114 | 0.042 | 2.682 |
| **E.N. Central** | 0.187 | 0.143 | 1.305 |
| **E.S. Central** | 0.071 | 0.057 | 1.258 |
| **W.S. Central** | 0.127 | 0.115 | 1.103 |
| **Pacific** | 0.215 | 0.235 | 0.915 |
| **Atlantic** | 0.083 | 0.093 | 0.898 |
| **Mountain** | 0.026 | 0.032 | 0.826 |
| **Mid Atlantic** | 0.156 | 0.240 | 0.652 |
| **New England** | 0.019 | 0.042 | 0.455 |

***$A_O$-$G_O$ comparison***

| 1996 | $S_{AO}$ | $S_{GO}$ | $S_{AO}/S_{GO}$ |
|---|---|---|---|
| **W.N. Central** | 0.199 | 0.042 | 4.681 |
| **Mountain** | 0.050 | 0.032 | 1.568 |
| **E.S. Central** | 0.079 | 0.057 | 1.392 |
| **W.S. Central** | 0.148 | 0.115 | 1.282 |
| **E.N. Central** | 0.144 | 0.143 | 1.008 |
| **Pacific** | 0.232 | 0.235 | 0.983 |
| **Atlantic** | 0.074 | 0.093 | 0.796 |
| **Mid Atlantic** | 0.067 | 0.240 | 0.279 |
| **New England** | 0.008 | 0.042 | 0.185 |

***$A_O$-$Y_O$ comparison***

| 1996 | $S_{YO}$ | $S_{AO}$ | $S_{AO}/S_{YO}$ |
|---|---|---|---|
| **Mountain** | 0.026 | 0.050 | 1.899 |
| **W.N. Central** | 0.114 | 0.199 | 1.745 |
| **W.S. Central** | 0.127 | 0.148 | 1.162 |
| **E.S. Central** | 0.071 | 0.079 | 1.107 |
| **Pacific** | 0.215 | 0.232 | 1.075 |
| **Atlantic** | 0.083 | 0.074 | 0.886 |
| **E.N. Central** | 0.187 | 0.144 | 0.772 |
| **Mid Atlantic** | 0.156 | 0.067 | 0.428 |
| **New England** | 0.019 | 0.008 | 0.406 |

***$Y_O$ levels***

| 1996 | $Y_O$ |
|---|---|
| **Pacific** | 21326.77 |
| **E.N. Central** | 18507.10 |
| **Mid Atlantic** | 15472.83 |
| **W.S. Central** | 12611.75 |
| **W.N. Central** | 11280.09 |
| **Atlantic** | 8267.24 |
| **E.S. Central** | 7056.03 |
| **Mountain** | 2602.47 |
| **New England** | 1901.55 |

***$A_O$ levels***

| 1996 | $A_O$ |
|---|---|
| **Pacific** | 9254.18 |
| **W.N. Central** | 7944.21 |
| **W.S. Central** | 5914.35 |
| **E.N. Central** | 5768.62 |
| **E.S. Central** | 3151.07 |
| **Atlantic** | 2955.56 |
| **Mid Atlantic** | 2672.21 |
| **Mountain** | 1994.58 |
| **New England** | 311.23 |

***$G_O$ levels***

| 1996 | $G_O$ |
|---|---|
| **Mid Atlantic** | 416409 |
| **Pacific** | 408961 |
| **E.N. Central** | 248711 |
| **W.S. Central** | 200424 |
| **Atlantic** | 161407 |
| **E.S. Central** | 98362 |
| **W.N. Central** | 73744.6 |
| **New England** | 73265.8 |
| **Mountain** | 55281.9 |

*Table 4, Average and Marginal Cost Economies and $Y_O$ Concentration, Gini data*

**$\varepsilon_{AC,IEF}$-$Y_O$ comparison, 1986**

| 1986 | $S_{YO}$ | $S_{AC,IEF}$ | $S_A/S_{YO}$ |
|---|---|---|---|
| **Mountain** | 0.026 | 0.110 | 4.259 |
| **New England** | 0.021 | 0.072 | 3.402 |
| **S. Atlantic** | 0.074 | 0.131 | 1.764 |
| **E.S. Central** | 0.071 | 0.117 | 1.644 |
| **W.N. Central** | 0.109 | 0.122 | 1.115 |
| **W.S. Central** | 0.114 | 0.103 | 0.905 |
| **E.N. Central** | 0.193 | 0.154 | 0.798 |
| **Pacific** | 0.206 | 0.117 | 0.569 |
| **Mid Atlantic** | 0.186 | 0.074 | 0.398 |

**$\varepsilon_{AC,IEF}$-$Y_O$ comparison, 1996**

| 1996 | $S_{YO}$ | $S_{AC,IEF}$ | $S_A/S_{YO}$ |
|---|---|---|---|
| **Mountain** | 0.026 | 0.078 | 2.967 |
| **New England** | 0.019 | 0.043 | 2.220 |
| **E.S. Central** | 0.071 | 0.104 | 1.453 |
| **S. Atlantic** | 0.083 | 0.120 | 1.437 |
| **W.N. Central** | 0.114 | 0.130 | 1.137 |
| **E.N. Central** | 0.187 | 0.162 | 0.865 |
| **W.S. Central** | 0.127 | 0.110 | 0.860 |
| **Pacific** | 0.215 | 0.175 | 0.813 |
| **Mid Atlantic** | 0.156 | 0.080 | 0.514 |

**$\varepsilon_{AC,IEF}$ levels, 1986**

| 1986 | $\varepsilon_{AC,IEF}$ |
|---|---|
| **E.N. Central** | -1256.69 |
| **S. Atlantic** | -1065.73 |
| **W.N. Central** | -994.59 |
| **E.S. Central** | -956.63 |
| **Pacific** | -955.84 |
| **Mountain** | -900.64 |
| **W.S. Central** | -840.99 |
| **Mid Atlantic** | -602.39 |
| **New England** | -586.01 |

**$\varepsilon_{AC,IEF}$ levels, 1996**

| 1996 | $\varepsilon_{AC,IEF}$ |
|---|---|
| **Pacific** | -3010.28 |
| **E.N. Central** | -2780.76 |
| **W.N. Central** | -2227.95 |
| **S. Atlantic** | -2063.57 |
| **W.S. Central** | -1883.58 |
| **E.S. Central** | -1780.75 |
| **Mid Atlantic** | -1380.16 |
| **Mountain** | -1341.10 |
| **New England** | -733.39 |

**$\varepsilon_{MC,IEF}$-$Y_O$ comparison, 1986**

| 1986 | $S_{YO}$ | $S_{MC,IEF}$ | $S_M/S_{YO}$ |
|---|---|---|---|
| **Pacific** | 0.206 | 0.383 | 1.863 |
| **E.N. Central** | 0.193 | 0.199 | 1.029 |
| **W.S. Central** | 0.114 | 0.109 | 0.959 |
| **Mid Atlantic** | 0.186 | 0.166 | 0.894 |
| **W.N. Central** | 0.109 | 0.071 | 0.652 |
| **S. Atlantic** | 0.074 | 0.033 | 0.452 |
| **E.S. Central** | 0.071 | 0.028 | 0.392 |
| **Mountain** | 0.026 | 0.006 | 0.248 |
| **New England** | 0.021 | 0.004 | 0.177 |

**$\varepsilon_{MC,IEF}$-$Y_O$ comparison, 1996**

| 1996 | $S_{YO}$ | $S_{MC,IEF}$ | $S_M/S_{YO}$ |
|---|---|---|---|
| **Pacific** | 0.215 | 0.403 | 1.870 |
| **E.N. Central** | 0.187 | 0.185 | 0.988 |
| **W.S. Central** | 0.127 | 0.124 | 0.975 |
| **Mid Atlantic** | 0.156 | 0.127 | 0.810 |
| **W.N. Central** | 0.114 | 0.081 | 0.711 |
| **S. Atlantic** | 0.083 | 0.046 | 0.551 |
| **E.S. Central** | 0.071 | 0.026 | 0.366 |
| **Mountain** | 0.026 | 0.006 | 0.223 |
| **New England** | 0.019 | 0.003 | 0.160 |

**$\varepsilon_{MC,IEF}$ levels, 1986**

| 1986 | $\varepsilon_{MC,IEF}$ |
|---|---|
| **Pacific** | -507.228 |
| **E.N. Central** | -262.795 |
| **Mid Atlantic** | -219.514 |
| **W.S. Central** | -144.602 |
| **W.N. Central** | -94.325 |
| **S. Atlantic** | -44.249 |
| **E.S. Central** | -37.021 |
| **Mountain** | -8.502 |
| **New England** | -4.940 |

**$\varepsilon_{MC,IEF}$ levels, 1996**

| 1996 | $\varepsilon_{MC,IEF}$ |
|---|---|
| **Pacific** | -827.639 |
| **E.N. Central** | -379.321 |
| **Mid Atlantic** | -260.112 |
| **W.S. Central** | -255.075 |
| **W.N. Central** | -166.570 |
| **S. Atlantic** | -94.598 |
| **E.S. Central** | -53.541 |
| **Mountain** | -12.039 |
| **New England** | -6.322 |

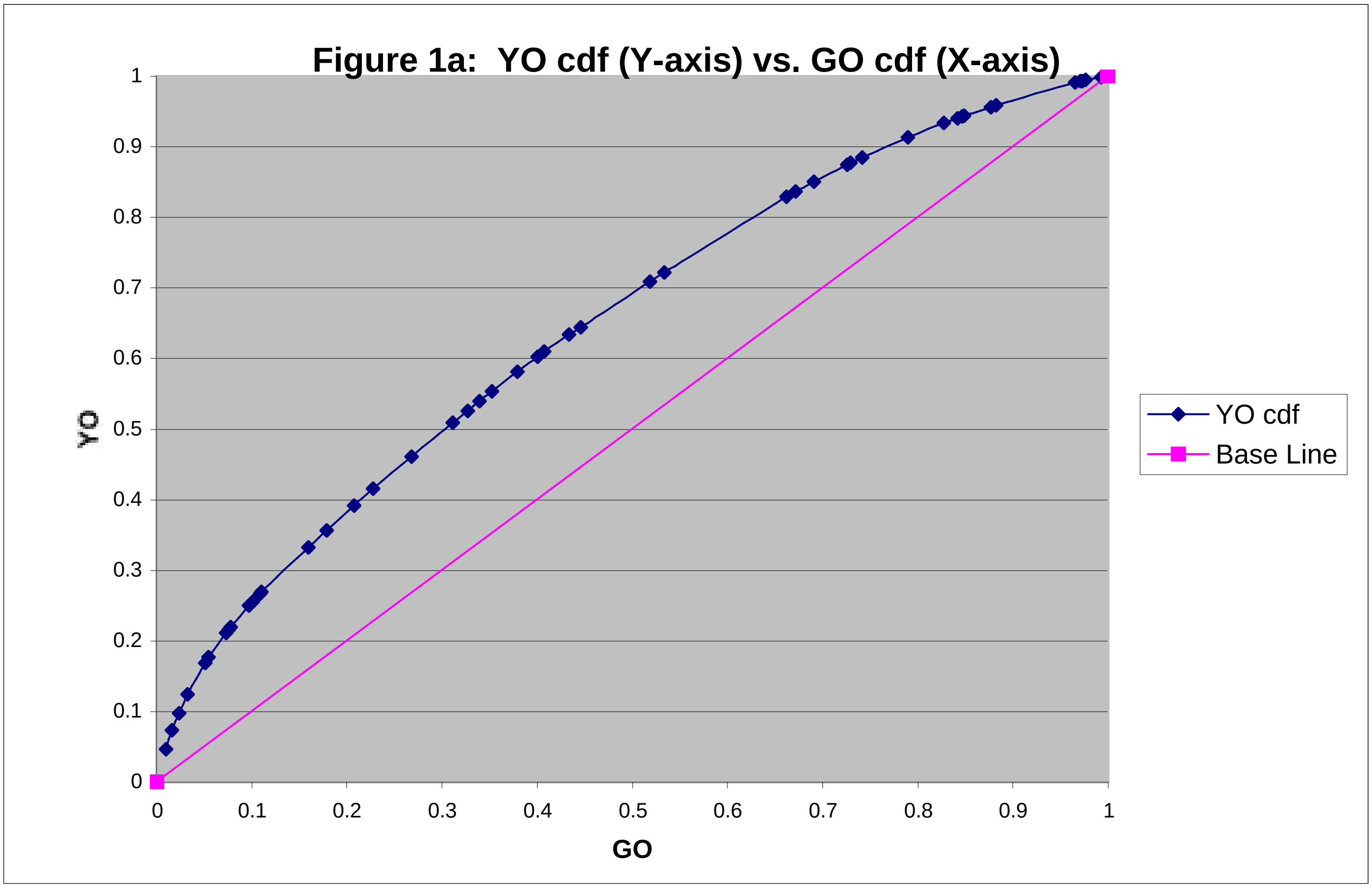
Figure 1a: YO cdf (Y-axis) vs. GO cdf (X-axis)
YO
GO
YO cdf
Base Line
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

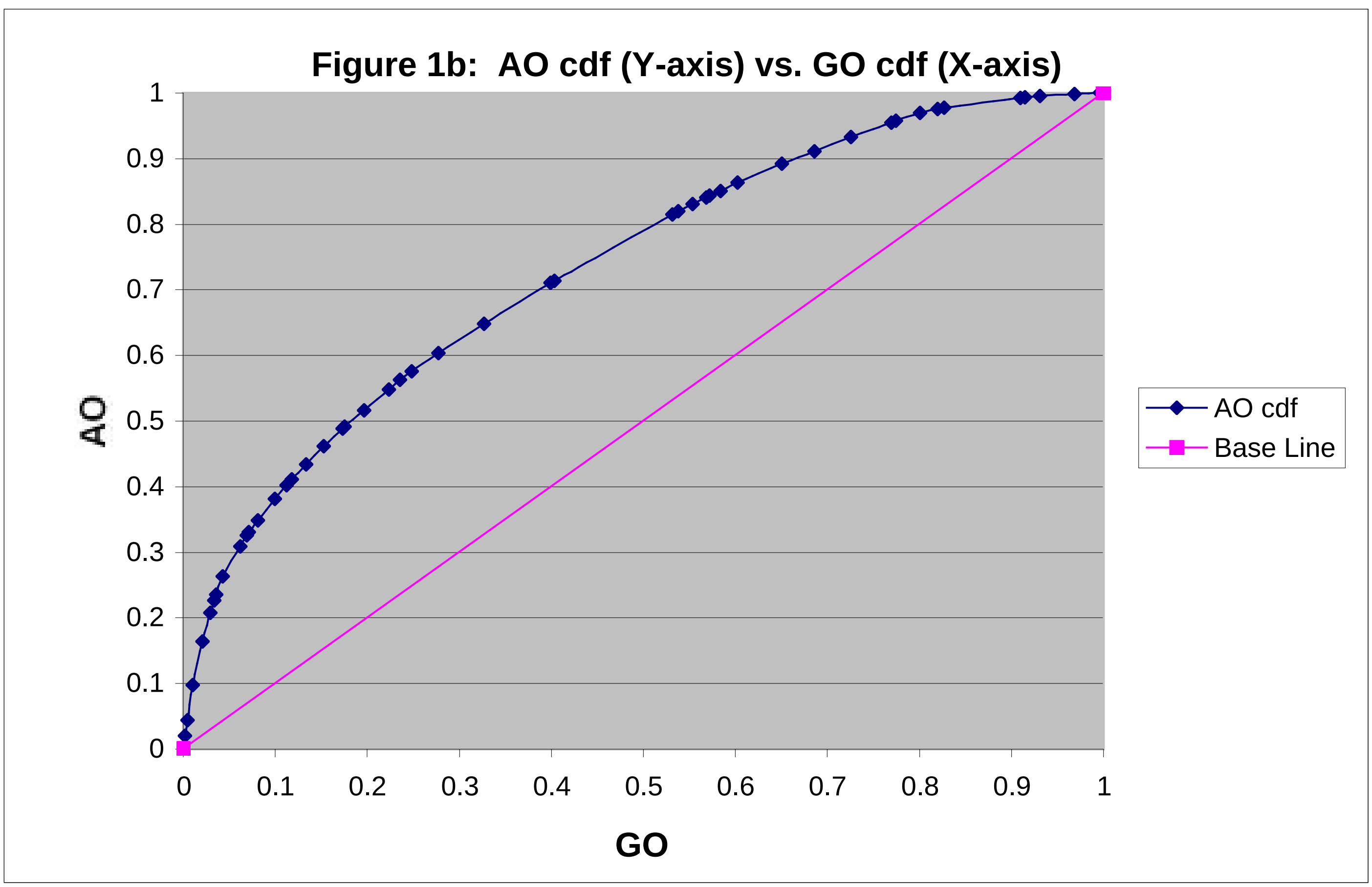
Figure 1b: AO cdf (Y-axis) vs. GO cdf (X-axis)
AO
GO
AO cdf
Base Line
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

***Appendix Table A1: Coefficient Estimates*** (dummies omitted, t statistics in italics)

| | | | | | |
|---|---|---|---|---|---|
| $\alpha_{N,P}$ | **1.30E+01** | *0.62* | $\delta_{AN,AN}$ | **-2.29E-10** | *-1.13* |
| $\alpha_{N,M}$ | **6.82E+01** | *2.06* | $\delta_{AO,AO}$ | **8.35E-10** | *0.80* |
| $\alpha_{N,K}$ | **3.58E+01** | *0.80* | $\delta_{YN,YN}$ | **2.86E-07** | *1.30* |
| $\alpha_{P,M}$ | **1.86E+02** | *4.15* | $\delta_{GO,GO}$ | **7.23E-13** | *6.77* |
| $\alpha_{P,K}$ | **1.81E+02** | *2.74* | $\delta_{GO,YO}$ | **1.09E-09** | *7.30* |
| $\alpha_{K,M}$ | **1.83E+01** | *0.24* | $\delta_{GO,YN}$ | **-1.52E-09** | *-6.49* |
| $\delta_{N,YO}$ | **2.00E-02** | *6.34* | $\delta_{GO,AO}$ | **-1.21E-11** | *-0.70* |
| $\delta_{P,YO}$ | **3.24E-02** | *10.15* | $\delta_{YO,YN}$ | **-2.05E-07** | *-1.04* |
| $\delta_{M,YO}$ | **4.87E-01** | *35.19* | $\delta_{YO,AO}$ | **-7.22E-09** | *-0.55* |
| $\delta_{K,YO}$ | **3.41E-02** | *5.89* | $\delta_{YO,GO}$ | **-5.50E-08** | *-2.11* |
| $\delta_{N,t}$ | **-1.86E+00** | *-1.56* | $\delta_{GO,AN}$ | **1.20E-11** | *0.93* |
| $\delta_{P,t}$ | **6.08E+00** | *5.21* | $\delta_{YO,AN}$ | **-3.00E-08** | *-1.94* |
| $\delta_{M,t}$ | **6.74E+01** | *8.63* | $\delta_{YN,AN}$ | **1.98E-08** | *1.84* |
| $\delta_{K,t}$ | **1.00E+01** | *3.90* | $\delta_{AO,AN}$ | **-8.63E-10** | *-1.27* |
| $\delta_{N,AN}$ | **2.31E-04** | *0.88* | $\delta_{GO,t}$ | **-4.14E-07** | *-5.10* |
| $\delta_{P,AN}$ | **1.03E-04** | *0.38* | $\delta_{YO,t}$ | **1.84E-05** | *0.36* |
| $\delta_{M,AN}$ | **-1.26E-02** | *-6.60* | $\delta_{YN,t}$ | **-2.71E-04** | *-2.98* |
| $\delta_{K,AN}$ | **-1.35E-03** | *-2.11* | $\delta_{AN,t}$ | **4.50E-06** | *0.60* |
| $\delta_{N,YN}$ | **1.70E-03** | *0.30* | $\delta_{AO,t}$ | **5.65E-05** | *5.89* |
| $\delta_{P,YN}$ | **-4.16E-03** | *-0.73* | $\rho$ | **3.22E-01** | *10.04* |
| $\delta_{M,YN}$ | **-7.08E-02** | *-2.45* | $\rho_{LD}$ | **3.28E-01** | *6.88* |
| $\delta_{K,YN}$ | **2.04E-03** | *0.22* | $\rho_{L}$ | **2.61E-01** | *5.78* |
| $\delta_{N,AO}$ | **4.07E-04** | *1.26* | $\rho_{M}$ | **3.29E-01** | *10.09* |
| $\delta_{P,AO}$ | **9.50E-04** | *2.69* | $\rho_{K}$ | **4.23E-04** | *0.41* |
| $\delta_{M,AO}$ | **1.69E-02** | *8.77* | | | |
| $\delta_{K,AO}$ | **2.78E-03** | *3.94* | $R^2$s | TC | ***0.9940*** |
| $\delta_{N,GO}$ | **-2.33E-05** | *-3.49* | | P | ***0.9939*** |
| $\delta_{P,GO}$ | **-2.79E-05** | *-4.18* | | N | ***0.9973*** |
| $\delta_{M,GO}$ | **-8.05E-05** | *-3.09* | | M | ***0.9916*** |
| $\delta_{K,GO}$ | **-4.44E-05** | *-4.27* | | K | ***0.9971*** |
| $\delta_{YO,YO}$ | **-1.69E-07** | *-3.81* | | | |