Tracing the Effects of Agricultural Commodity Prices on Food Processing Costs

Catherine J. Morrison Paul and James M. MacDonald

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ABSTRACT

Although food processing sector production is inherently linked to the availability and prices of agricultural materials (M_A), this link appears to be weakening due to adaptations in input costs, technology, and food consumption patterns. This study assesses the roles of these changes on food processors' costs and output prices, with a focus on the demand for primary agricultural commodities. Our analysis of the 4-digit U.S. food processing industries for 1972-1992 is based on a cost-function framework, augmented by a profit maximization specification of output pricing, and a virtual price representation for agricultural materials and capital. We find that falling virtual prices of M_A and input substitution have provided a stimulus for M_A demand. However, scale effects have been M_A-saving relative to intermediate food products, and disembodied technical change has strongly contributed to declining primary agricultural materials demand relative to most other inputs.

The authors are Professor, Department of Agricultural and Resource Economics, University of California, and member of the Giannini Foundation; and Senior Researcher, Food and Rural Economics Division, USDA/ERS.

Introduction

It is typically assumed that output levels and prices in the U.S. food processing sector are directly linked to the availability and prices of the agricultural products or materials (M_A) used for production. However, the traditional link between farm and food prices and production may be weakening. Adaptations in input costs and food consumption patterns are leading to changes in the production structure and technology of the food processing industries, that in turn affect demand patterns for primary agricultural materials. Such structural changes have been documented not only by anecdotal evidence, but in studies such as Goodwin and Brester, and Morrison and Siegel. In particular, Goodwin and Brester find that value-added by manufacture, both per worker hour and as a percentage of sales, increased in the 1980s in the U.S. food and kindred products industry overall, possibly implying an undermining of M_A demand.

Various economic and behavioral factors underlie these trends. As noted by Goodwin and Brester, relative prices of inputs important to food manufacturing, such as energy and labor prices relative to those for raw materials, shifted significantly in the past couple of decades. The business environment also has experienced quite a transformation, including market structure and regulatory (tax) changes in the early 1980s. Tax changes have, for example, had a direct impact on relative input prices, by affecting the prices of capital inputs.

Perhaps even more important than these alterations in the economic climate facing food processors are adaptations in food demand patterns. The fact that a greater proportion of adults are in the labor force today causes a higher demand for food products that require little home preparation time; they are at least in part prepared at the processing plant. These modifications in dietary preferences, combined with changes in food technology that allow processors to adapt foods to meet those preferences, could lead to more in plant processing of agricultural commodities. Other technical changes associated with capital equipment and the quality of agricultural materials, could also have an impact on the relative demand for agricultural products.

These adaptations in food product costs, demand, and characteristics may mean that food processors are responding by altering their input composition. If they are using more capital, skilled labor, and nonagricultural materials to produce food products than in the past, these factors could become increasingly important elements in processors' costs relative to agricultural commodities. The corresponding decline in agricultural materials input intensity is likely to result in weaker effects of changes in agricultural commodity prices on food prices, which has important impacts on both consumers of the final product and producers of the raw agricultural materials.

To address these issues, this study assesses the role of changes in food product demand, input prices, and food processing technology on food processors' costs and output prices, with a particular focus on the use of agricultural commodities as compared to other factor inputs. Our analysis of cost structure and input composition changes in the U.S. food processing industries is based on a cost-function representation of production processes in these industries.

In our model we recognize a full range of substitution patterns among capital, labor, energy, agricultural materials, food materials and "other" materials inputs resulting from input price changes or technological factors. This allows us to explore modifications in input mix, costs and commodity prices resulting from changing agricultural commodity prices and output demand. It also facilitates consideration of technological factors affecting M_A demand and production costs such as the quasi-fixed nature of capital (adjustment costs), scale economies, technical change associated with either time trends (disembodied) or capital composition (embodied in capital), and agricultural innovations or market power embodied in the M_A input price.

The model is estimated using data on 4-digit SIC level U.S. food processing industries, and the results summarized according to time period (1972-82 and 1982-92) and 3-digit code (meat, dairy, vegetables, grains, sugar and candy, oils, beverages, and miscellaneous). The base price and quantity data for output, capital, labor, and materials are from the National Bureau of Economic Research Productivity Database. The materials breakdown was drawn from data in the Census of Manufactures, which are only available at 5-year intervals – from 1972 to 1992. We therefore have a panel of data for 34 industries and 5 time periods, which are distinguished by fixed effects for estimation.[1]

Our empirical results suggest that agricultural materials (M_A) demand has been affected by various technological and market characteristics of the food processing industry. Although own price effects have had the potential to limit M_A demand, growth in the price of agricultural materials has fallen over time, and in the effective price has fallen even lower, so this effect was essentially erased – or even reversed direction – by the end of the 1980s. Substitution effects have also contributed to M_A demand. Rising capital costs, especially in effective units, and its implied limitations on production flexibility, have particularly enhanced M_A substitution. Scale effects have had a somewhat ambiguous effect, since M_A use has increased slightly more proportionately than output increases in effective units, but less than the use of intermediate food products, so M_A demand, especially in traditionally measured units, has weakened relative to these substitute inputs. We also, however, find a strong and increasing downward trend in M_A demand over time. The direct effect of disembodied technical change in the food processing industries, possibly induced by changing output demand, has clearly been M_A-saving, even adapted for the conflicting forces from innovation, and rigidities in the agricultural sector, that have affected the virtual prices of agricultural materials and capital.

The Model

Our goal is to evaluate costs, input demand (especially for agricultural materials), and output price (supply) behavior in the U.S. food processing industries, and their dependence on various pecuniary and technological forces. A cost function specification recognizing virtual prices, and augmented by an output pricing equation, provides the foundation for this exploration.

Such a framework assumes that cost minimizing input demand behavior based on observed input prices and output demand characterizes firms in the food processing industries. Fixed effects and a time trend represent industrial and temporal differences. The potential for imperfect markets from quasi-fixity and deviations from perfect competition is incorporated through the virtual price specification. The resulting cost structure representation allows us also to characterize profit maximizing output prices and quantities through an equality of the associated marginal cost and marginal revenue.

More formally, the technology and cost-minimizing behavior underlying the observed production structure are typically represented by a total cost specification of the form $TC(Y,\mathbf{p}, \mathbf{r})$, where Y is (food) output, $\mathbf{p}$ is a vector of variable input prices, and $\mathbf{r}$ is a vector of exogenous technological determinants. The TC-Y relationship, summarized by the $\varepsilon_{TC,Y}=\partial \ln TC/\partial \ln Y$ elasticity, represents the shape of the (minimized long run) cost curves, given observed factor prices and the existing technological base. Impacts on this cost relationship of changes in components of the **p** and **r** vectors, and thus on the implied overall costs and input-specific demands, can be derived via 1st- and 2nd-order elasticities with respect to these arguments of the cost function.

The ability to reach minimum possible production costs, as implied from such a cost function specification, is often recognized to be restricted by adjustment costs, which severs the equivalence of the observed input price, p_k, and its true economic return. Alternatively, something that looks like internal adjustment costs may stem from increased factor prices due to some other type of input market imperfection. This could arise from, for example, imperfect competition in the factor market, external adjustment costs or unmarketed (or unmeasured) characteristics.[2]

One way to deal with a deviation between the measured and virtual or shadow value of input x_k from imperfect markets is to include x_k instead of p_k as an argument of the (variable) cost function, thus implicitly representing the shadow value (Z_k) wedge as $\partial TC/\partial x_j = p_k - Z_k \neq 0$.[3] An alternative approach is to directly incorporate the virtual price of input x_k, $p^*_k=p_k+\lambda_k$, into the function, where λ_k represents the wedge between p_k and Z_k. This representation is particularly appealing if the interaction terms from the former model seem uninformative, but an imperfect market gap, λ_k seems to exist (λ_k statistically deviates from zero).[4] If instead Z_k (p^*_k) appears well approximated by p_k, or $\lambda_k \approx 0$, one can reasonably assume that rigidities or other input market imperfections are not binding constraints on, or determinant of, measured cost structure patterns.

We have adopted such a virtual price framework as that most consistent with our data, from preliminary investigation of estimation patterns. In this scenario, the total cost function for producing food output in the U.S. food-processing sector becomes TC = TC(Y,$\mathbf{p_v}$,$\mathbf{p^*_x}$,$\mathbf{r}$), where $\mathbf{p_v}$ represents the vector of observed variable input prices for factors that satisfy standard requirements for Shephard's lemma to be valid, and $\mathbf{p^*_x}$ is a vector of effective prices that deviate from observed prices by the additive factors $\lambda_{\mathbf{x}}$.[5]

In our analysis, the variable inputs – for which empirical investigation supported the $\lambda_k \approx 0$ assumption – are labor, (L) and materials (food, M_F, energy, E, and "other" M_O) inputs, with prices p_L, p_{MF}, p_E, and p_{MO}. Demand decisions for these inputs are thus represented by $v_j = \partial TC/\partial p_j$. Evidence was found, however, for deviations between observed and effective or virtual prices for capital (K) and agricultural materials (M_A).

The virtual price of capital was therefore defined as $p^*_K = p_K + \lambda_K$, with $\lambda_k \neq 0$ potentially attributable to capital rigidities (adjustment costs) or unmeasured taxation or quality impacts. Various forms for the deviation between p_K and $Z_K = p^*_K$ were tested to establish their empirical justification in terms of significance of the parameters, robustness of the overall results, and plausibility of resulting elasticities. The final chosen specification is an augmented version of an additive shift factor recognizing technical change trends; $\lambda_K = \lambda_{K1} + \lambda_{Kt} \bullet t + \lambda_{Kt} \bullet t2$, where t is a trend term and t2 a dummy variable representing post-1980 structural change. So $p^*_K = p_K + \lambda_{K1} + \lambda_{Kt} \bullet t + \lambda_{K2} \bullet t2$ appears as an argument of TC($\bullet$), with optimal K demand given by $K = \partial TC/\partial p^*_K$.

Similarly, treating M_A as an x_k factor, with effective price $p^*_{MA} = p_{MA} + \lambda_{MA}$, and $\lambda_{MA} = \lambda_{MA1} + \lambda_{MAt} \bullet t + \lambda_{MA2} \bullet t2$, was empirically supported. The finding that $\lambda_{MA} \neq 0$ is plausible for a variety of reasons. In particular, if the processing industries perceive some (market power) control over M_A prices, the (higher) marginal than (observed) average price drives M_A input demand behavior and $\lambda_{MA}>0$. This is of interest since the potential for (relatively large) processing facilities to depress prices paid to (relatively small) farmers, has often been recognized as a policy concern. In reverse, embodied technical change (and thus implied quality) could imply lower effective prices of agricultural materials compared to their measured values ($\lambda_{MA}<0$). Thus, p^*_{MA} becomes an argument of TC(•), with M_A choice represented by $M_A=\partial TC/\partial p^*_{MA}$, and the sign and thus interpretation of the λ_{MA} "wedge" to be established empirically.

The variables in the **r** vector reflecting the industry's technological base include the time counter t, as well as t2, to represent disembodied technical change trends and further structural change shifts in the 1980s as compared to the 1970s (t2=1 for 1982, 1987 and 1992). A capital equipment to structures ratio, (EQ/ST=ES), is also used to represent technology embodied in the capital stock.[6] And dummy variables for the different industries, D_I, are included to capture fixed effects.[7]

Output supply/pricing decisions are also accommodated in this cost-based model by specifying a pricing mechanism that allows for a difference between output price and marginal costs, or average (observed) and marginal (virtual) cost. This extension of the cost function framework is founded on imposing the standard profit maximizing condition underlying output choice, MR = MC (where MC is marginal cost and MR is marginal revenue), and assuming that any gap between output price p_Y and MR results from a dependency of p_Y on output levels; $p_Y(Y)$. This is implemented similarly to the specification of virtual input prices for M_A and K,[8] through the optimization equation $MR = p_Y + \partial p_Y/\partial Y \bullet Y = \partial TC/\partial Y = MC$, so $\partial p_Y/\partial Y \bullet Y$ reflects the wedge between MR and

MC.[9] We find $\partial p_Y/\partial Y$ to be well approximated by a parameter, λ_Y, so the effective (or virtual) price is $p^*_Y = p_Y+\lambda_Y Y$, and the resulting optimization equation becomes $p^*_Y=MC$ or $p_Y=-\lambda_Y Y+MC$. Alternative treatments with λ_Y specified as a function of other exogenous variables were also tried, with no significant impact.[10]

The resulting total cost function $TC(p^*_{MA},p^*_K,p_L,p_{MF}, p_E,p_{MO},Y,ES,t,t2,\mathbf{D_I})$ and associated input demand and output supply (pricing) optimization equations facilitate evaluating a broad range of production structure issues in the U.S. food processing industries. A useful way to characterize the impacts of changes in the economic and technological climate on the cost base and resulting choice behavior is through a decomposition of observed changes. This provides us with information on both individual elasticities, and their implied contribution or exogenous changes to observed cost, demand, and supply (pricing) changes.

That is, we can divide observed TC changes over time, dTC/dt, into its driving forces, by quantifying the total derivative:

1) $dTC/dt = \partial TC/dp^*_{MA}\bullet dp_{MA}/dt + \partial TC/\partial p^*_K\bullet dp_K/dt + \partial TC/dp_L\bullet dp_L/dt$

$+ \partial TC/\partial p_{MF}\bullet dp_{MF}/dt + \partial TC/dp_E\bullet dp_E/dt + \partial TC/\partial p_{MO}\bullet dp_{MO}/dt + \partial TC/\partial Y\bullet dY/dt$

$+ \partial TC/\partial ES\bullet dES/dt + \partial TC/\partial t_2\, dt_2/dt + \partial TC/\partial t$

which can be rewritten as:

2) $d\ln TC/dt = \partial\ln TC/d\ln p^*_{MA}\bullet d\ln p_{MA}/dt + \partial\ln TC/\partial\ln p^*_K\bullet d\ln p_K/dt$

$+ \partial\ln TC/d\ln p_L\bullet d\ln p_L/dt + \partial\ln TC/\partial\ln p_{MF}\bullet d\ln p_{MF}/dt + \partial\ln TC/d\ln p_E\bullet d\ln p_E/dt$

$+ \partial\ln TC/\partial\ln p_{MO}\bullet d\ln p_{MO}/dt + \partial\ln TC/\partial\ln Y\bullet d\ln Y/dt + \partial\ln TC/\partial\ln ES\bullet d\ln ES/dt$

$+ \partial\ln TC/\partial t_2\, dt_2/dt + \partial\ln TC/\partial t,$

or in terms of elasticities, as:

3) $d\ln TC/dt = \varepsilon_{TC,p*MA} \bullet d\ln p_{MA}/dt + \varepsilon_{TC,p*K} \bullet d\ln p_K/dt + \varepsilon_{TC,pL} \bullet d\ln p_L/dt$

$+ \varepsilon_{TC,pMF} \bullet d\ln p_{MF}/dt + \varepsilon_{TC,pE} \bullet d\ln p_E/dt + \varepsilon_{TC,pMO} \bullet d\ln p_{MO}/dt + \varepsilon_{TC,Y} \bullet d\ln Y/dt$

$+ \varepsilon_{TC,pES} \bullet d\ln ES/dt + \varepsilon_{TC,t2}\, dt_2/dt + \varepsilon_{TC,t}$,

where $\varepsilon_{TC,\bullet}$ are cost elasticities with respect to the various arguments of TC(•), and dY/dt, for example, represents the actual change in Y between two time periods.[11]

By defining "contributions" of individual arguments of TC(•), we can rewrite (3) as:

4) $d\ln TC/dt = C_{TC,p*MA} + C_{TC,p*K} + C_{TC,pL} + C_{TC,pMF} + C_{TC,pE} + C_{TC,pMO} + C_{TC,Y}$

$+ C_{TC,ES} + C_{TC,t2} + C_{TC,t}$,

where the $C_{TC,\bullet}$ cost-contributions capture the responsiveness or elasticity combined with the actual change in the exogenous variable. Note that the industry fixed effects fall out by construction since we are capturing within-industry changes. By contrast, t_2 appears even though it is a dummy variable; however, its impact is only reflected in the time period the dummy variable becomes one.[12]

Each of these measures has a specific interpretation as a cost driver. For example, the scale elasticity $\varepsilon_{TC,Y} = \partial\ln TC/\partial\ln Y$ captures the shape of (or movement along) the cost curve in TC-Y space, and thus the extent of (internal) scale economies. The contribution of such economies to observed cost changes, $C_{TC,Y}$, therefore depends on both the $\varepsilon_{TC,Y}$ elasticity and the observed output (scale of production) change, dln Y/dt.

Input prices also have well defined impacts on costs, which are represented by the elasticities and contributions $\varepsilon_{TC,j}$ and $C_{TC,j}$ (j=L,E,M_F,M_O). The $\varepsilon_{TC,j}$ measures, however, collapse to the estimated input j cost shares due to Shephard's lemma; $\varepsilon_{TC,j}=\partial\ln TC/\partial\ln p_j = (\partial TC(\bullet)/\partial p_j)\bullet p_j/TC = v_j p_j/TC = S_j$. The cost impact of a price change for the variable factor v_j therefore depends on its input-intensity in production. Similarly, for the x_k

variables, these measures depend on the virtual prices p^*_k, since $x_k(\bullet) = \partial TC(\bullet)/\partial p^*_k$ $(k=M_A,K)$; decision-making behavior is driven by the effective price of the factor. The associated "virtual share" is thus $\varepsilon_{TC,k} = \partial TC(\bullet)/\partial p^*_k \bullet p^*_k/TC = S^*_k$.

The $\varepsilon_{TC,rn}$ elasticities represent shifts in the cost function from external technological and economic forces. The elasticity $\varepsilon_{TC,t}=\partial \ln TC/\partial t$, for example, is typically interpreted as (disembodied) technical change that results in a downward shift of the cost relationship over time (cost diminution). A $\varepsilon_{TC,t2}=\partial \ln TC/\partial t_2$ elasticity similarly reflects the structural changes in the 1980s suggested by Goodwin and Brester. And cost impacts of adaptations in capital composition toward more effective capital equipment (embodied technical change) are measured by $\varepsilon_{TC,ES}=\partial \ln TC/\partial \ln ES$. The full expected impacts from changes in these factors will depend on the actual changes in the arguments of the function, as implied by the computed contributions, $C_{TC,\bullet}$.

Given the form empirically suggested for the virtual prices p^*_K and p^*_{MA}, we also may distinguish the direct (dir) and indirect (ind) impacts of t changes on costs, where the indirect impact works through the effects of t on λ_K and λ_{MA}. That is, writing $TC(\bullet)$ as $TC(p^*_{MA}(t),p^*_K(t),p_L,p_{MF},p_E,p_{MO},Y,ES,t,t2,\mathbf{D_I})$, the implied total (tot) t impact is:

5) $\varepsilon_{TC,t}\ (tot) = \partial \ln TC/\partial t + \partial \ln TC/\partial \ln p^*_{MA} \bullet \partial \ln p^*_{MA}/\partial t + \partial \ln TC/\partial \ln p^*_K \bullet \partial \ln p^*_K/\partial t$

$= \varepsilon_{TC,t}\ (dir) + \varepsilon_{TC,pMA} \bullet \varepsilon_{p^*MA,t} + \varepsilon_{TC,pK} \bullet \varepsilon_{p^*K,t}$

$= C_{TC,t}\ (dir) + C_{TC,p^*MA,t} + C_{TC,p^*K,t} = C_{TC,t}\ (dir) + C_{TC,t}\ (ind)$.

Perhaps even more important than the cost decomposition, in the context of this study with its focus on agricultural materials use, are the implied impacts on M_A demand. Characterizing this piece of the puzzle again relies on the Shephard's lemma result $M_A(\bullet) = \partial TC(\bullet)/\partial p^*_{MA}$. This demand equation depends on all arguments of the cost function if

TC(•) is approximated by a flexible form that recognizes second order relationships. The overall cost impacts represented by the $\varepsilon_{TC,\bullet}$ elasticities can therefore be divided into their input-specific effects through second-order cost elasticities capturing the dependence of input demand behavior on the pecuniary, technological, and market factors represented by the components of the $\mathbf{p_v}$, $\mathbf{p^*_x}$ and **r** vectors, and output demand Y.

This decomposition of observed changes in MA(•) demand can be derived similarly to that for TC(•) as:

6) $d\ln M_A/dt = \varepsilon_{MA,p^*MA}\bullet d\ln p_{MA}/dt + \varepsilon_{MA,p^*K}\bullet d\ln p_K/dt + \varepsilon_{MA,pL}\bullet d\ln p_L/dt$

$+ \varepsilon_{MA,pMF}\bullet d\ln p_{MF}/dt + \varepsilon_{MA,pE}\bullet d\ln p_E/dt + \varepsilon_{MA,pMO}\bullet d\ln p_{MO}/dt + \varepsilon_{MA,Y}\bullet d\ln Y/dt$

$+ \varepsilon_{MA,pES}\bullet d\ln ES/dt + \varepsilon_{MA,t}$,

$= C_{MA,p^*MA} + C_{MA,p^*K} + C_{MA,pL} + C_{MA,pMF} + C_{MA,pE} + C_{MA,pMO} + C_{MA,Y} + C_{MA,ES} + C_{MA,t.}$

The $\varepsilon_{MA,\bullet}$ elasticities therefore quantify the shape of and shifts in the M_A demand curve for 1% changes in p_{MA} and other arguments of the $M_A(\bullet)$ function, and the $C_{MA,\bullet}$ measures reflect the actual contributions given observed changes in these determinants.

In particular, $\varepsilon_{MA,pj} = \partial\ln M_A/\partial\ln p_j$ indicates the responsiveness of M_A demand to its own price for $j=M_A$, and substitutability between input v_j and M_A for $j=K,L,E,M_F,M_O$. Similarly, the M_A-specific impacts of changes in the scale of production or technological factors are captured by the $\varepsilon_{MA,Y} = \partial\ln M_A/\partial\ln Y$ and $\varepsilon_{MA,rn} = \partial\ln M_A/\partial\ln r_n$ elasticities. For example, if $\varepsilon_{MAY}>1$ expansions in demand for processed food products increase the demand for agricultural products more than proportionately; increases in the scale of production are relatively M_A-using. And if $\varepsilon_{MA,rn}<0$ for r_n=t2 (the dummy shifter representing the 1980s), the demand for agricultural commodities was more limited, given other economic and technological factors, in the 1980s than in the 1970s, suggesting a structural shift toward lower M_A-intensity of production (possibly induced by output demand composition changes). $\varepsilon_{MA,t}$ similarly indicates the force of disembodied technical change or trend on M_A demand. The total t-effect can also be divided into its direct and indirect (through p^*_k) impacts, as in (5); $\varepsilon_{MA,t}$ (tot) = $\varepsilon_{MA,t}$ (dir) + $\varepsilon_{MA,pMA}\bullet\varepsilon_{p^*MA,t}$ + $\varepsilon_{MA,pK}\bullet\varepsilon_{p^*K,t}$, or $C_{MA,t}$ (tot) = $C_{MA,t}$ (dir) + $C_{MA,p^*MA,t}$ + $C_{MA,p^*K,t}$. These indicators thus allow us to source the determinants of observed M_A changes. And the measured input demand patterns in turn provide implications about the prices that agricultural producers will receive for their products, p_{MA}.

Another set of second-order relationships that can provide us useful insights is based on the definition of marginal cost, $MC(\bullet)=\partial TC/\partial Y$. Again, for a flexible cost function this 1st-order relationship will depend on all arguments of the original TC(•) function, so we can decompose it as:

$$7)\quad d\ln MC/dt = \varepsilon_{MC,p^*MA}\bullet d\ln p^*_{MC}/dt + \varepsilon_{MC,p^*K}\bullet d\ln p^*_K/dt + \varepsilon_{MC,pL}\bullet d\ln p_L/dt$$
$$+ \varepsilon_{MC,pMF}\bullet d\ln p_{MF}/dt + \varepsilon_{MC,pE}\bullet d\ln p_E/dt + \varepsilon_{MC,pMO}\bullet d\ln p_{MO}/dt + \varepsilon_{MC,Y}\bullet d\ln Y/dt$$
$$+ \varepsilon_{MC,pES}\bullet d\ln ES/dt + \varepsilon_{MC,t},$$
$$= C_{MC,p^*MA} + C_{MC,p^*K} + C_{MC,pL} + C_{MC,pMF} + C_{MC,pE} + C_{MC,pMO} + C_{MC,Y} + C_{MC,ES} + C_{MC,t}\ .$$

Although not as fundamental for our analysis as that for TC(•) and MA(•), this decomposition allows consideration of at least two issues of interest, the differential impacts of economic and technological changes – in particular p_{MA} changes – on returns to scale, and on the extent of market power, in the food industries.[13]

That is, the TC(•) elasticities and contributions measure the impacts on total and thus average (for given Y) costs,[14] so comparison with the associated MC(•) measures allows us to impute the differential impacts on marginal and average costs, and thus on scale economies. For example, we can consider how p_{MA} changes affect marginal as compared to average cost (AC), and thus $\varepsilon_{TC,Y}$ = MC/AC. Similarly, using the pricing expression $p_Y = -\lambda_Y Y + MC$ specified above, we can construct a decomposition of p_Y analogous to those presented above, with the difference from that for $MC=p^*_Y$ depending on the form of λ_Y. This may be used to evaluate how p_{MA} (or other) changes impact p_Y as compared to MC, which provides information on the pass-through of agricultural materials prices to food prices, and on the implications for markup behavior (p_Y/MC).

In sum, the decompositions of the TC(•), MA(•), MC(•), and p_Y(•) functions, and their underlying elasticity and contribution estimates with respect to the $\mathbf{p_v}$, $\mathbf{p_x}$, Y and $\mathbf{r}$ variables, provide a detailed picture of the production structure relationships in the food industries, and the role of agricultural materials. These measures will provide the basis for the discussion of empirical results below.

Data

To empirically implement this model of the production structure of the U.S. food processing industries, we use a panel of input and output quantities and prices we have constructed from the Census of Manufactures, the NBER productivity database, the Bureau of Labor Statistics, and the U.S. Department of Agriculture.

In particular, we distinguished cost shares for three materials aggregates – agricultural materials, food materials (processed agricultural materials shipped to other food processing establishments), and other materials. To accomplish this, we used Census of Manufactures data to calculate the share of each materials aggregate in the industry value of shipments for which cost information is available.[15] These shares were then adjusted in two ways to arrive at our final estimated materials shares.

First, in some food industries, the industry value of shipments includes substantial amounts of materials resales – materials that are purchased but not processed before being resold. We subtracted resales from the value of shipments, to better capture manufacturing output. Second, some small establishments are not required to separately report individual materials purchases, but instead report all materials in an “n.s.k.” (not separately classified) category. We assumed that these establishments allocated n.s.k. shipments to agricultural, food, and other materials categories in proportions equivalent to those reported by the larger institutions.

Materials input price series were constructed primarily from commodity PPIs (Producer Price Indexes) from the Bureau of Labor Statistics. In cases where an industry consumed several specific agricultural or food materials, an aggregated materials price index was constructed from the constituent materials indexes, with each price index weighted by its expenditure share in the Census aggregate. In the few cases where PPI indexes were not available, we constructed indexes from average price series maintained by USDA’s National Agricultural Statistics Service. The resulting data panel covers 5-year intervals from 1972 through 1992, for the 40 4-digit SIC industries in the U.S. food processing sector (SIC 20).

The remaining data on output and input prices and quantities were taken from the 4-digit manufacturing NBER (National Bureau of Economic Research) productivity database, which is often used as a foundation for production structure studies.

Empirical Implementation

Empirical implementation of the model developed above requires more explicit specification of the cost function and the resulting system of estimating equations. In particular, a functional form must be assumed for TC(p^*_{MA},p^*_K,p_L,p_{MF}, p_E,p_{MO},Y,ES,t, t2,$\mathbf{D_I}$). We have used a version of the generalized Leontief (GL) cost function, called a GL-quadratic (GL-Q) by Paul, which takes the form (with fixed effects included through dummy variables DUM_{I3} and DUM_{I4} for the 3- and 4-digit industries, respectively):

8) $$TC(Y,\mathbf{p},\mathbf{r}) = \Sigma_{jI}\, p_j\, DUM_{I3}\, \delta_{jI} + \Sigma_{jIY}\, p_j\, DUM_{I4}\delta_{jYI}Y + \Sigma_{kI}\, p^*_k\, DUM_{I3}\, \delta_{kI}$$
$$+ \Sigma_{kIY}\, p^*_k\, DUM_{I4}\delta_{kYI}Y + \Sigma_j\Sigma_i\, \alpha_{ji}\, p_j^{.5}p_i^{.5} + \Sigma_j\Sigma_k\, \alpha_{jk}\, p_j^{.5}p^{*.5}_k + \Sigma_k\Sigma_l\, \alpha_{kl}\, p_k^{.5}p_l^{.5}$$
$$+ \Sigma_k\, \delta_{kY}\, p^*_k\, Y + \Sigma_k\Sigma_n\, \delta_{kn}\, p^*_k\, r_n + \Sigma_k p^*_k\, (\gamma_{YY}Y^2 + \Sigma_n\, \gamma_{Yn}\, r_nY + \Sigma_m\Sigma_n\, \gamma_{mn}\, r_mr_n)$$
$$+ \Sigma_j\, \delta_{jY}\, p_j\, Y + \Sigma_j\Sigma_n\, \delta_{jn}\, p_j\, r_n + \Sigma_j p_j\, (\gamma_{YY}Y^2 + \Sigma_n\, \gamma_{Yn}\, r_nY + \Sigma_m\Sigma_n\, \gamma_{mn}\, r_mr_n)\ .$$

The fixed effects were incorporated in such a manner that linear homogeneity in input prices is maintained. The 3-digit dummy variables on the input prices permit industry-specific intercepts in each of the input demand equations. The 4-digit cross-output interaction dummies allow for industry- and input- specific impacts in the output pricing equation. 4-digit dummies for these terms appeared important from preliminary estimation to accommodate large discrepancies in the output/input mixes of the different industries; the variation in the resulting elasticity estimates was too great to be plausible with only 3-digit dummies to adapt for differences across industries.[16]

The final estimating model is comprised of a system of demand equations for the inputs (L,K,E,M_A,M_F,M_O), and a pricing (supply) equation for output. The input demand equations are constructed according to Shephard's lemma; $v_j(\bullet) = \partial TC(\bullet)/\partial p_j$ (j=L,E,M_F,M_O) and $x_k(\bullet) = \partial TC(\bullet)/\partial p^*_k$ (k=M_A,K), where $p^*_k = p_k + \lambda_k$, and $\lambda_k = \lambda_{k1} + \lambda_{kt}\bullet t + \lambda_{k2}\bullet t_2$. The form of the output pricing equation resulted from equating MR and MC is $p_Y = -\lambda_Y\bullet Y + \partial TC/\partial Y$, as discussed above, where λ_Y was differentiated across industries to incorporate fixed effects into this relationship; $\lambda_Y = \Sigma_I\lambda_{YI}\bullet D_{I4}$.

Estimation was carried out by seemingly unrelated (SUR) estimation techniques for this system of equations, with the potential for heteroskedasticity accommodated by techniques in TSP that allow standard errors to be computed from a heteroscedastic-consistent matrix (Robust-White). An alternative approach to heteroskedasticity adjustment – to reconstruct the equations as input/output instead of input demand equations – was also tried in empirical estimation, but did not improve the estimates.

Although instrumental variables (IV) procedures are often used in the literature on which this study is based, to accommodate potential endogeneity or measurement errors in the data, we did not rely on them for a variety of reasons. First, IV techniques require a somewhat arbitrary specification of instruments, which can be problematic. In addition, models of this form are typically estimated with time series data, and often use lagged values of the observed arguments of the function as instruments. But this is not conceptually appealing for our application due to the short time series, as well as the 5-year gaps between data points. Although some preliminary investigation was carried out to determine the sensitivity of the results to other IV specifications, the results from these models were more volatile (less robust) and not as plausible as those from the basic SUR model, which was therefore relied on for the final estimation.

Our specification of the arguments of the **r** vector also warrants additional comment. Including ES as a determinant of the cost structure in addition to the standard time trend t initially seemed important for explaining cost and input demand patterns; the ES parameters, interpreted as the impact of technical change embodied in the capital stock, tended to be significant and plausible. When t2 was also included to capture the potential impact of structural changes in the 1980s, the t2 parameters became statistically significant but the ES parameters tended to be less definitive. Both variables thus seem to capture changes in the 1980s – perhaps toward greater capital- or high-tech- intensity of production. Since the ES parameters remained jointly statistically significant, however, they were retained in the final specification.

The Results

The parameters estimated from the cost-based model specification TC(p^*_{MA},p^*_K,p_L,p_{MF}, p_E,p_{MO},Y,ES,t, t2,$\mathbf{D_I}$) are presented in Appendix Table 1. The dummy terms are not included in the table since there are too many to be illuminating, but they are primarily statistically significant. The overall explanatory power of the model is indicated by the high R^2's for the estimating equations, including the TC(•) equation which was not estimated but was fitted to determine the implied R^2 (as denoted by the parentheses). Also, many parameter estimates that are not individually statistically significant are jointly significant, such as the ES parameters mentioned above.[17]

These estimates were used to construct the cost, input demand, and output supply elasticity and contribution estimates from the decompositions outlined in the modeling section. The measures were averaged across the whole sample, and separately for 1972-1982 and 1982-1992, and by 3-digit industry, to distinguish temporal and industrial patterns. The elasticity estimates were constructed by computing the indicators for each data point and then averaging across the sample under consideration. Statistical significance of these measures (since they are combinations of parameters) was imputed by constructing elasticity estimates instead over the averaged data; values significantly different from zero at the 5% level are indicated by an asterisk (*).[18] In most cases the significance implications were not data-dependent, although for some estimates the data point at which the measure was evaluated contributed to evidence of significance.

Patterns of Agricultural Materials Demand

To begin our investigation of agricultural materials use in U.S. food processing industries, we first assess M_A demand implications from the decomposition presented in the first panel of Table 1 for the full sample (corresponding to equation 6). Recall that such a decomposition weighs the estimated elasticities by the observed changes in the arguments of the function to determine their contribution to observed (or estimated) changes in the dependent variable (in this case M_A demand).[19]

First consider the elasticities. The largest M_A (in absolute value) demand elasticity as well as contribution (response taking the observed determinant change into account) is from its own price. The own elasticity of $\varepsilon_{MA,pMA}$ = –1.138 for U.S. food processing industries implies M_A demand is fairly elastic; p_{MA} increases have motivated a movement up the demand curve (holding other factors fixed) to a lower M_A demand level that more than compensated for the price change in proportional terms. Based on observed p_{MA} price changes, this provided a negative contribution of $C_{MA,pMA}$ = -0.062% to the overall observed increase in M_A use of 0.038 (or 3.8% per year); other factors outweighed the negative own-demand effect.[20]

By contrast, if the indirect implications from the deviation between the effective and observed input prices are taken into account this effect appears quite a bit smaller; p^*_{MA} changed by only 0.036% as compared to the p_{MA} change of 0.055%,[21] so the total contribution weighted by this price change would be $C^*_{MA,pMA}$ = -0.041. The lesser apparent growth in p^*_{MA} than p_{MA} could derive from various factors – including augmented quality that is not captured in the measured values – but is inconsistent with increases in market (monopsony) power.[22] That is, λ_{MA} appears to capture some form of technical change or productivity embodied in M_A, that represents the impact of technical innovation in *agricultural* markets transferred to the next level of the food chain – food processing.[23] This effect will be evaluated more explicitly below in the context of the indirect components of the t impact within the $C_{MA,t}$ (tot) decomposition.

All other inputs are substitutable with M_A, as is apparent from their positive price elasticities, and the observed increases in these input prices over the sample period thus imply positive shift effects on M_A demand that in sum seem to more than compensate for the own price effect. In particular, M_A seems somewhat substitutable with both M_F and M_O, but the contributions of p_{MF} and p_{MO} changes to observed M_A demand adaptations are not substantial since the price changes have not been large; $C_{MA,pMF}$=0.0035 and $C_{MA,pMO}$=0.016. Rising relative prices of labor and energy – which have been experienced in these industries for most of the recent past – have also had positive effects on M_A use, although their contributions are limited by smaller substitution elasticities; $C_{MA,pL}$=0.012 and $C_{MA,pE}$=0.004. The statistically insignificant elasticities for p_L and p_{MF} suggest that M_A-M_F substitution (where M_F might be expected to be more complementary with L) is driven more by demand than price (substitution) impacts.

The contribution of p_K increases to M_A demand is much greater than the price effects associated with other inputs, especially if adjustments in effective p_K, p^*_K, are recognized. Even based on observed p_K changes, $C_{MA,pK}$=0.044. If weighted by the greater increases p^*_K, the M_A demand augmenting impact of capital price changes would be $C^*_{MA,pK}$ =0.056. The implied higher growth (as well as level) of virtual compared to measured price of capital could result from various factors. Its drivers could include substantive and rising adjustment costs (perhaps from larger scale and more high-tech production resulting in greater production rigidities), environmental or safety standards, or taxes, that are not effectively captured in the measured user cost of capital. These capital costs motivate a substitution effect toward primary agricultural products.

In turn, growth in the scale of production, or output demand, has had a greater-than proportional effect on the augmentation of M_A demand; $\varepsilon_{MA,Y}$=1.095 on average for the full sample, implying $C_{MA,Y}$=0.024.[24] And although $\varepsilon_{MA,Y}>1$ implies scale effects are M_A-using, they are even more M_F-using, so in this sense they are relatively M_A-saving.

By contrast to the positive substitution and scale influences on M_A use, disembodied technological shift impacts on M_A demand have been negative, and in a direct sense, quite large. That is, an input-cost-diminution impact associated with M_A demand is evident ($C_{MA,t}$(tot) = -0.008 on average), that is typically interpreted as deriving from disembodied technical change. This trend is statistically relevant; the $\varepsilon_{MA,t}$ (tot) estimates are significantly different from zero for most individual observations.[25] And this tendency was augmented post-1980 ($C_{MA,t2}$ (tot) = -0.021).

The direct t- and t2- impacts are, however, much greater in magnitude than these total measures, since much of the direct trend effects are counteracted by effective price trends that may be interpreted as embodied technical change or adjustment costs, as alluded to above. These patterns can be seen from the decompositions of the total trend and structural change impacts in the first section of Table 2, that arise from the inclusion of t- terms in the p^*_{MA} and p^*_K (λ_{MA} and λ_K) specifications (as in equation (5)).

Recall that the full t impact is $\varepsilon_{MA,t}$ (tot) = $\varepsilon_{MA,t}$ (dir) + $\varepsilon_{MA,pMA} \bullet \varepsilon_{p*MA,t}$ + $\varepsilon_{MA,pK} \bullet \varepsilon_{p*K,t}$, so the indirect t-effect exhibited through the trend in $p*_{MA}$ is $C_{MA,p*MA,t} = \varepsilon_{MA,pMA} \bullet \varepsilon_{p*MA,t}$. For our scenario, although $\varepsilon_{MA,pMA} < 0$, since the trend component of $p*_{MA}$ is negative ($\varepsilon_{p*MA,t} = -0.125$), the indirect $p*_{MA}$ effect on M_A demand is positive – as is the $p*_K$ effect since K is a substitute but $p*_K$ is rising ($\varepsilon_{p*K,t} = 0.128$). Thus each of these components partially counteracts the large direct t-impact of -0.0525. This tendency is attenuated in the 1980s, however, since $\varepsilon_{p*MA,t2} = 0.073$ and $\varepsilon_{p*K,t} = -0.122$, so the negative $C_{MA,p*MA,t2}$ and $C_{MA,p*K,t2}$ terms further support the negative $C_{MA,t2}$(dir) = -0.013, causing the driving force of structural change in the 1980s to be M_A-saving.

This evidence is consistent with the embodied technical change interpretations of the t-impacts on effective prices implied by the discussions of the $p*_{MA}$ and $p*_K$ as compared to p_{MA} and p_K changes above. Declines in effective as compared to measured p_{MA}, and the reverse for p_K, both tend to augment M_A use. Escalation of the equipment-to-structure ratio, representing another form of embodied technical change, also had a positive (but statistically insignificant) impact on the demand for M_A; $C_{MA,ES} = 0.014$.

Total Cost Implications

In addition to the specific M_A impacts, the total cost effects of adaptations in the economic and technological climate are of interest individually, as well as providing indications of input biases (variations in M_A from overall input demand changes). The cost effect most directly associated with the use of M_A is represented by the $\varepsilon_{TC,pMA}$ = 0.025 elasticity, indicating the impact on costs of p_{MA} changes, which depends on the input intensity or average share of M_A for industries that use agricultural commodities.[26] This is larger than the corresponding elasticity for any other input; rising (falling) p_{MA}

has a substantive positive (negative) impact on production costs, and thus on output production/price, in the food processing industries. Note, however, that the overall p_{MA} contribution to total cost increases of $C_{TC,pMA}$=0.014 is not only smaller than that for capital (due to the high effective price of capital), but is also is even lower if the smaller increase in *effective* p_{MA} is recognized within this measure ($C^*_{TC,pMA}$, weighted by the change in p^*_{MA}, would be 0.008).

The $\varepsilon_{TC,Y}$ estimate of 0.868, which implies significantly increasing returns to scale, also deserves attention. This evidence is largely driven by a very small capital-output elasticity, that counteracts the $\varepsilon_{MA,Y}$ elasticity of slightly more than 1, and an $\varepsilon_{MF,Y}$ elasticity that is even higher (nearly twice that for M_A), which suggests scale expansion is somewhat M_A-using, and significantly K-saving and M_F-using.

This is of particular interest since this conclusion is closely linked to the inclusion of t in the λ_K and λ_{MA} specifications. When t is not included as an argument in these specifications (λ_{MAt}=λ_{MAt2}=0), output increases instead appear M_A-saving (ε_{MAY} is significantly smaller than 1), and both $\varepsilon_{K,Y}$ elasticity and $\varepsilon_{TC,Y}$ elasticity estimates are much closer to 1, implying close to constant returns to scale. These patterns highlight two issues alluded to above. First, apparent declines in the M_A-input-intensity of output production in the food industries are partly associated with increases in effective or quality-adjusted M_A-inputs, perhaps due to embodied technical change. Second, adjustment costs for capital implied by a higher and more quickly rising p^*_K than p_K may mean that these estimates should be interpreted as short-run, or at least capital-adjustment-constrained estimates. And both of these impacts, if ignored, affect estimation of the scale- or output-effects.

Finally, the elasticities associated with disembodied and capital-embodied technical change deriving from t and ES changes, and with structural changes in the 1980s (t2), suggest other technological forces have contributed to cost diminution. The negative (and significant) values for both $C_{TC,t}$ (dir) = -0.004 and $C_{TC,t2}$ (dir) = -0.012, augmented by the (insignificant) embodied technical change impact $C_{TC,ES}$ = -0.041, highlight such trends, and their enhancement in the 1980s, and from technological advance embodied in equipment. However, the total disembodied technical change impact becomes positive – $C_{TC,t}$ (tot) = 0.0004 – when the higher cost of capital (from the p^*_K trend) is recognized, even though the analogous effect for p^*_{MA} is in the opposite direction ($C_{TC,p^*MA,t}$ = -0.006). By contrast, $C_{TC,t2}$ (tot) is even more negative than its direct counterpart, since $C_{TC,p^*K,t2}$ = -0.0025 outweighs $C_{TC,p^*MA,t2}$ = 0.001.

Note also that the input-specific $C_{MA,t}$ (dir) = -0.0525 measure is much larger (in absolute value) than the associated *overall* input declines captured by $C_{TC,t}$ (dir) = -0.004, and the total M_A effect $C_{MA,t}$ (tot) is negative whereas that for TC, $C_{TC,t}$ (tot) is positive, indicating that "technical change" has been both relatively and absolutely, M_A-input-saving. Over time there has been a technical change bias toward reducing M_A use more than other inputs for a given level of output.[27]

Marginal Cost and Output Price

To move toward consideration of the pass-through of M_A prices (and other factors) to output price, as well as its impact on scale economies, we can compare these estimates to those for marginal cost in the third panel of Table 1. Note that the input price effects for the materials and labor inputs are slightly larger for MC than for total (and thus average) cost, implying a depressing impact on scale economies (MC increases more than AC with higher input prices, so their ratio rises). The reverse is true, however, for the p_K and p_E elasticities, supporting the notion that capital is subject to adjustment costs, and “lumpiness”, that are driving forces for returns to scale. This is also consistent with the virtually nonexistent MC impacts of changing output. And with the fact that marginal cost has decreased (statistically) significantly over time, both in terms of the direct and indirect effects, largely due to the smaller impact of p_K on MC than on TC.

Comparing these measures to those for p_Y provides some insights about markup (imperfectly competitive) behavior, and its determinants. The average $\varepsilon_{pY,pMA} = 0.272$ elasticity is larger than either $\varepsilon_{TC,pMA}$, or the (slightly smaller) $\varepsilon_{MC,pMA}$. So a 1 percent increase in p_{MA} drives a somewhat larger increase in AC than MC, and an even greater adaptation in p_Y than MC. This implies a higher markup p_Y/MC associated with a rise in p_{MA}, but also an increase in the scale economies that support such markups (since MC augmentation is lower than that for AC, so the associated profitability is less than would be implied for a constant returns technology).[28] Note also that p_Y decreases somewhat more than MC as time progresses, primarily due to the larger (indirect) p^*_{MA} effect.

Temporal and Industrial Variations

In addition to the indicators for the data averaged for the entire sample, it is useful to briefly consider variations in the estimates over time and by industry, which are presented in Tables 3 and 4, respectively.

The temporal decompositions presented in Table 3[29] show a much smaller depressing contribution of p_{MA} increases to M_A demand post-1980, that results from low p_{MA} growth; the measured $\varepsilon_{MA,pMA}$ elasticity is actually larger later in the sample. Also note that the trend in the effective price of M_A (p^*_{MA}) is actually downward for the post-

1980 period, so the full contribution of own price changes to M_A demand is positive. This tendency is particularly worth highlighting since measured p_{MA} changes that occurred after the end of our sample period (late 1990s) actually dropped, which implies that the implications from these measures may have been exacerbated. It also appears that although the growth rate of M_A demand in the 1980s was larger than in the 1970s, the individual input price contributions were generally smaller, with less of the growth arising from output increases. In fact, a large proportion of M_A demand expansion seems to have arisen from t-effects. In particular, the indirect p^*_{MA} effect has increased over time to the point where $C_{MA,t}$(tot) is positive post-1980, although the direct impact, $C_{MA,t}$(dir), reported in Table 2, remains negative (but smaller) in the later time period.

The TC measures for the 1970s as contrasted to the 1980s, presented in Table 3, indicate a much smaller average annual percentage increase in total costs for the food processing industries overall post-1980, that is only in part due to a slower output growth rate ($C_{TC,Y}$ is 0.019 in the 1970s and 0.015 post-1980, with slightly less scale economies implied in the later time period). All the contributions of individual TC determinants are smaller (the elasticities are lower as well as the changes in the arguments of the function), although they remain statistically significant.

In particular, the $\varepsilon_{TC,pMA}$ elasticity is slightly lower in the 1980s, but the contribution falls more since p_{MA} increased so little (in fact becoming negative if evaluated according to effective price changes). The (over)-estimate of the actual TC change in the 1980s seems to be driven by capital price effects, which appear in the $C_{TC,pK}$ measure of 0.014, as well as a positive $C_{TC,p^*K,t}$ measure of 0.009 which augments the direct $C_{TC,t}$(dir) = 0.004 (but is slightly counteracted by the downward TC contribution resulting from the negative $C_{p*Ma,t}$).[30]

Although a full analysis of the 3-digit industries within the food processing aggregate is beyond the scope of this study, it is worth briefly considering the differences in M_A demand that are apparent across these sub-samples, as reported in Table 4.

First note that for the meat products industries very little substitution (including own-price responsiveness) is apparent, as might be expected. The main impact on M_A changes during this sample period was from output demand. Note also that the t-effect is very small, at only about 10% the magnitude of that for these industries as a whole.

For the dairy industry, the own and cross-substitution responses seem similar to (a bit lower than) those for the overall food processing industries. But the t impact in total is very slightly positive, since the indirect adjustment – particularly the $C_{MA,p*MA,t}$ component – is quite large.

The vegetables sector of the industry seems to be fairly responsive to the own price of M_A. The $p*_K$ contribution, as well as the t elasticities (and their components) are also large. The substantial t impacts on $p*_{MA}$ and $p*_K$ in fact suggest a particularly significant amount of embodied technology in the primary agricultural vegetable inputs, as well as high and increasing adjustment costs, likely due to the great scale and processing expansion in this industry.

The grain mill and oil industries have exhibited quite different patterns.[31] We find a negative output impact on M_A demand for grains, both due to the very low ε_{MAY} elasticity (output increases have occurred with very little increase in primary inputs, likely due to expanding processing), and observed output declines for some observations.

Responsiveness to other (price and technical change) factors seems generally low in this industry, except perhaps for ES. For the oil industries, we find the own (p_{MA}) contribution to be smaller than for most industries, and even less responsiveness to prices of other inputs, and thus substitutability; the cross-demand contributions are only about half those for the food industries as a group. By contrast, the output response is the largest (by a small margin) of any other industry on average.

For sugar and confectionary products the own price contribution is by contrast very large, although other substitution effects are somewhat small relative to the other industries. The p_K impact is slightly more minor, and the $C_{MA,t}$ (tot) impact more major, than for the industry as a whole. And industries in the miscellaneous category have exhibited similar substitutability patterns to those apparent for the overall industry, except for very small capital/energy and technological (t,ES) contributions.

Impacts of M_A Price Changes

Finally, in Table 5 we report elasticities that facilitate an evaluation of responsiveness to p_{MA} changes, which may be thought of as a converse experiment to the evaluation of M_A demand changes that began our discussion of empirical results. These measures facilitate investigation of the potential implications of the declines in p_{MA} that were experienced by the food industries during the remainder of the 1990s not represented by our data sample.

Some evidence in this table also appeared in the decomposition tables; in particular, a 1 percent decline in the price of agricultural materials (holding other cost and demand determinants constant) would be expected to reduce total costs by $\varepsilon_{TC,pMA}$ = -.254% (with marginal costs declining by virtually the same amount, p_Y dropping slightly more, and all these responses falling over time), and increase M_A demand by $\varepsilon_{MA,pMA}$ = 1.137% (and more over time). The expected reduction in total cost can in turn be decomposed from the values reported in Table 5 into declines in all other factors of production, with L and K decreasing the least relative to the average, and other materials (M_O) falling the most. The responsiveness of the materials inputs, however, is clearly rising over time, and that for the value added (K and L) inputs falling.[32]

Concluding Remarks

In this study we have investigated the production structure of the U.S. food processing industries, with a focus on the role and impact of agricultural input (M_A) markets. Our results show that the demand for primary agricultural inputs in the food processing industries, and overall production costs, have been increasingly impacted over time, but in contradictory directions, by a broad range of production factors. These factors include input price changes (and substitutability), output demand changes (and scale effects), interrelationships with capital (and associated embodied technical change and adjustment costs), and both disembodied technical change and innovations embodied in the agricultural materials input from technical progress in the agricultural sector.

In particular, our data suggest that although M_A use has risen less than the demand for M_F (intermediate food products) in the food processing industries overall between 1972 and 1992, it has increased more than both other-input use and output production, especially in the latter part of our sample. During this period growth in the price of agricultural commodities has fallen off, and the effective price of agricultural materials has dropped further relative to its measured price, reducing the own-price impact that would stimulate declines in M_A demand, and in fact reversing it in the 1980s.

This is to some extent related to an increasing price elasticity of demand for agricultural materials, which was also found by Goodwin and Brester. M_A demand has been further stimulated, at least to some extent, by substitution among inputs, and especially from effective capital price increases.

Expansion in output demand has also has augmented M_A demand, since at least when effective prices are taken into account output increases have been associated with slightly greater than proportional M_A changes on average. However, this is not true relative to M_F use, since scale biases are much more M_F-input-using. We also find a declining effect of agricultural materials prices on output prices, which provides an indication of a weakening linkage between the primary and processed foods markets.

Technical change embodied in capital equipment also appears to have enhanced M_A use, but this impact is statistically insignificant, whereas disembodied technical change has clearly driven declines in M_A use, holding all other determining factors constant. The direct t-impact has been large and negative, particularly in the early part of the sample period, and has only been partially counteracted by the positive technological impacts embodied in the effective M_A and K prices. The implied drop in primary agricultural product demand has also been stronger than the overall cost diminution effect, which implies a relative M_A-input-saving bias. And the post-1980 (t2) structural change impact suggests that this trend is intensifying, and is further exacerbated by diminishing effective price (p^*_{MA} and p^*_K) changes.

Overall, the measured share of primary agricultural materials in total costs has been dropping, so the contribution of M_A price increases to cost changes has fallen over time. Thus, the link between M_A demand and costs of production has weakened, especially compared to capital due to its higher and increasing effective price, and in relative terms to partly processed food inputs, M_F. These patterns are largely due to output effects and disembodied technical changes, that are likely associated with output demand adaptations. However, a complex combination of economic, technological and demand forces have contributed to changing the role of agricultural materials in the food processing industries.

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Table 1: decompositions, full sample average										
	Agricultural Materials					*Total Cost*				
full change										
	% Δ MA			***actual***	***0.0381***	***% Δ TC***			***actual***	***0.0839***
price impacts			**contribution**		*(weight x % Δ)*			**contribution**		
				(denotes significant at 5% level)*						
=	$\varepsilon_{MA,pMA}$	-1.1375				$\varepsilon_{TC,pMA}$	0.2497			
x	$\%\Delta p_{MA}$	0.0547	=	$C_{MA,pMA}$	-0.0622*	$\%\Delta p_{MA}$	0.0547	=	$C_{TC,pMA}$	0.0137*
+	$\varepsilon_{MA,pMF}$	0.0868				$\varepsilon_{TC,pMF}$	0.1031			
x	$\%\Delta p_{MF}$	0.0403	+	$C_{MA,pMF}$	0.0035	$\%\Delta p_{MF}$	0.0403	+	$C_{TC,pMF}$	0.0042*
+	$\varepsilon_{MA,pMO}$	0.2399				$\varepsilon_{TC,pMO}$	0.1293			
x	$\%\Delta p_{MO}$	0.0653	+	$C_{MA,pMO}$	0.0157*	$\%\Delta p_{MO}$	0.0653	+	$C_{TC,pMO}$	0.0084*
+	$\varepsilon_{MA,pL}$	0.1306				$\varepsilon_{TC,pL}$	0.0836			
x	$\%\Delta p_{L}$	0.0908	+	$C_{MA,pL}$	0.0119	$\%\Delta p_{L}$	0.0908	+	$C_{TC,pL}$	0.0076*
+	$\varepsilon_{MA,pK}$	0.6490				$\varepsilon_{TC,pK}$	0.4213			
x	$\%\Delta p_{K}$	0.0680	+	$C_{MA,pK}$	0.0441*	$\%\Delta p_{K}$	0.0680	+	$C_{TC,pK}$	0.0287*
+	$\varepsilon_{MA,pE}$	0.0312				$\varepsilon_{TC,pE}$	0.0130			
x	$\%\Delta p_{E}$	0.1186	+	$C_{MA,pE}$	0.0037*	$\%\Delta p_{E}$	0.1186	+	$C_{TC,pE}$	0.0015*
output effect										
+	$\varepsilon_{MA,Y}$	1.0946				$\varepsilon_{TC,Y}$	0.8677			
x	$\%\Delta Y$	0.0218	+	$C_{MA,Y}$	0.0238*	$\%\Delta Y$	0.0218	+	$C_{TC,Y}$	0.0191*
embodied tech										
+	$\varepsilon_{MA,ES}$	0.7159				$\varepsilon_{TC,ES}$	-0.0176			
x	$\%\Delta ES$	0.0200	+	$C_{MA,ES}$	0.0143	%+H39ΔI	0.0200	+	$C_{TC,ES}$	-0.0008
disembodied (total)										
+	$\varepsilon_{MA,t}$ (tot)	-0.0390	+	$C_{MA,t}$(tot)	-0.0078*	$\varepsilon_{TC,t}$ (tot)	-0.0354	+	$C_{TC,t}$(tot)	0.0004*
+	$\varepsilon_{MA,t2}$(tot)	-0.4248	+	$C_{MA,t2}$(tot	-0.0207*	$\varepsilon_{TC,t2}$(tot)	0.0187		$C_{TC,t2}$(tot)	-0.0141*
=	***% Δ MA (tot)***			***estimate***	***0.0439***	***% Δ TC (tot)***			***estimate***	***0.0813***
	Marginal Cost					*Output Price*				
full change										
	% Δ MC			***actual***	***0.0540***	***% Δ p_Y***			***actual***	***0.0573***
price impacts			**contribution**					**contribution**		
	$\varepsilon_{MC,pMA}$	0.2533				$\varepsilon_{pY,pMA}$	0.2725			
x	$\%\Delta p_{MA}$	0.0547	=	$C_{MC,pMA}$	0.0139	$\%\Delta p_{MA}$	0.0547	=	$C_{pY,pMA}$	0.0149*
+	$\varepsilon_{MC,pMF}$	0.2080				$\varepsilon_{pY,pMF}$	0.2131			
x	$\%\Delta p_{MF}$	0.0403	+	$C_{MC,pMF}$	0.0084*	$\%\Delta p_{MF}$	0.0403	+	$C_{pY,pMF}$	0.0086*
+	$\varepsilon_{MC,pMO}$	0.1938				$\varepsilon_{pY,pMO}$	0.2078			
x	$\%\Delta p_{MO}$	0.0653	+	$C_{MC,pMO}$	0.0127*	$\%\Delta p_{MO}$	0.0653	+	$C_{pY,pMO}$	0.0136*
+	$\varepsilon_{MC,pL}$	0.1611				$\varepsilon_{pY,pL}$	0.1732			
x	$\%\Delta p_{L}$	0.0908	+	$C_{MC,pL}$	0.0146*	$\%\Delta p_{L}$	0.0908	+	$C_{pY,pL}$	0.0157*
+	$\varepsilon_{MC,pK}$	0.1773				$\varepsilon_{pY,pK}$	0.1887			
x	$\%\Delta p_{K}$	0.0680	+	$C_{MC,pK}$	0.0121*	$\%\Delta p_{K}$	0.0680	+	$C_{pY,pK}$	0.0128*
+	$\varepsilon_{MC,pE}$	0.0065				$\varepsilon_{pY,pE}$	0.0086			
x	$\%\Delta p_{E}$	0.1186	+	$C_{MC,pE}$	0.0008*	$\%\Delta p_{E}$	0.1186	+	$C_{pY,pE}$	0.0010*
output effect										
+	$\varepsilon_{MC,Y}$	-0.0157				$\varepsilon_{pY,Y}$	-0.0776			
x	$\%\Delta Y$	0.0218	+	$C_{MC,Y}$	-0.0003	$\%\Delta Y$	0.0218	+	$C_{pY,Y}$	-0.0017
embodied tech										
+	$\varepsilon_{MC,ES}$	0.0328				$\varepsilon_{pY,ES}$	0.0340			
x	$\%\Delta ES$	0.0200	+	$C_{MC,ES}$	0.0007	$\%\Delta ES$	0.0200	+	$C_{pY,ES}$	0.0007
disembodied (total)										
+	$\varepsilon_{MC,t}$(tot)	-0.0139*	+	$C_{MC,t}$(tot)	-0.0028*	$\varepsilon_{PY,t}$ (tot)	-0.0149	+	$C_{PY,t}$(tot)	-0.0030*
	$\varepsilon_{MC,t2}$(tot)	-0.0042*		$C_{MC,t2}$(tot	-0.0002*	$\varepsilon_{PY,t2}$(tot)	-0.0042*		$C_{PY,t2}$(tot)	-0.0002*
	% Δ MC (tot)			***estimate***	***0.0634***	***% Δ p_Y (tot)***			***estimate***	***0.0654***

Table 2: disembodied technical change: direct and indirect effects

	Agricultural Materials				*Total Cost*		
Full Sample							
	$C_{MA,t}$ (tot)	-0.0078*			$C_{TC,t}$ (tot)	0.0004*	
	=	$C_{MA,t}$ (dir)	-0.0525*		=	$C_{TC,t}$ (dir)	-0.0042*
	+	$C_{MA,p*MA,t}$	0.0284*		+	$C_{TC,p*MA,t}$	-0.0062*
	+	$C_{MA,p*K,t}$	0.0166*		+	$C_{TC,p*K,t}$	0.0108*
	$C_{MA,t2}$ (tot)	-0.0207*			$C_{TC,t2}$ (tot)	-0.0141*	
	=	$C_{MA,t2}$ (dir)	-0.0126*		=	$C_{TC,t2}$ (dir)	-0.0123*
	+	$C_{MA,p*MA,t2}$	-0.0041*		+	$C_{TC,p*MA,t2}$	0.0009*
	+	$C_{MA,p*K,t2}$	-0.0039*		+	$C_{TC,p*K,t2}$	-0.0025*
1970s	$C_{MA,t}$ (tot)	-0.0235*			$C_{TC,t}$ (tot)	-0.0071*	
	=	$C_{MA,t}$ (dir)	-0.0632*		=	$C_{TC,t}$ (dir)	-0.0126*
	+	$C_{MA,p*MA,t}$	0.0222*		+	$C_{TC,p*MA,t}$	-0.0062*
	+	$C_{MA,p*K,t}$	0.0174*		+	$C_{TC,p*K,t}$	0.0118*
	$C_{MA,t2}$ (tot)	-0.006*			$C_{TC,t2}$ (tot)	-0.0052*	
	=	$C_{MA,t2}$ (dir)	-0.0126*		=	$C_{TC,t2}$ (dir)	-0.0026*
	+	$C_{MA,p*MA,t2}$	-0.0054*		+	$C_{TC,p*MA,t2}$	0.0011*
	+	$C_{MA,p*K,t2}$	-0.0060*		+	$C_{TC,p*K,t2}$	-0.0036*
1980s	$C_{MA,t}$ (tot)	0.0076*			$C_{TC,t}$ (tot)	0.0078*	
	=	$C_{MA,t}$ (dir)	-0.0420*		=	$C_{TC,t}$ (dir)	0.0041*
	+	$C_{MA,p*MA,t}$	0.0353*		+	$C_{TC,p*MA,t}$	-0.0061*
	+	$C_{MA,p*K,t}$	0.0147*		+	$C_{TC,p*K,t}$	0.0092*
	$C_{MA,t2}$ (tot)	0.0000			$C_{TC,t2}$ (tot)	0.0000	

Table 3: temporal decompositions

full change, 70s

	% Δ MA			*actual*	***0.0360***	*% Δ TC*			*actual*	***0.1386***
price impacts			**contribution**		*(weight x % Δ)*			**contribution**		
=	$\varepsilon_{MA,pMA}$	-0.9731				$\varepsilon_{TC,pMA}$	0.2734			
x	$\%\Delta p_{MA}$	0.1021	=	$C_{MA,pMA}$	-0.0994	$\%\Delta p_{MA}$	0.1021	=	$C_{TC,pMA}$	0.0279
+	$\varepsilon_{MA,pMF}$	0.0791				$\varepsilon_{TC,pMF}$	0.1096			
x	$\%\Delta p_{MF}$	0.0687	+	$C_{MA,pMF}$	0.0054	$\%\Delta p_{MF}$	0.0687	+	$C_{TC,pMF}$	0.0075
+	$\varepsilon_{MA,pMO}$	0.2094				$\varepsilon_{TC,pMO}$	0.1382			
x	$\%\Delta p_{MO}$	0.1048	+	$C_{MA,pMO}$	0.0219	$\%\Delta p_{MO}$	0.1048	+	$C_{TC,pMO}$	0.0145
+	$\varepsilon_{MA,pL}$	0.1082				$\varepsilon_{TC,pL}$	0.0951			
x	$\%\Delta p_{L}$	0.1334	+	$C_{MA,pL}$	0.01443	$\%\Delta p_{L}$	0.1334	+	$C_{TC,pL}$	0.0127
+	$\varepsilon_{MA,pK}$	0.5484				$\varepsilon_{TC,pK}$	0.3715			
x	$\%\Delta p_{K}$	0.1076	+	$C_{MA,pK}$	0.0590	$\%\Delta p_{K}$	0.1076	+	$C_{TC,pK}$	0.0400
+	$\varepsilon_{MA,pE}$	0.0281				$\varepsilon_{TC,pE}$	0.0122			
x	$\%\Delta p_{E}$	0.2410	+	$C_{MA,pE}$	0.0068	$\%\Delta p_{E}$	0.2410	+	$C_{TC,pE}$	0.0030
output effect										
+	$\varepsilon_{MA,Y}$	1.0452				$\varepsilon_{TC,Y}$	0.8677			
x	$\%\Delta Y$	0.0266	+	$C_{MA,Y}$	0.0278	$\%\Delta Y$	0.0266	+	$C_{TC,Y}$	0.0191*
embodied tech										
+	$\varepsilon_{MA,ES}$	0.7008				$\varepsilon_{TC,ES}$	-0.0189			
x	$\%\Delta ES$	0.0244	+	$C_{MA,ES}$	0.0171	$\%\Delta ES$	0.0244	+	$C_{TC,ES}$	0.0238*
disembodied (total)										
+	$\varepsilon_{MA,t}$(tot)	-0.1174	+	$C_{MA,t}$(tot)	-0.0235	$\varepsilon_{TC,t}$(tot)	0.0020	+	$C_{TC,t}$(tot)	0.0004*
+	$\varepsilon_{MA,t2}$(tot)	-0.0608	+	$C_{MA,t2}$(tot	-0.0060	$\varepsilon_{TC,t2}$(tot)	-0.2530*		$C_{TC,t2}$(tot)	-0.0123*
=	*% Δ MA (tot)*			*estimate*	***0.0302***	*% Δ TC (tot)*			*estimate*	***0.0813***

full change, 80s

	% Δ MA			*actual*	***0.0402***	*% Δ TC*			*actual*	***0.0300***
price impacts			**contribution**		*(weight x % Δ)*			**contribution**		
=	$\varepsilon_{MA,pMA}$	-1.2992				$\varepsilon_{TC,pMA}$	0.2263			
x	$\%\Delta p_{MA}$	0.0080	=	$C_{MA,pMA}$	-0.0104	$\%\Delta p_{MA}$	0.0080	=	$C_{TC,pMA}$	0.0018
+	$\varepsilon_{MA,pMF}$	0.0943				$\varepsilon_{TC,pMF}$	0.0967			
x	$\%\Delta p_{MF}$	0.0123	+	$C_{MA,pMF}$	0.0012	$\%\Delta p_{MF}$	0.0123	+	$C_{TC,pMF}$	0.0012
+	$\varepsilon_{MA,pMO}$	0.2699				$\varepsilon_{TC,pMO}$	0.1206			
x	$\%\Delta p_{MO}$	0.0264	+	$C_{MA,pMO}$	0.0071	$\%\Delta p_{MO}$	0.0264	+	$C_{TC,pMO}$	0.0032
+	$\varepsilon_{MA,pL}$	0.1527				$\varepsilon_{TC,pL}$	0.0723			
x	$\%\Delta p_{L}$	0.0489	+	$C_{MA,pL}$	0.0075	$\%\Delta p_{L}$	0.0489	+	$C_{TC,pL}$	0.0035
+	$\varepsilon_{MA,pK}$	0.7479				$\varepsilon_{TC,pK}$	0.4703			
x	$\%\Delta p_{K}$	0.0291	+	$C_{MA,pK}$	0.0217	$\%\Delta p_{K}$	0.0291	+	$C_{TC,pK}$	0.0137
+	$\varepsilon_{MA,pE}$	0.0343				$\varepsilon_{TC,pE}$	0.0138			
x	$\%\Delta p_{E}$	-0.0019	+	$C_{MA,pE}$	-0.00007	$\%\Delta p_{E}$	-0.0019	+	$C_{TC,pE}$	-0.00003
output effect										
+	$\varepsilon_{MA,Y}$	1.1433				$\varepsilon_{TC,Y}$	0.8871			
x	$\%\Delta Y$	0.0170	+	$C_{MA,Y}$	0.0194	$\%\Delta Y$	0.0170	+	$C_{TC,Y}$	0.0150
embodied tech										
+	$\varepsilon_{MA,ES}$	0.7307				$\varepsilon_{TC,ES}$	-0.0592			
x	$\%\Delta ES$	0.0156	+	$C_{MA,ES}$	0.0114	$\%\Delta ES$	0.0156	+	$C_{TC,ES}$	-0.0009
disembodied (total)										
+	$\varepsilon_{MA,t}$(tot)	0.0381	+	$C_{MA,t}$(tot)	0.0076	$\varepsilon_{TC,t}$(tot)	0.0388	+	$C_{TC,t}$(tot)	0.0077
+	$\varepsilon_{MA,t2}$(tot)	-0.7828	+	$C_{MA,t2}$(tot	0.0000	$\varepsilon_{TC,t2}$(tot)	-0.5203		$C_{TC,t2}$(tot)	0.0000
=	*% Δ MA (tot)*			*estimate*	***0.0573***	*% Δ TC (tot)*			*estimate*	***0.0483***

Table 4: industry decompositions, MA

	meat			***dairy***			***vegetables***			***grains***	
full change			**full change**			**full change**			**full change**		
	% Δ MA			*% Δ MA*			*% Δ MA*			*% Δ MA*	
	actual	0.0307		*actual*	0.0140		*actual*	0.0895		*actual*	0.0427
contribution			**contribution**			**contribution**			**contribution**		
	(weight x % Δ)			*(weight x % Δ)*			*(weight x % Δ)*			*(weight x % Δ)*	
=	$C_{MA,pMA}$	-0.0015	=	$C_{MA,pMA}$	-0.0521	=	$C_{MA,pMA}$	-0.0634	=	$C_{MA,pMA}$	-0.0297
+	$C_{MA,pMF}$	0.0001	+	$C_{MA,pMF}$	0.0034	+	$C_{MA,pMF}$	0.0071	+	$C_{MA,pMF}$	0.0017
+	$C_{MA,pMO}$	0.0006	+	$C_{MA,pMO}$	0.0136	+	$C_{MA,pMO}$	0.0212	+	$C_{MA,pMO}$	0.0127
+	$C_{MA,pL}$	0.0003	+	$C_{MA,pL}$	0.0104	+	$C_{MA,pL}$	0.0150	+	$C_{MA,pL}$	0.0093
+	$C_{MA,pK}$	0.0015	+	$C_{MA,pK}$	0.0354	+	$C_{MA,pK}$	0.0626	+	$C_{MA,pK}$	0.0339
+	$C_{MA,pE}$	0.0001	+	$C_{MA,pE}$	0.0029	+	$C_{MA,pE}$	0.0053	+	$C_{MA,pE}$	0.0025
+	$C_{MA,Y}$	0.0344	+	$C_{MA,Y}$	0.0338	+	$C_{MA,Y}$	0.0339	+	$C_{MA,Y}$	0.0033
+	$C_{MA,ES}$	0.0004	+	$C_{MA,ES}$	0.0033	+	$C_{MA,ES}$	0.0252	+	$C_{MA,ES}$	0.0182
+	$C_{MA,t}$(tot)	-0.0008	+	$C_{MA,t}$(tot)	0.0007	+	$C_{MA,t}$(tot)	-0.0188	+	$C_{MA,t}$(tot)	-0.0045
+	$C_{MA,t2}$(tot	-0.0006	+	$C_{MA,t2}$(tot	-0.0191	+	$C_{MA,t2}$(tot	-0.0242	+	$C_{MA,t2}$(tot	-0.0151
($C_{MA,p*MA,t}$		0.0008)	($C_{MA,p*MA,t}$		0.0238)	($C_{MA,p*MA,t}$		0.0377)	($C_{MA,p*MA,t}$		0.0233)
($C_{MA,p*K,t}$		0.0006)	($C_{MA,p*K,t}$		0.0133)	($C_{MA,p*K,t}$		0.0241)	($C_{MA,p*K,t}$		0.0127)
=	*% Δ MA*		=	*% Δ MA*		=	*% Δ MA*		=	*% Δ MA*	
	est'd	0.0328	*est'*	0.0229		*est'*	0.0849		*est'*	0.0410	0.0328

	sugar			***oils***			***beverages***			***misc***	
full change			**full change**			**full change**			**full change**		
	% Δ MA			*% Δ MA*			*% Δ MA*			*% Δ MA*	
	actual	0.0218		*actual*	0.0068		*actual*	0.0493		*actual*	-0.0022
contribution			**contribution**			**contribution**			**contribution**		
	(weight x % Δ)			*(weight x % Δ)*			*(weight x % Δ)*			*(weight x % Δ)*	
=	$C_{MA,pMA}$	-0.0689	=	$C_{MA,pMA}$	-0.0256	=	$C_{MA,pMA}$	-0.1025	=	$C_{MA,pMA}$	-0.0542
+	$C_{MA,pMF}$	0.0011	+	$C_{MA,pMF}$	0.0014	+	$C_{MA,pMF}$	0.0088	+	$C_{MA,pMF}$	0.0018
+	$C_{MA,pMO}$	0.0103	+	$C_{MA,pMO}$	0.0086	+	$C_{MA,pMO}$	0.0309	+	$C_{MA,pMO}$	0.0062
+	$C_{MA,pL}$	0.0083	+	$C_{MA,pL}$	0.0064	+	$C_{MA,pL}$	0.0285	+	$C_{MA,pL}$	0.0044
+	$C_{MA,pK}$	0.0277	+	$C_{MA,pK}$	0.0228	+	$C_{MA,pK}$	0.1053	+	$C_{MA,pK}$	0.0173
+	$C_{MA,pE}$	0.0028	+	$C_{MA,pE}$	0.0020	+	$C_{MA,pE}$	0.0102	+	$C_{MA,pE}$	0.0014
+	$C_{MA,Y}$	0.0156	+	$C_{MA,Y}$	0.0315	+	$C_{MA,Y}$	0.0254	+	$C_{MA,Y}$	0.0003
+	$C_{MA,ES}$	0.0145	+	$C_{MA,ES}$	0.0093	+	$C_{MA,ES}$	0.0098	+	$C_{MA,ES}$	0.0057
+	$C_{MA,t}$(tot)	-0.0102	+	$C_{MA,t}$(tot)	-0.0072	+	$C_{MA,t}$(tot)	-0.0128	+	$C_{MA,t}$(tot)	-0.0034
+	$C_{MA,t2}$(tot	-0.0128	+	$C_{MA,t2}$(tot	-0.0136	+	$C_{MA,t2}$(tot	-0.0512	+	$C_{MA,t2}$(tot	-0.0117
($C_{MA,p*MA,t}$		0.0160)	($C_{MA,p*MA,t}$		0.0128)	($C_{MA,p*MA,t}$		0.0645)	($C_{MA,p*MA,t}$		0.0145)
($C_{MA,p*K,t}$		0.0103)	($C_{MA,p*K,t}$		0.0086)	($C_{MA,p*K,t}$		0.0396)	($C_{MA,p*K,t}$		0.0065)
=	*% Δ MA*		=	*% Δ MA*		=	*% Δ MA*		=	*% Δ MA*	
	est'd	-0.0037		*est'd*	0.0410		*est'd*	0.0949		*est'd*	-0.0049

Table 5: p_{MA} change impacts for a 1% price decline

	total	*70s*	*80s*	*meat*	*dairy*	*vegetables*	*grains*	*sugar*	*oils*	*beverages*	*misc*
	(denotes significant at 5% level)*										
changes	**% impact**										
TC	-0.250*	-0.273	-0.226	-0.585	-0.254	-0.093	-0.214	-0.215	-0.503	-0.125	-0.423
MA	1.137*	0.973	1.299	0.037	0.919	1.655	0.876	0.715	0.595	2.718	0.445
MF	-0.225	-0.168	-0.282	-0.023	-0.025	-0.138	-0.055	-0.054	-0.745	-0.058	-1.339
MO	-0.476*	-0.433	-0.519	-0.075	-0.229	-0.081	-0.202	-0.646	-1.401	-1.501	-0.306
L	-0.164	-0.170	-0.157	-0.018	-0.197	-0.069	-0.124	-0.197	-0.390	-0.260	-0.154
K	-0.147*	-0.178	-0.116	-0.121	-0.130	-0.092	-0.121	-0.193	-0.212	-0.172	-0.225
E	-0.275*	-0.295	-0.256	-0.056	-0.281	-0.207	-0.241	-0.362	-0.216	-0.350	-0.464
MC	-0.253*	-0.287	-0.220	-0.513	-0.375	-0.134	-0.159	-0.259	-0.566	-0.202	-0.149
p_Y	-0.272*	-0.308	-0.237	-0.473	-0.381	-0.137	-0.166	-0.328	-0.560	-0.300	-0.147

Footnotes

[1] Although we have data for 40 industries, since 6 use no primary agricultural inputs (such as bakery, which uses flour but not wheat directly), these industries were deleted from the sample.
[2] The latter case is typically interpreted as increased demand putting cost pressure on suppliers.
[3] See Morrison [1985] or Morrison and Siegel for further discussion of a more detailed representation of quasi-fixity, including in the latter case a dynamic structure explicitly capturing adjustment costs. Paul [1999, 2000] also specifies fuller models of market structure. For the current study, however, the limited impact of these imperfections on the estimates for this largely cross-section data set seem sufficiently captured by the virtual price model.
[4] That is, incorporating x_k directly into the cost function allows the deviation of the market and shadow price, Z_k-p_k, to depend on all arguments of the function if VC($\bullet$) has a sufficiently flexible functional form. However, the cross-terms in this case were insignificant in preliminary empirical investigation, so this more complex model seemed unnecessary. Also, the chosen p^*_k characterization allows estimating equations to be specified for the x_k factors, which adds structure, and thus facilitates obtaining significant x_k coefficients.
[5] See Fulginiti and Perrin [1993] for a motivation and development of a similar approach.
[6] Ball and Chambers instead use equipment and structures measures separately in their exploration of substitution, scale, and trend effects in the meat processing industry. We found, however, that this disaggregation generated multicollinearity problems, and so left capital in its aggregated form.
[7] The resulting measures should therefore be interpreted as "within" estimates; they are relative to industry-specific means and thus reflect intra-industry variation.
[8] By contrast to the p^*_K and p^*_{MA} treatments above, this expression simply but directly recognizes the dependence of the wedge between p_Y and p^*_Y on the output level due to imperfect markets.
[9] Causation issues emerge for estimation of this equation if perfect competition prevails and thus p_Y is exogenous. But for the more general case, which might well be assumed for our scenario, p_Y is affected by the choice of Y so the price and quantity of output become joint decisions.
[10] Note that λ_Y represents the slope of the output demand function so only arguments with second order effects (impacts on the slope as well as just a shift impact) would appear in $\lambda_Y(\bullet)$. Fixed effects to reflect industry-specific differences were also incorporated for estimation of p^*_Y.
[11] Note that the ε_{TC,p^*k} elasticities are weighted by the observed changes in p_k, since (as elaborated below) we have expanded our interpretation of the t effect to include the indirect effect via the dp^*_k/dt trend, so this impact is double-counted if it also appears multiplicatively with ε_{TC,p^*k}.
[12] For our analysis, therefore, the impact is captured for 1977-82 since t_2 is defined as one for the 1982, 1987 and 1992 time periods. Note also that since the time dimension of our data is over 5-year intervals, to make these changes into annual averages these measures are divided by 5.
[13] Note also that there is a direct relationship between, for example, the $\varepsilon_{MA,Y}$ elasticity discussed above and the $\varepsilon_{MC,pMA}$ elasticity. The 2nd order derivative both measures are based on are equal by Young's theorem (and imposed by symmetry); $\partial^2TC/\partial p_{MA}\partial Y=\partial^2TC/\partial Y\partial p_{MA}$. Thus their signs will be the same, although their magnitudes will deviate due to the different multiplicative factors incorporated in the elasticity computation. Similarly, information on substitution between M_A and M_F from the $\varepsilon_{MA,pMF}$ elasticity has implications for the substitution impact on M_F from a p_{MA} change, as elaborated in the next section.
[14] This is somwhat more complex for the output elasticity, for which $\varepsilon_{AC,Y} = \varepsilon_{TC,Y}$-1 is the average cost elasticity, based on the quotient rule for AC=TC/Y.
[15] Establishments are required to report consumption of major materials that are important components of production costs, where important is defined as expenditures exceeding a given value – usually $10,000.

[16] Dummies for M_A=0 and M_F=0 observations analogous to those for the 3-digit industries were initially included to act as shifters in the M_A and M_F demand equations for industries in which these materials inputs are not used, although these estimates tended to be statistically insignificant. For the final estimation results, however, since our focus is on M_A use, the M_A=0 industries were removed from the sample.

[17] One issue of significance worth specific mention is the neither the λ_{MA1} or λ_{MA2} estimates in the final specification reach statistical significance at the 5% level. This was primarily due to insignificance of the simple shift factor, λ_{MA1}, since if this is set to zero λ_{MA2} is significant. However, the measured elasticities varied negligibly with this adaptation, so to retain symmetry of the virtual price treatments we retained both parameters in the specification.

[18] We used the ANALYZ command in PC-TSP to construct these estimates, which required evaluating the significance for a single data point. We alternatively constructed t-statistics for the elasticities for individual observations and for averaged data.

[19] Note that the observed and estimated changes in the dependent variables in this exercise sometimes are very similar but in other cases vary quite a bit. This variation is to be expected due to the estimation in levels (and then imputing differences), as well as the cross-section nature of the data and the averaging process used to construct final estimates.

[20] These contributions were computed by multiplying the averaged elasticity and price change measures, rather than averaging the multiplied measures. Although most measure differ little across these two methods, the $C_{MA,pMA}$ and $C_{MA,Y}$ contribution does appear larger this way than it does when the contributions are first computed and then averaged (-0.62 as compared to -0.44 for the former, and 0.24 versus .017 for the latter).

[21] The values for p^*_{MA} and p^*_K changes are not included in the tables, in order to keep the presentation as simple as possible, since they are not directly crucial to the analysis, and are indirectly implied by the $C_{MA,p^*MA,t}$ (for example) terms in Table 2.

[22] Monopsony power is not evident overall for these markets, unless it is counteracted by quality changes, since it is generally (and on average) the case that $p^*_{MA}<p_{MA}$ rather than the reverse.

[23] Note also that the p^*_{MA}-p_{MA} gap might be affected by quality change in the agricultural commodity marketing system between the farm gate and the processing plant. For example, quality changes that could be stemming from improvements in transportation, storage, cleaning, and sorting would not directly be measured here since the PPIs that provide the basis for our market price measures are measured at the farm, and M_A demand at the processing plant.

[24] The * for this measure in the table denotes significantly different from one, the comparison point, rather than zero.

[25] However, since the average t stays constant the t-impact is essentially neutralized for the averaged data used for computation of the t-statistics.

[26] The bakery industry, for example, uses no primary agricultural products, but instead relies on partially processed materials such as those from the grain industry.

[27] These patterns contrast with statements made by Heien that suggest technical change generally increases the marginal product of farm output.

[28] This pattern is also evident for p_{MF} increases, although in this case the input price change affects the MC-AC difference more than the p_Y-MC deviation.

[29] Since the statistical significance of the estimates varies negligibly across data points, so the statistical significance of the averages is representative of that for the sub-samples, the *'s denoting significance are left out of these tables.

[30] The t2 measures for the 1980s are zero, since 1977-82 growth is reflected in the first time period, and this is when the t2 dummy variable exhibits its impact since it becomes 1 in 1982.

[31] These industries are often reported in a group with the bakery industry, but, as noted above, the bakery industry was omitted here since it does not report any primary agricultural materials use.

[32] Note that although the signs of these measures are established by the inverse second order elasticities, such as $\varepsilon_{MA,Y}$ as compared to $\varepsilon_{MC,pMA}$, and $\varepsilon_{MA,pMF}$ versus $\varepsilon_{MF, pMA}$, the magnitudes of the elasticities depend on the price and quantity levels and therefore differ.