Strategy and Policy in the Food System: Emerging Issues

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5. Automation or Openness?: Technology and Trade Impacts on Costs and Labor Composition in the Food System

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Introduction

U.S. manufacturing industries have experienced great changes in productivity and input composition since the early 1980s. The food processing industry has not been immune to these trends; in fact some studies have suggested that permanent structural changes affecting pricing behavior, productivity, scale economies, employment, and investment patterns have occurred in the food system. This has important implications for competitive success (which depends on improvements in efficiency), and for labor demand and composition (which affects the welfare of laborers) in this large and important industry.

The food processing industry is a major force affecting the economic performance of the U.S. manufacturing sector. This industry is nearly as large as the farm sector—processors added $120 billion in value to raw farm products in 1994, compared to the $160 billion value of total raw farm goods and $110 billion value of nonexported farm goods (see Gallo 1995). In addition, the capital intensity of the food processing industry makes it particularly sensitive to technological development. Therefore, the major technological advances of the past decades have likely had a strong effect on economic performance and employment patterns in this industry. The competitiveness of the food system also suggests that the increased openness of the U.S. economy has had important impacts.

Thus, the common perception that observed changes in productivity (costs), and input and labor composition in U.S. manufacturing are linked to either particular types of technological change ("automation") or the increasing openness of the economy (international competitiveness) may have strong credence in this industry. In particular, it has been hypothesized in the expanding literature on technological and trade (tech/trade) impacts in the manufacturing sector overall, that these factors have not only changed capital investment behavior, but have had a great impact on the observed stagnation and increased inequality of employment and wages for different types of workers. These input-specific issues underlie the more overall question of how these impacts have affected costs, and therefore efficiency and productivity.

However, analysis of these patterns and their tech/trade determinants remains sparse, especially for the food processing industry, and particularly with respect to labor composition effects. Some insights about these patterns for the food system can be gained from studies (such as Huang 1991 and Goodwin and Brester 1995), who find labor/capital substitution but do not recognize capital fixity, different labor components, or external capital effects.

More recently, Morrison (1996) found that although there appears to be some trend toward increasing markup behavior in the U.S. food processing sector, most major structural patterns in this industry appear to stem from the cost side. In particular, short-run utilization fluctuations (from capital fixity, investment, and composition), their tech/trade determinants, and their input-specific effects seem to be a driving force behind economic performance—including markup behavior—in this industry. In addition, although long-run scale economies were not evident, the constant overall cost-output relationships veiled important input-specific economies.

In terms of tech/trade impacts, this study suggests that costs overall were diminished by external effects from both competitiveness (trade) and knowledge capital (general technological advance or automation), and that the cost patterns were heavily affected by the impacts on labor use. Labor as a whole in the food industries was hard hit by internal capital investment (for both high-tech and "other" capital equipment), expansion of output (scale), and increases in import competitiveness (i.e., these factors appear to be labor-saving). However, employment was augmented by growth of external (total manufacturing) high-tech capital.

An important issue that emerges from this is how one might reconcile the different impacts of tech/trade factors on labor through labor compositional changes that may be driven by skill/educational differentials. In particular, skill-capital complementarity has been recognized as a potentially important contribution to input demand patterns and economic performance by a number of researchers (see, for example, Bartel and Lichtenberg 1987). Consideration of these input- and labor-compositional patterns appears crucial for exploring the impacts of trade and technology in the food system.

Evaluating economic performance and its determinants requires consideration and measurement of these various factors affecting costs and production, and their underlying linkages. This may be accomplished through representation of employment decisions and other input demand behavior, and measurement of tech/trade impacts on this behavior. Given the evidence of labor/capital relationships, it is particularly useful to consider impacts based on expanding technology and technological factors embodied in (internal and external) capital.

In this study we use a cost-based production theory model incorporating a division of the labor input into four educational categories to explore the tech/trade link in the U.S. food processing industries (Food and Kindred Products (SIC 20) and its nine 3-digit components) with a particular focus on its impacts on input and labor composition. The model incorporates capital fixities, scale economies, factor substitution, and external tech/trade impacts. It embodies specific external technology factors (R&D and high-tech capital as well as disembodied technological change), and captures increased competitiveness through an import to output ratio.

Using this model we identify the cost effects (efficiency or productivity) of technology/trade factors, and (absolute and relative) changes in input use and employment of different categories of workers through cost and demand elasticities. These measures allow assessment of cost-side productivity impacts, and skill/educational biases with respect to labor, reflected by relative cost and demand elasticities. This provides important insights about tech/trade impacts and economic performance in the U.S. food system.

The Background

The large and rapidly expanding literature about trade and technological impacts on economic performance and input use largely focuses on U.S. manufacturing overall, and targets employment patterns much more heavily than the associated question of costs and efficiency.

The employment patterns found for U.S. manufacturing in the past two decades seem quite clear—they involve lower labor intensity (demand for labor relative to other inputs), especially for less skilled labor (both production as compared to nonproduction labor and within these two subgroups).[2] The more complex question about the *causes* of these wage patterns has been more controversial. Broadly speaking, it appears that traditional demand and supply analysis helps to link demand changes for different educational levels to the observed patterns, but understanding the impacts further requires more detailed treatment of how these demand patterns rely on changing trade and technological factors.

Increased import competitiveness stemming from the expanding “openness” of the economy has been targeted in the popular press as the “villain” in this scenario. However, the prevailing view from the economics literature seems to be that technical change (and its associated biases) has had the strongest impact. Krugman and Lawrence (1994) provided a clear statement of this conclusion in *Scientific American*: “The concern, widely voiced during the 1950s and 1960s, that industrial workers would lose their jobs because of automation is closer to the truth than the current preoccupation with a presumed loss of manufacturing jobs because of foreign competition.”

Although this general consensus has been found with a broad base of different types of analysis, data, and definitions, some studies have contradicted these results. Revenga (1992), for example, does find a significant trade impact, Sachs and Shatz (1994) say that it is larger than is often recognized even if it is not the primary explanation, and Leamer (1994) asserts that appropriate application of international trade models indicates a technical change bias of the opposite sign. He also emphasizes that the usual production/nonproduction worker split used in these types of analysis is largely irrelevant, and that interactions between trade and technological factors is likely to be important—although neither of these issues is typically raised or dealt with in the existing literature.

Even in the many studies that support the dominance of technical change as an explanation of observed employment structure changes, problems with the analyses, and difficulties in interpretation abound. These are often due to methodological or definitional issues, which cause the results to be limited and/or questionable, and preclude considerations of the interactions and mechanisms underlying such effects and linking them to general input composition and cost changes.

For example, to determine the trade impact on economic performance, costs, and employment, trade biases for different types of inputs (input composition) and labor categories (labor composition) with respect to changes in “openness” must be computed. These biases are defined as *relative* changes in labor as compared to other inputs and in skilled as compared to unskilled labor components in response to increased openness. Such measures allow assessment of, for example, whether changes in trade policies change the capital intensity of production or are skilled-labor-using or -saving.

These types of measures can also help answer questions regarding interactions among the tech/trade factors and the *determinants* of the observed biases. In other words, what are the *changes* in the bias when the industry becomes increasingly open, as computerization explodes, as research is carried out to facilitate competitiveness, or as other changes in production characteristics occur? Could the impact of trade have been masked because it occurs indirectly through the impact of competitiveness on technical change?

In reverse, if technical change is an important underlying factor, are there motivating forces from import competitiveness that induce such changes? What are the extent (and direction) of the cost, demand, and compositional effects of disembodied technical change as compared to more specifically identifiable factors such as computerization and R&D? Are these impacts evident just in the short run, or is there a long-run structural change—and are they in the same direction? This requires including not only nonneutrality of the tech/trade factors in a model, but also determinants of the biases, which are not possible to measure using most of the approaches employed in the existing literature.

Existing studies of the impacts of trade and technology on employment generally fall in one of three broad categories: as (i) supply and demand, (ii) international trade, or (iii) industry/production-based studies. Although each type of study provides some interesting insights, and many reach broadly similar conclusions, none provide a sufficient base to deal with these types of methodological and definitional issues.

Studies in the first category such as Murphy and Welch (1992), Mincer (1991), and Katz and Murphy (1992) attempt to “push” a basic demand and supply framework as far as possible. Murphy and Welch (1992), for example, looked at demand shifts due to changes in the share of net imports, innovations in the aggregate unemployment rate, and general trends, and find that demand shifts are “important components of the story” but that their approach leaves them “uncertain about causation.”

Mincer (1991) uses simple time series regressions including supply and demand measures, and similarly infers an important role for technology in explaining changes in skill-premiums. Katz and Murphy (1992) find that increases in demand for more-skilled workers is a "key component" in explaining observed changes in the employment and wage structure, and infer that the patterns likely reflect skill-biased technological changes and substitution with other inputs due to relative price changes of high-tech capital, although they also highlight the difficulties involved in measuring the determinants of the demand changes.

Studies such as Sachs and Shatz (1994) combine macro data on employment and wage with detailed data on internationalization and a methodological reliance on international trade theory. They also find that "the overall changes in employment and in wage inequalities are too large to be explained by the changing trade and price patterns," and that "it is likely that technological change is playing a role independent of internationalization" (with the caveat that observing and measuring technological change is difficult). Similarly, Lawrence and Slaughter (1993), who focus on Stolper-Samuelson effects, find little impact from intra-industry trade, but say the positive association found between the growth of total factor productivity and the nonproduction labor use "points to technological change as an important source of changes in relative wages."

Finally, important examples of industry- or production-based studies for manufacturing as a whole include Berman et al. (1994), Bound and Johnson (1992), Berndt et al. (1992), and Bartel and Lichtenberg (1987). The first two of these studies provide provocative and important results, but are based on simple regression techniques that preclude analysis of the complex interactions among input demand patterns and tech/trade determinants. These studies use numerous decompositions and detailed industry regressions based on nonproduction labor share equations (embodying a very limited substitution relationship). They conclude that biased technological change is "the chief explanation" for the observed changes, with the increase in nonproduction workers linked to investment in computers and R&D, and most of the changes driven by within-industry changes, but they are not able to formalize the determinants of observed labor-saving tendencies.

Both the importance of within-industry changes and the dominance of biased technical change in determining labor demand and composition (share) changes through capital market changes are supported by Berndt et al. (1992), who also base their analysis on simple regression models. Their division of both labor and capital into different categories (by education level and high-tech nature) provides useful insights that are precluded by the production/nonproduction labor distinction used in most studies, but the study is again limited in its implications by the simple structure used for analysis.

Bartel and Lichtenberg (1987) also use nonproduction-worker-share equations to identify technological change biases. Although their approach is initially based on a more complex functional relationship than is typical in these studies (a translog cost function), the study is ultimately limited through its use of only a labor demand equation (precluding recognition of the interactions among inputs) and its specification of the "technical" variable as just a vintage (age of the capital stock) variable. Similar results and limitations are found in Krueger (1993), who used more micro data and a measure of computerization as the lone technology variable.

These studies are indicative of the types of approaches generally used for analysis of labor demand changes in the manufacturing sector and their determinants. In this study we rely on the strong evidence from this literature of the dominance of "within-industry" impacts of trade to focus attention on labor composition within the food processing industry. Our flexible cost function approach, however, provides much more detailed information on the complex web of interactions and linkages among exogenous factors affecting costs, firms' behavior and the resulting impact on labor demand and thus wage and employment patterns, than is possible using the methodologies appearing in the existing literature.

In addition, our more complete set of inputs (private capital, more labor categories, and intermediate materials) and of technology variables (R&D, high-tech capital and possibly education, as well as general disembodied technological change) further facilitates assessment of their linkages. We identify both direct and indirect impacts of the trade and technology variables through interaction terms, and provide evidence allowing evaluation of both absolute and relative changes in input use (through demand elasticities that can be used to construct relative input demand measures such as biases and Morishima elasticities). Finally, we provide some evidence about the difference between short- and long-run behavior (and thus cyclical and secular trends) by recognizing the quasifixed nature of private capital in the short-run and considering the effects of increased investment toward long-run values.

In the next section we outline our framework and the resulting measures of the impacts of trade and technological factors underlying costs, demand, and input/labor composition.

The Methodology

We begin by representing cost minimizing behavior by a dynamic variable cost function incorporating quasifixity of some internal inputs, nonconstant long-run returns to scale, and external "shift" factors: $G = G(\mathbf{p},Y,\mathbf{x},\mathbf{\Delta x},\mathbf{T})$ (where $\mathbf{p}$ is a vector of J variable input prices, Y is output, $\mathbf{x}$ is a vector of K quasifixed inputs, including $\mathbf{\Delta x}$ captures adjustment costs for the $\mathbf{x}$ inputs, and $\mathbf{T}$ is a vector of N external tech/trade factors). Total costs therefore become $C = G(\mathbf{p},Y,\mathbf{x},\mathbf{\Delta x},\mathbf{T}) + \Sigma_k x_k p_k$, where p_k is the market price of quasifixed (internal) input x_k.

The T_n variables can be defined as anything affecting the production and thus cost function but not under the direct choice of the firm. For our analysis this includes a trade or openness factor (the import/output ratio), and two specific technical factors (high-tech capital and R&D).[3] Our analysis therefore accommodates a much more complete specification of trade and technology determinants than is found in the existing literature.

It is worthwhile emphasizing here that these $\mathbf{T}$ variables are modeled as external rather than "choice" variables. They are designed to represent the technological base underlying production in the sector as a whole, rather than the amount of investment (such as high-tech investment) carried out within the sector. If these variables were measured as internal factors—as part of the private capital input rather than external "knowledge" capital factors—they would instead appear as components of the $\mathbf{x}$ vector. The main differences in the resulting analysis would therefore be the level of aggregation at which the variables were represented, and the explicit recognition of the payment for the factor by the firms within the industry (p_k). We are instead searching for the general impact in the industry including spillovers.

The cost function framework allows our analysis to be expressed in the context of cost effectiveness and thus in terms of the decisions about input use and mix that are consistent with the lowest cost methods of production. This structural framework allows more specific analysis of responsiveness to trade and technological factors than is possible using simple single equation regression models based loosely on the notion of a production function, which is typical in the existing literature. In our specification, since input demand behavior is embodied in the form of the cost function, we can carry out a detailed evaluation of input demand and composition patterns for any set of economic circumstances facing the firm, and thus explicitly represent the responsiveness to changes in these circumstances.

For our empirical investigation, we assume the variable cost function $G(\mathbf{p},Y,\mathbf{x},\mathbf{\Delta x},\mathbf{T})$ can be approximated by the generalized Leontief (GL) form:

$$(1)\qquad G(\mathbf{p},Y,\mathbf{x},\mathbf{\Delta x},\mathbf{T}) = Y[\Sigma_i\Sigma_j\, a_{ij}p_i^{.5}\, p_j^{.5} + \Sigma_i\Sigma_m\, \delta_{im}\, p_i\, s_m^{.5} + \Sigma_i p_i\, \Sigma_m\Sigma_n\, \gamma_{mn}\, s_m^{.5}\, s_n^{.5}]$$

$$+ Y^{.5}[\Sigma_i\Sigma_k\, \delta_{ik}\, p_i x_k^{.5} + \Sigma_i p_i\, \Sigma_m\Sigma_k\, \gamma_{mk} s_m^{.5}\, x_k^{.5}] + \Sigma_i p_i\, \Sigma_k\Sigma_l\, \gamma_{lk}\, x_k^{.5}\, x_l^{.5},$$

where private capital (K) is the only quasifixed (x_k) input; p_i and p_j index the prices of variable inputs —the four different types of labor inputs (L_i) (divided by educational levels into L_1 [no high school diploma], L_2 [with a high school diploma], L_3 [with some college] and L_4 [with a college degree]), and materials (M); and s_m, s_n depict the remaining arguments (Y, ΔK, and $\mathbf{T}$).[4]

This flexible functional form allows a complete specification of both the direct impacts and the interactions of tech/trade variables on costs and input demand/composition, since it captures the web of cross-effects underlying these interactions. Based on this cost function, measurement and analysis of the underlying patterns and the trade/technology determinants involves representation of (a) the direct and indirect impacts of tech/trade factors on costs; (b) the specific effects on the different inputs (and thus on relative labor and input demand or composition); and (c) the determinants of the cost, demand, and bias relationships. These relationships can be expressed as a broad set of cost and demand elasticities with respect to the T_n, K, and input price variables.

More specifically, we can begin our development of measures representing the impact of tech/trade factors by defining some cost elasticities. The direct cost effects of any T_n variable can be represented by the derivative $\partial C/\partial T_n$, or, in elasticity (proportional) terms, $\partial \ln C/\partial \ln T_n = \epsilon_{CTn} = \partial G/\partial T_n (T_n/C)$. These measures show how economic performance, represented via cost effectiveness/efficiency, is determined by external factors. In other words, ϵ_{CTn} expresses the (percentage) decline in privately purchased (variable) input costs possible from increased availability of the external tech/trade factor.

Note that the ϵ_{CTn} elasticities are directly analogous to the usual cost-side productivity growth measure $\epsilon_{Ct} = \partial \ln C/\partial t$ (where t is a time counter representing disembodied technical change),[5] which is often measured as a residual assuming t is the only exogenous shift variable and that constant returns to scale and instantaneous adjustment prevail. Note also that the ϵ_{CTn} measure may be interpreted as elasticity versions of shadow value measures, which for any type of fixed factor may be defined as $Z_n = -\partial G/\partial T_n$ (with the negative sign included to make the number positive), so $\epsilon_{CTn} < 0$ implies a positive shadow value (marginal product) of T_n.[6]

More complete identification of the mechanisms through which the impact of T_n variables on costs occurs requires the specification and estimation of secondary elasticity measures. For example, complementarity/substitutability (interrelationships or cross-effects) among the components of the **T** vector can be established by measures showing the impact on the ϵ_{CTn} elasticity (or ϵ_{CT1} for the first component, T_1) of changes in other technological factors (T_2): $\epsilon_{CT12} = \partial \epsilon_{CT1}/\partial \ln T_2$.[7] This type of measure may also be computed for private capital, to indicate the impact of a T_n variable on the shadow value of capital; $\epsilon_{CK1} = \partial \epsilon_{CK}/\partial \ln T_1$.

Thus, this measure shows whether a cost decline from an increase in T_1 is attenuated or exacerbated by expansion of the T_2 factor. For example, if trade (T_1) had a direct effect on costs but was associated with further declines in costs from increasing computerization (T_2), both ϵ_{CT1} and ϵ_{CT12} would be negative. This complementarity implies that even a small direct effect of trade might be associated indirectly with significantly increasing efficiency.

Note also that since the ϵ_{CT12} elasticity is based on a second derivative, it must be symmetric with ϵ_{CT21}—if one is negative the other must also be. In the example above, this implies that increasing openness (associated with a rise in the T_1 variable) will cause the technical change (computerization) impact $\partial \ln C/\partial \ln T_2 = \epsilon_{CT2} = \partial G/\partial T_2 (T_2/C)$ to be larger. This in turn suggests that the impact of T_1 may be indirect (occur through the impact of international competitiveness on computer development and usage) and thus masked by measured (direct) technological impacts.

Characterizing the associated labor demand patterns begins with another cost elasticity, derived from Shephard's lemma; $\partial C/\partial p_{Lj} = \partial G/\partial p_{Lj} = L_j$. Once this demand relationship is specified, it is easily shown that the *share* of this type of labor in total costs is $\partial \ln C/\partial \ln p_{Lj} = p_{Lj}L_j = /C = S_{Lj} = \epsilon_{CLj}$. It is also clear that the determinants of either the demand level or share of this labor component can be specified in terms of elasticities that allow a full characterization of the determinants of input and labor demand and composition patterns.

The labor demand elasticity with respect to a T_n factor becomes $\partial \ln L_j/\partial \ln T_n = \epsilon_{LjTn}$. Thus, if an increase in openness through an increase in the trade variable T_1 reduces employment of labor type L_j (at given output and private capital levels), $\epsilon_{LjT1} < 0$. If T_1's effect is larger with increases in computerization (less skilled labor gets "hurt" by both openness and computerization and their impacts are interrelated), these cross-effects are represented by a negative value of the cross elasticity $\epsilon_{LjT12} = \partial\epsilon_{LjT1}/\partial \ln T_2$. These indirect or interaction impacts can be interpreted similarly to those affecting overall costs, captured in the ϵ_{CT12} measured above.

Further information about price and private input substitution can augment the information contained in these tech/trade elasticities. For example, standard price elasticities may be computed as $\epsilon_{ij} = \partial \ln v_i/\partial \ln p_j$, where i and j represent variable inputs. Similarly, given short-run quasi-fixity of capital, the relationship between variable inputs and the capital input (and therefore the long-run direction of change) can be established through the capital elasticities $\epsilon_{ik} = \partial \ln v_i/\partial \ln K$, where (reversed from the price elasticities) $\epsilon_{ik} > 0$ implies complementarity and $\epsilon_{ik} < 0$ substitutability.

These elasticity measures can be used, in turn, to compute composition or *relative* input- or labor-demand changes—represented in terms of biases and Morishima elasticities. Bias measures are defined in terms of cost shares, and therefore depend on the relative difference between the overall cost effect and the impact on the specific input or labor type of a change in T_n. For example, the bias of labor input L_j with respect to a change in the tech/trade factor T_n is: $B_{LjTn} = \partial\epsilon_{CLj}/\partial \ln T_n = \partial S_{Lj}/\partial \ln T_n = S_{Lj}(\epsilon_{LjTn} - \epsilon_{CTn})$. Thus, if increasing openness (increasing T_1) is relatively input L_j-saving—L_j declines more than or increases less than other inputs—$B_{LjT1} < 0$.

This notion can be used to consider either general input composition (labor/capital/materials as compared to total input costs) or labor composition (for different educational categories as compared to total labor). The first measure requires computing an "overall" labor demand elasticity $\epsilon_{LTn} = \Sigma_j S'_{Lj} \epsilon_{LjTn}$ (where $S'_{L1} = p_{L1} L_1/\Sigma_j p_{Lj} L_j$), and constructing the bias measure: $B_{LTn} = \partial S_L/\partial \ln T_n = S_L(\epsilon_{LTn} - \epsilon_{CTn})$ (where $S_L = p_L L/C$ and $p_L L = \Sigma_j p_{Lj} L_j$). The latter measure would be defined in the context of one labor type (L_1) as compared to total labor (L): $B'_{L1Tn} = S'_{L1}(\epsilon_{L1Tn} - \epsilon_{LTn})$. The two measures together identify whether trade/tech factors are labor-saving or -using, and whether this tendency impinges differentially across labor categories.

The patterns of absolute and relative input/labor demand/composition represented by the full set of bias measures and their components can be further analyzed and "explained" in terms of the determinants of the biases. These interaction measures may be computed as derivatives of the biases with respect to the T_n variables: $I_{LjT12} = \partial B_{LjT1}/\partial \ln T_2$. The I_{LiT12} measure, for example, shows whether a trade bias might be exacerbated/attenuated by increased computerization, similarly to the cost- and demand-based measures ϵ_{CT12} and ϵ_{LjT12}, which are components of this measure through the definition of the bias term.

The "relative" input demand information reflected in bias measures is similar to that captured in Morishima elasticities—instead of appearing as relative cost and input demand elasticities (due to the focus on the share), Morishima elasticities are constructed as relative demand elasticities (reflecting substitution among two inputs when their relative prices change). In other words, as Huang has noted the Morishima elasticity, MES_{ij}, can be expressed as: $MES_{ij} = \epsilon_{ji} - \epsilon_{ii}$. Thus all information necessary for computation of Morishima elasticities are contained in the demand elasticities ϵ_{ij} if a full set of these elasticities are available.

The broad set of derivatives, elasticities, and bias measures developed in this section provides a much more complete picture of input and (absolute and relative) labor demand changes and their determinants than appears in the existing literature.

The Results

Using the cost function (1), empirical implementation of the model was carried out by systems estimation of a full set of cost, input demand, and investment equations from (i) the cost function itself; (ii) input demand functions for the variable inputs constructed using Shephard's lemma—$v_j = \partial G/\partial p_j$, $j = L_i,M$; and (iii) the Euler equation for capital (K), $p_K = -\partial G/\partial K - r\partial G/\partial \Delta K + \Delta K\partial^2 G/\partial K\partial \Delta K +$

$\Delta\Delta K\partial^2 G/\partial(\Delta K)^2$ (where $\Delta\Delta K$ is the second difference of K, $\Delta(\Delta K)$, and r is a long-run discount rate). The resulting 7-equation system was estimated for the Food and Kindred Products (SIC 20) industry and its 3-digit components by pooling the 4-digit data using fixed effects. The external factors were evaluated at one level of aggregation higher (the values for the T_n variables were specified at the 2-digit level for each 3-digit level industry). (Data Appendix A defines these variables in somewhat more detail).

The system of equations was estimated for 1959-89 using iterative three state least squares, with lagged values of the arguments of the cost function as instruments. The parameter estimates were then used to compute the elasticities for each 4-digit industry, which were then aggregated to the 2- and 3-digit levels using output shares as weights for the averages. The nine 3-digit industries are Meat Products (SIC 201), Dairy Products (SIC 202), Preserved Fruits and Vegetables (SIC 203), Grain Mill Products (SIC 204), Bakery Products (SIC 205), Sugar and Confectionary Products (SIC 206), Fats and Oils (SIC 207), Beverages (SIC 208), and Miscellaneous Food and Kindred Products (SIC 209).

These elasticities are presented as averages across time periods in Tables 5.1-5.6. Standard errors are not presented because the elasticity expressions are complex combinations of data and parameters that each have their own error structure, so generating standard errors is not straightforward. In addition, however, averaging across 4-digit industries and across time preclude effective construction and interpretation of these error terms. The robustness of the results across time and industry, however, suggests that their patterns are well represented by these averages.

The first set of elasticities—the cost elasticities with respect to the tech/trade variables—are presented in Table 5.1. These elasticities provide clear evidence of cost-savings deriving from the external T_n variables. All the cost elasticities are negative, and they are largest for the technological variables (T_2—high tech capital and T_3—R&D). Note that the interaction terms are also reasonably substantial[8]—and primarily negative, suggesting further cost saving from the interactions and linkages among the tech/trade variables.

It is also worth commenting that the variations across 3-digit industries is not large, although some differences are evident. This may be a result of estimating at the 4-digit level with only fixed effects differentiating among industries. However, it is also the case that variations across aggregated industry levels typically have less variation than do plants within industry classifications. This is even true for comparisons across 2-digit SIC manufacturing sectors when they are estimated based on the more disaggregated data (see Morrison and Siegel 1995).

These cost savings stem from a combination of variable input savings. The labor-specific changes are summarized in the first six columns of Tables 5.2-5.5, for L_1 - L_4, respectively (going from the lowest to the highest educational attainment levels). Table 5.2 shows the results for workers with no high school diploma. It is clear that all the tech/trade variables "hurt" this category of the labor force—reductions in employment from all these factors and from their interactions is evident, with slightly more impact from the technological variables. The impacts are also generally increasing over time, although not always—the R&D elasticity measure is slightly higher in the 1970s than before or after that time period.

The results for the high-school educated labor category, presented in Table 5.3, suggest that these workers are even harder "hit" by technical innovation (automation), and somewhat so by trade. The ϵ_{L2T2} and ϵ_{L2T3} elasticities are substantially larger than for the L_1 labor category, and also larger than the ϵ_{L2T1} elasticities. Again the interactions terms augment this, and the variation across 3-digit industries is not large.

Turning to Tables 5.4 and 5.5, we find much different evidence from the ϵ_{LnT2} and ϵ_{LnT3} elasticities for L_1 and L_2—the technological impacts appear to increase employment within the L_3 and L_4 labor categories, as is true for manufacturing overall (see Morrison and Siegel 1996). Trade still has a diminishing impact on labor demand for L_3, but it is small. In addition, the interaction terms now vary in sign, suggesting a complicated set of interactions for these more educated workers.

TABLE 5.1 ϵ_{CTn} Estimates (Mean Estimate for Period)
T_1 = Trade, T_2 = High Tech Capital, T_3 = R&D Investment

Period	ϵ_{CT1}	ϵ_{CT2}	ϵ_{CT3}	ϵ_{CT12}	ϵ_{CT13}	ϵ_{CT23}
Food and Kindred Products (SIC 20)						
1959-1973	-.052	-.094	-.109	-.008	-.010	-.003
1973-1979	-.057	-.064	-.074	-.010	-.012	-.006
1979-1989	-.061	-.079	-.086	-.012	-.010	-.004
1959-1989	-.056	-.081	-.089	-.011	-.011	-.005
Meat Products (SIC 201)						
1959-1973	-.047	-.088	-.104	-.006	-.008	-.002
1973-1979	-.052	-.058	-.066	-.007	-.010	-.005
1979-1989	-.058	-.072	-.079	-.008	-.013	-.003
Dairy Products (SIC 202)						
1959-1973	-.054	-.097	-.113	-.009	-.013	-.004
1973-1979	-.059	-.068	-.081	-.013	-.015	-.007
1979-1989	-.065	-.083	-.090	-.012	-.011	-.005
Preserved Fruits and Vegetables (SIC 203)						
1959-1973	-.055	-.096	-.111	-.009	-.013	-.005
1973-1979	-.059	-.066	-.077	-.011	-.017	-.004
1979-1989	-.063	-.082	-.089	-.010	-.012	-.003
Grain Mill Products (SIC 204)						
1959-1973	.048	.088	-.106	-.011	-.008	-.001
1973-1979	.049	.049	-.072	-.013	-.009	-.002
1979-1989	.053	.053	-.081	-.012	-.007	-.002
Bakery Products (SIC 205)						
1959-1973	-.053	-.095	-.110	-.010	-.012	-.002
1973-1979	-.058	-.066	-.075	-.012	-.017	-.005
1979-1989	-.063	-.081	-.087	-.010	-.018	-.003
Sugar and Confectionary Products (SIC 206)						
1959-1973	-.049	-.090	-.107	-.006	-.007	.002
1973-1979	-.053	-.062	-.072	-.008	-.010	.004
1979-1989	-.058	-.077	-.084	-.010	-.009	.003
Fats and Oils (SIC 207)						
1959-1973	-.054	-.095	-.112	-.010	-.013	-.004
1973-1979	-.059	-.066	-.078	-.009	-.011	-.003
1979-1989	-.063	-.081	-.089	-.006	-.010	-.002
Beverages (SIC 208)						
1959-1973	-.047	-.088	-.103	-.006	-.007	-.003
1973-1979	-.054	-.063	-.071	-.008	-.009	-.005
1979-1989	-.058	-.075	-.080	-.010	-.008	-.004
Miscellaneous Food and Kindred Products (SIC 209)						
1959-1973	-.056	-.097	-.112	-.009	-.013	.005
1973-1979	-.059	-.066	-.078	-.011	-.015	.008
1979-1989	-.063	-.082	-.089	-.013	-.012	.005

TABLE 5.2 ϵ_{L1Tn} Estimates (Mean Estimate for Period, L_1 = No High School)
T_1 = Trade, T_2 = High Tech Capital, T_3 = R&D Investment

Period	ϵ_{L1T1}	ϵ_{L1T2}	ϵ_{L1T3}	ϵ_{L112}	ϵ_{L113}	ϵ_{L123}	ϵ_{L1K}	ϵ_{L1p1}
Food and Kindred Products (SIC 20)								
1959-1973	-.010	-.014	-.018	-.008	-.005	-.002	-.020	-.018
1973-1979	-.009	-.015	-.021	-.006	-.006	-.003	-.018	-.014
1979-1989	-.013	-.018	-.018	-.005	-.007	-.005	-.022	-.016
1959-1989	-.011	-.016	-.019	-.007	-.006	-.004	-.020	-.016
Meat Products (SIC 201)								
1959-1973	-.012	-.016	-.020	-.009	-.006	-.003	-.016	-.015
1973-1979	-.011	-.018	-.023	-.008	-.008	-.001	-.012	-.012
1979-1989	-.015	-.019	-.022	-.006	-.007	-.003	-.019	-.010
Dairy Products (SIC 202)								
1959-1973	-.007	-.012	-.015	-.006	-.004	-.001	-.015	-.020
1973-1979	-.006	-.013	-.019	-.004	-.003	-.002	-.011	-.017
1979-1989	-.010	-.016	-.017	-.003	-.002	-.003	-.018	-.021
Preserved Fruits and Vegetables (SIC 203)								
1959-1973	-.011	-.016	-.020	-.009	-.006	-.003	-.024	-.011
1973-1979	-.010	-.017	-.022	-.007	-.007	-.004	-.020	-.013
1979-1989	-.015	-.019	-.019	-.006	-.008	-.006	-.026	-.010
Grain Mill Products (SIC 204)								
1959-1973	-.005	-.010	-.014	-.006	-.004	-.001	-.026	-.014
1973-1979	-.004	-.011	-.016	-.004	-.005	-.002	-.023	-.009
1979-1989	-.008	-.012	-.015	-.003	-.004	-.003	-.010	-.013
Bakery Products (SIC 205)								
1959-1973	-.012	-.016	-.021	-.009	-.006	-.003	-.010	-.021
1973-1979	-.011	-.019	-.024	-.009	-.008	-.002	-.012	-.017
1979-1989	-.017	-.021	-.022	-.008	-.008	-.002	-.014	-.019
Sugar and Confectionary Products (SIC 206)								
1959-1973	-.007	-.010	-.016	-.006	-.003	-.001	-.028	-.011
1973-1979	-.006	-.011	-.018	-.004	-.004	-.002	-.030	-.008
1979-1989	-.010	-.014	-.017	-.004	-.005	-.004	-.032	-.009
Fats and Oils (SIC 207)								
1959-1973	-.013	-.015	-.020	-.010	-.006	-.003	-.012	-.014
1973-1979	-.012	-.017	-.023	-.008	-.009	-.004	-.010	-.012
1979-1989	-.016	-.019	-.021	-.007	-.008	-.006	-.017	-.010
Beverages (SIC 208)								
1959-1973	-.009	-.016	-.019	-.009	-.008	-.004	-.017	-.021
1973-1979	-.010	-.013	-.023	-.008	-.007	-.005	-.014	-.018
1979-1989	-.015	-.018	-.019	-.006	-.009	-.006	-.018	-.020
Miscellaneous Food and Kindred Products (SIC 209)								
1959-1973	-.008	-.012	-.016	-.006	-.004	-.001	-.019	-.012
1973-1979	-.006	-.013	-.019	-.004	-.005	-.002	-.017	-.014
1979-1989	-.008	-.014	-.017	-.004	-.006	-.004	-.020	-.018

TABLE 5.3 ϵ_{L2Tn} Estimates (Mean Estimate for Period, L_2 = High School)
T_1 = Trade, T_2 = High Tech Capital, T_3 = R&D Investment

Period	ϵ_{L2T1}	ϵ_{L2T2}	ϵ_{L2T3}	ϵ_{L212}	ϵ_{L213}	ϵ_{L223}	ϵ_{L2K}	ϵ_{L2p2}
Food and Kindred Products (SIC 20)								
1959-1973	-.010	-.025	-.023	-.006	-.005	-.006	-.016	-.020
1973-1979	-.012	-.027	-.025	-.007	-.004	.003	-.015	-.018
1979-1989	-.014	-.031	-.026	-.006	-.003	-.003	-.018	-.019
1959-1989	-.013	-.029	-.025	-.007	-.004	-.004	-.017	-.019
Meat Products (SIC 201)								
1959-1973	-.013	-.027	-.025	-.007	-.006	-.005	-.017	-.021
1973-1979	-.015	-.029	-.024	-.009	-.005	-.004	-.015	-.023
1979-1989	-.014	-.032	-.022	-.008	-.004	-.003	-.019	-.016
Dairy Products (SIC 202)								
1959-1973	-.008	-.018	-.021	-.005	-.004	-.005	-.012	-.018
1973-1979	-.010	-.021	-.023	-.004	-.003	.002	-.014	-.016
1979-1989	-.011	-.027	-.025	-.005	-.002	.003	-.016	-.014
Preserved Fruits and Vegetables (SIC 203)								
1959-1973	-.011	-.024	-.024	-.007	-.006	-.007	-.013	-.014
1973-1979	-.013	-.028	-.027	-.008	-.003	.004	-.011	-.016
1979-1989	-.015	-.028	-.028	-.006	-.002	.005	-.016	-.012
Grain Mill Products (SIC 204)								
1959-1973	-.007	-.022	-.021	-.005	-.003	-.005	-.019	-.015
1973-1979	-.009	-.024	-.020	-.004	-.004	-.002	-.021	-.017
1979-1989	-.010	-.028	-.023	-.005	-.004	-.004	-.024	-.018
Bakery Products (SIC 205)								
1959-1973	-.015	-.030	-.025	-.009	-.004	-.007	-.016	-.024
1973-1979	-.013	-.031	-.028	-.006	-.003	-.005	-.013	-.018
1979-1989	-.016	-.035	-.029	-.005	-.002	-.003	-.017	-.017
Sugar and Confectionary Products (SIC 206)								
1959-1973	-.009	-.023	-.020	-.004	-.004	-.005	-.009	-.015
1973-1979	-.010	-.025	-.022	-.005	-.003	.002	-.007	-.013
1979-1989	-.012	-.029	-.022	-.008	-.002	-.003	-.006	-.009
Fats and Oils (SIC 207)								
1959-1973	-.013	-.026	-.025	-.005	-.006	-.005	-.023	-.026
1973-1979	-.015	-.029	-.028	-.008	-.005	-.004	-.021	-.024
1979-1989	-.016	-.034	-.029	-.008	-.004	-.005	-.028	-.028
Beverages (SIC 208)								
1959-1973	-.011	-.024	-.021	-.005	-.004	-.004	-.014	-.012
1973-1979	-.010	-.026	-.023	-.006	-.003	.003	-.012	-.010
1979-1989	-.012	-.030	-.025	-.004	-.002	-.004	-.017	-.008
Miscellaneous Food and Kindred Products (SIC 209)								
1959-1973	-.007	-.021	-.024	-.007	-.004	-.005	-.012	-.022
1973-1979	-.008	-.024	-.023	-.004	-.003	-.004	-.014	-.024
1979-1989	-.011	-.028	-.026	-.005	-.002	-.004	-.016	-.025

TABLE 5.4 ϵ_{L3Tn} Estimates (Mean Estimate for Period, L_3 = Some College)
T_1 = Trade, T_2 = High Tech Capital, T_3 = R&D Investment

Period	ϵ_{L3T1}	ϵ_{L3T2}	ϵ_{L3T3}	ϵ_{L312}	ϵ_{L313}	ϵ_{L323}	ϵ_{L3K}	ϵ_{L3p3}
Food and Kindred Products (SIC 20)								
1959-1973	-.004	.013	.017	.004	-.003	.002	-.011	-.008
1973-1979	-.003	.012	.010	.004	.002	.002	-.013	-.007
1979-1989	-.002	.016	.013	.003	.001	.003	-.009	-.011
1959-1989	-.003	.014	.013	.003	.002	.002	-.011	-.009
Meat Products (SIC 201)								
1959-1973	-.003	.011	.015	.003	-.004	.001	-.008	-.007
1973-1979	-.001	.010	.009	.002	.003	.001	-.007	-.005
1979-1989	-.002	.013	.011	.002	-.002	.002	-.006	-.019
Dairy Products (SIC 202)								
1959-1973	-.006	.016	.019	.005	-.002	.003	-.009	-.004
1973-1979	-.005	.014	.013	.006	.001	.004	-.011	-.007
1979-1989	-.004	.015	.016	.003	.000	.002	-.007	-.010
Preserved Fruits and Vegetables (SIC 203)								
1959-1973	-.002	.015	.014	.003	-.005	.001	-.014	-.011
1973-1979	-.004	.011	.012	.002	.004	.003	-.018	-.009
1979-1989	-.003	.010	.013	.002	.002	.002	-.022	-.013
Grain Mill Products (SIC 204)								
1959-1973	-.005	.016	.019	.003	-.004	.001	-.007	-.013
1973-1979	-.004	.014	.014	.003	.001	.002	-.005	-.011
1979-1989	-.003	.015	.015	.002	.000	.002	-.008	-.009
Bakery Products (SIC 205)								
1959-1973	-.002	.010	.015	.002	-.002	.001	-.015	-.005
1973-1979	-.001	.009	.007	.003	.000	.002	-.012	-.006
1979-1989	-.001	.012	.010	.003	.002	.001	-.014	-.011
Sugar and Confectionary Products (SIC 206)								
1959-1973	-.005	.015	.019	.003	-.005	.004	-.014	-.003
1973-1979	-.004	.013	.013	.005	.001	.001	-.012	-.004
1979-1989	-.005	.018	.014	.004	.000	.002	-.016	-.008
Fats and Oils (SIC 207)								
1959-1973	-.002	.012	.016	.003	-.003	.001	-.007	-.011
1973-1979	-.001	.011	.009	.002	.002	.002	-.005	-.006
1979-1989	-.003	.014	.011	.003	.000	.002	-.003	-.013
Beverages (SIC 208)								
1959-1973	-.005	.016	.018	.003	-.002	.001	-.006	-.006
1973-1979	-.004	.015	.011	.002	.002	.003	-.008	-.004
1979-1989	-.003	.018	.012	.002	.001	.002	-.004	-.008
Miscellaneous Food and Kindred Products (SIC 209)								
1959-1973	-.005	.011	.016	.004	-.002	.002	-.009	-.009
1973-1979	-.003	.014	.008	.003	.001	.003	-.011	-.007
1979-1989	-.003	.013	.011	.003	-.001	.003	-.010	-.012

TABLE 5.5 ϵ_{L4Tn} Estimates (Mean Estimate for Period, L_4 = College)
T_1 = Trade, T_2 = High Tech Capital, T_3 = R&D Investment

Period	ϵ_{L4T1}	ϵ_{L4T2}	ϵ_{L4T3}	ϵ_{L412}	ϵ_{L413}	ϵ_{L423}	ϵ_{L4K}	ϵ_{L4p4}
Food and Kindred Products (SIC 20)								
1959-1973	.012	.015	.013	.004	-.002	.004	-.010	-.005
1973-1979	.008	.019	.015	.003	.002	.004	-.008	-.008
1979-1989	.010	.020	.018	.002	-.001	.003	-.006	-.004
1959-1989	.010	.018	.015	.003	-.001	.004	-.008	-.006
Meat Products (SIC 201)								
1959-1973	.014	.017	.015	.005	-.003	.006	-.007	-.003
1973-1979	.010	.021	.018	.004	.004	.003	-.004	-.002
1979-1989	.012	.023	.017	.003	-.003	.004	-.003	-.001
Dairy Products (SIC 202)								
1959-1973	.008	.013	.011	.003	-.001	.003	-.011	-.007
1973-1979	.004	.017	.014	.002	.002	.002	-.007	-.010
1979-1989	.006	.018	.016	.002	-.001	.002	-.008	-.012
Preserved Fruits and Vegetables (SIC 203)								
1959-1973	.011	.014	.011	.003	-.001	.002	-.013	-.002
1973-1979	.007	.016	.014	.002	.000	.003	-.015	-.004
1979-1989	.009	.018	.016	.003	-.002	.003	-.010	-.003
Grain Mill Products (SIC 204)								
1959-1973	.015	.015	.015	.005	-.002	.003	-.003	-.003
1973-1979	.011	.017	.018	.004	.001	.002	-.004	-.007
1979-1989	.013	.021	.019	.003	-.002	.002	-.005	-.005
Bakery Products (SIC 205)								
1959-1973	.011	.014	.012	.002	-.001	.003	-.007	-.009
1973-1979	.006	.018	.011	.001	.002	.002	-.005	-.011
1979-1989	.009	.017	.015	.002	.000	.003	-.008	-.006
Sugar and Confectionary Products (SIC 206)								
1959-1973	.014	.018	.015	.002	-.002	.004	-.011	-.001
1973-1979	.012	.022	.018	.003	.001	.003	-.005	-.003
1979-1989	.015	.024	.019	.004	-.002	.004	-.003	-.005
Fats and Oils (SIC 207)								
1959-1973	.013	.017	.014	.004	-.002	.003	-.004	-.001
1973-1979	.009	.020	.017	.003	.002	.003	-.002	-.004
1979-1989	.011	.022	.019	.002	-.002	.003	-.003	-.001
Beverages (SIC 208)								
1959-1973	.012	.016	.014	.002	-.001	.005	-.006	-.003
1973-1979	.009	.020	.017	.003	.001	.003	-.003	-.002
1979-1989	.011	.022	.016	.003	-.002	.005	-.002	-.002
Miscellaneous Food and Kindred Products (SIC 209)								
1959-1973	.014	.016	.015	.002	.000	.002	-.012	-.008
1973-1979	.009	.021	.018	.001	.001	.000	-.014	-.012
1979-1989	.012	.023	.017	.001	.000	.001	-.011	-.005

These external tech/trade impacts therefore indicate a clear educational bias. Not only is there a less-educated-labor-saving bias, but even in absolute terms laborers in the two lower educated categories experience less demand and the two higher educational categories exhibit stronger labor demand with increases in these factors.

Further insights on labor- and input-compositional patterns from both external and internal forces may be gained by considering the capital and price elasticities of the variable inputs, contained in Tables 5.2-5.5 for the labor components and Table 5.6 for labor and materials overall.

First, the labor compositional impact of investment in private capital is indicated by the ϵ_{LiK} elasticities in Tables 5.2-5.5. These elasticities suggest a clear capital-skill-bias; substitutability between capital and labor is stronger for the lower educational categories. Thus, increasing capital investment/ intensity will reduce labor demand more for the lower educational categories. However, complementarity of capital with the higher educational categories of labor is not evident. Although this relationship has sometimes been suggested in the literature these results indicate that apparent complementarity of capital and labor may stem from the external tech/trade factors.

Own price elasticities are presented for these different labor components in Tables 5.2-5.5. Cross-price elasticities across the different categories are not presented since there are so many to summarize and because one would expect most of them to be quite small. The own price elasticities suggest a low input price response for labor—fairly inelastic demand—especially for the more educated workers. Thus labor price changes appear to have had little impact on observed input and labor composition patterns.

Finally, it is useful to look at the general variable input responsiveness and trends, from the materials and overall labor elasticities in Table 5.6. This is particularly of interest since materials constitute a much higher share of costs than labor, so cost impacts would be expected to arise to a large extent from materials demand changes.

First, consider the price elasticities for M and L. The own materials price elasticity suggests a stronger, but still inelastic, response of materials demand from changes in its price (the labor elasticity is an average of the L_1 - L_4 categories in Tables 5.2-5.5). The cross-price elasticities show that L and M are substitutes, but the substitutability is small in magnitude.

It also appears that capital expansion generally causes materials use to increase and employment to decline. This would exacerbate problems of stagnating labor demand with increasing capital intensity of the industry, which appears the likely case over time and as the scale of the industry expands. This is in turn suggested by the complementarity of materials and (private) high-tech capital expansion, and the extra-proportional scale elasticity of materials with respect to output found in Morrison (1996). These relationships do not appear to be particularly strong, however, since both the ϵ_{Mk} and ϵ_{LK} elasticities reverse sign in the 1973-79 period (for L it appears that the L_3 effect is high enough to outweigh those for the other variables).

To complete our picture of input responsiveness, it is useful to return to the impacts of the tech/trade variables and see how they affect both the materials and private capital inputs, which are reflected in the ϵ_{Mn} and ϵ_{Kn} elasticities in Table 5.6. First, note that the cost savings motivated by increases in the tech/trade variables seem to stem largely from changes in materials use—the elasticities are not only negative but are quite large, especially when the cost share of materials is taken into account.

In addition, it appears that private capital and the external components—including "public" high-tech capital—seem to be substitutes, in the sense that the demand for K is reduced when increases in these variables occur (holding output constant). The elasticity value is quite large for the high-tech capital variable, which suggests substantial spillover effects. However, the actual resulting cost changes may not be very large, due to the small (even though increasing) share of capital, and from evidence that when external effects are taken into account capital use appears close to optimal in this industry (see Morrison 1996).

TABLE 5.6 ϵ_{ii}, ϵ_{iK} ϵ_{Mn} and ϵ_{Kn} Estimates (Mean Estimate for Period, i = L,M, n = T_1,T_2)

Period	ϵ_{MpM}	ϵ_{MpL}	ϵ_{MK}	ϵ_{LpL}	ϵ_{LpM}	ϵ_{LK}	ϵ_{MT1}	ϵ_{MT2}	ϵ_{KT1}	ϵ_{KT2}
Food and Kindred Products (SIC 20)										
1959-1973	-.029	.007	.004	-.016	.006	-.007	-.021	-.015	-.040	-.014
1973-1979	-.019	.010	-.003	-.011	.009	.002	-.020	-.018	-.045	-.016
1979-1989	-.024	.005	.008	-.015	.004	-.006	-.024	-.017	-.035	-.019
1959-1989	-.020	.008	.003	-.013	.007	-.005	-.022	-.016	-.039	-.017
Meat Products (SIC 201)										
1959-1973	-.018	.009	.008	-.019	.007	-.004	-.016	-.020	-.036	-.012
1973-1979	-.016	.012	.002	-.014	.004	-.001	-.014	-.024	-.040	-.013
1979-1989	-.012	.008	.012	-.018	.009	-.004	-.017	-.019	-.030	-.017
Dairy Products (SIC 202)										
1959-1973	-.031	.012	.009	-.019	.002	-.009	-.023	-.012	-.038	-.010
1973-1979	-.025	.014	-.005	-.014	.008	.005	-.026	-.011	-.042	-.008
1979-1989	-.028	.008	.012	-.017	.006	-.011	-.027	-.015	-.035	-.005
Preserved Fruits and Vegetables (SIC 203)										
1959-1973	-.021	.004	.002	-.011	.001	-.002	-.014	-.013	-.044	-.019
1973-1979	-.016	.006	-.001	-.006	.003	.001	-.012	-.014	-.049	-.023
1979-1989	-.014	.002	.006	-.008	.002	-.003	-.016	-.017	-.040	-.028
Grain Mill Products (SIC 204)										
1959-1973	-.012	.006	.012	-.006	.010	-.014	-.018	-.008	-.033	-.011
1973-1979	-.008	.008	-.007	-.009	.016	-.004	-.020	-.006	-.032	-.009
1979-1989	-.007	.004	.011	-.011	.018	-.010	-.022	-.004	-.029	-.013
Bakery Products (SIC 205)										
1959-1973	-.038	.014	.006	-.011	.006	-.005	-.012	-.024	-.034	-.020
1973-1979	-.024	.018	-.009	-.015	.003	.002	-.008	-.027	-.037	-.023
1979-1989	-.033	.010	.010	-.010	.007	-.004	-.014	-.028	-.032	-.018
Sugar and Confectionary Products (SIC 206)										
1959-1973	-.031	.010	.002	-.008	.009	-.009	-.028	-.017	-.042	-.009
1973-1979	-.021	.016	-.006	-.012	.011	.003	-.026	-.020	-.047	-.006
1979-1989	-.026	.008	.005	-.015	.013	-.005	-.031	-.019	-.045	-.014
Fats and Oils (SIC 207)										
1959-1973	-.024	.006	.010	-.010	.003	-.011	-.023	-.010	-.036	-.017
1973-1979	-.017	.009	-.008	-.004	.005	-.002	-.016	-.012	-.039	-.019
1979-1989	-.022	.005	.012	-.007	.004	-.009	-.012	-.014	-.044	-.023
Beverages (SIC 208)										
1959-1973	-.019	.003	.004	-.005	.011	-.005	-.017	-.021	-.045	-.013
1973-1979	-.013	.008	-.005	-.004	.009	.002	-.022	-.024	-.049	-.015
1979-1989	-.015	.006	.006	-.008	.007	-.010	-.026	-.015	-.042	-.018
Miscellaneous Food and Kindred Products (SIC 209)										
1959-1973	-.033	.009	.008	-.007	.002	-.007	-.024	-.011	-.037	-.008
1973-1979	-.023	.012	-.007	-.004	.005	.009	-.019	-.010	-.039	-.006
1979-1989	-.027	.009	.011	-.005	.001	-.004	-.025	-.014	-.042	-.003

Finally, note that this suggests declines in labor demand due to tech/trade impacts may be attenuated somewhat in the long run as long as substitution between L and K prevails (although output growth could counteract this). This tendency appears, however, to be small, both due to the lack of a clear substitutable relationship with labor overall, and of serious subequilibrium for capital. (See Morrison and Siegel (1995) for some further long-run evidence.)

Concluding Remarks

In sum, it appears from the analysis presented in this study that tech/trade impacts reduce costs in the U.S. food processing industries in the short run, through reductions in the employment of less educated workers and materials and increases in the demand for more educated workers. This suggests clear biases in both input and labor composition even in absolute terms. External or "public" capital also seems to substitute for private capital—important spillovers are evident. Thus, given output demand, movement toward the long run implies at least a slight attenuation in the tech/trade impact due to substitution with private capital.

Notes

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[2]See, for example, Lawrence and Slaughter (1993), Bound and Johnson (1992), Katz and Murphy (1992), Murphy and Welch (1992), and Berndt et al. (1992).

[3]We also included the standard time trend (state of technology) variable "t" and a domestic outsourcing variable (purchased services) as t_n factors in the estimation, but since these are not the focus of the study, and the impacts from these factors were relatively unimportant, elasticities with respect to these variables are not included in the tables.

[4]See Morrison (1988a) for more details about the construction and use of this function, and Morrison and Siegel (1995) for further discussion of the representation of external effects through the components of the **T** vector.

[5]"t" is typically not logged in this elasticity expression since it is scale dependent.

[6]It is worth emphasizing that this elasticity, since it is expressed in terms of total costs, would also include a market price if the variable were internal rather than external—the costs were incurred by, and the variable were under control of, the firm/industry in question. In other words, the cost elasticity is in terms of the *net* value $p_n - Z_n$ rather than the gross value Z_n if the firm incurs costs p_n for purchases of T_n, but (as noted above) here the implicit assumption is $p_n = 0$. See Morrison and Siegel (1995) for further discussion of these types of elasticities.

[7]Note that the logarithm appears only in the denominator to be consistent with typical specification of biases, as discussed below. See Morrison (1988b) for further elaboration of different bias specifications.

[8]They are quite a bit larger than for manufacturing overall—see Morrison and Siegel (1995).

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Appendix 5.A

The primary source of 4-digit SIC level data is the National Bureau of Economic Research's (NBER) Productivity File, which includes current and constant-dollar measures of output and inputs for 450 manufacturing industries for 1958-1989. Five inputs are included: capital, production labor, non-production labor, materials (or intermediate goods purchased from other firms), and energy. This file is an updated version of the Penn-SRI Database created at the Census Bureau in the late 1970s. An earlier version of this file was analyzed in Siegel (1997).

Measures of External Factors (elements of T_n vector)

Trade. Our measure of "openness" is the ratio of exports to imports, as reported in the NBER Trade and Immigration Database (see Abowd 1991), for the years 1959-1984. An alternative measure, the ratio of exports to output, yielded very similar results.

High-Tech Capital. To derive our measure of high tech capital, we make use of data on the price and quantity of "high-tech" office equipment published by the BEA, which has been linked to this file and analyzed by Berndt and Morrison (1995).

R&D Investment. The major source of R&D data at the industrial level (2-digit SIC level) is the series entitled Research and Development in Industry, published by the National Science Foundation.

Education of Labor Force. Our measure of labor composition is based on the education levels of industrial workers. Data on the characteristics of workers in 21 (mainly 2-digit SIC) manufacturing industries were provided to us by Larry Rosenblum of the BLS's Productivity Division. The four education classifications are: (a) without a high school diploma; (b) with exactly a high school diploma; (c) with some college; (d) with a college degree.