"The Pin Factory Revisited: Diversification and Productivity Growth"

by

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Abstract

Manufacturing plants have been producing an increasingly homogeneous product mix over recent years. Individual plants have been manufacturing fewer and less dissimilar products. The trend is ubiquitous across industries and is unlikely to be a random event. An index of product diversification is introduced into a fixed–effects model of productivity growth derived formally from a factor–minimal cost function. Specialization at the production site is found to have spurred productivity growth. Over the 1963–87 period, decreasing product heterogeneity has accounted for about 17 percent of productivity growth in U.S. manufacturing, second in importance only to technical change and equaling the contribution of traditional scale economies.

It is a well–known phenomenon that manufacturing firms have become increasingly diversified over recent decades. What is less well known is that production activity at individual manufacturing plants has become increasingly homogeneous. Gollop and Monahan (1991) report that while enterprise–based diversification increased in 14 of 20 two–digit manufacturing industries between 1963 and 1982, product specialization in individual establishments increased in 17 of the same 20 industries.[1] When viewed over the 1963–87 period, this proportion increases to 18 of 20 industries representing more than 86 percent of manufacturing shipments.

The pattern is persistent and unmistakable. Plant–level diversification declined between every pair of Census of Manufactures years in the 1963–87 period in 17 of 20 industries. In fact, the percent of establishments producing no more than a single 5–digit product increased in 19 of 20 two–digit industries over the full period.

Such a ubiquitous pattern is unlikely to be random. It most likely is the result of rational cost–minimizing behavior. As Gollop and Monahan (1991) conclude: "Enterprises appear to be restructuring their production activity, moving toward more homogeneous production within establishments while holding a more diversified portfolio of establishments."[2]

This revealed behavior begs the relevant question: How much, if any, of measured total factor productivity growth in U.S. manufacturing can be explained by the increasing specialization of manufacturing plants? This paper addresses this question by formally embedding a measure of product diversification into a behavioral model of producer behavior. The diversification index developed in Gollop and Monahan (1991) is combined with an updated sector–specific production data set described in Jorgenson, Gollop, and Fraumeni (1987). The productivity effect of increasingly homogenous production activity in manufacturing plants is identified and quantified.

The characterization of diversification at the production plant is critical. Section 1 opens the paper with a brief description of the form and properties of the diversification index applied in the paper. Section 2 formally incorporates the index into a cost–minimizing model of producer behavior. The relationship between productivity growth and product diversification is derived from this behavioral model. The data set is described briefly in Section 3 along with particular econometric issues arising from the panel–nature of the data set. Among the results reported in this paper, the most important is that 17 percent of measured productivity growth in U.S. manufacturing over the 1963–87 period is the direct result of plants engaging in increasingly homogeneous production. This contribution is second only to that of technical change.

1. The Index of Diversification

It is important to emphasize at the outset that the diversification index developed by Gollop and Monahan (1991) is wholly supply–side based. The concept of diversification is not defined by demand–side conditions corresponding to consumer–defined substitution possibilities. This, however, is not a weakness of the index but its unique strength. The production–based index is particularly appropriate for a study examining the relationship between product diversification at the manufacturing plant site and measured productivity growth.

The index is designed so that it is sensitive to the number of distinct 5–digit products produced in an establishment, the changing distribution of those products within the plant, and the extent of heterogeneity among the products. Derivation of the index (d) for a representative manufacturing plant, presented in formal detail in Gollop and Monahan (1991), begins with the Herfindahl index, actually one minus the Herfindahl index:

$$(1) \qquad d = 1 - \Sigma\, s_i^2,$$

where s_i is the share of the ith 5–digit product in the establishment's shipments.

Adding and subtracting 1/n (where n is the number of distinct 5–digit products produced in the plant) to the right–hand side of (1) decomposes the index into distinct product number and distribution components:

$$(2) \qquad d = (1 - \frac{1}{n}) + \Sigma\, (\frac{1}{n^2} - s_i^2).$$

The first term in (2) identifies the effect of changing product number on the index d. It varies directly with the number of products produced at the plant. The second term focuses on product distribution and is based on the maintained hypothesis that diversification decreases as production shifts more and more to a single product. Holding n fixed, the index d increases (decreases) as a plant adopts a more (less) uniform product distribution.[3]

The major contribution in Gollop and Monahan (1991) is the generalization of the index in (1) to a form incorporating the notion of product dissimilarity or "heterogeneity" among the products manufactured within a plant. The central idea follows from recognizing that any application of a Herfindahl–based index begins from a primitive notion of product heterogeneity. After all, if two products are identical, they are simply merged within a common product code. If dissimilar, the products adopt distinct subscripts in the plant's list of products.

This bivariate notion of product heterogeneity can be made explicit by identifying the effect on the Herfindahl index of deciding that two products, previously defined as dissimilar, are in fact identical. Under this scenario, the value of the Herfindahl index increases by $2s_m s_n$, where the mth and nth products are the two products now judged identical.[4]

A continuous generalization of this bivariate result, derived fully in Gollop and Monahan (1991), leads to an independent term that can be appended additively to the index d in (1) so that the index takes the expanded form

$$(3) \qquad d = 1 - \sum_i s_i^2 + \sum_i \sum_{k \neq i} s_i s_k \sigma_{ik}.$$

The variable σ_{ik} is a continuous distance function quantifying the heterogeneity between the ith and kth products. It takes a zero value when the two products being evaluated are identical and approaches the unit value as the products become increasingly dissimilar. As the last term in (3) makes clear, product distance is evaluated at all product pairs.

The notion of heterogeneity or "distance" between products is captured by differences in product characteristics as defined by each product's production parameters. In particular, assume that the ith and kth products are produced according to the Cobb–Douglas technologies $y_k = \Pi X_{kj}^{\beta_{kj}}$ and $y_i = \Pi X_{ij}^{\beta_{ij}}$, respectively. As differences between β_{kj} and β_{ij} increase, product dissimilarity increases. Assuming competitive factor markets, input cost shares provide estimates of the corresponding production parameters. As described in Gollop and Monahan (1991), the distance function σ_{ik} takes the final form

$$(4) \qquad \sigma_{ik} \equiv \left(\sum_j \frac{|w_{kj} - w_{ij}|}{2} \right)^{1/2}$$

where $0 \leq \sigma_{ik} < 1$,

$w_{kj} \equiv$ input cost share of the jth input in the kth product, and

$w_{ij} \equiv$ input cost share of the jth input in the ith product.

The distance function σ_{ik} therefore quantifies the difference between the products described by $\{\beta_{kj}\}$ and $\{\beta_{ij}\}$.[5]

The final form of the diversification index (D) is formed by multiplying the expression in (3) by one–half, thereby ensuring that the final index is bounded in the zero–one interval.

$$(5) \qquad D = 1/2[1 - \sum_i s_i^2 + \sum_i \sum_{k \neq i} s_i s_k \sigma_{ik}].$$

The index D takes a zero value for any establishment that produces only a single product: $D = 0$ when $s_i = 1$ and σ_{ik} is undefined. In contrast, D approaches unity as a plant approaches a state of complete diversification: $\lim D = 1$ as $s_i^2 \rightarrow 0$ and $\sigma_{ik} \rightarrow 1$ for all i,k.

One nice feature of this Herfindahl–based index is that it can be decomposed into unique number (N), distribution (S), and heterogeneity (H) components. This is accomplished by simply replacing $(1 - \Sigma s_i^2)$ in (5) with its decomposition in (2)

$$(6) \qquad D = 1/2[(1 - \frac{1}{n}) + \sum_i (\frac{1}{n^2} - s_i^2) + \sum_i \sum_{k \neq i} s_i s_k \sigma_{ik}].$$

The desirable properties of the index now become apparent. *Ceteris paribus*, D is an increasing function of the number of distinct 5–digit products, varies directly with the increasingly equal distribution of products (i.e., as the product shares s_i become more equal, the distribution term S takes on increasingly positive values), and increases in product dissimilarity.

Diversification indexes are constructed for each manufacturing establishment which is then assigned to its appropriate four, three, and two–digit industry aggregates based on its primary product.[6] Shipments–weighted mean diversification indexes are calculated for each industry aggregate in each Census year. The two–digit aggregates are used in this study.

2. Model of Cost–Minimizing Behavior

The model developed in this paper is based on a factor–minimal cost function for a representative manufacturing plant. Production cost (C) is modeled as a function of input prices ($\underline{w}$), a vector of distinct outputs ($\underline{y}$), and a state–of–technology variable (T)

(7) $C = C(\underline{w}, \underline{y}, T)$.

Producers choose the optimal mix of inputs in response to the exogenous arguments of the cost function. Factor markets are assumed to be competitive. It is unnecessary to impose any structure on the nature of competition in output markets.

Assume that all outputs y can be characterized in terms of the quantity of some underlying elemental unit (q) common to all outputs and some composite variable (h) of attributes that uniquely differentiate the y outputs from each other.[7] The cost function becomes

(8) $C = C\ [\underline{w}, y_1\ (q_1, h_1), y_2\ (q_2, h_2),...,y_n\ (q_n, h_n), T]$.

The plant's output then can be modeled in terms of its aggregate production of the common units q and the extent of the differentiating characteristics h defining the plant's product mix

(9) $C = C\ (\underline{w}, q^*, \underline{h}, T)$,

where $q^* = \Sigma\, q_i$.

The diversification index D introduced in Section 1 captures the spirit of $\underline{h}$. It is a function of the number (N) of distinct products y, their share distribution (S), and their heterogeneity (H) so that

(10) $C = C\,[\underline{w},\ q^*,\ D(N,S,H),\ T]$.

It is useful to digress for a moment from the formal derivation of the model. The ultimate objective of this paper is to examine how much (if any) of productivity growth in U.S. manufacturing can be explained by product heterogeneity at the plant level. It makes sense to conduct this analysis in the context of productivity as measured in a major productivity study. For this purpose, this paper relies on detailed output, input, and price data constructed for 2–digit manufacturing industries by Jorgenson, Gollop, and Fraumeni (1987).

Measures of constant dollar output for the 2–digit manufacturing industries in the Jorgenson, Gollop, and Fraumeni (1987) study are taken directly from 2–digit output measures prepared by the Bureau of Economic Analysis (BEA).[8] The BEA output measure for each 2–digit industry is formed as the simple ratio of current dollar shipments across all manufacturing plants assigned to the 2–digit industry and a 2–digit output price deflator. Each 2–digit deflator is constructed by BEA as the price ratio resulting from dividing the sum of current dollar shipments in all 4–digit industries assigned to that particular 2–digit industry by the sum of constant dollar shipments over all 4–digit industries. Put simply, measures of BEA manufacturing output effectively assume that constant dollar 2–digit output is simply the sum of constant dollar output at the 4–digit level.

The importance of this digression is that all major productivity studies, through their use of BEA output data, effectively disregard the changing level of product diversification within 2–digit manufacturing industries. Aggregate 2–digit output is defined as the arithmetic sum of constant dollar output over disaggregated 4–digit industries. Productivity studies therefore have measured output as $q^* = \Sigma q_i$ as defined in (9), not as $y^* = f(\underline{y})$ as described in (7). Any resulting "bias" in the measure of output is captured in the productivity residual. The role of the index D in (10) becomes clear.

Applying the model developed in this section to industry–level data requires a modification to the model. Two–digit industry output q^* can be defined as the product Q·E·F, where Q is the average level of output at each plant within the industry, E represents the average number of establishments per firm in the industry, and F represents the number of firms found in the industry. This leads to a respecification of equation (10)

$$\text{(11)} \quad C = C[\underline{w}, Q, E, F, D, T].$$

Equation (11) can be interpreted as the factor–minimal cost function applicable to the representative plant within a particular industry. That representative plant faces mean prices $\underline{w}$ and produces a diversified product mix D at output scale Q. As described in Section 1 above, the diversification index D is calculated at the plant level and represents the average level of diversification over all establishments in the parent 2–digit industry. One advantage of this approach is that scale economies associated with the average plant output Q in (11) is preserved as a plant–level concept.

Logarithmically differentiating the cost function (11) with respect to time (t) decomposes the rate of growth of total cost into its source components:

$$(12) \quad \frac{d\ell nC}{dt} = \sum_j \frac{\partial \ell nC}{\partial \ell np_j} \frac{d\ell np_j}{dt} + \frac{\partial \ell nC}{\partial \ell nQ} \frac{d\ell nQ}{dt} + \frac{\partial \ell nC}{\partial \ell nE} \bullet \frac{d\ell nE}{dt}$$

$$+ \frac{\partial \ell nC}{\partial \ell nF} \frac{d\ell nF}{dt} + \frac{\partial \ell nC}{\partial \ell nD} \bullet \frac{d\ell nD}{dt} + \frac{\partial \ell nC}{\partial T} \frac{dT}{dt} .$$

The rate of change in total production cost for an industry can be expressed as the cost elasticity weighted average of rates of growth in input prices, the scale elasticity weighted rate of growth in average plant output, the cost elasticity weighted changes in the number of establishments per firm and the number of firms in the industry, the cost elasticity weighted rate of change in product diversification at the representative plant, and the rate of cost reduction due to technical change.[9]

The logarithmic partial derivatives in (12) have particular economic interpretations. Applying Shephard's Lemma, the cost elasticities premultiplying the input price terms are simply input cost shares (v_j) in total cost

$$(13) \quad \frac{\partial \ell nC}{\partial \ell np_j} = \frac{p_j X_j}{C} = v_j \qquad (j = 1,2,...n).$$

The cost elasticity associated with plant–level output represents traditional scale economies at the representative plant

$$(14) \quad \frac{\partial \ell nC}{\partial \ell nQ} = v_Q .$$

If industry cost responds proportionally to changes in plant output, v_Q takes the unit value indicating the presence of constant returns to scale. If cost responds less (more) than proportionally to changes in output, v_Q is less (more) than unity suggesting the technology exhibits scale economies (diseconomies).

The elasticity associated with the average number of establishments per firm identifies the presence and magnitude of economies flowing from multi–plant operations

$$(15)\quad \frac{\partial \ell nC}{\partial \ell nE} = v_E .$$

If v_E equals unity, there are no multi–plant economies. If v_E < (>) unity, multi–plant economies (diseconomies) are present.

The corresponding elasticity of cost with respect to the number of firms within the industry can be interpreted as the effect of increasing competition (additional firms) on production costs

$$(16)\quad \frac{\partial \ell nC}{\partial \ell nF} = v_F .$$

Note that this elasticity is defined in terms of representative firms, those operating an industry average number of plants of average industry size.

The elasticity of cost with respect to the diversification index, of course, is the term of interest

$$(17)\quad \frac{\partial \ell nC}{\partial \ell nD} = v_D .$$

Holding constant input prices, the number of firms, establishments per firm, the scale of plant operation, and the state of technology, v_D defines the impact of changing product diversification on production cost.

Finally, the rate of technical change is defined by the last term in (12). Adopting the standard sign convention, the rate of technical change (v_T) equals the negative of the partial elasticity of cost with respect to the technology index T

$$(18) \qquad -\frac{\partial \ell n C}{\partial T} = v_T .$$

If, as is common practice, the technology index is defined in units of time denominated in years, $dT/dt = 1$ and the cost elasticity in (18) equals the annual rate of technical change.

Subtracting the cost–share weighted growth rate of input prices and the growth rate of industry output (q^*) from both sides of (12) and multiplying the equation by minus one transforms (12) into a decomposition of total factor productivity (TFP) growth

$$(19) \qquad -\left[\frac{d\ell nC}{dt} - \sum_j v_j \frac{d\ell np_j}{dt} - \frac{d\ell nq^*}{dt} \right]$$

$$= (1-v_Q) \frac{d\ell nQ}{dt} + (1-v_E) \frac{d\ell nE}{dt} + (1-v_F) \frac{d\ell nF}{dt} - v_D \frac{d\ell nD}{dt} + v_T \frac{dT}{dt} ,$$

where $\frac{d\ell nq^*}{dt} = \frac{d\ell nQ}{dt} + \frac{d\ell nE}{dt} + \frac{d\ell nF}{dt}$.

The left–hand side of (19) is the dual to the standard definition of productivity growth: total factor productivity growth ($T\dot{F}P$) equals the reduction in average cost not accounted for by changes in input prices

$$(20) \qquad T\dot{F}P = -\left[\frac{d\ell n(C/q^*)}{dt} - \sum_j v_j \frac{d\ell np_j}{dt} \right].$$

Subtracting the growth rate of industry output from both sides of (19) not only transforms the left–hand side of (19) into a measure of TFP growth but also makes transparent the productivity effects of growth in the scale of plant production (Q), multi–plant operations (E), and the number of competitive firms within an industry (F).

Consider, for example, the term $(1 - v_Q)$ premultiplying the growth in plant output. Under constant returns to scale, $v_Q = 1$ and changes in the scale of plant production in (19) have no effect on TFP growth. Under scale (dis)economies, however, $v_Q < 1$ (> 1) and growth in plant output augments (retards) productivity growth. Identical interpretations apply to the terms premultiplying the logarithmic partials with respect to E and F.

The expression for $\dot{TFP}$ in (19) is a Divisia index number. It equals the sum of productivity contributions through traditional scale economies, multi–plant economies, competition, changing product diversification, and technical change. The objective of this paper is to quantify each distinct source of productivity growth. Primary attention focuses on the role of product diversification.

3. Estimating Model

The development of an econometric model suitable for this research involves three steps. First, an explicit functional form must be specified for the implicit cost function (11). Second, the continuous model of productivity growth and its source components must be extended to incorporate data at discrete points in time. Finally, an appropriate error structure must be formulated for the model.

The analysis begins with specifying a particular functional form. For this purpose, consider the Cobb–Douglas cost function, a first–order approximation to the cost function C in (11)

$$(21) \quad C = \exp\left[\alpha_o + \sum_j \beta_j \ln p_j + \beta_Q \ln Q + \beta_E \ln E + \beta_F \ln F + \beta_D \ln D + \beta_T T\right].$$

The logarithmic partials of cost (C) with respect to each argument identify the parameters specifying the elasticities defined in (13) through (18)

$$
\begin{aligned}
(22) \qquad & v_j = \beta_j && (j = 1,2,\ldots,n) \\
& v_m = \beta_m && (m = Q,E,F,D) \\
& -v_T = \beta_T \, .
\end{aligned}
$$

Substituting these parameters into (19) yields an expression for TFP growth in terms of the Cobb–Douglas parameters

$$
(23) \qquad \dot{TFP} = (1-\beta_Q)\frac{d\ell nQ}{dt} + (1-\beta_E)\frac{d\ell nE}{dt} + (1-\beta_F)\frac{d\ell nF}{dt} - \beta_D\frac{d\ell nD}{dt} - \beta_T \, .
$$

An estimable form of the productivity growth expression (23) requires that its continuous time derivatives be defined in terms of discrete data. This requires evaluating the cost function (11) at two points in time, say t and t–1. Given (11) and (19), the average rate of TFP growth ($\dot{TFP}$) over the period t–1 to t can be expressed as the negative of the difference between successive logarithms of total cost less (i) a weighted average of the differences between successive logarithms of input prices and (ii) the logarithmic difference in industry output q^*

$$
(24) \qquad \dot{TFP} = -\left\{ [(\ell nC(t) - \ell nC(t-1)] - \Sigma_j \bar{v}_j[(\ell np_j(t) - \ell np_j(t-1)] - [(\ell nq^*(t) - \ell nq^*(t-1)] \right\},
$$

where $\bar{v}_j = 1/2\left[v_j(t) + v_j(t-1)\right]$.

The expression $\dot{TFP}$ is a Törnqvist index number representing the standard measure of TFP growth. It can be measured in terms of price and quantity data at discrete points in time.

Applying the quadratic approximation lemma leads to the decomposition of $\dot{TFP}$ into its source components[10]

$$(25) \quad \dot{TFP} = (1-\bar{v}_Q)\left[\ell nQ(t) - \ell nQ(t-1)\right] + (1-\bar{v}_E)\left[\ell nE(t) - \ell nE(t-1)\right]$$

$$+ (1-\bar{v}_F)\left[\ell nF(t) - \ell nF(t-1)\right] - \bar{v}_D\left[\ell nD(t) - \ell nD(t-1)\right] + \bar{v}_T\left[T(t) - T(t-1)\right],$$

where $\bar{v}_m = 1/2\left[v_m(t) + v_m(t-1)\right]$ $\qquad (m = Q,E,F,D,T)$.

The form of the estimating model follows directly from (23), (24), and (25)

$$(26) \quad \dot{TFP} = (1-\beta_Q)\left[\ell nQ(t) - \ell nQ(t-1)\right] + (1-\beta_E)\left[\ell nE(t) - \ell nE(t-1)\right]$$

$$+ (1-\beta_F)\left[\ell nF(t) - \ell nF(t-1)\right] - \beta_D\left[\ell nD(t) - \ell nD(t-1)\right]$$

$$- \beta_T\left[T(t) - T(t-1)\right].$$

The measured rate of productivity growth ($\dot{TFP}$) between t–1 and t becomes the dependent variable in a single equation model. The first–order nature of the Cobb–Douglas function conveniently defines each average cost elasticity specified in (25) as a constant equal to its corresponding Cobb–Douglas parameter

$$(27) \quad \bar{v}_m = 1/2\left[v_m(t) + v_m(t-1)\right] = \frac{2\beta_m}{2} = \beta_m \qquad (m = Q,E,F,D,T).$$

The final step is the formulation of an error structure appropriate for equation (26). Its first–difference form has particular econometric implications. The analysis begins by adding a random disturbance e_{TFP} to the underlying Cobb–Douglas expression (23) for

TFP growth. Moving from the continuous time equation (23) to its discrete data form (26) implies that the error terms (e_{TFP}) in the transformed specification (26) are no longer uncorrelated over time. The error terms in two adjacent time periods are both functions of $e_{TFP}(t-1)$

$$\bar{\varepsilon}(t) = 1/2\left[\varepsilon(t) + \varepsilon(t-1)\right]$$

$$\bar{\varepsilon}(t-1) = 1/2\left[\varepsilon(t-1) + \varepsilon(t-2)\right].$$

The pattern of serial correlation among adjacent error terms therefore has the following form:

$$V\left[\bar{\varepsilon}(t)\right] = \frac{1}{2}\sigma^2$$

$$\mathrm{Cov}\left[\bar{\varepsilon}(t)\ \bar{\varepsilon}(t-1)\right] = \frac{1}{4}\sigma^2$$

$$\mathrm{Cov}\left[\bar{\varepsilon}(t)\ \bar{\varepsilon}(t-2)\right] = 0.$$

It follows that the variance–covariance matrix of average disturbances (e_{TFP}) takes the form

$$\mathrm{Var}\begin{pmatrix}\bar{\varepsilon}(2)\\ \bar{\varepsilon}(3)\\ \cdot\\ \cdot\\ \bar{\varepsilon}(n)\end{pmatrix} = \sigma^2 \begin{bmatrix} \frac{1}{2} & \frac{1}{4} & 0 & \ldots & 0\\ \frac{1}{4} & \frac{1}{2} & \frac{1}{4} & \ldots & 0\\ 0 & \frac{1}{4} & \frac{1}{2} & \ldots & 0\\ \vdots & \vdots & \vdots & & \vdots\\ 0 & 0 & 0 & & \frac{1}{2}\end{bmatrix}$$

$$= \sigma^2\Omega,$$

where Ω is a Laurent matrix and n is the limit of t under analysis. Although the disturbances are autocorrelated, the data can be transformed to eliminate the autocorrelation. Using a procedure outlined in Jorgenson, Gollop, and Fraumeni (1987), the data are transformed so that the covariance matrix of transformed disturbances has the required form $\sigma^2 I$.[11] Applied to the transformed data, equation (26) becomes the final estimating equation.[12]

A panel data set for the 21 two–digit manufacturing industries is developed for this study.[13] The data points represent observations for each industry at the six Census of Manufactures years spanning the 1963–87 period.[14] The data points are limited to the census years because the diversification indexes developed by Gollop and Monahan (1991) are available only in census years.

Constant dollar output, production cost, and input price and quantity data for the two–digit industries are taken from Jorgenson, Gollop, and Fraumeni (1987), with the data updated through 1987. The set of inputs includes labor, capital, energy, and materials. This production data set is sufficient for the construction of the productivity growth rate variable (TFP) required by the estimating equation (26).

Data describing the number of firms and establishments in each industry are taken from the data files used by Gollop and Monahan (1991) to construct the diversification indexes. These data are used to form values for the variables E and F described in Section 1.

Finally, the technology index T at each observation simply takes a value equal to the calendar year of the corresponding Census year. As a result, the first–difference form for the technology variable T in (26) simply indicates the number of years between adjacent Census years and thereby controls for the varying time interval over which productivity growth ($\dot{TFP}$) is being evaluated. The cost elasticity v_T therefore equals the annual rate of technical change.

Finally, it is necessary to recognize the importance of the first–difference form of the estimating model. The panel data set admittedly represents diverse manufacturing industries. First differencing the data, however, not only enables the continuous time derivatives in (23) to be characterized in terms of data at discrete points in time but also controls for industry–specific effects.

4. Sources of Productivity Growth

The productivity growth equation (26) was estimated using ordinary least squares. The cost function parameters were estimated directly. Estimates of these coefficients and their standard errors are reported in the left–hand panel of Table 1. Each coefficient has its expected sign and, with the exception of the technical change coefficient β_T, is statistically significant at the 1% level.

The economic significance of these estimates for productivity growth becomes clear when the cost parameters are re–expressed in terms of the productivity growth coefficients specified in equation (26). These coefficients are listed in the right–hand panel of Table 1. The negative signs preceding each cost parameter follow directly from the above derivation

Table 1

Parameter Estimates
(Standard Errors in Parentheses)

Cost Function Parameter	Estimate	Productivity Equation Parameter	Estimate
β_Q	.897	$(1-\beta_Q)$	.103
	(.033)		(.033)
β_E	.757	$(1-\beta_E)$	.243
	(.147)		(.147)
β_F	.923	$(1-\beta_F)$	.077
	(.054)		(.054)
β_T	−.003	$-\beta_T$	.003
	(.002)		(.002)
β_D	.148	$-\beta_D$	−.148
	(.030)		(.030)

of equation (26). The negative signs reflect the inverse relationship between cost and productivity growth. The difference between unity (a state of constant returns) and each cost elasticity β_Q, β_E, and β_F identifies the productivity contribution of cost economies resulting, respectively, from increased plant scale, multi–plant operations, and competitive stimuli. Elasticity values below (above) unity suggest that growth in the associated variable augments (diminishes) productivity growth.

Estimates of the productivity coefficients together with their standard errors are reported in the right–hand panel of Table 1. Note that testing whether the productivity growth coefficients associated with the production variables Q, E, and F are statistically different from zero is equivalent to testing whether the corresponding cost elasticities β_Q, β_E, and β_F are statistically different from unity (constant returns).

The reported estimates suggest that productivity growth in manufacturing is augmented by cost economies resulting from both the increasing scale of establishment output and the presence of multi–plant operations. The former is significant at the 1% level; the latter is significant at the 5% level. Interestingly, the multi–plant elasticity is slightly more than twice as large as the conventional plant–level scale elasticity. A one percent increase in the growth of output at each establishment within a manufacturing industry contributes a tenth of a percentage point to the industry's TFP growth. This is the result of conventional scale economies. The same growth, however, achieved not through any change in either plant scale or the number of firms but through a one percent expansion in the number of establishments per firm appears to lead to nearly a quarter of a percentage point increase in the industry's TFP growth. A potential explanation for the apparent dominance of multi–plant economies will be offered below.

Competition from additional firms within an industry appears to stimulate cost–reducing behavior (i.e., productivity growth) but the effect is numerically small. A one percent increase in the number of representative firms within an industry (those operating an average number of establishments and having industry–wide average output per establishment) leads to less than a .08 percentage point increase in the industry's TFP growth. The coefficient estimate $(1 - \beta_F)$, however, is significant at the 8% level.

Technical change appears to have a correctly–signed (positive) and significant effect on productivity growth in manufacturing. The coefficient estimate is statistically significant at the 7% level. Though the point estimate of β_T has the smallest numerical magnitude among the five coefficients defining the model, it should not be inferred that technical change is unimportant. Unlike the four other parameters specified in (26), β_T is not an elasticity. It provides a direct estimate of the year–to–year effect of technical change on TFP growth. The .003 estimate suggests that technical change contributes three–tenths of a percentage point to annual TFP growth. Given that the annual rate of productivity growth has averaged just below one percent in recent years, this contribution is not insubstantial.

The coefficient of interest, of course, is β_D or, in terms of equation (26), $-\beta_D$. Holding constant industry production (the number of firms, establishments per firm, and output per establishment), the coefficient estimate reported in Table 1 indicates that TFP growth in an industry declines as product diversification increases in the industry's manufacturing plants. Each percent decrease in an industry's product diversification leads to a .15 percentage point increase in the industry's rate of productivity growth. It is also interesting to note that the estimate of $-\beta_D$ has the highest significance level among all productivity coefficients.

This pattern of results and, in particular, the important role of product heterogeneity persists under a more detailed analysis of the sources of productivity growth. Table 2 reports a parallel set of parameter estimates for equation (26) when product diversification is decomposed into its number (N), product distribution (S), and heterogeneity (H) terms defined above in Section 1. Comparing the cost function elasticities and productivity coefficients reported in Tables 1 and 2 reveals that the estimates of cost economies corresponding to plant scale, multi–plant operations, and

Table 2

Parameter Estimates
(Standard Errors in Parentheses)

Cost Function		Productivity Equation	
Parameter	Estimate	Parameter	Estimate
β_Q	.885	$(1-\beta_Q)$	.115
	(.035)		(.035)
β_E	.771	$(1-\beta_E)$	.229
	(.142)		(.142)
β_F	.932	$(1-\beta_F)$	.068
	(.059)		(.059)
β_T	−.002	$-\beta_T$	.002
	(.002)		(.002)
β_N	.062	$-\beta_N$	−.062
	(.100)		(.100)
β_S	−.009	$-\beta_S$	.009
	(.062)		(.062)
β_H	.130	$-\beta_H$	−.130
	(.054)		(.054)

competitive stimuli remain unchanged both in magnitude and statistical significance. The same holds for the annual rate of technical change.

All three diversification coefficients have the expected sign but only the heterogeneity term is statistically significant. Holding constant the overall level of output (constant dollars) as well as the organization of multi–plant operations and the number of firms, productivity growth decreases as (i) the number of distinct products increases, (ii) the share distribution of products becomes more equal, and (iii) products become increasingly dissimilar. Only the latter, however, is statistically significant and it is so at the 1% level.

Comparing the magnitudes and significance levels of the diversification coefficients in Tables 1 and 2 suggests that the full TFP effect of any change in product diversification flows through the heterogeneity term. This makes intuitive sense. If productivity growth is sensitive to the changing specialization of production within plants, one would expect those economies to be a function of the heterogeneity of products, not their simple number or share distribution. Producing an increasing number, even a large number, of nearly identical products ($\sigma_{ik} \rightarrow 0$ for all i and k), regardless of their share distribution, has little implication for specialization economies and therefore productivity growth. It is the extent of product heterogeneity that matters. The estimates reported in Table 2 affirm this.

Each estimated coefficient reported in the right–hand panels of Tables 1 and 2 identifies the responsiveness of TFP growth to some hypothetical change in an associated variable. Identifying the actual historical importance of each productivity determinant, however, requires evaluating the product of each coefficient and the measured change in its associated variable. Equation (26) provides the formal framework. The contribution of changing plant scale, for example, equals the product of the coefficient $(1-\beta_Q)$ and the observed rate of change in output per establishment.

Equation (26) is used to decompose productivity growth in U.S. manufacturing over the 1963–87 period into its source components. The average annual contribution of each source to annual productivity growth is calculated using the productivity coefficients reported in the right–hand panel of Table 1 and the average annual rates of change in each source variable.

The resulting decomposition is presented in Table 3. Each entry is to be interpreted as the annual percentage point contribution of that source to annual TFP growth in manufacturing, the average of which is found to equal .82 percent per year across all manufacturing industries. As expected, technical change dominates with a three–tenths of one percentage point TFP contribution each year. At the other extreme, neither changes in multi–plant operations nor competitive stimuli have contributed much to productivity growth in the 1963–87 period. In the case of multi–plant economies, there simply has been little change in the number of plants per firm over the 24–year period. That ratio has increased at a rate less than 6 one–hundredths of a percent per year. The multi–plant elasticity reported in Table 1 may be large, but its impact is insubstantial. In the case of competitive pressure resulting from the entry of new firms, the number of manufacturing firms has indeed increased over the period, at a rate equal to nearly three–fourths of a percent per year. The small elasticity estimate reported in Table 1, however, destines the overall effect of competitive stimuli to be small.

The important finding, however, is that increasing product specialization in manufacturing establishments has been an important source of productivity growth. On average over the 1963–87 period, it has contributed 14 hundredths of a percentage point each year to TFP growth in U.S. manufacturing. Its contribution is second in importance only to technical change and equals in importance the contribution of traditional scale economies. The bad news is that, since there is a definitional limit to product specialization within manufacturing plants, future contributions through this source of productivity growth may become increasingly small.

Table 3

Source Decomposition of Productivity Growth:
U.S. Manufacturing 1963–87

Source Contribution	Average Annual Change (Percentage Points)
Productivity Growth	.82
Increasing Scale of Plant Production	.14
Multi–Plant Operations	.02
Competitive Stimuli	.06
Technical Change	.30
Increasing Specialization in Production	.14

5. Conclusion

This study has been conducted at the two–digit industry level because of a desire to draw inferences about the aggregate economy––at least its manufacturing sector. The risk in any industry–level analysis is that the aggregate data may mask important microeconomic relationships. That, fortunately, does not appear to be true in this study, perhaps because of the care taken to distinguish scale, multi–plant, and pure firm effects. In any case, the results are both robust and striking.

The evidence suggests that the pervasive increase in specialization in manufacturing plants witnessed by Gollop and Monahan (1991) is, as expected, the result of rational behavior. Increasing product homogeneity in 18 of 20 two–digit industries over the 1963–87 period was not a random event. Specialization at the production site spurs productivity growth. Not only is the estimated coefficient associated with product heterogeneity the most statistically significant of all productivity sources, but its magnitude suggests that a one percent increase in product specialization has a larger productivity contribution than does a one percent change in the scale of a manufacturing establishment.

The important conclusion is that the ubiquitous shift to increasingly homogeneous production in manufacturing plants has had a significant impact on manufacturing productivity growth. The average annual rate of decline in product heterogeneity over all manufacturing industries in the 1963–87 period is .96 percent. Over this same period, the average annual rate of TFP growth in manufacturing industries has been .82 percent. The estimated elasticities reported in Table 1 suggest that the .96 percent annual decrease in product heterogeneity contributed .14 percentage points to annual TFP growth in manufacturing. That contribution accounts for slightly more than 17 percent of annual productivity growth. The conscious move within manufacturing industries to establish plants as more homogeneous production sites has been both rational and beneficial. It appears the pin factory is as relevant today as it was for Adam Smith.

Notes

1. Gollop and Monahan (1991), p. 327.

2. Ibid., p. 329.

3. The index posits that a firm producing n products each having a 1/n share in the plant's total production is more diversified than another plant producing the identical n products but with one representing, say, 90% of plant production. The importance of the distribution property has been recognized previously. See, for example, Berry (1971) and McVey (1972).

4. Economists familiar with merger analysis make frequent use of this property of Herfindahl indexes. See Gollop and Monahan (1991), pp. 321–22 for a numerical example.

5. Division by 2 in equation (4) ensures that σ_{ik} is bounded in the zero–one interval. The one–half power guarantees that the heterogeneity term has curvature conditions consistent with the number and distribution terms introduced above. The index increases at a decreasing rate in all three terms. See Gollop and Monahan (1991), p. 324.

6. For this study, the two–digit industry for motor vehicles (SIC 37) is split between automobiles and other motor vehicles. This leads to 21 industry groups.

7. If, for example, the firm were an oil refinery producing various petroleum products, the variable q would likely be measured in barrels while the chemical attributes differentiating grades of petroleum products would be defined by h.

8. This is also the case for other major productivity studies. Kendrick (1961) and Kendrick and Grossman (1980), for example, also rely on BEA measures of manufacturing output.

9. The time derivative dT/dt in (12) represents the change in technology per unit of time.

10. See Diewert (1976), p. 118.

11. Jorgenson, Gollop, and Fraumeni (1987), pp. 229–34.

12. Note that the estimating model does not include an intercept among its estimable parameters. The intercept in the underlying Cobb–Douglas cost function (21) disappears when time derivatives are taken.

13. See note 6.

14. The six census years are 1963, 1967, 1972, 1977, 1982, and 1987.

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