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INDUSTRIAL CONCENTRATION, PRICE-COST MARGINS, AND INNOVATION

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abstract

This paper explores a panel data set matching establishment-based production statistics from Japan's *Census of Manufacturers* with wholesale price indices from the Bank of Japan, and Herfindahl indices from the Japan Fair Trade Commission. The data include annual observations over the period 1961-1990, for 74 industries at the 4-digit s.i.c. level. We estimate Cobb-Douglas production functions and Solow residuals for each industry and then use these estimates to further analyze the determinates of industrial concentration and innovation. The industries having great capital intensity, small employment of labor, and with high price-cost margins tend to be more concentrated. Cross-section estimates reveal a U-shaped mapping from concentration to innovation. JEL classifications L11, L13, L60, O30.

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1. Introduction

This paper estimates the annual average rate of Hicks neutral technical change in 74 Japanese manufacturing industries, 1961-1990, and relates these estimates to industrial concentration and price-cost margins. We do this by first estimating Cobb-Douglas production functions, under the maintained assumption of constant returns to scale. The residuals from these regressions measure technical change, and the labor coefficients measure labor's share in total cost for each industry. Price-cost margins are computed as the percentage by which value added minus total cost exceeds value of shipments (where total cost is the wage bill divided by the Cobb-Douglas labor coefficient). We find that the industries having great capital intensity, small employment of labor, and with high price-cost margins tend to be more concentrated. Cross-section estimates reveal a U-shaped mapping from concentration to innovation.

The data are drawn on 4-digit s.i.c. industries, from Japan's *Census of Manufacturers*, for which wholesale price indices could be closely matched. These industries are defined as the sets of establishments –not firms– primarily producing like commodities. The close matching of the industries with corresponding wholesale price index categories affords a real output measure that is likely to be much more accurate than ones typically found in the empirical literature on production functions. That our data is observed at the industry level rather than the firm level poses aggregation issues which we do address. A strong point in the data set we examine is that, unlike firm-based micro-data, it allows us to precisely observe cross-industry variation at a fairly narrow (4-digit s.i.c.) level. Individual firms tend to be much more diversified than their constituent production establishments, and can often only be clearly assigned to industries at the 2-digit level. Yet the theories relating industrial competitiveness or industrial concentration to innovation seem much more applicable at the 4-digit level. Our data also include annual time series of Herfindahl index of industrial concentration, matched from yet another source, the Japan Fair Trade Commission which is the antitrust enforcement agency of Japan.

Because our panel data set matches *establishment-based* measures of factor inputs, wages, revenues and value-added with *product-market* observations on prices and industrial concentration, it affords a particularly clear look at the year-to-year co-movement in industrial concentration, pricing, and innovation for a wide set of manufactured goods, as well as supporting cross-industry analysis of the same variables.

2. Basic Framework

We begin by addressing the aggregation issue. We will only observe production data at the industry level, so we need to make assumptions about how the aggregate variables we observe are related to the firm-level variables we do not observe. The maintained hypothesis underlying our approach is constant returns to scale at the firm level.

Let us posit that each firm is constrained by a Cobb-Douglas production function with two inputs: labor and capital. Suppose further that the output elasticities of labor and capital are the same for all firms in the same industry, though total factor productivity may vary from firm to firm. Suppose also that firms in the same industry face the same factor prices and thus employ capital and labor in the same proportions to one another (We presume that all firms are equally adjusted to the same factor prices). Denote the production of firm f by

$$(1) \qquad y_f = a_f l_f^{\theta} k_f^{(1-\theta)} ,$$

where y_f=output, l_f = labor, and k_f= capital. Then, under our stated assumptions, the industry-level production function is

$$(2) \qquad Y = \Sigma(z_f a_f)\, L^{\theta} K^{(1-\theta)} = A L^{\theta} K^{(1-\theta)} ,$$

where $Y=\Sigma y_f$, $L=\Sigma l_f$, $K=\Sigma k_f$, and $z_f=k_f/K=l_f/L$.

The industry-level technology parameter, $\Sigma(z_f a_f)=A$, reflects both the firm-level technologies a_i and the allocation of factor inputs within the industry. So, for example, a technological change at the industry level ΔA comprises not only technical change by firms Δa_f, but also any changes in shares of the respective firms'employment of industry inputs that are induced through the posited oligopolistic equilibrium. The basic logic here is that of Zarembka (1968).

A further serious issue in estimates of industry level production functions is identification. Specifically, when shifts in the production function are anticipated by firms, then they can be expected to adjust their employment of labor and capital. In this case the employment of labor and capital is correlated with the statistical error term in econometric estimates of the production function, and the estimated OLS coefficients are thus biased and inconsistent, as fully elucidated by Griliches and Mairesse (1998). Valid instruments for labor and capital might be found, particularly if one of these (capital) responds to productivity shocks with a lag. Then lagged values of capital become suitable instruments for contemporaneous employment of labor. This is the basic approach of the dynamic panel data literature (Olley and Pakes (1996), Blundell and Bond (2000), and Ackerberg, Caves, and Fraser (2004)). But that literature focuses on micro-panel data, that is with many cross-sections but relatively few time periods. Typically the unit of analysis in such panel data is the firm, not, as here, the industry. A different way forward is needed. Again the maintained assumption of constant returns to scale is helpful.

First note that for the Cobb-Douglas production function as in (2) above, we have that for each industry,

$$Y = A\,L\,(K/L)^{(1-\theta)} \,, \tag{3}$$

and the identification problem is simply that of estimating the coefficient on K/L. That is, if businesses adjust their employment of both capital and labor *equally* in response to perceived productivity shocks, then endogeneity bias is absent. Notice that the maintained assumption of constant returns to scale is crucial to this. But is it plausible that employment of capital and labor would be equally flexible? Labor is typically regarded as a variable input and capital as fixed in the short run. However in Japanese manufacturing industries, the well-documented practice of lifetime employment should weaken this presumption. It is reasonable to suppose that Japanese manufacturers'employment of both labor and capital respond sluggishly to anticipated productivity shocks, mitigating the problem of endogeneity bias.

3. Econometric Model

In the empirical literature on production functions, econometric specification is very much dependent upon the nature of the available data. Ours is a panel data set of calender year observations 1961-1990, for 74 manufacturing industries, including observations of average annual wholesale price index, Herfindahl index of production, and various establishment-based items including value added, value of shipments, employment, wages and book value of fixed tangible assets. All data were not available for all years so this represents an unbalanced panel data set. For a description of the data sources see Appendix 1. One important aspect of these data has already been noted: It is aggregated to the 4-digit s.i.c. level. Another thing to note is that we observe physical units of labor, number of employees, but only observe nominal units of capital, namely, book value of tangible assets. Accordingly, I will adopt a specification in which the multiplicative factor for converting units of capital from nominal book value to economically meaningful units of measurement is an estimable parameter.

We estimate an equation on the pooled annual time-series, cross-section of 74 industries at the 4-digit s.i.c. level, 1961-1990. The regression equation is the following:

(4) $$\ln Q_{it} = A_i + (1-\theta_i) A_t + \theta_i \ln L_{it} + (1-\theta_i) \ln K_{it} + v_{it}, \qquad i=1\ldots, n;\ t=1,\ldots,T.$$

or equivalently,

(5) $$\ln Q_{it} = A_i + \theta_i \ln L_{it} + (1-\theta_i) \ln e^{At} K_{it} + v_{it}, \qquad i=1\ldots, n;\ t=1,\ldots,T.$$

Here Q_{it} represents value of shipments by industry i in year t divided by average monthly wholesale price index for the corresponding product during the same year. The labor input is L_{it}, defined as the number of workers employed in the industry i in year t. And K_{it} is the book value of the fixed tangible assets of the industry i at the beginning of year t.

The error term v_{it} is likely to exhibit autocorrelation. Technological advance manifests itself as positive autocorrelation, and in principle at least, perfect autocorrelation. But few things in life are perfect, and in any case there are additional forces at work. For instance, if our dependent variable shipments varies with the business cycle it would induce some negative autocorrelation, abnormally high shipments in a boom year followed by abnormally low shipments the following year. We estimate these equations with adjustment for first-order autocorrelation, that is in which for each industry i, the error term in equation (5) is presumed to follow the stochastic process

(6) $$v_{it} = \rho_i v_{i,t-1} + u_{it}, \qquad \text{and } u_{it} \sim (0, \sigma_i^2).$$

We estimate the parameters A_i, A_t, θ_i and ρ_i . This was accomplished by an iterative application of two-way fixed effects and AR1 regression estimates using the SAS software. See Appendix 2 for details. Now the parameters A_t , t=1,...,T, comprise both the deflator of the nominal book-value measure of capital K_{it} and also include Hicks-neutral technological change that is common to all of the industries. That is, $e^{At}K_{it}$ represents the capital stock of industry i in year t measured in efficiency units calibrated to the pan-industry state of technology. Klette (1999) uses the same technique of statistically estimating the deflator of book-value of capital stock rather than constructing it from price indices and questionable assumptions about tax rates and depreciation.

Our estimates of the implicit capital deflator e^{At}* seem to embody substantial technological improvement. If there were merely inflation of nominal book value of capital stock, and no pan-industry technological advance, our adjustment factor e^{At}* , calibrated so that 1990=1, should decline as prices rise. But in fact it rises. By how much would inflation alone cause e^{At} to fall? The deflator for non-residential investment used in Japan's System of National Accounts (SNA) affords one measure of inflation. This is represented in Table 1, along with our estimates of e^{At}*. The fact that e^{At}* tends to rise even as prices rise indicates that technological advance embodied in our implicitly constructed "efficiency units" measure of capital outstrips inflation. An estimate of the efficiency unit per actual physical unit of capital in each year can be constructed by multiplying e^{At}* by the SNA investment deflator. The sense of this is that e^{At}* = capital in efficiency units/ capital in nominal units; SNA investment deflator = capital in nominal units/ capital in physical units; and so e^{At}* × SNA investment deflator = capital in efficiency units/ capital in physical units. The last column of Table 1, which is also plotted in Figure 1, depicts this measure of efficiency unit per actual physical unit of capital in each year.

Because our measure of labor is the number of workers employed each year, which is a physical unit of measurement, virtually all (pan-industry) technological advance is reflected in our "efficiency units" measure of capital. Not only improvements in machines and tools themselves, but also improvements in the quality of labor, including advances in education or enhancement of skills, will show up in our estimates as improvements in the efficiency of capital. Thus the increase in efficiency unit per actual unit of capital embodies the entirety of pan-industry technological advance. This measure grows from 0.305 in 1961 to 1.0 in 1990, an average annual exponential growth rate of 3.96 percent. Given our estimated average elasticity of output with respect to capital of 0.43, this implies an overall average rate of Hicks neutral technological advance of about 1.7 percent (= 0.43× 3.96 percent). This is a very plausible estimate of technological advance in our set of industries, most of which are old-line, mature manufacturing industries. Since 1935, Japan's average rate of increase in real GDP per capita, one rough measure of technological advance, is around 3 percent. Flath (2005, at p. 89).

Estimates of industry-specific parameters and related statistics are represented in Table 2. These estimates include, for each industry, an estimate of the elasticity of output with respect to labor θ_i*. The residuals v_{it}* from these regressions represent estimates of the industry-specific technical change, that is deviations from the pan-industry technical change embodied in A_t*, in effect *Solow residuals*. These residuals are the difference between actual observation of dependent variable and that predicted based on the structural equation. Later in the paper I will further describe the residuals from these regressions.

The estimated coefficients on $\ln L_{it}$ vary from industry to industry in a way that comports with common sense notions as to which industries are likely to employ more capital intensive methods. So for example the most capital intensive industries are estimated to be:

Synthetic Fibers (1- θ_i* = 0.69)

Medicines (1- θ_i* = 0.67)

Glass Bulbs For Use In Cathode Ray Tubes (1- θ_i* = 0.63)

Wrist Watches (1- θ_i* = 0.63)

Plastic-working Machines (1- θ_i* = 0.58)

Pumps (1- θ_i* = 0.58)

...and the least capital intensive are

Briquettes (1- θ_i* = 0.05)

Weaving Machines (1- θ_i* = 0.22)

Jute Yarn (1- θ_i* = 0.23)

Worsted Yarn (1- θ_i* = 0.26)

Miso (1- θ_i* = 0.26)

Our specification presumes constant returns to scale, both at the unobserved level of individual firms and at the level of the industry. We make no presumption regarding the state of competition in each industry. But we are able to construct estimates of price-cost margins for each industry in each year. The basic logic here follows that of Hall (1988). For each industry i we directly observe nominal value-added Y_{0it} and wage payments $W_{0it}L_{it}$. (Let the subscript "0" in "Y_{0it}" and W_{0it}" remind us that these are expressed in nominal units). We presume that labor's share of total cost in each industry equals our estimate of the output elasticity with respect to labor. Thus nominal total cost C_{0it}, including both labor cost and capital cost, is estimated as the wage bill divided by our estimate of the output elasticity with respect to labor

(7) $C_{0it}{*} = (W_{0it}L_{it})/\theta_i{*}$.

And our estimate of the nominal profit π_{0it} in each industry i in each year t is value-added minus cost:

(8) $\pi_{0it} = Y_{0it} - C_{0it}{*}$.

From these data we further construct industry-level *price-cost margins* m_{it} as the ratio of profit to value of shipments:

(9) $m_{it} = \pi_{0it}/Q_{0it}$.

These price-cost margins average 11.5 percent over all industries and years as shown in the last column of Table 4. A companion paper to this one (Flath , 2009), explores the temporal relation between these price-cost margins and the annual time series of Herfindahl index of concentration in each industry. Under the simple homogenous product Cournot model, industry price-cost margin is proportionate to Herfindahl, and the constant of proportionality is the reciprocal of elasticity of demand facing the industry. If, on the other hand, each industry comprises a collection of price-setting and product differentiated firms –i.e is in a Bertrand pricing equilibrium– then the industry price-cost margin is a weighted average of the reciprocal demand elasticities facing each firm. A non-nested test (Vuong test based on Vuong (1989)) comparing these two specifications for each of the 74 industries shows that product differentiated Bertrand is a better characterization than homogeneous product Cournot for most of the industries.

Our main focus here is on determinates of industrial concentration and of innovation, and upon the relation between the two. We first examine the extent to which our estimates of Cobb-Douglas labor coefficients and industry price-cost margins adequately explain the observed pattern of concentration. Then we consider whether there is any association between industrial concentration and rate of innovation. And finally, we ask, is there an inverted-U mapping from price-cost margin to the rate of innovation as argued by Aghion et al. (2005).

4. Empirical Results

4.1 Determinates of industrial concentration

The data we have constructed enable a simple empirical analysis of inter-industry variation in concentration. It is quite reasonable to suppose that industries that employ more capital intensive methods of production should be more concentrated *ceteris paribus*. This is because capital inputs are inherently lumpy and thus likely to be employed only by large firms. But an industry that employs capital intensely can nevertheless accommodate many firms if the scale of demand facing the industry is large. Further, a larger number of firms can profitably coexist in industries that face less elastic demand, *ceteris paribus*, as argued by Sutton (1998). On the other hand, inelastic demand may well be associated with customer loyalty to incumbent firms, which would tend to discourage entry and thus promote concentration. I break no new ground here and simply restate textbook propositions of industrial organization, common to many specific oligopoly theories, but the empirical content of these propositions remains an open question. To the extent incumbent firms have superior technology to that of potential entrants, there is no necessary relation between any of these variables –capital intensity, scale of demand, elasticity of demand– and industrial concentration. A modest step toward addressing this issue is possible here by estimating the following simple regression:

$$(12) \qquad H_{it} = \beta_0 + \beta_1 m_{it} + \beta_2 \theta_i^* + \beta_3 \ln L_{it} + \varepsilon_{it} ,$$

where H_{it} is the Herfindahl index for industry i, in year t; m_{it} is the price-cost margin; θ_i^* is our estimate of the elasticity of output with respect to labor of industry i ;and $\ln L_{it}$ is the natural log of employment of labor by industry i. In other words, the Herfindahl index is a linear function of price-cost margin, capital intensity, and industry scale. We estimate the equation using a pooled two-way random effects procedure. That is we presume that the error term has a cross-section component, time-series component, and pooled component :

$$\varepsilon_{it} = \varepsilon_i + \varepsilon_t + \upsilon_{it} ,$$

and weight observations according to sample estimates of their corresponding conditional variances. This is an unbalanced panel data set. Observations are weighted according to the Wansbeek and Kapteyn (1989) modification of the Fuller and Battese (1974) procedure.

Table 3 has the random-effects estimates of equation (12). Effectively, the time-series component of variance is estimated to be zero. The variables explain only about seven percent of the variation in Herfindahl index. Price-cost margin is statistically significant and has a positive sign, which comports with the idea that high price-cost margin is associated with customer loyalty to incumbent firms, which impedes entry and promotes concentration. The capital coefficient and industry scale are highly significant and have the expected signs. Industries that use capital intensely tend to be more concentrated. Industries that employ more workers tend to be less concentrated.

4.2 Technical advance, concentration and price-cost margins

We now turn attention to the interrelation between technical change and concentration. There are many theories with conflicting predictions as to whether industrial concentration promotes innovation, or retards it, or indeed whether it has any significant effect at all. For a recent discussion of this literature consult Okada (2005).

Our measures of technical advance are residuals v_{it}^* from Cobb-Douglas regressions of real value of shipments on measures of labor and capital. We now consider how is this measure of technical advance related to industrial concentration and to price-cost margins. This is primarily a question about the variation in technical change across industry, so we need to construct industry-level measures of technical advance. To do this, we calculate trend regressions:

$$(13) \qquad v_{it}^* = \gamma_{0i} + \gamma_{1i}\, t + \varepsilon_{it}, \qquad\qquad i=1,\ldots,n.$$

The slope coefficients γj_1^* from these regressions represent relative measures of average rate of technical advance for each industry. That is, γ_{1i}^* represents the average annual exponential growth rate in the Solow residual constructed from AR1 estimates of Cobb-Douglas production functions. These statistics are reported in Table 4, along with industry-by-industry averages for Herfindahl index and for the price-cost-margins m_{it} we constructed from earlier estimates.

Actually these represent deviations from the pan-industry rate of technical advance embodied in our capital stock deflator.

We regress this measure γ_{1i}* of average rate of technical advance on the mean and squared mean of the Herfindahl index for each industry i:

(14) $$\gamma_i^* = \beta_0 + \beta_1 \overline{H}_i + \beta_2 \overline{H}_i^2 + \varepsilon_i ,$$

Further we regress the same measures of technical change on the mean and squared mean of the price-cost margin for each industry:

(15) $$\gamma_{1i}^* = \beta_0 + \beta_1 \overline{m}_i + \beta_2 \overline{m}_i^2 + \varepsilon_i .$$

The estimates of equations (14) and (15) are in Table 5. The regression curve and plots of observations for estimates of equation (14) are in the Figure 1. These results amount to a nearly flat, but U-shaped, pattern in which industries with either high concentration ($H > 0.4$) or low concentration ($H < 0.2$) exhibit substantially more innovation (around 0.5 percent per year faster rate of change in Hicks neutral innovation) than those with moderate levels of concentration. The relation between price-cost margin and rate of innovation is similar but much weaker. In short, we do not find in these data the inverted U-shaped mapping from industry price-cost margins to innovation touted by Aghion, et al (2005).

5.Conclusion

This paper has explored a panel data set matching establishment-based production statistics from Japan's *Census of Manufacturers* with wholesale price indices from the Bank of Japan, and Herfindahl indices from the Japan Fair Trade Commission. The data include annual observations over the period 1961-1990 for 74 industries at the 4-digit s.i.c. level. We estimated Cobb-Douglas production functions and Solow residuals for each industry and then used these estimates to further analyse the determinates of industrial concentration and innovation.

We found that the industries in our sample tended to be more concentrated the more intensely they employed capital and the smaller their overall scale. There is also some indication that industries that face less elastic demand tend to be more concentrated.

The industries that exhibited the highest rates of technical advance included both highly concentrated ones (Glass Bulbs for CRTs, Wrist Watches, Jute Yarn) and more atomistic ones (Cotton Yarn, Medicines, Valve Cocks). We could discern no monotonic relation between concentration and innovation nor between price-cost margins and innovation. But there does appear to be a U-shaped mapping from concentration to innovation in these data.

Appendix 1. Data Sources

I have constructed a panel data set by merging 1961-1990 calender year observations from three different sources for the intersecting subset of 4-digit s.i.c. industries, of which there were 74.

From Japan's *Census of Manufacturers – Report by Industries*, listed in the references under the author MITI, we draw value-added, value of shipments, employment, wages, and book value of fixed tangible assets. The book value of tangible assets is observed for establishments employing 10 or more. All other items are for establishments employing 4 or more. The book value of tangible assets is observed at the beginning of the calender year. These data and continuation of like data through 2002, are available for downloading from the website of the Ministry of Economy, Trade and Industry (METI) here:
http://www.meti.go.jp/statistics/kougyou/arc/index.html

From two published sources and a website we compile observations of Herfindahl index of industrial concentration of production. The two published sources are JFTC (1975) and Senou (1983). These data are collected by the Japan Fair Trade Commission in fulfillment of its charge under the antimonopoly law . The two sources comprise overlapping time-series, respectively: (1960-1972) and (1971-1980). The series are continued (1975-2002) in data posted on the website of the Japan Fair Trade Commission from which I was able to extend my data through 1990:
http://www.jftc.go.jp/ruiseki/ruisekidate.htm,
The FTC observations on Herfindahl indices, both from the published sources and the web site, represent the summation of squared shares of industry production for nearly 500 industries. These data are, in principle, shares of physical units produced, not shares of revenues. But apparently for many of the industries a production index is used in lieu of physical units.

Finally we collect the monthly observations of wholesale price index series for each commodity, from the Bank of Japan for 1962-1990. Monthly data from 1985 on are available in electronic format from the website of the BOJ here:
http://www.boj.or.jp/en/type/stat/dlong/index.htm
Earlier data were drawn from the BOJ serial *Price Indices Annual*. From these sources I converted linked series to common 1980 base year units and calculated calender year averages for each.

The three sets of data correspond to imperfectly matched industries. I was able to identify an overlapping subset of 74 industries with observations from all three sources (corresponding to the 4-digit s.i.c. level in the *Census of Manufacturers*). This is a relatively small subset of any of the three sources. For example there are about 450 industries for which the JFTC reports Herfindahl indices and more than a thousand commodities for which the BOJ tracks wholesale price indices. And Japan's *Census of Manufacturers* identifies around 700 of 4-digit s.i.c. industries. Other scholars have merged these same three sources in approximately the same way as I have, and so I cross checked my list of matched industries with theirs. The three are Nishikawa (1973), Shinjou (1977), and Kusuda and Ike (1979).

Appendix 2. Iterative procedure for estimating implicit capital deflator.

We here detail the procedure used to estimate the implicit capital deflator $\mathbf{A_t}$ of equation (5) from the text:

(A1) $\ln Q_{it} = A_i + \theta_i \ln L_{it} + (1-\theta_i)\ln e^{\mathbf{A_t}}K_{it} + v_{it}$, i=1..., n; t= 1,...,T.

This is accomplished by iterative application of SAS procedures "proc tscs" and "proc autoreg". We first estimate the parameters ($A_i^{(1)}$, $A_t^{(1)}$, $\theta_L^{(1)}$, $\theta_K^{(1)}$) in a two-way fixed effects regression equation on the pooled sample:

(A2) $\ln Q_{it} = A_i^{(1)} + B_t^{(1)} + \theta_L^{(1)} \ln L_{it} + \theta_K^{(1)} \ln K_{it} + \xi_{it}$, i=1..., n; t= 1,...,T.

or equivalently,

(A3) $\ln Q_{it} = A_i^{(1)} + \theta_L^{(1)} \ln L_{it} + \theta_K^{(1)} \ln[K_{it} \exp(B_t^{(1)}/\theta_K^{(1)})] + \xi_{it}$, i=1..., n; t= 1,...,T.

We next estimate, for each industry i, parameters ($a_i^{(1)}$, $\theta_i^{(1)}$, $\rho_i^{(1)}$) in AR1 regression equations of the following sort,

(A4) $\ln Q_{it} = a_i^{(1)} + \theta_i^{(1)} \ln L_{it} + (1-\theta_i^{(1)})\ln[K_{it} \exp(B_t^{(1)*}/\theta_K^{(1)*})] + v_{it}$, t = 1,...,T.

$v_{it} = \rho_i^{(1)} v_{i,t-1} + u_{it}$, and $u_{it} \sim (0, \sigma_i^2)$.

where asterisks * denote estimates from a previous regression.

We continue the iteration, replacing $\ln L_{it}$ and $\ln K_{it}$ in equations (A2) and (A3) with

(A5) $\theta_i^{(1)*}\ln L_{it}$

and

(A6) $(1-\theta_i^{(1)*})\ln[K_{it} \exp(B_t^{(1)*}/\theta_K^{(1)*})]$.

That is, we again estimate parameters ($A_i^{(2)}$, $B_t^{(2)}$, $\lambda_L^{(1)}$, $\lambda_K^{(1)}$) of a two-way fixed effects regression for the pooled sample:

(A7) $$\ln Q_{it} = A_i^{(2)} + B_t^{(2)} + \lambda_L^{(1)}\,\theta_i^{(1)*}\ln L_{it} + \lambda_K^{(1)}(1-\theta_i^{(1)*})\ln[K_{it}\exp(B_t^{(1)*}/\theta_K^{(1)*})] + \xi_{it}\,, \qquad i=1,\ldots,n;\ t=1,\ldots,T.$$

or equivalently,

(A8) $$\ln Q_{it} = A_i^{(2)} + \lambda_L^{(1)}\,\theta_i^{(1)*}\ln L_{it} + \lambda_K^{(1)}(1-\theta_i^{(1)*})\ln[K_{it}\exp(B_t^{(1)*}/\theta_K^{(1)*})\exp(B_t^{(2)}/\lambda_K^{(1)})] + \xi_{it}\,, \qquad i=1,\ldots,n;\ t=1,\ldots,T.$$

And again we estimate, for each industry i, parameters ($a_i^{(2)}$, $\theta_i^{(2)}$, $\rho_i^{(2)}$) of AR1 regression equations of the following sort:

(A9) $$\ln Q_{it} = a_i^{(2)} + \theta_i^{(2)}\ln L_{it} + (1-\theta_i^{(2)})\ln[K_{it}\exp(B_t^{(1)*}/\theta_K^{(1)*})\exp(B_t^{(2)*}/\lambda_K^{(1)*})] + v_{it}\,, \qquad t=1,\ldots,T.$$

$$v_{it} = \rho_i^{(2)}\,v_{i,t-1} + u_{it}\,, \qquad \text{and } u_{it} \sim (0, \sigma_i^2).$$

We continue the iteration, replacing $\theta_i^{(1)*}\ln L_{it}$ and $(1-\theta_i^{(1)*})\ln[K_{it}\exp(B_t^{(1)*}/\theta_K^{(1)*})]$ in equation (A8) with

(A10) $$\theta_i^{(2)*}\ln L_{it}$$

and

(A11) $$(1-\theta_i^{(2)*})\ln[K_{it}\exp(B_t^{(1)*}/\theta_K^{(1)*})\exp(B_t^{(2)*}/\lambda_K^{(1)*})]\,,$$

and so on. We continue iterations until $B_t^{(n)*}\rightarrow 0$. The resulting final estimate of A_t is

(A12) $$A_t^* = B_t^{(1)*}/\theta_K^{(1)*} + B_t^{(2)*}/\lambda_K^{(1)*} + \ldots + B_t^{(n)*}/\lambda_K^{(n-1)*}$$

Satisfactory convergence required three iterations.

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Table 1. Implicit deflator of capital stock and SNA deflator.

	$e^{At}{}_*$	SNA Deflator	Implied Efficiency Units of Capital per Actual Unit
1961	0.667	0.458	0.305
1962	0.225	0.464	0.104
1963	0.246	0.464	0.114
1964	0.3	0.468	0.140
1965	0.301	0.473	0.142
1966	0.333	0.484	0.161
1967	0.443	0.495	0.219
1968	0.504	0.501	0.252
1969	0.56	0.506	0.283
1970	0.625	0.519	0.324
1971	0.634	0.531	0.336
1972	0.657	0.548	0.360
1973	0.736	0.616	0.453
1974	0.595	0.762	0.453
1975	0.535	0.798	0.427
1976	0.62	0.830	0.514
1977	0.739	0.868	0.641
1978	0.789	0.888	0.701
1979	0.88	0.923	0.812
1980	0.948	0.977	0.926
1981	0.845	0.995	0.841
1982	0.796	1.003	0.798
1983	0.817	1.000	0.817
1984	0.835	1.002	0.837
1985	0.859	1.005	0.863
1986	0.811	0.994	0.806
1987	0.795	0.980	0.779
1988	0.890	0.973	0.866
1989	0.956	0.979	0.936
1990	1	1.000	1.000

Sources:

$A_t{}^*$ = estimate of parameter in Equation (5) from the text:

$$(5) \qquad \ln Q_{it} = A_i + \theta_i \ln L_{it} + (1-\theta_i)\ln e^{At}K_{it} + v_{it}\,, \qquad i=1..., n;\ t= 1,...,T.$$

See appendix for details of estimation method.

SNA Deflator = non-residential fixed investment deflator from system of national accounts Japan (1990 basis). Cabinet Office, Government of Japan: http://www.esri.cao.go.jp/en/sna/qe011-68/gdemenue68.html

Table 2. Cobb-Douglas Production Functions, AR1 Regression Estimates

$$\ln Q_{it} = a_i + \theta_i \ln L_{it} + (1-\theta_i)\ln A_t{*}K_{it} + v_{it}\,, \text{ where } v_{it} = \rho v_{i,\,t-1} + u_{it} \text{ and } u_{it} \sim (0, \sigma^2)$$

	OLS	Yule-Walker Estimates	Estimates of Autoregressive Parameters			Yule-Walker Estimates				Test of Restriction (Constant returns to scale)			
INDUSTRY	**Durbin-Watson**	**Durbin-Watson**	**ρ**	**S.E.**	**t Value**	**θ_i**	**S.E.**	**t Value**	**R-Square**	**Value**	**S.E.**	**t Value**	**Pr > |t|**
SYNTHETIC FIBERS	1.36	1.78	0.28	0.3	0.9	0.31	0.04	7.8	0.99	-0.95	0.64	-1.5	0.14
MEDICINES	0.3	1.49	0.8	0.12	6.9	0.33	0.03	9.7	1	0.07	0.04	1.9	0.06
GLASS BULBS FOR USE IN CATHODE RAY TUBES	0.82	1.53	0.58	0.25	2.4	0.37	0.08	4.7	0.96	0.06	0.04	1.8	0.08
WRIST WATCHES	0.63	1.69	0.64	0.16	3.9	0.37	0.05	7.9	0.98	-0.04	0.02	-1.9	0.05
PLASTIC-WORKING MACHINES	0.47	1.92	0.71	0.15	4.7	0.42	0.04	9.6	0.99	-0.01	0.04	-0.3	0.78
PUMPS	1.43	1.84	0.28	0.18	1.5	0.42	0.03	15.2	0.93	-2.02	0.63	-3.2	0.00
ALUMINUM INGOTS	0.9	1.68	0.39	0.18	2.1	0.44	0.04	11.9	0.97	0.11	0.07	1.5	0.13
SPEED CHANGERS	0.35	1.41	0.73	0.13	5.6	0.44	0.02	18.3	1	-0.14	0.09	-1.6	0.12
BEARINGS	0.62	1.36	0.42	0.17	2.4	0.45	0.03	17.1	0.98	0.02	0.04	0.5	0.62
CELLOPHANE	1.47	1.84	0.26	0.23	1.1	0.45	0.02	18.6	0.93	0.02	0.04	0.4	0.68
PIANOS	0.9	1.7	0.39	0.18	2.2	0.45	0.05	9.5	0.79	-0.21	0.08	-2.6	0.01
BOILERS	2.12	2.01	-0.07	0.19	-0.4	0.46	0.03	13.5	0.76	0.03	0.06	0.5	0.64
FISHMEAT SAUSAGE	1.57	1.91	0.21	0.3	0.7	0.47	0.06	7.8	0.9	-0.06	0.03	-2.0	0.05
SANITARY WARE	1.5	1.74	0.14	0.19	0.8	0.48	0.02	23.1	0.98	0.13	0.10	1.2	0.23
CHEMICAL SEASONING	1.63	1.63	0	0.24	0	0.49	0.02	21.5	0.96	0.09	0.12	0.8	0.47
SHEET GLASS	1.27	1.77	0.22	0.19	1.2	0.49	0.02	28.3	0.96	0.21	0.14	1.5	0.15
STORAGE BATTERIES	0.61	1.67	0.63	0.15	4.2	0.49	0.04	11.7	0.98	0.00	0.02	0.2	0.84
ORDINARY STEEL PIPES AND TUBES	0.57	1.75	0.69	0.14	5	0.5	0.04	13.1	0.98	-0.16	0.05	-3.1	0.00
SYNTHETIC RUBBER	1.27	1.64	0.3	0.29	1	0.5	0.06	9.1	0.97	-0.19	0.05	-4.0	<.0001
RECTIFIERS	0.53	1.59	0.69	0.17	4	0.51	0.04	11.7	0.99	-0.21	0.06	-3.2	0.00

	OLS	Yule-Walker Estimates	Estimates of Autoregressive Parameters			Yule-Walker Estimates				Test of Restriction (Constant returns to scale)			
INDUSTRY	**Durbin-Watson**	**Durbin-Watson**	**ρ**	**S.E.**	**t Value**	**θ_i**	**S.E.**	**t Value**	**R-Square**	**Value**	**S.E.**	**t Value**	**Pr > |t|**
THERMOS BOTTLES	1.5	1.77	0.15	0.21	0.7	0.51	0.05	10.3	0.85	0.10	0.10	1.0	0.34
TRACTORS	1.31	1.57	0.29	0.23	1.2	0.51	0.03	15.3	0.98	-0.05	0.02	-2.2	0.02
ELECTRICAL WIRES AND CABLES	0.74	1.26	0.61	0.19	3.2	0.52	0.05	10.5	0.96	-0.17	0.09	-2.0	0.04
SPINNING MACHINES	1.59	1.92	0.19	0.24	0.8	0.52	0.03	17.4	0.93	-0.01	0.02	-0.3	0.75
ZINC	0.79	1.66	0.57	0.16	3.6	0.52	0.04	13.9	0.86	-0.10	0.07	-1.5	0.13
BICYCLES	1.15	1.73	0.33	0.18	1.8	0.53	0.01	38	0.99	0.02	0.02	1.6	0.12
COLD-ROLLED STEEL PLATE	1	1.49	0.4	0.2	2.1	0.53	0.03	21	0.96	-0.06	0.08	-0.8	0.47
ELECTRICAL COPPER	0.39	1.56	0.77	0.12	6.3	0.53	0.04	12.2	0.91	-0.37	0.12	-3.2	0.00
HAM SAUSAGE	1.34	1.52	0.14	0.24	0.6	0.53	0.02	33.9	0.99	-0.04	0.04	-1.0	0.32
MIXED FEED	1.27	1.42	0.09	0.24	0.4	0.53	0.02	31.3	0.97	-0.09	0.04	-2.5	0.01
PAPER PULP	0.77	1.94	0.57	0.16	3.6	0.53	0.04	14.6	0.86	0.20	0.06	3.6	<.0001
RECORDS	1.6	1.99	0.18	0.24	0.8	0.53	0.05	11.4	0.96	0.05	0.02	2.3	0.02
TIRES AND TUBES FOR MOTOR VEHICLES	0.69	1.63	0.65	0.15	4.5	0.53	0.03	17.4	0.98	-0.09	0.12	-0.8	0.48
VEGETABLE OIL	1.95	1.95	0	0.29	0	0.53	0.05	10.8	0.74	-0.12	0.10	-1.3	0.21
POWER TILLERS	1.35	1.76	0.22	0.24	1	0.54	0.02	28.8	0.98	0.00	0.01	0.2	0.83
EIGHTEEN LITER CANS	1.3	1.65	0.28	0.18	1.5	0.55	0.01	48.2	0.99	0.04	0.02	1.9	0.05
ROLLED AND WIRE-DRAWN COPPER PRODUCTS	1.03	1.82	0.41	0.22	1.8	0.55	0.03	19.5	0.96	0.00	0.01	-0.1	0.96
ALUMINUM WINDOW SASHES	1.34	1.78	0.25	0.19	1.3	0.56	0.01	38.4	0.99	0.04	0.03	1.3	0.19
COMBED FABRICS	0.59	1.47	0.61	0.19	3.1	0.56	0.04	14.5	0.8	-0.09	0.04	-2.5	0.01
COTTON FABRICS	0.91	1.77	0.47	0.17	2.8	0.56	0.02	24.8	0.38	0.01	0.01	0.9	0.38
CHARGING GENERATORS	0.88	2	0.55	0.16	3.4	0.57	0.04	14.5	0.99	-0.09	0.10	-0.8	0.42
COKE	0.31	1.74	0.75	0.13	5.9	0.58	0.05	10.8	0.98	0.06	0.03	2.1	0.04
CAST IRON PIPES AND TUBES	1.12	1.7	0.38	0.22	1.7	0.59	0.04	16.6	0.95	-0.51	0.30	-1.7	0.08

	OLS	Yule-Walker Estimates	Estimates of Autoregressive Parameters			Yule-Walker Estimates				Test of Restriction (Constant returns to scale)			
INDUSTRY	Durbin-Watson	Durbin-Watson	ρ	S.E.	t Value	θ_i	S.E.	t Value	R-Square	Value	S.E.	t Value	Pr > |t|
GRINDING STONES	0.93	1.98	0.53	0.16	3.2	0.59	0.03	17	0.93	0.09	0.05	1.6	0.11
BEER	1.34	1.92	0.33	0.18	1.8	0.6	0.01	45.8	0.98	0.05	0.02	2.1	0.03
GALVANIZED	1.48	1.99	0.25	0.19	1.3	0.6	0.02	25.7	0.89	-0.03	0.01	-1.9	0.06
COTTON YARN	0.56	1.99	0.64	0.15	4.3	0.61	0.04	13.9	.	0.00	0.03	0.0	0.97
GLASS CONTAINERS FOR BEVERAGES	0.68	1.46	0.61	0.15	4	0.61	0.02	28.7	0.96	-0.47	0.12	-3.8	<.0001
PAINTS	0.64	1.62	0.63	0.15	4.2	0.61	0.02	38.1	0.99	-0.09	0.03	-2.7	0.00
VINYL CHLORIDE RESIN	1.68	1.73	0.03	0.3	0.1	0.61	0.04	14.3	0.91	0.22	0.19	1.1	0.27
CEMENT	0.55	1.32	0.61	0.15	4	0.62	0.02	32	0.95	0.08	0.04	2.3	0.02
CAUSTIC SODA	0.57	1.6	0.7	0.14	5.1	0.63	0.03	19.3	0.91	0.02	0.02	1.2	0.22
PETROLEUM PRODUCTS	0.3	1.61	0.72	0.13	5.4	0.63	0.04	16.2	0.98	0.07	0.05	1.4	0.15
PRINTING MACHINES	0.85	1.97	0.57	0.2	2.9	0.63	0.02	27	0.98	-0.10	0.06	-1.6	0.12
PRINTING INK	0.53	1.7	0.69	0.14	5	0.65	0.02	30.1	0.99	-0.17	0.08	-2.3	0.02
TILE	0.45	1.63	0.74	0.13	5.7	0.65	0.03	23.5	0.97	-0.03	0.01	-2.0	0.04
CANNED SEAFOOD	1.05	1.72	0.37	0.18	2.1	0.66	0.02	39.5	0.86	-0.01	0.02	-0.5	0.63
FISHING NETS	0.3	1.33	0.78	0.12	6.6	0.66	0.03	25	0.95	0.18	0.11	1.7	0.08
SUGAR	1.12	1.71	0.41	0.22	1.9	0.66	0.03	21.7	0.91	0.01	0.04	0.3	0.77
DISSOLVING PULP	0.77	1.36	0.52	0.21	2.5	0.67	0.03	20.7	0.93	-0.03	0.02	-1.8	0.07
FIREPROOF BROOKS	1.56	1.61	0.04	0.24	0.2	0.68	0.02	27.4	0.89	-0.07	0.04	-1.9	0.05
CALCIUM CARBIDE	0.68	1.13	0.56	0.2	2.8	0.69	0.04	17.6	0.91	-0.06	0.08	-0.8	0.48
MANMADE-GRAPHITE ELECTRODES	1.97	1.96	-0.01	0.22	0	0.69	0.02	45.1	0.92	0.12	0.18	0.6	0.54
SAKE	1.2	1.88	0.33	0.18	1.8	0.69	0.02	29.6	0.78	-0.02	0.03	-0.6	0.56
VALVE COCKS	0.84	1.83	0.53	0.21	2.6	0.69	0.03	20.1	0.97	-0.06	0.03	-2.3	0.02
MEN'S SHOES	1.31	1.52	0.11	0.24	0.4	0.71	0.01	52.8	0.98	0.09	0.05	1.7	0.09
RAW SILK	0.87	1.58	0.42	0.22	1.9	0.71	0.02	34.1	0.52	0.01	0.03	0.5	0.61
SOY	0.48	1.61	0.68	0.14	4.9	0.71	0.02	47.3	0.89	0.03	0.03	1.3	0.22
WHEAT FLOUR	0.81	2.35	0.55	0.16	3.4	0.73	0.02	41.7	0.86	0.11	0.06	1.8	0.08

	OLS	Yule-Walker Estimates	Estimates of Autoregressive Parameters			Yule-Walker Estimates				Test of Restriction (Constant returns to scale)			
INDUSTRY	**Durbin-Watson**	**Durbin-Watson**	**ρ**	**S.E.**	**t Value**	**θ_i**	**S.E.**	**t Value**	**R-Square**	**Value**	**S.E.**	**t Value**	**Pr > |t|**
MISO	0.81	2.01	0.56	0.16	3.5	0.74	0.01	63.1	0.97	-0.16	0.24	-0.7	0.52
WORSTED YARN	0.89	1.92	0.53	0.16	3.2	0.74	0.05	13.9	0.78	-0.05	0.02	-2.3	0.02
JUTE YARN	1.95	1.96	-0.21	0.28	-0.7	0.77	0.03	24.1	0.88	-0.27	0.14	-1.9	0.05
WEAVING MACHINES	2.01	1.91	-0.06	0.24	-0.2	0.78	0.06	12.9	0.14	-0.02	0.04	-0.5	0.67
BRIQUETTES	0.76	2.11	0.55	0.2	2.8	0.95	0.04	24.3	0.99	-0.33	0.17	-2.0	0.04
mean	1.02	1.72	0.42	0.19	2.6	0.57	0.03	22.1	0.91	-0.07		-0.4	0.26
s.d.	0.47	0.22	0.25	0.05	1.9	0.11	0.01	12.2	0.14	0.29		1.8	0.28

Table 3. Regression analysis of Herfindahl index ; two-way random effects.

$$H_{it} = \beta_0 + \beta_1 m_{it} + \beta_2 \theta_i^* + \beta_3 \ln L_{it} + \varepsilon_i + \varepsilon_t + \upsilon_{it}$$

Variable	Estimate	Standard Error	t value	Pr > |t|
Intercept	0.66	0.08	8.3	<.0001
θ_i^*	-0.41	0.12	-3.3	0.001
$\ln L_{it}$	-0.03	0.00	-8.7	<.0001
m_{it}	0.11	0.02	5.9	<.0001

R-Square 0.068

Number of Cross Sections 74
Time Series Length 30

Variance Component for Cross Sections 0.014
Variance Component for Time Series 0.000
Variance Component for Error 0.002

Table 4. Estimates of average rate of technical advance in each industry, 1961-1990.

Estimated OLS trend

$$v_{it}^* = \gamma_{0i} + \gamma_{1i}\, t + \varepsilon_{it}, \qquad i=1,...,n$$

where v_{it}^* is the estimated error term in the regression equations reported in Table 2 above.
The table also reports average Herfindahl Index $\overline{H}_i$ and average price-cost margin $\overline{m}_i$.

INDUSTRY	n	γ_{1i} *	$\overline{H}_i$	$\overline{m}_i$
GLASS BULBS FOR USE IN CATHODE RAY TUBES	14	1.35%	0.460	1.2%
COTTON YARN	30	0.99%	0.034	3.2%
ELECTRICAL COPPER	30	0.91%	0.181	8.8%
CALCIUM CARBIDE	20	0.89%	0.252	10.0%
MEDICINES	28	0.87%	0.025	30.1%
WRIST WATCHES	30	0.75%	0.382	-13.9%
RECORDS	10	0.72%	0.101	25.6%
VALVE COCKS	10	0.72%	0.037	16.1%
RAW SILK	20	0.58%	0.030	5.2%
CAUSTIC SODA	30	0.57%	0.047	17.6%
JUTE YARN	10	0.53%	0.396	12.7%
PAPER PULP	30	0.52%	0.068	10.8%
COTTON FABRICS	30	0.40%	0.007	8.1%
GLASS CONTAINERS FOR BEVERAGES	24	0.40%	0.174	19.3%
FISHMEAT SAUSAGE	14	0.39%	0.144	6.3%
WEAVING MACHINES	20	0.38%	0.133	19.6%
ORDINARY STEEL PIPES AND TUBES	30	0.33%	0.128	10.7%
SOY	30	0.32%	0.074	23.2%
WORSTED YARN	30	0.29%	0.037	8.4%
ALUMINUM INGOTS	30	0.29%	0.353	-11.9%
PIANOS	28	0.28%	0.464	7.2%
TILE	24	0.25%	0.090	17.0%
GALVANIZED	30	0.24%	0.146	5.6%
CHEMICAL SEASONING	14	0.23%	0.352	9.3%
TRACTORS	20	0.21%	0.292	14.1%
CEMENT	30	0.19%	0.086	27.6%

INDUSTRY	n	γ_{1i} *	$\overline{H}_i$	$\overline{m}_i$
SHEET GLASS	30	0.17%	0.388	45.4%
PLASTIC-WORKING MACHINES	28	0.16%	0.110	-0.1%
SANITARY WARE	24	0.15%	0.442	7.9%
MANMADE-GRAPHITE ELECTRODES	28	0.13%	0.183	21.9%
CAST IRON PIPES AND TUBES	14	0.12%	0.383	26.8%
COMBED FABRICS	20	0.12%	0.012	12.7%
TIRES AND TUBES FOR MOTOR VEHICLES	30	0.12%	0.288	14.7%
BICYCLES	24	0.11%	0.062	10.9%
SUGAR	30	0.10%	0.065	7.9%
ALUMINUM WINDOW SASHES	24	0.09%	0.157	7.0%
BEER	30	0.08%	0.394	6.1%
MIXED FEED	20	0.08%	0.107	8.1%
SYNTHETIC FIBERS	20	0.08%	0.127	26.3%
EIGHTEEN LITER CANS	24	0.08%	0.041	16.0%
HAM SAUSAGE	20	0.07%	0.070	8.6%
MEN'S SHOES	10	0.04%	0.037	13.5%
POWER TILLERS	20	0.04%	0.148	15.2%
ROLLED AND WIRE-DRAWN COPPER PRODUCTS	20	0.03%	0.039	3.5%
STORAGE BATTERIES	30	0.03%	0.221	16.2%
FIREPROOF BROOKS	20	0.02%	0.050	9.2%
MISO	24	0.00%	0.017	26.9%
CANNED SEAFOOD	24	0.00%	0.060	9.0%
COLD-ROLLED STEEL PLATE	30	-0.04%	0.176	5.7%
CELLOPHANE	14	-0.05%	0.208	6.1%
SPINNING MACHINES	14	-0.07%	0.244	1.5%
VEGETABLE OIL	14	-0.08%	0.096	15.2%
BEARINGS	30	-0.09%	0.209	2.5%
PAINTS	24	-0.14%	0.057	20.5%
SAKE	30	-0.14%	0.005	20.0%
GRINDING STONES	28	-0.15%	0.069	14.2%
WHEAT FLOUR	30	-0.16%	0.147	14.5%
BRIQUETTES	14	-0.20%	0.080	15.0%
PRINTING INK	30	-0.21%	0.137	7.6%
CHARGING GENERATORS	20	-0.22%	0.322	2.8%

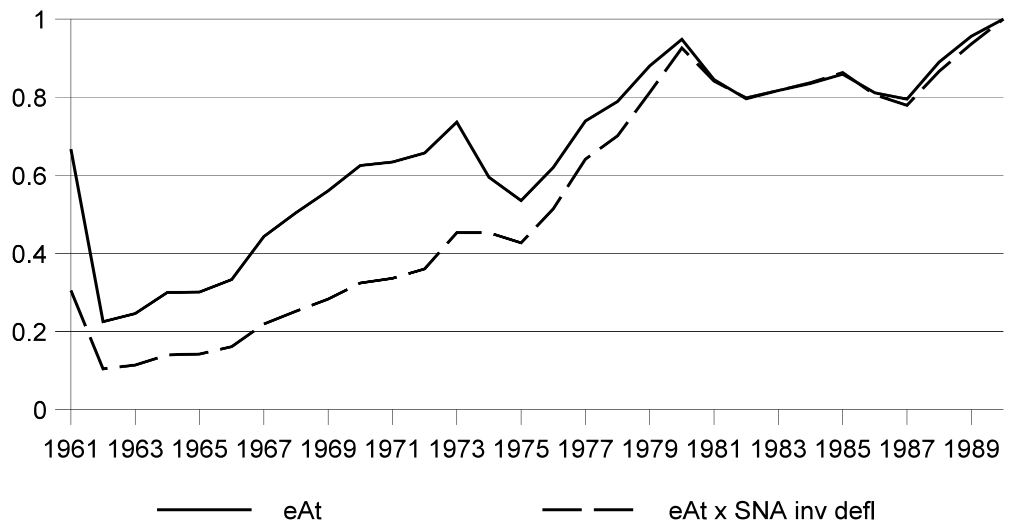
INDUSTRY	**n**	**γ_{1i} ***	**$\overline{H}_i$**	**$\overline{m}_i$**
THERMOS BOTTLES	20	-0.22%	0.250	15.0%
ZINC	24	-0.23%	0.180	5.3%
SYNTHETIC RUBBER	20	-0.23%	0.322	34.0%
VINYL CHLORIDE RESIN	14	-0.27%	0.059	8.0%
RECTIFIERS	14	-0.27%	0.111	3.7%
PUMPS	24	-0.31%	0.077	1.5%
PRINTING MACHINES	14	-0.32%	0.114	12.8%
SPEED CHANGERS	24	-0.33%	0.073	-3.1%
DISSOLVING PULP	20	-0.35%	0.299	8.6%
ELECTRICAL WIRES AND CABLES	20	-0.45%	0.077	6.3%
BOILERS	24	-0.47%	0.274	4.4%
FISHING NETS	24	-0.49%	0.050	10.0%
PETROLEUM PRODUCTS	30	-0.65%	0.065	8.6%
COKE	24	-0.87%	0.148	3.8%
mean		0.11%	0.159	11.5%
s.d.		0.40%	0.126	9.5%

Table 5. Regression analysis of average rate of technical advance

Dependent variable = γ_{i1}*, trend rate of growth in technical advance from regression in Table 3.

	Model 1				Model 2				Model 3				Model 4			
	Coeff.	S.E.	t value	Prob>|t|	Coeff.	S.E.	t value	Prob>|t|	Coeff.	S.E.	t value	Prob>|t|	Coeff.	S.E.	t value	Prob>|t|
Intercept	0.001	0.001	1.3	0.186	0	0.001	1.6	0.108	0.001	0.001	0.7	0.471	0.003	0.001	2.5	0.015
$\overline{m}_i$	0.002	0.005	0.4	0.675	-0.006	0.009	-0.7	0.519								
$\overline{m}_i^2$					0.028	0.027	1.0	0.312								
$\overline{H}_i$									0.004	0.004	1.1	0.260	-0.029	0.013	-2.2	0.030
$\overline{H}_i^2$													0.078	0.030	2.6	0.011
error DF	72				71				72				71			
R=Square	0.0024				0.016				0.017				0.102			

Figure 1. Implicit Deflator of Capital, Adjusted for Inflation and Not, 1990=1



Note:

e^{At} = efficiency units of capital per nominal unit based on estimates

e^{At} × SNA investment deflator = efficiency units of capital per physical unit

Figure 2. Plot of regression estimate in Table 6, Model 4.