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Using the Manufacturing Productivity Distribution to Evaluate Growth Theories

by

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Abstract:

Some multi-sector endogenous growth models make strong predictions about productivity differences across sectors in the form of a distribution or density function. In this paper it is demonstrated that this distribution is left-skewed for a wide range of plausible parameter values. This stands in strong contrast to the right-skewed shape of the respective empirical distribution estimated by kernel methods for a measure of relative productivity for more than 450 four-digit U.S. manufacturing industries during 1958-96. This difference is interpreted as evidence in favor of devoting more emphasis on the effects of structural change on the sectoral level in growth models.

JEL classification: D24, O47, L60

Keywords: multisector growth models, manufacturing productivity distribution, skewness

1 Introduction

Recent multi-sector Schumpeterian growth models are endowed with microfoundations that lead to theoretical predictions about differences in the productivity levels across sectors. Thus even on a balanced growth path there exits persistent heterogeneity in productivity levels across sectors which can be expressed in form of a stationary distribution. In the models of Aghion and Howitt (1998, ch. 3) and Aghion et al. (2001) the density functions associated with this distribution are explicitly derived or numerically computed through simulation, respectively. In both models the shape and in particular the skewness of this distribution crucially depends on the size of an innovative step on the quality ladder, which is treated as an exogenous parameter.

In this paper the value of the step size on the quality ladder that governs productivity growth or the inseparably associated cost reduction is calibrated using information of a variety of sources, such as the values used in numerical studies of the above mentioned growth models. In addition, we derive a plausible range of values from the stylized result of the 80 percent learning curve that seems to be representative for a wide variety of manufacturing production processes. All these values lead to a left-skewed theoretical distribution of relative productivity levels. This finding stands in stark contrast to the distribution of relative productivity levels across the four-digit U.S. manufacturing industries which is estimated using kernel methods and appears to be consistently right-skewed during the years 1958-96.

The paper proceeds as follows: Section 2 briefly presents the origin of the theoretical distribution of relative productivity levels and depicts the shape of the density function for various values of the innovation step size. Section 3 calibrates the plausible range of values of the innovation step size using the 80 percent learning curve model. Section 4 calculates relative productivity levels for the four-digit U.S. manufacturing industries using nonparametric methods of efficiency measurement and presents the respective kernel density plots. The diametrically opposed skewness properties of the theoretical and the empirical distribution point to the need of paying more attention to differential growth and structural change on the sectoral level which is discussed in the concluding section 5.

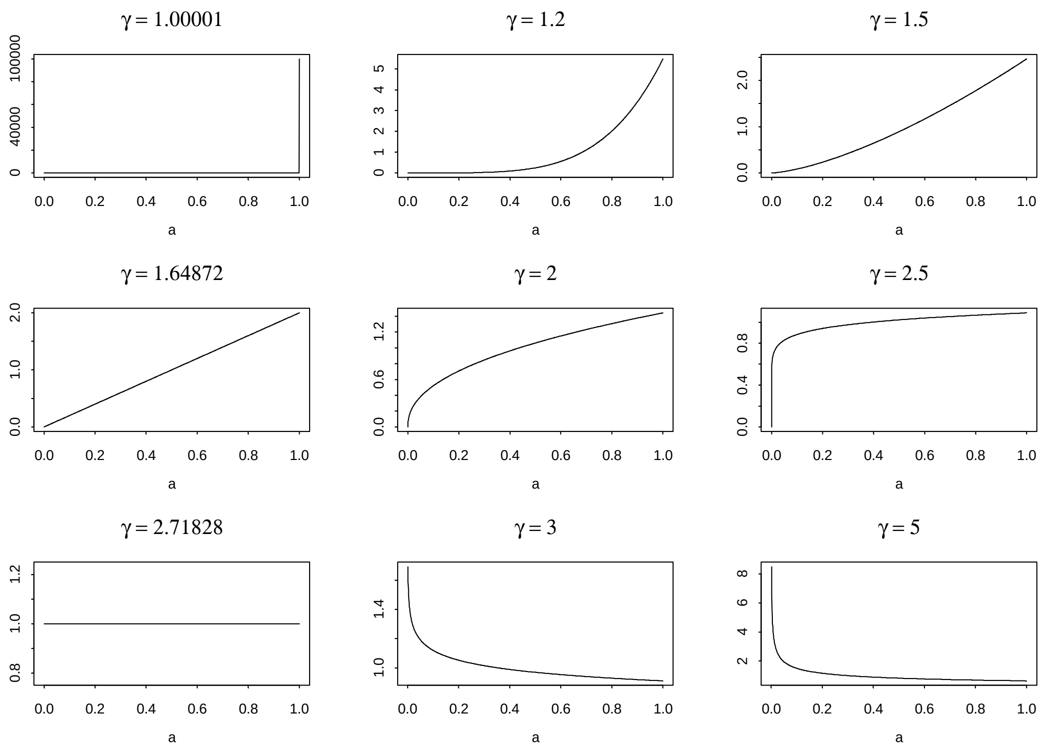
2 The Theoretical Distribution

In most multi-sector growth models the sectors of the economy are treated symmetrically, see Romer (1990) for a leading example. This implies that all sectors have the same productivity level and thus the distribution of productivity across sectors is uniform. By this, these models are useless for any analysis concerning structural change in form of the change of the sectoral composition of an economy. An exception from this rule is the growth model of Aghion and Howitt (1998, ch. 3) which makes an explicit prediction about the shape of the distribution of productivity across sectors.

In this model the state of knowledge of the economy at time t is described by the level of the productivity parameter of the „leading-edge" technology $A_t^{\max}$. Each sector of the economy invests a certain amount of labor in research which determines the Poisson arrival rate λn_{it} with which a new innovation occurs, where n_{it} denotes the amount of labor input invested in research in sector i at time t and λ is a parameter. An innovation in a particular sector i leads to a jump of the productivity level of this sector A_{it} to $A_t^{\max}$. The growth of $A_t^{\max}$ is governed by the aggregate flow of innovations in the economy of λn_t per unit of time, where n_t is the total research labor input of the economy. The steady-state growth rate of aggregate productivity is then derived as $d \ln A_t^{\max}/dt = \lambda n_t \ln \gamma$, which is identical to the steady-state growth rate of output. Herein, $\gamma > 1$ denotes the step-size of the quality ladder in the form of a constant factor by which each innovation increases the productivity level. In the model, an intertemporal spillover effect is at work postulating that each innovation serves as the basis for discovering other innovations in other sectors of the economy, even though the current innovation can only be used by the generating sector.

The different productivity levels of the whole continuum of sectors can be succintly summarized by a distribution of the productivity levels across sectors which has support $[0, A_t^{\max}]$. This distribution extends to the right when $A_t^{\max}$ grows and also becomes increasingly left-skewed. Aghion and Howitt normalize all productivity levels by $A_t^{\max}$ to reach the relative productivity levels $a_{it} = A_{it}/A_t^{\max} \in [0,1]$ and are able to derive the cross-sectional cumulative distribution function of this relative productivity measure which is given by $H(a) = a^{1/\ln \gamma}$ for $a \in [0,1]$, irrespective of what happens to the aggregate rate of innovation over time.[1] The density function associated with this distribution is $h(a) = (a^{1/\ln\gamma - 1})/\ln\gamma$ for $a \in [0, 1]$ and zero otherwise. Figure 1 shows this density function of the theoretical distribution of relative productivity for various values of γ.

Figure 1
Density Functions of the Theoretical Distribution of Relative Productivity



Since the shape of this density function is solely determined by the step-size of the quality ladder γ we just have to find reasonable values for this parameter in order to compare the shape of this theoretical distribution with the shape of the distribution found in productivity data of industries. It is immediate that this distribution is left-skewed for all $1 < \gamma < e$, where, as usual, $e = 2.71828...$.

In particular, this range contains the benchmark value $\gamma = 1.135$ used in the numerical evaluations of the related step-by-step innovation model of Aghion et al. (2001) in which the time unit is taken to be one year (see Aghion et al. (2001, p. 484)). This magnitude implies that

[1] See appendix 1 on p. 115f. in Aghion and Howitt (1998) for an elegant derivation of this result.

there are relatively more sectors with productivity levels within the vicinity of the leading-edge productivity level and therefore small technology gaps. The numerical evaluations of the step-by-step innovation model in Hoernig (2003) use a 'middle-of-the-road' parameter value of $\gamma = 1.3$ which is also within the interval of parameter values that are associated with a left-skewed distribution of relative productivity levels (see Hoernig (2003, p. 251)).

In their related work on step-by-step innovation models, Aghion et al. (2001, fig. 5 on p. 486) also report the steady-state distribution of the technological leads which are essentially technology gaps measured in discrete units of innovation steps. The distribution depicted there is right-skewed, implying a high frequency of small technology gaps and correspondingly a high frequency of large technology gaps. Since the measure of technology gaps is inversely related to the measure of relative productivity levels the step-by-step innovation model also predicts a left-skewed distribution in the latter case.

Although the step-by-step innovation model expresses the effect of technological progress in terms of cost reductions, the step-size parameter of the quality ladder is the same as in models where technological progress is expressed directly in terms of productivity improvements. One can say that after k innovations production increases to γ^k units of output per unit of labor employed or can state that γ^{-k} units of labor are required to produce one unit of output which implies that cost per unit of output is proportional to γ^{-k}. Both statements are equivalent. In the next section we exploit this equivalence to calibrate γ using a stylized result from the learning curve literature.

3 Calibration from the Learning Curve

As the previous section has shown, the range of reasonable values of γ is crucial for the shape of the distribution of productivity across sectors. This parameter can be related to the basic origins of learning-by-doing: the widespread result of the 80 percent learning curve. This stylized fact states that in many production processes each doubling of the *cumulative* output is associated with a unit cost reduction of 20 percent to about 80 percent of the previous unit cost level, due to workers becoming increasingly familiar with their tasks. Cooper and Johri (2002) and Jovanovic and Nyarko (1995) contain brief surveys and further references.

Formally, we start from the assumption of a constant growth rate of output of a particular sector, $g = d\ln y(t)/dt$, expressed in continuous time. This is consistent with the focus on steady-state dynamics and balanced growth paths in growth theory. The growth path of output is thus $y(t) = y_0 e^{gt}$ with $y(0) = y_0$. Integrating output over time gives the cumulative output

$$s(t) = \int_{-\infty}^{t} y(j)dj = y_0 \cdot \int_{-\infty}^{t} e^{gj}dj = y_0 \cdot \frac{e^{gt}}{g},$$

whose logarithm $\ln s(t) = \ln y_0 - \ln g + gt$ is the basis for calculating the growth rate of the cumulative output which is $d\ln s(t)/dt = g$ and thus identical to the growth rate of output. The time t_d that it takes to double the cumulative output can then be obtained from

$$s(t+t_d) = 2 \cdot s(t) \Leftrightarrow y_0 \cdot \frac{e^{g(t+t_d)}}{g} = 2y_0 \cdot \frac{e^{gt}}{g},$$

which implies that $e^{gt_d} = 2$ and therefore the doubling time $t_d = \ln 2/g$.

Given that each doubling of cumulative output is associated with a 20 percent reduction of unit cost the unit cost dynamics can be stated as

$$c(t+t_d) = 0.8 \cdot c(t).$$

The annual rate of cost reduction z can be deduced from $0.8 = e^{-zt_d}$ and using the previous expression for the doubling time we obtain $z = -g \cdot (\ln 0.8/\ln 2)$. When we assume a balanced growth rate of about 3 percent, $g = 0.03$, the doubling time is approximately 23 years and the annual rate of cost reduction is approximately $z \approx 0.01$. Assuming a balanced growth rate of 2 percent reduces this rate even more.

However, the further problem arises that this number cannot be used directly since the model of Aghion et al. (2001) is not casted in real time but instead uses an index for the innovation sequence. Thus, unit cost dynamics in this model are given by $c_{\tau+1} = \gamma^{-1} \cdot c_\tau$, where γ denotes the step-size of the quality ladder as above and $\tau = 0, 1, 2, ...$ denotes the innovation count.

When innovations arrive with a Poisson rate of λn this innovation count sequence can be translated into real time. Given that $\varepsilon(t)$ innovations arrive between t and t+1 in real time, unit cost dynamics can be equivalently expressed as

$$\ln c(t+1) = \ln c(t) - \varepsilon(t) \cdot \ln \gamma, \text{ with } \varepsilon(t) \sim Po(\lambda n),$$

where $Po(\lambda n)$ denotes a Poisson distribution with expectation λn. Thus the expected rate of decline of unit costs is

$$\mathrm{E}(\ln c(t+1) - \ln c(t)) \; - \lambda n \cdot \ln \gamma$$

(see Aghion and Howitt (1998, p. 59) for this kind of argument).

Collecting results and neglecting the expectations operator (or invoking a law of large numbers) we can state that $\ln c(t+1) - \ln c(t) = -z \approx -0.01 \approx -\lambda n \cdot \ln \gamma$ and thereby that $\gamma \approx e^{0.01/\lambda n}$. The latter magnitude is smaller than e whenever $0.01/\lambda n < 1$ and consequently whenever $\lambda n > 0.01$. Interpreting λn as the probability of innovation between t and t+1 this implies that $\gamma < e$ and therefore the distribution of relative productivity is left-skewed whenever there is a minimal probability of innovation that leads to a Poisson arrival rate which is larger than 0.01.

Thus, all exercises performed to deduce γ agree on a value that is associated with a left-skewed distribution of the relative productivity levels. As will be shown in the next section this result stands in strong contradiction to the right-skewed shape of the distribution of relative productivity levels in the U.S. manufacturing sector.

4 The Empirical Distribution

In this section the theoretical distribution of relative productivity is confronted with the distribution of an empirically calculated relative measure of total factor productivity. To quantify total factor productivity a nonparametric frontier function approach is used that is particularly suited to the construction of the relative productivity variable of the theoretical model. The specific method used is the Andersen-Petersen variant of data envelopment analysis (see Andersen and Petersen (1993)). This is a nonparametric method that calculates an index of total factor productivity by the distance of the input-output combinations of the industries from a piece-wise linear frontier production function that is determined from the data alone without any assumptions about the functional form of the production relationship and without having to rely on price data. The Andersen-Petersen model calculates productivity by computing an index that indicates to which level the output of an industry has to be increased in order to reach a facet of the frontier production function that is determined by the observations of the other $N-1$ industries, excluding the industry for which efficiency is evaluated. Formally, this distance measure of industry i in year t is the solution ϕ_{it} of the following linear programming problem

$$\max\left\{\phi_{it} : \phi_{it} y_{it} \leq \sum_{h\in\{1,\ldots,N\}\backslash i} \lambda_h y_{ht} \; ; \sum_{h\in\{1,\ldots,N\}\backslash i} \lambda_h \boldsymbol{x}_{ht} \leq \boldsymbol{x}_{it} \; ; \boldsymbol{\lambda}_{-i} \geq 0\right\}$$

which is specialized in the present application to a single output variable y_{it} and a 6×1-vector of input variables $\boldsymbol{x}_{it}$ of industry i in year t. $\boldsymbol{\lambda}_{-i}$ denotes the (N–1)-vector of the weight factors λ_h omitting the i-th element.[2] This distance measure essentially quantifies the technological gap towards the frontier function from which a measure of relative total factor productivity can be obtained by simple inversion, i.e. ϕ_{it}^{-1}.

The data used to calculate the productivity scores are from the NBER-CES manufacturing industry database which is described in detail by Bartelsman and Gray (1996). This unique database provides consistent annual time series over the period 1958-96 for quantity and price data of more than 450 manufacturing industries on the four-digit level of saggregation.[3] The nonparametric productivity measurement is performed using the following specification of the output variable and the six labor, capital and material/energy input variables (the abbreviations in square brackets refer to those defined in the data appendix of Bartelsman and Gray (1996)):

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[2] This procedure is completely deterministic. There exists an alternative econometric approach to the estimation of fontier functions that promises to be able to divide measurement error from the productivity measure (see e.g. Greene 1993). However, the Monte Carlo studies of Banker et al. (1993) and Ruggiero (1999) show that this advantage of the econometric appoach is absent in small to medium sized samples.

[3] Due to outlying or missing data 5 industries were eliminated from the data set used here.

w output:
real value of shipments [VSHIP/PISHIP]

w labor inputs:
number of non-production workers [EMP–PRODE]
production worker hours [PRODH]

w capital inputs:
real equipment capital stock [EQUIP]
real structures capital stock [PLANT]

w material and energy:
real cost of materials other than electricity and fuels [(MATCOST–ENERGY)/PIMAT]
real expenditures on fuels and electricity [ENERGY/PIEN]

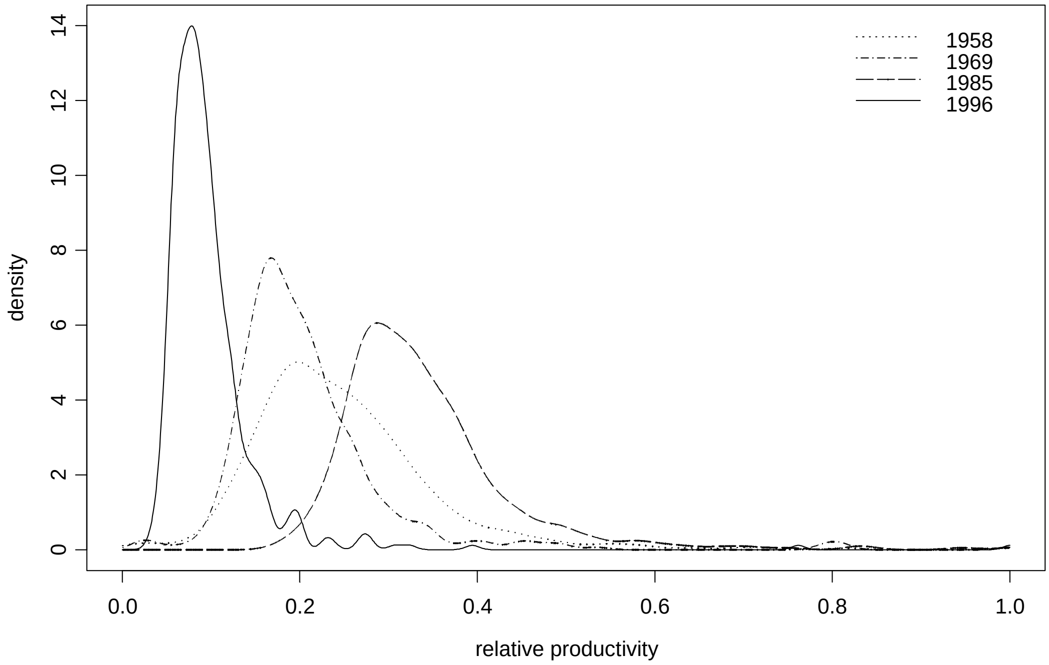
The computations of the Andersen-Petersen model for each year separately results in a balanced panel of total factor productivity scores ϕ_{it}^{-1} $(i = 1, ..., N,\ t = 1, ..., T)$ that range between zero and infinity for $N = 454$ four-digit industries over the $T = 39$ years covering the period 1958-96. The majority of the observations that do not determine the frontier function get a productivity score smaller than unity by the solution of the linear programming problem. Those observations that determine the frontier function get a productivity score larger than unity. To be consistent with the definition of relative productivity in the theoretical model these productivity scores are normalized to $a_{it} = \phi_{it}^{-1} / \max\{\phi_{1t}^{-1}, ..., \phi_{Nt}^{-1}\}$ for each period and are thus bounded within the inverval $[0, 1]$.

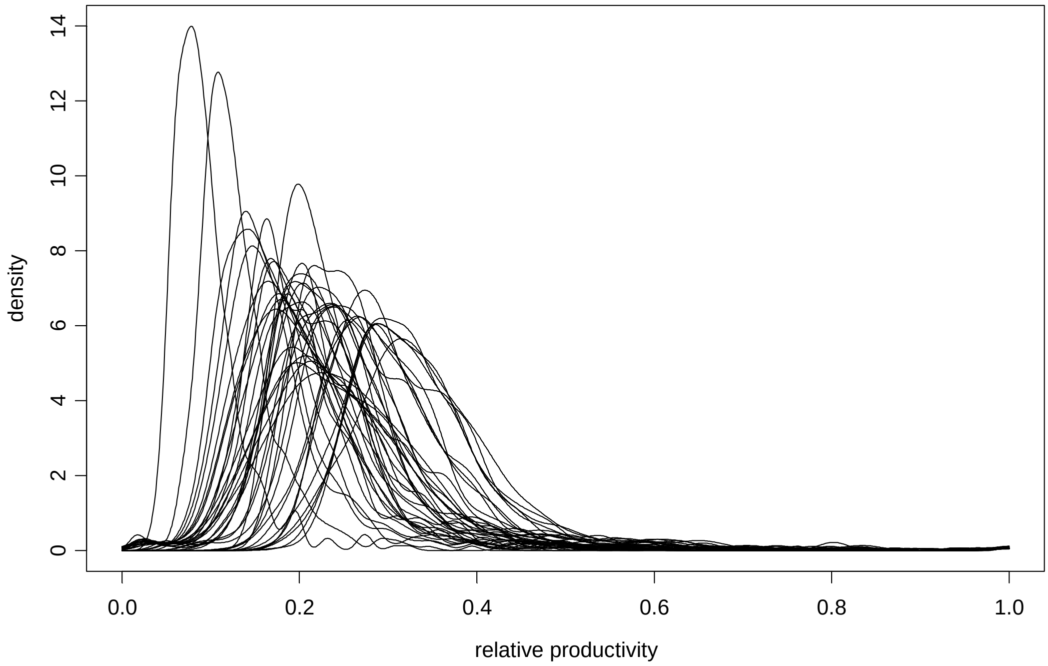
The density functions for each period are nonparametrically estimated by the univariate kernel density estimator (see Wand and Jones (1995, ch. 2)) for the normalized relative productivity scores on a grid of points $x \in [0, 1]$

$$\hat{f}_t(x) = \frac{1}{Nh_t} \sum_{i=1}^{N} K\left(\frac{x - a_{it}}{h_t}\right),$$

where the standard normal density is used as kernel function $K(\cdot)$ and the bandwidth h_t is chosen by the Sheather-Jones 2nd generation bandwidth estimator (Sheather and Jones (1991)) for each period separately. This bandwidth estimator has been found to be the preferred method for one-dimensional kernel density estimation in the comparison of Jones et al. (1996).

Figure 2
Density Functions of the Empirical Distribution of Relative Productivity





The upper panel of figure 2 shows the kernel density estimates of the productivity distribution for the years 1958, 1969, 1985 and 1996 which are chosen with regard to Jorgenson (1990) and provide an approximately equidistant subdivision of the sample period. It is immediate that the density functions are right-skewed with the bulk of the industries showing relatively low productivity scores and a few industries with substantially larger productivity scores. This stands in contrast to the theoretical distribution which is left-skewed for a wide range of reasonable parameter values for the innovation step-size. The years chosen are in no way exceptional as the lower panel of figure 2 shows in which the kernel density estimates for all years 1958-96 are plotted together.

This visual impression can by sharpened by calculating the empirical skewness measure $N^{-1}\sum_{i=1}^{N}(a_{it}-\bar{a}_t)^3$ for each year separately, where $\bar{a}_t$ is the arithmetic mean of the normalized productivity scores of period t. Empirical skewness ranges between 0.0017 and 0.0033 and is thus positive in each year, consistent with the visual impression of the figures. With this range of skewness we can gain further evidence regarding the step-size parameter γ of the theoretical model.

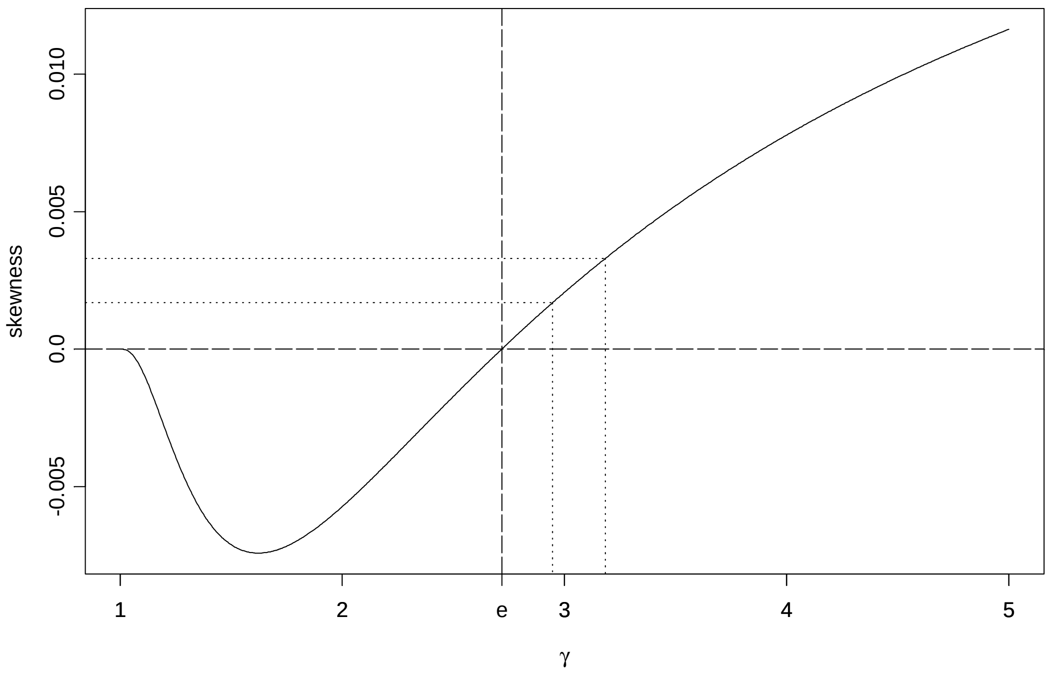
Rewriting the density function as $h(a) = ca^{c-1}, a \in [0,1]$ with $c = 1/\ln\gamma$ the first three moments of the theoretical distribution are easily computed as $\mathrm{E}(a) = c/(c+1)$, $\mathrm{E}(a^2) = c/(c+2)$ and $\mathrm{E}(a^3) = c/(c+3)$. This allows to express the skewness of the theoretical distribution as

$$\mathrm{E}((a-\mathrm{E}(a))^3) = \mathrm{E}(a^3) - 3\,\mathrm{E}(a^2)\,\mathrm{E}(a) + 2\,\mathrm{E}(a)^3 = -\frac{2c(c-1)}{(c+1)^3(c+2)(c+3)}.$$

Setting this formula equal to the minimum and maximum value of empirical skewness, solving numerically for c and translating back to the γ scale results in the interval $[2.947, 3.185]$ for γ which lies entirely in the range larger than e.

These findings are illustrated in figure 3, where the solid line is the skewness of the theoretical distribution depending on γ. The horizontal and vertical dashed lines mark the zero line and the position of e, respectively. Consistent with the previous results skewness is negative for $\gamma < e$ and the distribution is therefore left-skewed in this range. For $\gamma > e$ skewness becomes positive and the distribution right-skewed accordingly. The empirically estimated range of skewness and the associated values of γ are indicated by the dotted lines. These values lie in the range of positive skewness and are therefore associated with the right-skewed density found in the productivity data and plotted in figure 2 above.

Figure 3
Skewness of the Theoretical Distribution



5 Conclusion

To sum up, the analysis in this paper shows that the distribution of relative productivity generated by the models of Aghion and Howitt (1998, ch. 3) and Aghion et al. (2001) is fundamentally different from the distribution of a relative measure of total factor productivity for the four-digit industries of the U.S. manufacturing sector. The striking difference is that the theoretical cross-sectoral distribution is left-skewed for a wide range of plausible values for the innovation step-size parameter on which it solely depends, whereas the empirical cross-sectoral distribution is consistently right-skewed in each single year during the period 1958-96.

The most likely explanation for the left-skewed shape of the theoretical distribution is the strong intertemporal spillover effect working in the model which postulates that the leading-edge technology discovered by any one sector is available as basis for further improvements to all other sectors of the economy. This implies that all sectors are closely tied to the leading-edge technology. Without doubt, technological spillover effects across firms and industries exist (see Mohnen (1996)) but it seems to be the case that such spillover effects are much more limited than is assumed in the multi-sector growth models referred to in this paper.

Besides this criticism, it is important to consider structural change in the framework of multi-sector growth models to reach a fuller understanding of the growth process which is inseparably related to the generation and diffusion of innovation across sectors. Not too long ago, Harberger (1998) stressed the need to spend more emphasis to the processes of differential growth at the sectoral level. In Harberger’s "yeast versus mushrooms" story the view that all sectors expand evenly (like yeast) is confronted with the view that different sectors grow in unpredictable ways (like mushrooms) caused by a multitude of influences. The empirical results he reviews are much more favorable for the mushrooms story as a valid description of industry dynamics both across and within industries. In his own words, "the 'mushrooms' story prevails just as much among firms within an industry as it does among industries within a sector or broader aggregate" (Harberger (1998, p.11)). For growth theory this implies that it is important to devote more attention to the details of structural change on the level of sectors or industries not at least because structural change as a medium-run phenomenon is of enormous importance for economic policy.

Notwithstanding this critique of a neglected concern with the issues of structural change on the sectoral level in growth theory, it does not affect the validity of the assumption of a balanced growth path. At least in the case of the U.S. aggregate economy the time series of log GDP per capita over the period 1870-1994 fluctuates remarkably close around a linear time trend with an increasing slope (important exceptions being the years around the great depression and the second world war) as demonstrated in figure 1 of Jones (2002). Thus, the long-run aggregate output dynamics of the U.S. economy are well described by a balanced growth path. This holds also theoretically if structural change occurs on the sectoral level due to nonhomothetic preferences since the concept of a generalized balanced growth path introduced by Kongsamut et al. (2001) and Meckl (2002) assures that structural change and aggregate balanced growth are not incompatible with each other.

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