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COMPARING APPLES TO ORANGES: PRODUCTIVITY CONVERGENCE AND MEASUREMENT ACROSS INDUSTRIES AND COUNTRIES

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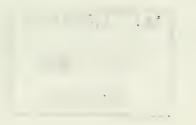
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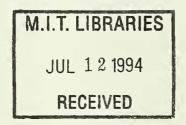
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Comparing Apples to Oranges: Productivity Convergence and Measurement across Industries and Countries^{*}

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Abstract

This paper examines the role of sectors in the convergence of aggregate productivity levels in 14 OECD countries from 1970-1987. The major finding is that manufacturing shows little evidence of either labor productivity or multi-factor productivity convergence while other sectors, especially services, are driving the aggregate convergence result. The paper introduces a new measure of multi-factor productivity which avoids problems inherent to traditional TFP measures when comparing productivity levels. A model of trade, learningby-doing, and spillovers is developed which can explain convergence in some sectors and divergence in others.

JEL Classification: 041, 047

1. Introduction

Comparisons of productivity performance across countries are central to many of the questions concerning long-run economic growth: are less productive nations catching up to the most productive countries, and if so, how quickly and by what means? Groups as disparate as economic growth theorists and business leaders express profound interest in the answer to the question of whether the U.S. can maintain its role as the world productivity leader.¹ The question itself is potentially misleading; should we be interested in the productivity of the entire private sector or that of individual industries; and whatever the level of analysis. are we concerned with labor productivity or a more general notion of technological advance? Using data for a group of 14 industrialized countries from 1970-1987, we ask whether trends in aggregate productivity are also reflected at the individual industry level taking care to distinguish between productivity of labor and that of all factors taken together. In the process, we consider the complicated question of how to compare multi-factor productivity levels across economies and provide a new measure of total technological productivity.

The results for individual industries are quite striking. While aggregate productivity was converging over the period, the sectors show disparate behavior. For all measures of productivity, the manufacturing sector shows no or little convergence, while other sectors. especially services, show strong evidence in favor of convergence. This finding for services together with the declining share of manufacturing in all 14 countries contributes to the convergence found at the aggregate level. The lack of convergence within manufacturing over this seventeen year period indicates that convergence is not an automatic phenomenon. Most theories of economic growth predict that openness and spillovers from R&D investment would contribute to convergence across countries and thus are not easily reconciled with these findings. However, we interpret this result in the context of a simple model of trade and learning-by-doing and argue that the lack of convergence within manufacturing may not be all that surprising. These results are especially pertinent to the study of convergence in countries at more heterogeneous levels of development. In a recent paper Young (1992) showed that while Hong Kong and Singapore apparently followed similar growth paths, their productivity performances were quite dramatically different. Our results suggest further that convergence of aggregate productivity may mask substantial differences at the sectoral level.

Previous work on convergence across countries has concentrated almost exclusively on labor productivity using GDP per capita as the measure. This is due largely to a lack of data on labor and capital inputs necessary to construct broader measures of productivity. Using cross-section regressions, Baumol (1986), Barro and Sala-i-Martin (1991, 1992) and Mankiw. Romer and Weil (1992) argue that countries and regions are converging, or catching-up, since initially poor areas grow faster than their richer counterparts. However, the crosssection evidence is not uniform. Barro (1991) and DeLong (1988) show that the particular sample of countries determines whether catch-up holds. Time series results on longer series for OECD countries also show evidence of common trends but no tendency for convergence in levels (for example, see Bernard and Durlauf 1991).

The use of labor productivity necessarily entails restrictions on the depth of analysis. By its very definition, a change in labor productivity confounds potential changes in tech-

¹For example, see Dertouzos et al. (1989) and Baumol et al. (1989).

nology and factor accumulation. Convergence in a neo-classical growth framework places heavy emphasis on the accumulation of capital as the driving force behind convergence, but analysis of labor productivity does not allow the identification of separate influences of technology and capital. To this end we consider both multi-factor productivity measures and labor productivity measures.

To conduct our analysis of convergence we require both growth rates of productivity and the productivity levels themselves. Most analyses of productivity concentrate on the changes, thus avoiding complicated issues concerning the measurement and comparison of productivity levels across industries and countries, which is particularly difficult for multifactor productivity. In section 2, we describe in detail our measure of Total Technological Productivity (TTP). This measure is constructed to ensure that we can conduct crosscountry and cross-industry comparisons with as few assumptions as necessary.

1.1. Aggregate Convergence

The fundamental piece of evidence on cross-national growth in the OECD countries is that productivity and output per capita differences have narrowed over time. Log levels of labor productivity, Y/L, and TFP are shown for total industry, excluding government, for 14 OECD countries from 1970-1987 in Figure 1.² Y/L has grown on average at a rate of 2.4% per year, but the gap between the most productive country, the U.S. over the entire period, and the least productive country declined consistently from 1970 to 1987. The same qualitative results hold for the measure of TFP; there is substantial narrowing of the gap between the leader, again the U.S., and the less productive countries. However, the degree of catch-up is less for the TFP measure, suggesting that capital accumulation is playing a role in the convergence of labor productivity.

The reduction in cross-section dispersion can be seen again in the lower half of Figure 1 which plots the cross-section standard deviations of Y/L and TFP. Cross-section dispersion declines steadily throughout the period from 24% to 14% for both labor productivity and from 17% to 12% for multi-factor productivity. Tests for catch-up, regressions of average growth rates on initial levels of the productivity measures for the 14 countries, confirm the visual evidence.³

$$\Delta \left(\frac{Y}{L}\right)_{i} = \alpha + \beta \left(\frac{Y}{L}\right)_{i}^{1970} + \varepsilon_{i}$$

$$coef \quad 0.3109 \quad -0.0298 \quad \bar{R}^{2}: \ 0.71$$

$$s.e. \quad (0.0501) \quad (0.0052)$$
(1.1)

 ${}^{2}Y/L$ is constructed as output per worker. TFP is constructed as a weighted average of capital and labor productivities with the weights being the average factor shares over time and across countries. All analysis with productivity is done using the logs of the levels. Throughout the paper we maintain the assumptions of constant returns to scale and perfect competition. This means we calculate our labor shares using output rather than cost shares, not an innocent assumption. Here we hold the labor share constant across countries and time. In Section 2 we discuss this assumption in greater detail. The countries in the sample are the U.S., Canada, Japan, Germany, France, Italy, U.K., Australia, the Netherlands, Belgium, Denmark, Norway, Sweden and Finland. The U.S. is denoted by a "o" and Japan by a "+" in most figures.

³Average growth rates here and throughout the paper are constructed as the trend coefficient from a regression of the log level on a constant and a linear trend. This minimizes problems with measurement error and business cycles.

$$\Delta TFP_{i} = \alpha + \beta TFP_{i}^{1970} + \varepsilon_{i}$$

$$coef \quad 0.1428 \quad -0.0226 \quad \bar{R}^{2}: \ 0.54$$

$$s.e. \quad (0.0322) \quad (0.0056)$$
(1.2)

The coefficients on the initial levels are negative and strongly significant for both measures. Both labor and total factor productivity measures for aggregate output indicate that less productive countries are catching-up to the most productive countries.⁴ Based on the simple model presented in the third section, these estimates imply that labor productivity is converging at a rate of 3.85% per year, faster than the 2.87% for TFP.⁵ The results from Equations 1.1 and 1.2 suggest that convergence is continuing for these economies even into the 1970's and 1980's.

To understand what is driving this strong evidence of convergence for total industry productivity, we now turn to the evidence from the sectoral data. First, we examine problems with simple TFP measures and construct an alternative measure called total technological productivity, or TTP. We then construct six broadly defined sectors for each economy and test for convergence in labor productivity and TTP within each sector across countries. Finally we develop a model of trade, learning-by-doing and spillovers which accords with many of the empirical facts on sectoral convergence.

The rest of the paper is divided into 5 parts: Section 2 discusses problems measuring multi-factor productivity levels and introduces a new measure; Section 3 presents a simple model of technological change within sectors; Section 4 analyzes the movements of labor productivity and technological productivity within industries across countries and tests for convergence; Section 5 develops a model of trade, leaning-by-doing and spillovers; Section 6 concludes and discusses further research.

2. Measuring Factor Productivity

Beginning with the work of Solow (1957), growth accounting and comparisons of factor productivity have played a prominent role in macroeconomics. Most such analyses have compared growth rates of multi-factor productivity (MFP), and the theoretical foundations for measuring multi-factor productivity growth rates are well-established. Following Solow (1957). one can define MFP growth as the amount by which output would grow if the inputs were held constant, and this growth rate can be calculated as

$$\Delta lnY_t - \alpha \Delta lnL_t - (1-\alpha)\Delta lnK_t,$$

⁴Time series tests also provide evidence of convergence for measures of Total Industry TFP. See Bernard and Jones (1993).

⁵In contrast, Barro and Sala-i-Martin (1992) have found 2% convergence for aggregate output per capita for a range of regions.

i.e. as the Solow residual, where α is labor's share of final output. The motivation for this calculation is extremely general; no assumptions on the specific functional form of the production function are required.⁶ In recognition of the fact that the labor share varies over time, it is common to employ a Divisia index of multi-factor productivity growth, which in this case corresponds to the Solow index where $\bar{\alpha}_t = .5(\alpha_t + \alpha_{t-1})$ is used in place of α (e.g. see Caves, Christiansen, and Diewert (1982)). This is the measure of multi-factor productivity growth that we employ throughout the paper. In contrast, the question of convergence is intrinsically a question of comparing productivity levels, not growth rates. Moreover, the theoretical foundations for comparing multi-factor productivity levels are less well established.⁷

Combining these observations, the problem of comparing productivity levels at all points in time reduces to a problem of comparing productivity levels at a single point in time: the remaining levels can be calculated using the Divisia productivity growth rates. In the context of convergence, then, it is natural to think of the problem as one of comparing initial levels of multi-factor productivity.

In this section, we argue that the most obvious method of comparing multi-factor productivity levels, examining Hicks-neutral TFP level measures, results in comparisons that can be arbitrarily altered under very simple assumptions. We document the use of such measures in empirical work relevant to this paper. Finally, we introduce a new measure of multi-factor productivity.

Assuming a Cobb-Douglas production function, $Y = AK^{1-\alpha}L^{\alpha}$, the Hicks-neutral measure of TFP is given by A, which is equal to a weighted average of capital and labor productivity:

$$\ln TFP = \alpha \ln(\frac{Y}{L}) + (1 - \alpha) \ln(\frac{Y}{K}).$$
(2.1)

The problem with this measure is that if the parameter α differs across countries, comparisons of this measure of TFP can be misleading, for at least two reasons. First, suppose that two countries have exactly the same inputs (i.e. the same capital and the same labor) as well as the same level of A, but they have different α 's. Clearly, these two countries will produce different quantities of output. The problem with A as a measure of technology here is that it is incomplete: the technology of production varies with the α parameters as well as with the A's, and the simple Hicks-neutral measure of TFP does not take this into account.

However, there is another more serious problem with the Hicks-neutral measure; arbitrarily small differences in the α parameters across countries imply that changes in the units of measurement for an input can change the ranking of productivity levels. This is easily seen in equation 2.1 above. Suppose that two countries have capital-output ratios that are equal to one, so that the TFP is simply equal to $(Y/L)_i^{\alpha}$. Notice that TFP is now measured in, for example, dollars per worker raised to some power that differs across countries. By changing the units of measure (e.g. measuring labor in millions of workers),

⁶The key assumptions, of course, are constant returns and competitive factor markets.

⁷Authors such as Kendrick and Sato (1963), Christiansen, Jorgenson, and Lau (1971), and Caves, Christensen, and Diewert (1982) have proposed methods for comparing multi-factor productivity levels, and we consider these methods below.

this will rescale TFP by a factor that varies across countries. It is easy to show formally that one can always reverse ranks in pairwise comparisons of TFP levels given arbitrarily small differences in the α parameters.⁸

It is tempting to infer that the same problem must exist in comparing TFP levels at two points in time, implying that computations of TFP growth rates are arbitrary. In fact, this is the motivation for using Divisia growth rates when factor exponents vary over time. In the Divisia calculation, the *same* factor share (an average) is used to compare the productivity levels in two different years to produce a growth rate, eliminating the problem. As the interval between the two periods gets small, the changes in factor shares also get small so that using the average factor share imposes very little distortion on the productivity measure. The problem with cross-country comparisons is that there is no sense in which the factor shares will necessarily be getting closer together: we can reduce differences in time by increasing the frequency of observation and invoking continuity; we cannot reduce differences across countries.

2.1. A Solution: Total Technological Productivity (TTP)

According to the results in the previous section, if factor shares vary substantially across countries, comparisons of productivity levels using the Hicks-neutral measure of TFP can be misleading. The first question we must ask, therefore, is whether or not this variation in factor shares is a problem empirically. Figure 2 illustrates that it is: for total industry in our data, the labor share varies substantially both across countries and over time.⁹ With this motivation, we turn now to a new method for comparing productivity levels.

The joint productivity of capital and labor varies with both the "A" term in front of the production function and with the factor exponents. To capture both of these contributions to productivity, we define a new measure that will be referred to as total technological productivity (TTP). At any point in time for country (or country-sector) i, TTP is defined as

$$TTP_{it} = F(K_o, L_o, i, t).$$
 (2.3)

TTP has a very intuitive interpretation: it shows which country would produce more output if all countries employed exactly the same quantities of capital and labor. Since K_o and L_o are constant across time and country or sector, comparisons using this measure incorporate only variation in the production function itself, not in the quantities of the inputs. In

$$D_{TFP}(\theta) \equiv \ln A_1(\theta) - \ln A_2(\theta)$$

$$= \ln(Y_1/Y_2) - \ln(K_1/K_2) + \alpha_1 \ln K_1 - \alpha_2 \ln K_2 - \alpha_1 \ln(\theta L_1) + \alpha_2 \ln(\theta L_2)$$

$$= D_{TFP}(1) + \ln \theta(\alpha_2 - \alpha_1).$$
(2.2)

By choosing non-negative values of θ , $D_{TFP}(\theta)$ can take on any value. QED

⁹Labor share varies over time and across countries for other sectors as well, especially manufacturing and services.

⁸We show the following: If the factor exponents in the production function differ, then a pairwise comparison of TFP using the simple measure defined above can generate differences that are arbitrarily large and either positive or negative by choosing the appropriate unit of measure for a single input.

Proof: Consider comparing TFP in region 1 with TFP in region 2. Without loss of generality, alter the units used to measure the labor input by a multiple, θ . The difference between the two TFP levels, denoted $D_{TFP}(\theta)$ is

this sense, this definition of multi-factor productivity is closely related to the definition of MFP growth given by Solow (1957). In practice, we will assume that the function $F(\cdot)$ is Cobb-Douglas so that

$$\ln TTP_{it} = \ln A_{it} + (1 - \alpha_{it}) \ln K_o + \alpha_{it} \ln L_o$$
(2.4)

where $\ln A_{it}$ is defined as:

$$\ln A_{it} = (1 - \alpha_{it}) \ln \left(\frac{Y_{it}}{K_{it}}\right) + \alpha_{it} \ln \left(\frac{Y_{it}}{L_{it}}\right).$$
(2.5)

Here, the labor share is allowed to vary across countries, sectors, and time to allow for the possibility that different industries in different countries have access to different technologies. Similarly, recognizing that we are usually dealing with aggregate data, we allow the exponents in the aggregate production function to vary over time. This variation could result from true technological variation or from changing sectoral composition within a country.

It is easy to show that this definition of multi-factor productivity is robust to the criticisms of Hicks-neutral TFP given above. First, by its very definition, countries with the same levels of inputs and the same technology will produce the same output. Second, the measure is also robust to changes in the units used to measure the inputs. Intuitively, whatever scale changes are induced by changes in the units of an input affect the calculation of $\ln A$ in exactly the opposite way, leaving TTP unaffected.

2.2. Other Production Functions and Productivity Measures

The variation in factor shares across countries and over time suggests that the standard Cobb-Douglas production function must be generalized. We choose to generalize in the straightforward way of allowing the factor exponents in the Cobb-Douglas form to vary across countries, sectors, and time. However, two alternative generalizations are the CES production function and the translog production function, which have been used elsewhere in the literature on productivity comparison. While extending our analysis to these more general functional forms might be useful, we discuss below the limitations of such an exercise.

One alternative is the CES specification, recommended by Kendrick and Sato (1963), which allows factor shares to vary monotonically with the capital-labor ratio. In our data, however, it appears that factor shares do not vary monotonically with the capital-labor ratio, nor do the factor shares behave similarly across countries. Within a country, for example, the relationship is typically not monotonic, and across countries, factor shares differ substantially. Thus, to examine productivity differences using the CES production function, we would have to allow the elasticity of substitution between factors to vary across countries and even, perhaps, over time.

Another alternative is the definition of productivity proposed by Caves, Christensen and Diewert (1982). Their definition is based on the translog production function first considered by Christensen, Jorgenson, and Lau (1971). While we feel it would be useful to extend the empirical results in this paper using the translog definition of productivity, tentative explorations in this direction suggest that the extension would not be straightforward. For example, as with the CES production function, factor shares corresponding to the translog production function depend on the level of capital and the level of labor. Specifically, Caves, Christensen, and Diewert (1982) show that

$$s_{it} = \beta_L^i + \beta_{KL} \ln K_{it} + \beta_{LL} \ln L_{it}$$

where s_{it} represents factor payments to labor as a share of output. Notice that the intercept in this equation is allowed to vary by country, but the other coefficients are constant across countries and over time. Empirical estimates of this equation using our data reveal that the null hypothesis that the coefficients on $\ln K$ and $\ln L$ are constant across countries is strongly rejected. For example, the F test of this hypothesis for the total industry aggregate produces a statistic of 9.35 compared to the 1% critical value of 1.70; for manufacturing, the statistic is 7.54, which can be compared to the same critical value.

Using either the CES or translog production setup does not address the fundamental problem that the parameters of the production function may vary across countries. For this reason and with an appeal to simplicity, we maintain the assumption of Cobb-Douglas functional form and allow the factor shares to vary across time, country, and sector.

As will be discussed in more detail later, Dollar and Wolff (1993) also focus on productivity convergence using industry data and employ the following measure of productivity:

$$TFP_{it}^{DW} = \frac{Y_{it}}{\alpha L_{it} + (1 - \alpha) K_{it}}$$

where α is the labor share of total compensation, assumed constant across units of observation.

It is easy to show, using the arguments provided above, that this measure of productivity is not robust to a change of units. For example, by choosing the units in which to measure L, one can make the contribution of L to this measure arbitrarily small so that comparisons will look exactly like comparisons of capital productivity Y/K. Similarly, by choosing the units in which to measure K, one can make the contribution of K arbitrarily small so that comparisons will look exactly like comparisons of labor productivity. If the rankings of capital productivity and labor productivity differ for two countries, then either country can be shown to be the more productive by choosing the appropriate units at which to measure the inputs. Our data suggests that such problems are not simply theoretical oddities: for all three key aggregates (total industry, manufacturing, and services) in 1970, Japan has a higher capital productivity level than the U.S. while the U.S. has higher labor productivity. Thus, productivity comparisons of the U.S. and Japan using the measure of Dollar and Wolff (1993) will depend critically on the units in which capital and labor are measured.

In addition, it is worth noting that the problem here may be more severe than with the measure of TFP discussed above because this criticism holds even when the factor exponents (the α 's) are constant across countries. This measurement argument provides one possible explanation for the differences between our results and those emphasized by Dollar and Wolff.

2.3. Remaining Issues

Several issues concerning Total Technological Productivity remain to be discussed. First, the TTP measure will vary depending on the values chosen for K_o and L_o . Moreover,

comparisons of TTP may be sensitive to the capital-labor ratio K_o/L_o , as is obvious from Equation 2.4. If two countries have different capital-labor ratios the TTP measure may change rank depending on which capital-labor ratio is chosen. This is shown graphically in Figure 3.

This aspect of the TTP measure is unfortunate. Ideally, we would like a single answer to the question, "In the aggregate, which country is more productive, the U.S. or Japan?" However, the answer may depend on whether we use the U.S. capital-labor ratio or the Japanese capital-labor ratio. This is analogous to the classic index number problem. Suppose we wish to compare the total output of two economies that produce different quantities of apples and oranges. Depending on the relative price used to weight apples and oranges, one country may appear to be more productive than the other.¹⁰

Several other candidate measures of multi-factor productivity also share this problem. For example, one can imagine constructing a TFP measure by converting labor units into dollars to make the measured labor input comparable to capital and labor. However, the choice of the real wage used in the conversion can alter the productivity rankings. It can be shown that this choice is analogous to choosing a capital-labor ratio since the two are related under cost minimization. By focusing only on the "A" term in the production function, this measure can also provide misleading results. Once again, countries (or sectors) with identical K, L, and A terms can have differing outputs as a result of different factor exponents. A comparison of the "A" terms would not capture this productivity differential.

Alternatively, one could return to the "naive" measure of TFP based on constant factor exponents across countries and time. This measure now seems less naive because it is the only TFP measure that is comparable across countries and time. However, the choice of the factor exponent still remains, and the rankings of the productivity levels will typically be sensitive to this decision. Moreover, this measure has the drawback of ignoring convergence that results from intertemporal movement in the factor exponents. That is, it looks at only one of the two dimensions along which factor productivity varies. Despite these drawbacks, we will report results based on the Hicks-neutral measure of TFP for comparison.

There does not seem to be an easy way around the choice of the appropriate capitallabor ratio. In the remainder of the paper, we proceed by evaluating TTP at the median capital-labor ratio for the initial year in the sample and then examine robustness.¹¹

2.4. Comparing TFP and TTP

Our proposed method for comparing productivity levels is TTP whose construction requires a measure of total factor productivity (TFP), factor shares, and capital and labor data. To construct TTP levels in practice for 1970-87, we apply Equation 2.4 to calculate the level in 1970 and generate levels for the subsequent years by cumulating the Divisia multi-factor productivity growth rates. The 1970 level is used as an initial value.¹²

Figure 1 compared labor productivity and the constant- α measure of TFP based on constant factor shares across time and countries, and the results were fairly similar. However,

¹⁰We thank John Taylor for pointing this out to us.

¹¹The results are robust to this choice. Choosing the lowest capital-labor ratio causes convergence for total industry and agriculture to weaken.

 $^{^{12}}$ As an alternative, we also used TTP levels calculated at each point in time using the TTP formula. The results are very similar with this approach.

factor shares vary across time and countries, as was shown earlier. Therefore, this simple TFP measure may distort productivity comparisons. Figure 4 plots a TTP measure as well as a TFP measure constructed using α 's that vary across country, i.e. a measure that is subject to the problems discussed above. The differences between the two measures are readily apparent. The cross country standard deviation for the varying α version of TFP shows episodes of some convergence and divergence leaving the overall dispersion essentially unchanged. In addition, the relative ranks of countries are dramatically different, with the U.S. in the middle of the 14 country group and Japan near the bottom. In contrast, TTP is well-behaved and consistent with the data on labor productivity. TTP for total industry exhibits substantial convergence over the period 1970-1987, as is obvious from both parts of the figure.

3. A Basic Model of Productivity Convergence

The neoclassical growth model without technology predicts convergence in output per worker for similar, closed economies based on the accumulation of capital. However, even in the neoclassical model, if the exogenous technology processes follow different long-run paths across countries, then there will be no tendency for output levels to converge. To see this we construct a simple model of productivity catch-up.

We abstract from issues of multi-factor productivity measurement and assume that multi-factor productivity, P_{it} , evolves according to

$$\ln P_{it} = \gamma_{ij} + \lambda \ln D_{it} + \ln P_{it-1} + \ln \epsilon_{it}$$
(3.1)

with γ_{ij} being the asymptotic rate of growth of sector j in country i, λ parameterizing the speed of catch-up denoted by D_{it} , and ϵ_{it} representing an industry and country-specific productivity shock. We allow D_{it} , the catch-up variable, to be a function of the productivity differential within sector j in country i from that in country 1, the most productive country,

$$\ln D_{it} = -\ln \hat{P}_{it-1} \tag{3.2}$$

where a hat indicates a ratio of a variable in country i to the same variable in country 1, i.e.

$$\hat{P}_{it} = \frac{P_{it}}{P_{1jt}}.$$
(3.3)

This formulation of productivity catch-up implies that productivity gaps between countries are a function of the lagged gap in the same productivity measure. For example, if TTP is the measure of productivity, then lagged gaps in TTP determine the degree of catch-up. This simple diffusion process is subject to criticism. Dowrick and Nguyen (1989) allow the catch-up in TTP to be determined by labor productivity differentials; however, it seems appropriate to suppose that technological catch-up may be occurring independent of capital deepening.

This formulation of output leads to a natural path for productivity:

$$\ln \hat{P}_{it} = (\gamma_{ij} - \gamma_{1j}) + (1 - \lambda) \ln \hat{P}_{it-1} + \ln \hat{\epsilon}_{it}.$$
(3.4)

In this framework, values of $\lambda > 0$ provide an impetus for "catch-up": productivity differentials between two countries increase the relative growth rate of the country with lower productivity. However, only if $\lambda > 0$ and if $\gamma_i = \gamma_1$ (i.e. if the asymptotic growth rates of productivity are the same) will countries exhibit a tendency to converge. Alternatively, if $\lambda = 0$, productivity levels will grow at different rates permanently and show no tendency to converge asymptotically.¹³ Considering the relationship between long-run growth rates across countries, we can rewrite the difference equation in 3.4 to yield

$$\bar{p}_{i} = -\frac{\left(1 - (1 - \lambda)^{T}\right)}{T} \ln \hat{P}_{i0} + \frac{1}{T} \sum_{j=0}^{T} (1 - \lambda)^{T-j} (\gamma_{i} - \gamma_{1} + \ln \hat{\epsilon}_{ij})$$
(3.5)

where \bar{p}_i denotes the average growth rate relative to country 1 between time 0 and time T.¹⁴ This is the familiar regression of long-run average growth rates on the initial level, where catch-up is denoted by a negative coefficient on the level.¹⁵

This simple set-up for analyzing productivity movements across countries is convenient because the regression specification is not dependent on the form of the production function.

4. Convergence in Industry Productivity

In this section we present cross-section convergence results for labor productivity, a "naive" measure of TFP, and our proposed measure of TTP for six sectors for 14 countries. We describe the data set before looking at the changing composition of output across countries. Results for β -convergence and σ -convergence follow. Finally, we review previous empirical work on industry productivity and convergence.

4.1. Data

The empirical work for this paper employs data for six sectors and total industry for (a maximum of) fourteen OECD countries over the period 1970 to 1987. The fourteen countries are Australia, Belgium, Canada, Denmark, Finland, France, Italy, Japan, Netherlands, Norway, Sweden, U.K., U.S., and West Germany. The six sectors are agriculture, mining, manufacturing, electricity/gas/water (EGW), construction, and services. The basic data source is an updated version of the OECD Intersectoral Database (ISDB), constructed by Meyer-zu-Schlochtern (1988).¹⁶

¹³Of course, if the country with the lower initial level has a higher γ_i , the countries may appear to be converging in small samples – this case is extremely difficult to rule out in practice.

¹⁴An alternative testing approach, employed in Bernard and Jones (1993), is to estimate Equation 3.4 directly. If $\lambda > 0$, then the difference between the technology levels in the two countries will be stationary. If there is no catch-up ($\lambda = 0$), then the difference of TFP in country i from that in country 1 will contain a unit root. The drift term $\gamma_{i-}\gamma_{1}$ will typically be small but nonzero if the countries' technologies are driven by different processes (i.e. under the hypothesis of no convergence). Under the hypothesis of convergence, $\gamma_{i} = \gamma_{1}$ is plausible.

¹⁵For potential problems with this type of regression, see Bernard and Durlauf (1993).

¹⁶With the exception of the services aggregate, all the other sectors are taken directly from the ISDB. The services aggregate is constructed by summing Retail Trade, Transportation/Communication, F.I.R.E., and Other Services. Government Services are excluded. Our measure of aggregate output also excludes the government sector.

The ISDB database contains data on GDP, total employment, number of employees, capital stock, and the wage bill. All of the currency denominated variables are in 1980 dollars, having been converted by the OECD using purchasing power parities. We construct our labor productivity and multi-factor productivity measures using these variables. In particular, since we do not have hours data, we measure labor by total employment.

We measure labor productivity as the log of value-added per worker. Since we must obtain levels of multi-factor productivity to conduct our convergence analysis, we construct a measure of the log of total factor productivity (TFP), designated A_{it} . This measure is constructed in a standard way, as a weighted average of capital and labor productivity, where the weights are the factor shares calculated assuming perfect competition and constant returns to scale. In order to be able to make cross-country comparisons, we restrict our labor share to be sector-specific, i.e. it is calculated as an average over time and country for each sector.¹⁷ Finally, we construct data on TTP by applying the formula in equation 2.4, evaluated at the median capital-labor ratio for each sector in 1970. Whatever the measure of productivity levels we employ, we continue to use the Divisia growth rates, and subsequent productivity levels are calculated by cumulating the growth rates using the initial level to pin the series down.

To summarize the data, Table 6.1 reports average annual labor productivity and Divisia growth rates by country and sector for the period 1970 to 1987.¹⁸ Similarly, Figures 5 and 6 plot the log of labor productivity and TTP respectively by sector for each country.¹⁹ The table shows substantial heterogeneity in growth rates across both industries and countries. Average sectoral growth rates of labor productivity vary from 4.0% per year in mining to 0.9% in construction. The Divisia growth rates show similar variation with agriculture experiencing the fastest multi-factor productivity growth, 3.0%, and mining and construction actually showing negative growth over the period. Within sectors, there is also substantially different growth experiences. Manufacturing growth in labor productivity varies from a high of 5.9% in Japan to a low of 1.7% in Norway. MFP growth in manufacturing was highest in Belgium, 3.5% per year, and lowest again in Norway, 0.7% per year. Labor productivity in services, the largest sector in these economies, grew at a 2.8% rate in Japan and only 0.6% in Italy.

For every sector, average labor productivity growth was faster than MFP growth suggesting a continuing role for capital accumulation in changes in labor productivity even for these developed economies over the 1970's and 1980's. The difference was most dramatic in mining which had the fastest labor productivity growth but the lowest, even negative, multi-factor productivity growth. The differences between labor productivity and multifactor productivity was smallest in services.

As a check on the validity of these numbers, we can compare the growth rates for productivity in the U.S. to productivity growth rates calculated by the Bureau of Labor Statistics (1991), as shown in the following table:²⁰

¹⁷We relax this assumption later.

¹⁸For a few sectors, 1986 is taken as the endpoint because of data availability.

¹⁹The TFP figures look very similar.

²⁰The BLS use data on labor hours as opposed to the total employment measure used by the ISDB.

	Y/	'L	MFP		
	Total Ind.	Manufac.	Total Ind.	Manufac.	
BLS	1.5%	2.8%	0.8%	2.2%	
ISDB	0.6%	2.6%	0.2%	1.8%	

The growth rates for the manufacturing sector agree nicely, while those for total industry are somewhat different. Because the key findings in this paper focus on the manufacturing sector, the slightly anomalous results for the total industry measure is less disconcerting.

Looking at the labor productivity and TTP levels by sector in Figures 5 and 6, we can see several immediate differences from the aggregate movements shown earlier. Sectors do not show the same patterns in either trend or dispersion over time. Neither labor productivity nor MFP show much change in dispersion for manufacturing, while in services, both measures display a narrowing of the gap between the highest productivity country and the lowest. The figures also bear out the substantial heterogeneity of productivity performances across sectors.

One perhaps puzzling feature of the figures concerns Japanese productivity in the services sector. According to the labor productivity measure, Japanese productivity in the service sector in 1970 was at the bottom of the sample, while the TTP measure (and the TFP measure, although this is not reported) place Japan right at the top. As a comparison, Baily (1993) cites numbers from the McKinsey Global Institute that suggest that total factor productivity in Japanese general merchandise retailing was only 55% of that of the U.S. as of 1987, which suggests that measurement error may plague the service sector data. Once again, however, as long as the manufacturing data are accurate, the key results of this paper hold up.

4.2. Industry Shares in GDP

To help us focus on the sources of convergence in total industry productivity we first examine the share of sectors in GDP. Even if there is convergence within sectors, aggregate convergence may not occur. For example, if output shares of industries vary across countries, then once all sectors have converged to their sector-specific long-run productivity levels there will still be differences in aggregate productivity levels across countries. Convergence in output shares together with sector-specific convergence is sufficient for aggregate convergence. In this section, we examine the evidence on the share of output accounted for by each of our six sectors.

Figure 7 shows the share of total industry output (excluding the government) for each country in the six broad sectors. Both the level and change in shares differs dramatically over time. Within manufacturing, services, construction, and agriculture, most countries show similar trends over time. Generally, the share of manufacturing is declining (Japan is a notable exception to this trend), as are the shares of construction and agriculture. Services is the only sector to show substantial share growth for most countries, accounting for at least 49% and as much as 64% of total industry output in 1987. These figures suggest that manufacturing and services make up at least two thirds of total output in every country throughout the period.²¹

²¹To test whether these countries are becoming more similar in output composition, broadly defined, we

In testing for convergence at the industry level, we will concentrate on the results for these two sectors.

4.3. Cross-Country Convergence

Distinct definitions of convergence have emerged in recent empirical work. Cross-section analyses focus on the tendency of countries with relatively high initial levels of output per worker to grow relatively slowly (β -convergence) or on the reduction in cross-sectional variance of output per worker (σ -convergence), as in Barro and Sala-i-Martin (1991, 1992). This idea of convergence as catching-up is linked to the predicted output paths from a neo-classical growth model with different initial levels of capital. Once countries attain their steady-state levels of capital, there is no further expected reduction in cross-section output variance. Time series studies define convergence as identical long-run trends, either deterministic or stochastic. This definition assumes that initial conditions do not matter within sample and tests for convergence using the framework of cointegration.²²

The model of catch-up in Section 3 implies that both types of convergence should hold given a long enough sample. If the 14 OECD countries are on their long-run steady state growth paths as of 1970 then the appropriate framework for testing industry level convergence is that of cointegration. However, if technology catch-up is still taking place as of 1970 then the cross-section tests are more informative. In this paper, we will focus on the cross-section analysis of convergence and examine β -convergence and σ -convergence. Elsewhere (Bernard and Jones, 1993) we have tested for convergence using the sectoral data in a time series framework.

Tables 6.2 presents the results on β -convergence for labor productivity. For each sector, the growth rate of productivity is regressed on its initial level (and a constant) generating an estimate of β . The implied speed of converge, λ , is then calculated using the formula from Equation 3.5. In this framework, the speed of convergence λ can be interpreted as the rate at which the productivity level is converging to some worldwide productivity level, which may itself be growing over time.

For labor productivity, the basic convergence result for total industry shown in Equation 1 appears to hold for some sectors but not for others. For services, construction, and EGW, a significant negative estimate of β is obtained, implying that there has been catch-up in labor productivity during this period. The convergence rates for these industries vary from 2.46% per year in EGW to 2.83% per year in services. However, even within these converging sectors, the simple regression formulation differs widely in its ability to explain cross-country

²²For a discussion of the theoretical and empirical inconsistencies associated with these two measures of convergence see Bernard and Durlauf (1993).

tested for convergence in the sectoral output shares. Only agriculture and construction showed a narrowing of the differences of output shares across countries during the sample. Mining shares diverge, due most likely to dramatic changes in the oil industry, while shares of manufacturing, services and EGW do not show much change in the cross-country dispersion. The cross-section growth rate regressions confirm these results. Agriculture and construction show convergence in shares with negative and significant coefficients on initial levels, Services is negative and significant at the 10% level, and the others have negative coefficients but are insignificant. These results on sectoral output shares suggest that while services is growing as a share of output and manufacturing is declining in most countries, there remain substantial differences in sectoral shares across countries. In particular, there is little tendency for shares to become more similar, as measured by standard convergence criteria.

growth rates. In services, the regression accounts for 56% of total cross-country growth rate variation while \bar{R}^2 is only 0.19 in the construction sector.

Surprisingly, the evidence for convergence is weak in manufacturing as the null hypothesis of no convergence is not rejected even at the 10% level. The \bar{R}^2 is correspondingly low. Similar results hold for mining and agriculture as well.

Table 6.3 shows comparable results for the TFP measure of multi-factor productivity. Looking at TFP, we find less evidence for convergence within manufacturing as the coefficient, although still negative, is smaller and the *t*-statistic is lower. The \bar{R}^2 for the manufacturing regression is also smaller at 0.02. Services, once again, shows convergence at a rate of 1.34% per year and the simple regression explains 56% of the cross-country variation. Agriculture now shows strong evidence of convergence, suggesting that capital accumulation may even be offsetting technological convergence. Mining, construction, and EGW all show broadly similar patterns for TFP and labor productivity.

Table 6.4 reports our preferred estimates of β -convergence in multi-factor productivity using TTP. We see results on convergence roughly similar to those from the labor and TFP productivity measures used earlier. However, manufacturing now shows even less convergence, both the level and significance of the coefficient are reduced and the \bar{R}^2 is now negative. Total industry TTP is catching-up at a rate of 2.68% per year. This compares to a point estimate for the manufacturing sector of only 0.86% year which is insignificantly different from zero. Four sectors show strong evidence of convergence in TTP, services, agriculture, construction and EGW with negative significant estimates of β and high \bar{R}^2 statistics.

To more clearly understand the movements and convergence of productivity, we now turn to a measure of σ -convergence, the cross-section standard deviation of productivity over time.²³ In the graphs, σ -convergence is indicated by a declining standard deviation, reflecting the fact that countries' productivity levels are getting closer together over time. The different sectoral contributions to aggregate labor productivity can be seen more clearly in Figure 8 which plots the cross-country sectoral standard deviations of labor productivity over time. Services and EGW display substantial evidence of catch-up, as σ_t is declining throughout the period. The results for manufacturing are particularly interesting: during the 1970s there is gradual convergence as the standard deviation of productivity falls from 22% to 18%; however, after 1982 the standard deviation rises sharply for the remainder of the 1980s reaching more than 23% by 1987. Evidence on the other sectors is less clear-cut, construction and agriculture fall initially and then steady, and mining rises dramatically and then falls back somewhat. These results do not change if the U.S. is removed from the sample. In fact, the increase in manufacturing TFP dispersion is augmented.

Figure 9 plots the cross-country standard deviation in the log of TTP for the six major sectors.²⁴ The results are similar to those for labor productivity and the β -convergence regressions. Services, agriculture, and EGW all exhibit substantial convergence, confirming the regression results. In contrast, productivity in the manufacturing sector shows no convergence in the 1970s and diverges during the 1980s.

²³Combining the β - and σ -convergence results allows us to avoid potential problems associated with Galton's Fallacy. Quah (1993) shows that negative coefficients on β are consistent with a constant cross-section distribution.

²⁴The results for the TFP measure are similar.

4.4. Convergence within Manufacturing and Services

To compare our results with previous work we also estimate β -convergence regressions for 9 2-digit sub-sectors of manufacturing and 4 2-digit sub-sectors of services.²⁵ Table 6.5 presents the results for manufacturing. Only 4 of the 9 manufacturing industries show evidence of convergence, textiles, chemicals, non-metallic minerals, and basic metals. Machinery and equipment, a sector which has been associated with growth in recent work, shows little evidence of convergence in TTP.²⁶ This suggests that the lack of convergence for manufacturing as a whole extends to individual industries as well.

The convergence regressions for services are shown in Table 6.6. Once again the general finding of convergence in services is borne out by negative and significant estimates of β in 3 of the 4 sub-sectors. Only the coefficient for Finance, Insurance and Real Estate is not significant at the 5% level. The explanatory power of the regressions is higher here as well.

4.5. Robustness of the TTP Results

The TTP results of the previous section highlight one of the key results of this paper: the aggregate convergence in technological productivity within the OECD economies over the last two decades is driven by the non-manufacturing sectors; within manufacturing, there is virtually no evidence of convergence and even weak evidence for divergence. These results are based on TTP evaluated at the median capital-labor ratio for each sector in 1970. This result does not appear to be sensitive to the choice of the capital-labor ratio, however, a point we now examine in more detail.

Instead of presenting additional tables of regression results, we demonstrate the point graphically. Figures 10 and 11 plot the log of TTP for total industry and for the manufacturing sector for a subsample of the OECD economies. Log of TTP is plotted for each country for 1970 and 1986, together with U.S. TTP in 1970 and 1986. The symbol 'o' in the figure indicates the U.S. capital-labor ratio for each year (together with the min and the max for each sector), while the symbol 'x' does the same thing for another OECD economy.

Figure 10 illustrates that the convergence of TTP in total industry is robust to the choice of the capital-labor ratio, at least in these pairwise comparisons. Within the relevant range (i.e. between the min and max capital-labor ratio for the sector), there are few crossings of the TTP lines, and the convergence result appears to apply at virtually every capital-labor ratio. As an example, consider the picture for Japan. U.S. TTP grows relatively slowly during this period, indicated by the relatively smaller shift upward in the TTP line for the U.S. when compared to the shift for Japan. This is true at all (relevant) capital-labor ratios, indicating that regardless of the capital-labor ratio chosen, Japanese technological productivity was catching up to U.S. productivity in total industry.

Figure 11 illustrates that the lack of convergence within manufacturing is also robust to the choice of the capital-labor ratio. For example, consider the picture for West Germany. U.S. TTP growth is clearly faster than West German TTP growth at all capital-labor ratios that are relevant, including the U.S. and West German capital-labor ratios. Since the U.S.

²⁵There are often fewer countries for the regressions within sub-industries thus the results must be taken as suggestive.

²⁶The labor productivity results for these sectors show even less convergence with some industries registering positive coefficients.

is the technological leader here, there is divergence in technological productivity for these two countries. Of the six pairwise comparisons in the figure, only Japan (and perhaps Italy) potentially are converging to the U.S. TTP level over this period, and even this convergence appears to be sensitive to the choice of capital-labor ratio (e.g. evaluated at the largest capital-labor ratio of 11.5, TTP growth for the U.S. is faster than that of Japan).

Overall, the results from this section confirm that the empirical results for TTP documented earlier are robust to the choice of the capital-labor ratio.

4.6. Previous Empirical Work on Sectors

Most previous work on convergence has concentrated on aggregate data, looking in particular at output per capita or labor productivity, output per worker. A notable exception to this is work by Dollar and Wolff (1988),Wolff (1991), and especially Dollar and Wolff (1993) who consider convergence using industry data. Dollar and Wolff (1993) consider many of the same issues addressed in this paper, such as convergence within sectors and the differences between labor productivity and TFP. Largely in opposition to our findings, they conclude that there has been substantial convergence in most sectors, and in particular within manufacturing during the period 1963-1985. However, they show that most of the convergence occurred prior to 1973, and since that time any convergence has been weak at best for most sectors.

Several important differences in data and methodology exist between Dollar and Wolff (1993) and this analysis. First, they use an early version of the OECD data set we employ, which may contribute to the different findings. A symptom of the problems with their data is that Dollar and Wolff (1993) find Norway to be the most productive country after 1982, a result not confirmed by any outside source. However, the dominant disparities between the empirical analyses in that work and those in this paper stem from differences the measures of multi-factor productivity. As discussed in Section 2, their primary measure of multi-factor productivity is not robust to a simple choice of units (and this is true even if the factor exponents do not differ across countries or sectors).

Stockman (1988) and Costello (1993) have also examined industry-level data for OECD economies, although not in the context of convergence. Stockman (1988) decomposed the growth rate of industrial production for eight OECD countries and ten two-digit manufacturing industries into a country-specific component and an industry-specific component (by using the appropriate combination of indicator variables). With this setup, Stockman reports the fraction of the variance of output growth that is explained by the country-specific component, the industry-specific component, and the covariation between the two. His results indicate that the two types of shocks explain roughly the same percentage of variation in output growth.

Costello (1993) follows the methodology of Stockman (1988) but focuses on multi-factor productivity (MFP) growth instead of output growth and examines five industries in six countries. Costello's results are consistent with those of Stockman and suggest the presence of national effects that are at least as important as sectoral effects in explaining the variation of MFP growth. Costello also provides some evidence using pairwise correlations suggesting that MFP growth is more highly correlated within a country across industries than within an industry across countries.²⁷

4.7. Summary

The results on convergence in this section are in stark contrast to the picture given in previous work at the aggregate level. Convergence, defined as catch-up by low productivity countries to high productivity countries, is occurring at the aggregate level and within some sectors, such as services, for both labor productivity and multi-factor productivity. However, surprisingly, manufacturing shows little or no evidence for convergence for both measures and, in particular, shows divergence during the 1980's.²⁸ These results are confirmed when we examine sub-sectors of both manufacturing and services. The lack of convergence for manufacturing holds for most sub-industries and the convergence found for services is also broad-based. While this work with a relatively short time horizon and a small group of countries is perhaps not conclusive, it is suggestive of problems associated aggregate movements to sectors and vice versa. In particular, these results suggest that international flows, associated mostly with manufacturing, may not be contributing substantially to convergence either through capital accumulation or technological transfer.

5. A Theoretical Framework: Trade, Spillovers, and Sectoral Convergence

This section presents a stylized model designed to explain the catch-up/convergence of technological productivity in some one-digit sectors together with the lack of convergence, and even divergence, of technological productivity in other one-digit sectors. The explanation centers on the distinction between tradeable and non-tradeable goods. In the non-tradeable goods sectors, the model will look very much like an aggregate growth model, and technological productivity levels will converge in these sectors as the technology for producing similar goods diffuses over time. For example, if you walk into a supermarket in either Boston, Frankfurt, or Tokyo a laser scanner will record the price of each item you purchase, and you can stop by an ATM machine on your way home to replenish your liquidity: the technologies used to offer the same service across advanced countries are potentially similar.²⁹ On the other hand, in the tradeable goods sectors, comparative advantage leads to specialization, and to the extent that countries are producing different goods, there is no a priori reason to expect the technologies of production to be the same or to converge over time. Thus, computer-related products and aircraft are produced in the U.S., rotary printing presses and production machinery are produced in Germany, and a myriad of consumer electronics are produced in Japan. There is no reason for the multi-factor productivity for these different commodities to be the same. Of course, this effect may be mitigated somewhat by technological spillovers across goods, an effect that is highlighted by the model.

For simplicity, the model contains two countries that potentially produce in three dif-

²⁷Note that our productivity model in Section 3 may be extended to incorporate within country as well as across country contributions to technological progress.

²⁸Further work with longer time series is necessary to determine whether the 1970s or the 1980s is the anomalous period.

²⁹Of course, the word "potentially" is extremely relevant here, as illustrated by Baily's (1993) comparison of multi-factor productivity in general merchandise retailing, discussed above.

ferent sectors.³⁰ Sector 0 is a non-tradeable good (e.g. services), while sectors 1 and 2 are tradeable goods (e.g. subsectors of manufacturing). In equilibrium, each country will specialize in one of the manufacturing subsectors and will therefore be producing in two sectors. Production in sector i in each of the two countries is given by

$$X_i = K_i^{\epsilon} L_i, \qquad x_i = k_i^{\epsilon} l_i \qquad i = 0, 1, 2$$
 (5.1)

where X_i , K_i , and L_i represent output, cumulated learning (which is completely external), and labor input in the home country, respectively. Lower case letters are used to denote the corresponding variables in the foreign country. The elasticity of output with respect to experience, ϵ , is assumed to be between zero and one, the same across sectors, and constant over time. Finally, we assume total labor in each country (L,l) grows at the same rate n, and labor is immobile across countries but perfectly mobile across sectors within a country, implying that all producing sectors in the economy will pay the same wage.

The manufacturing goods produced in sectors 1 and 2 are tradeable, and the open economy leads to specialization provided that K_i and k_i are not the same at time 0. We define $\alpha \equiv (k_i/K_i)^c$ as the relative productivity of sector i;³¹ then a simple Ricardian argument leads to specialization immediately: the foreign country will specialize in the good with the higher relative productivity. Without loss, we arbitrarily assume this is good 2, which implies that the home country specializes in good 1.

Instead of specifying a general form for consumer demand which would then determine the allocation of labor across sectors, we make the simplifying assumption that the share of labor in each sector is constant over time for each country.³² Together with identical population growth rates in the two countries, this implies that $\lambda_i \equiv l_i/L_i$ is constant over time as well.

We depart from Krugman (1987) in modelling productivity growth. As in Krugman (1987) and Lucas (1988), productivity growth in this model is external to the firm and the economy and occurs via learning-by-doing. Our version nests both of these models and allows for spillovers across different goods and across countries. For the manufacturing sectors, learning-by-doing proceeds according to

$$\dot{K}_{i} = \delta_{i}X_{i} + \psi_{i}X_{j} + \gamma_{i}x_{i} + \phi_{i}x_{j}$$
for $i = 1, 2$ and $j = -i$

$$\dot{k}_{i} = \delta_{i}x_{i} + \psi_{i}X_{i} + \gamma_{i}X_{i} + \phi_{i}X_{j}$$
(5.2)

while for the services sector we have

$$\dot{K}_{0} = \delta_{0}X_{0} + \gamma_{0}x_{0}$$

$$\dot{k}_{0} = \delta_{0}x_{0} + \gamma_{0}X_{0}$$
(5.3)

³⁰The initial setup of the model closely follows Krugman (1987).

³¹This model focuses primarily on technological convergence, although as there is no capital in the model the distinction is hard to make. However, factor price utilization need not imply convergence in labor productivity if the α 's differ across goods: $Y/L = w/\alpha$.

³²This assumption can be derived if we are willing to assume a CES utility function with unitary elasticity of substitution between goods. Allowing the elasticity to differ from unity leads to a labor share in the services sector (nontradables) that either rises or falls continually over time, which is related to the Balassa-Samuelson effect discussed in Balassa (1964). We plan to extend the model in this direction, which may help to explain the rising share of services in output observed in these countries.

Several remarks are now in order. First, within a sector, both countries have symmetric learning functions-there is no country-specific learning effect. This is an important assumption because, of course, with country-specific effects anything is possible. Second, we allow spillovers between different manufactured goods, but not between the non-traded good and the traded goods. Finally, the parameters can be interpreted as follows: δ_i is the efficiency of the direct learning effect from own production: ψ_i is the efficiency of the learning spillover from the domestic production of the other tradeable good; γ_i is the efficiency of the spillover from the foreign production of the same good; and ϕ_i is the efficiency of the spillover from the foreign production of the other good. Notice that we permit different goods to have different learning parameters. This can be interpreted as allowing some goods to be "high-tech" goods and other goods to be "low-tech" goods in the sense that learning proceeds very rapidly or very slowly.

As discussed above, comparative advantage leads to specialization at any point in time so that $X_2=0$ and $x_1=0$, which simplifies the learning equations in 5.2. The set of equations can be simplified even further if we are willing to assume that the spillovers across goods do not change the pattern of comparative advantage over time. Initially, we assumed that $\alpha_2(0) > \alpha_1(0)$ so that the Home country specializes in good 1 and vice versa. Switching can occur if $\alpha_2(0) < \alpha_1(0)$ at any point in time. A sufficient condition to rule this possibility out is $\dot{\alpha}_2/\alpha_2 \geq \dot{\alpha}_1/\alpha_1$ for all t, which holds if and only if

$$\frac{\dot{k}_2}{k_2} + \frac{\dot{K}_1}{K_1} \ge \frac{\dot{k}_1}{k_1} + \frac{\dot{K}_2}{K_2} \tag{5.4}$$

i.e. if the total growth in the productivity of the goods produced by each country exceeds the total growth in the productivity of the goods not produced by each country. This is certainly a reasonable case to consider, although we will relax this assumption in future work.

Once we eliminate the switching case from consideration, we can focus only on the goods that are produced, and the differential equations governing productivity growth are

For each of these broadly-defined sectors we have a simple differential system to analyze. Notice that the system for the services sector is a special case of the system for the manufacturing sector, where $\delta_1 = \delta_2 = \delta_0$ and $\phi_1 = \phi_2 = \gamma_0$.

5.1. Dynamics and Solution

With this setup, the dynamics are most easily analyzed by defining two state variables that are constant in steady state. Let z = k/K denote the relative human capital levels between the two countries, either in manufacturing (in which case $k = k_2$ and $K = K_1$) or in services (in which case $k = k_0$ and $K = K_0$), and let y = X/K denote the output to human capital ratio in the home country, again either in the first manufacturing sector or in services. We will analyze the dynamic system for manufacturing first, and then use the fact that the system for services is just a special case of this analysis. With these definitions, one can derive the following system of equations:

$$\frac{\dot{z}}{z} = y \left(\frac{\phi_2}{z} + \delta_2 \lambda z^{\epsilon - 1} - \delta_1 - \phi_1 \lambda z^{\epsilon}\right)$$
(5.6)

$$\frac{\dot{y}}{y} = n - (1 - \epsilon) y \left(\delta_1 + \phi_1 \lambda z^{\epsilon}\right)$$
(5.7)

which can be solved for the equilibrium state in which $\dot{z} = 0$ and $\dot{y} = 0$ to yield

$$z^{\star} = \frac{\phi_2 + \delta_2 \lambda z^{\epsilon}}{\delta_1 + \phi_1 \lambda z^{\epsilon}} \tag{5.8}$$

$$y^{\star} = \frac{n}{(1-\epsilon)\left(\delta_1 + \phi_1 \lambda z^{\epsilon}\right)}$$
(5.9)

which implicitly determine the equilibrium. Moreover, phase diagram analysis reveals that this equilibrium is globally stable: the system converges to this equilibrium from any starting values z(0) and y(0). This last equation implies that X/K is constant in steady state, so that one can show easily that

$$\frac{\dot{X}}{X} = \frac{\dot{x}}{x} = \frac{n}{1-\epsilon}$$
(5.10)

That is, output (and therefore output per worker) in each sector and in each country grows at the same constant rate that depends on the rate of population growth and the elasticity of output with respect to human capital.³³

5.2. Analysis of Convergence Properties

Fundamentally, we are interested in the dynamics of the relative productivity level $\alpha \equiv z^{\epsilon}$. The stability property of the system implies that regardless of the initial value of α , the system will converge to $\alpha^* \equiv (z^*)^{\epsilon}$. The various cases are displayed in Figure 12. Arbitrarily, we assume that $\alpha(0)$ is less than unity and present three cases of interest: $\alpha^* = 1$, $\alpha^* < 1$, and $\alpha^* > 1$.

The first case of $\alpha^* = 1$ is the standard convergence case. In equilibrium productivity levels are equal and we have smooth, monotonic convergence to this equilibrium. This will be the case most relevant for the services sector. In the second case, $\alpha(0) < \alpha^* < 1$ and the system exhibits catchup but not convergence. Asymptotically, productivity levels remain different. Notice that if instead $\alpha(0) > \alpha^*$ in this case, productivity levels would actually diverge along the transition path until the steady state distribution of productivity levels was reached. Finally, in the third case, $\alpha^* > 1$. This is the "overtaking" case in which the initial follower exhibits sufficiently rapid productivity growth that it overtakes the leader. Because of initial comparative advantage, the follower specializes in the high-tech good while the leader specializes in the low tech good. Over time, then, the dynamics lead to overtaking: productivity levels cross and then diverge to a steady state distribution. This

³³ Jones (1993) and Kremer (1993) provide favorable evidence concerning the plausibility of the result that per capita output growth depends on the rate of population growth.

case appears to correspond to several empirical examples: the U.K. and the U.S. at the turn of the century, and Japan and Europe in manufacturing since 1970.

The question now is which of these three cases is relevant, i.e. under what parameter values is α^* equal to, less than, or greater than unity? Rewriting the equilibrium equation 5.6 above, α^* is determined implicitly by the learning parameters, the spillover parameters, and relative employment according to

$$\alpha^{1/\epsilon} = \frac{\phi_2 + \delta_2 \lambda \alpha}{\delta_1 + \phi_1 \lambda \alpha} \tag{5.11}$$

We analyze this equation in a series of remarks.

1. Non-tradeable Sectors. In the non-tradeable sectors, we have already noted that $\delta_1 = \delta_2 = \delta_0$ and $\phi_1 = \phi_2 = \gamma_0$. It is then easy to show the following:

- If $\lambda = 1$, or if we can ignore the scale effects implicit in this formulation, then $\alpha^* = 1$ and the productivity levels converge.
- $d\alpha^*/d\lambda > 0$ so that the country with the larger non-tradeable sector will have a higher productivity level in steady state. This is essentially a scale effect: larger employment produces larger output for any given productivity level and this raises the quantity of learning and human capital. This scale effect can be eliminated, we conjecture, by tying learning to per capita output (which may be closer in spirit to what is meant by human capital). Empirically, the question is whether the learning process is tied to individuals or to the total volume of output.
- Increases in tend to reinforce productivity differences: if $\alpha^* > 1$, then $d\alpha^*/d\delta > 0$ and vice versa. That is, a higher efficiency of learning helps the larger sector more than the smaller one as a result of the size effect.
- Increases in tend to mitigate productivity differences: if $\alpha^* > 1$, then $d\alpha^*/d\phi < 0$ and vice versa. That is, higher spillovers across countries help the smaller sector relatively more as the spillovers from the larger sector will be greater.

2. Tradeables with No Spillovers: $\phi_1 = \phi_2 = 0$. In this case, one can solve to find $\alpha^* = (\delta_2 \lambda / \delta_1)^{\epsilon/1-\epsilon}$. If $\lambda = 1$, then equilibrium productivity levels depend only on the ratio of learning parameters: the "high-tech" sector will have the higher productivity level in steady state. However, a sufficiently large market may partially offset differences in learning efficiency: in this setup, learning can be increased either directly by increasing output or indirectly by raising the efficiency of learning.

3. Tradeables with Spillovers: The General Case. In the general case, we must analyze equation 5.11. In this case, the following results can be obtained:

• If $\lambda = 1$ (or if scale effects can be ignored), then $\alpha^* > 1$ if and only if $\delta_2 + \phi_2 > \delta_1 + \phi_1$, and vice versa. That is, we are only in the "overtaking" case if the sum of the learning and spillover parameters are larger for the sector in which the foreign country specializes.

- Define spillovers to be large relative to learning if $\delta_1 \delta_2 < \phi_1 \phi_2$ and small relative to learning if $\delta_1 \delta_2 > \phi_1 \phi_2$. Then if spillovers are small relative to learning, $d\alpha^*/d\lambda > 0$ and vice versa. That is, if spillovers are small, then an increase in the size of the foreign sector relative to the domestic sector will favor the foreign sector in steady state. However, with large spillovers, an increase in the size of the foreign sector will favor the domestic sector because a larger foreign sector will produce more domestic spillovers than foreign learning.
- Finally, the following comparative statics can be obtained: $d\alpha^*/d\delta_1 < 0$, $d\alpha^*/d\phi_1 < 0$, $d\alpha^*/d\delta_2 > 0$, $d\alpha^*/d\phi_2 > 0$, all of which are to be expected.

4. Per Capita Learning. It is an open question as to whether or not learning is tied to the total volume of output produced or is a per capita phenomenon – i.e. is tied to the individual worker and therefore has the flavor of human capital. Lucas (1988) chooses this latter interpretation, and this formulation can be incorporated here by writing the learning equations as functions of output per worker instead of sectoral output. Of course, there is then a question of how spillovers work: are they to be divided by own labor or by the other sector's labor? This is an extension of the model we plan to explore more carefully.

5. Growth Effects versus Level Effects. In this model all sectors grow at the same rate asymptotically, and differences in learning efficiency and spillovers translate into level effects instead of growth effects. The model can be generalized to allow for some growth effects by tying the learning process to output per worker and by allowing $\epsilon = 1$. In this framework, in addition to the three cases considered in Figure 12, one may also find cases in which no stationary state exists and productivity levels diverge. This is another extension we plan to explore more carefully.

5.3. Summary and Extensions

This model provides a simple, stylized framework that offers a potential explanation for the puzzling empirical results documented earlier: the aggregate convergence of technological productivity in OECD economies is apparently driven by the non-manufacturing sectors; within manufacturing, we see no evidence of convergence since 1970 and even modest evidence of divergence. According to the model presented here, this result may not be so puzzling after all. When countries are producing similar products, as is the case for non-traded goods, convergence is to be expected. However, when countries specialize in the production of tradeable goods, there is no reason to expect the technologies to converge; different goods may employ very different technologies of production.

The external learning-by-doing framework is a straightforward way to illustrate the result, but it is not completely satisfactory. In the future, we plan to construct a model with a more realistic production structure. For example, observational evidence suggests that one country (or a few) specializes in the production of laser scanners or ATM machines and then the retail and financial sectors of all countries take advantage of these technologies. By incorporating intermediate goods into the production function, we may be able to capture these effects.

Finally, our model was designed to explain the empirical results obtained from the OECD data, so it is not surprising that the model fits the facts. To conduct a better

test of the model, we propose examining a different data set. Using U.S. data by state on manufacturing industries, we may be able to document a lack of convergence in technological productivity. This would be a valuable result in light of the strong evidence in favor of convergence in labor productivity (which we would argue is due to a combination of labor mobility and capital accumulation) across U.S. states (see Barro and Sala-i-Martin, 1992).

6. Conclusion

This paper asks whether the trends observed in aggregate productivity are representative of movements at the industry level. Many sectors, such as services, show evidence of convergence at least as strong as that found in the aggregate. In contrast, we find that manufacturing does not display the pattern of convergence in labor and technological productivity found in other sectors. A simple model of sectoral convergence based on trade and specialization provides a potential explanation for these results.

To measure productivity for all factors we construct a new measure of Total Technological Productivity which is robust to several problems inherent in traditional formulations of Total Factor Productivity. We show that whatever the measure of total productivity chosen, there remain inherent assumptions to be faced by the researcher and suggest that both the constant factor share and TTP techniques be used to confirm the robustness of any level-based results.

The results from this paper raise many questions about productivity performance comparisons over time and across countries at an aggregate level. Work on industry productivity for less developed countries will potentially reveal much about the underlying processes of convergence and industrial growth. More needs to be done on separating the role of capital accumulation and technological change. Also our results hint that the 1970s and 1980s may have been very different times for productivity performance across countries and sectors. Longer time series on productivity at the industry level will help us understand the nature of longer trends in productivity.

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LABOR PRODUCTIVITY									
	Agric.	Min.	Mfg.	Svs.	E/G/W	Constr.	Tot. Ind.		
U.S.	0.021	-0.034	0.026	0.002	0.012	-0.020	0.006		
Canada	0.017	-0.038	0.018	0.011	0.035	0.022	0.013		
Japan	0.022	0.052	0.059	0.028	0.027	-0.007	0.038		
W. Germany	0.055	-0.012	0.024	0.021	0.028	0.010	0.025		
France	0.054	0.023	0.030	0.021	0.048	0.019	0.031		
Italy	0.036	NA	0.045	0.006	0.003	0.004	0.024		
U.K.	0.042	0.064	0.026	0.011	0.022	-0.001	0.020		
Australia	0.023	0.017	0.025	0.007	0.024	0.019	0.014		
Netherlands	0.057	0.041	0.038	NA	0.008	0.005	0.025		
Belgium	0.047	-0.001	0.051	0.012	0.056	0.020	0.028		
Denmark	0.056	0.217	0.029	0.016	0.044	-0.004	0.024		
Norway	0.035	0.169	0.017	0.012	0.016	0.018	0.029		
Sweden	0.032	-0.007	0.022	0.016	0.041	0.026	0.022		
Finland	0.034	0.032	0.037	0.027	0.026	0.020	0.033		
AVERAGE	0.038	0.040	0.032	0.015	0.028	0.009	0.024		
Multi-Factor Productivity - Divisia									
Country	Agric.	Mining	Mfg.	Services	EGW	Constr.	Tot. Ind.		
U.S.	0.007	-0.038	0.018	0.002	0.006	-0.019	0.002		
Canada	0.004	-0.066	0.008	0.006	0.003	0.016	0.004		
Japan	0.077	0.016	0.033	0.006	-0.013	-0.026	0.017		
W. Germany	0.062	-0.018	0.015	0.004	0.004	0.006	0.012		
France	0.037	-0.003	0.018	0.011	0.028	0.010	0.018		
Italy	0.026	na	0.029	0.007	-0.020	-0.036	0.010		
U.K.	0.030	-0.008	0.017	0.006	0.010	-0.006	0.010		
Australia	0.014	-0.014	0.014	na	0.019	0.008	0.005		
Netherlands	0.043	-0.005	0.024	na	-0.012	-0.008	0.014		
Belgium	0.028	na	0.035	na	0.039	0.007	0.015		
Denmark	0.039	0.109	0.023	0.010	0.033	-0.009	0.015		
Norway	0.004	0.016	0.007	0.008	0.003	0.009	0.016		
Sweden	0.021	-0.026	0.014	0.010	0.018	0.022	0.013		
Finland	0.031	0.024	0.025	0.013	0.014	0.015	0.019		
AVERAGE	0.030	-0.001	0.020	0.008	0.009	-0.001	0.012		

Table 6.1: Productivity Growth Rates, 1970-1987

Notes: Growth rates computed as the coefficient on a time trend in a regression of the log(Productivity) on a constant and the trend.

Labor Productivity								
Sector	Beta	SE	TStat	λ	\overline{R}^2			
Agriculture	-0.0122	0.0078	-1.57	0.0134	0.10			
Mining	-0.0290	0.0210	-1.38	0.0364	0.07			
Manufacturing	-0.0262	0.0147	-1.78	0.0326	0.14			
Services	-0.0244	0.0086	-2.85	0.0283	0.56			
Electricity/Gas/Water	-0.0208	0.0095	-2.20	0.0246	0.23			
Construction	-0.0227	0.0112	-2.03	0.0274	0.19			
Total Industry	-0.0298	0.0052	-5.73	0.0385	0.71			

Table 6.2: Convergence Regressions: Within Sector Results

Table 6.3: Convergence Regressions: Within Sector Results

TFP								
Sector	Beta	SE	TStat λ		\overline{R}^2			
Agriculture	-0.0390	0.0113	-3.45	0.0650	0.46			
Mining	-0.0267	0.0198	-1.35	0.0350	0.07			
Manufacturing	-0.0146	0.0132	-1.11	0.0168	0.02			
Services	-0.0120	0.0033	-3.69	0.0134	0.56			
Electricity/Gas/Water	-0.0253	0.0072	-3.49	0.0331	0.46			
Construction	-0.0281	0.0148	-1.90	0.0384	0.17			
Total Industry	-0.0226	0.0056	-4.03	0.0287	0.54			

Total Technological Productivity (Median K/L)								
Sector	Beta	SE TStat		λ	\bar{R}^2			
Agriculture	-0.0242	0.0055	-4.38	0.0313	0.58			
Mining	-0.0428	0.0240	-1.78	0.0737	0.17			
Manufacturing	-0.0080	0.0129	-0.62	0.0086	-0.05			
Services	-0.0109	0.0033	-3.32	0.0120	0.50			
Electricity/Gas/Water	-0.0246	0.0069	-3.59	0.0320	0.48			
Construction	-0.0323	0.0122	-2.65	0.0472	0.32			
Total Industry	-0.0215	0.0059	-3.66	0.0268	0.49			

Table 6.4: Convergence Regressions: Within Sector Results

Notes: λ represents the speed of convergence calculated as described in the text.

TTP (Median Ko/Lo)								
Sector	Beta	SE	TStat	λ	\bar{R}^2	N		
Food	-0.0181	0.0112	-1.62	0.0217	0.14	11		
Textiles	-0.0332	0.0138	-2.40	0.0494	0.32	11		
Wood	-0.0140	0.0157	-0.89	0.0160	-0.03	7		
Paper	-0.0140	0.0136	-1.03	0.0160	0.01	11		
Chemicals	-0.0325	0.0158	-2.05	0.0476	0.24	11		
Non-metallic Minerals	-0.0313	0.0104	-3.02	0.0451	0.47	10		
Basic Metals	-0.0387	0.0099	-3.93	0.0642	0.59	11		
Machinery	-0.0064	0.0235	-0.27	0.0068	-0.10	11		
Other Manufactures	-0.0049	0.0138	-0.36	0.0051	-0.11	10		
Total Manufacturing	-0.0080	0.0126	-0.62	0.0086	-0.05	14		

Table 6.5: Convergence Regressions: Within Manufacturing Results

TTP (Median Ko/Lo)								
Sector	Beta	SE	TStat	λ	\bar{R}^2	N		
Wholesale, Retail Trade	-0.0238	0.0098	-2.42	0.0300	0.33	11		
Transport	-0.0276	0.0082	-3.38	0.0374	0.46	13		
FIRE	-0.0156	0.0084	-1.85	0.0179	0.21	10		
Community, Personal	-0.0157	0.0052	-3.01	0.0183	0.40	13		
Total Services	-0.0109	0.0033	-3.32	0.0120	0.50	11		

Table 6.6: Convergence Regressions: Within Services Results

Notes: λ represents the speed of convergence calculated as described in the text.

Figure 1

Total Industry Convergence in Labor Productivity and Total Factor Productivity

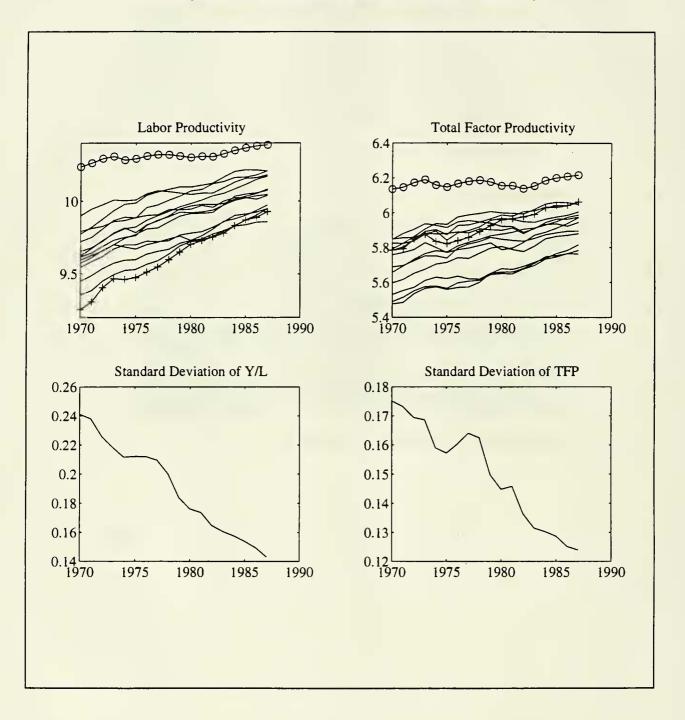


Figure 2 Labor Share in Total Output, Total Industry

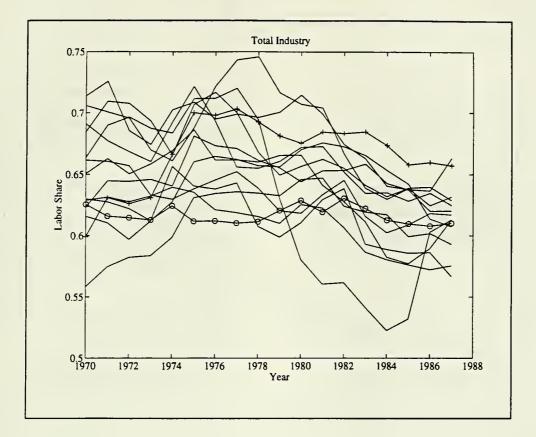


Figure 3 Graphical Analysis of TTP

$$\ln TTP_{i} = \ln A_{i} + (1 - \alpha_{i}) \ln(\frac{K_{0}}{L_{0}}) + \ln L_{0}$$

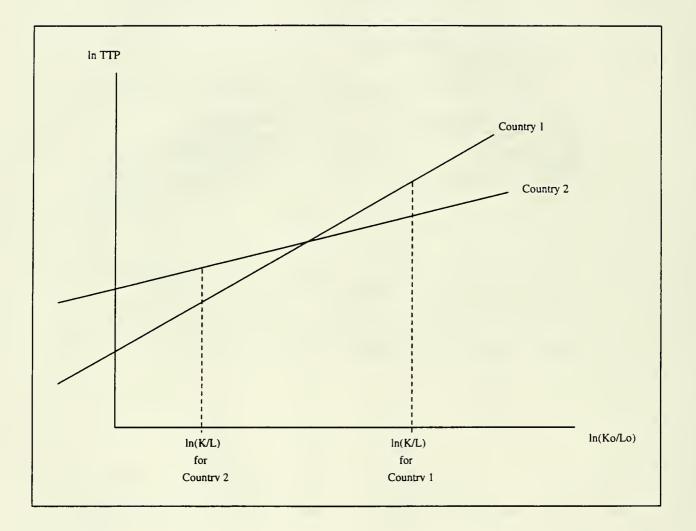


Figure 4 Total Technological Productivity and TFP (With Varying Factor Shares) Total Industry (Natural Logs)

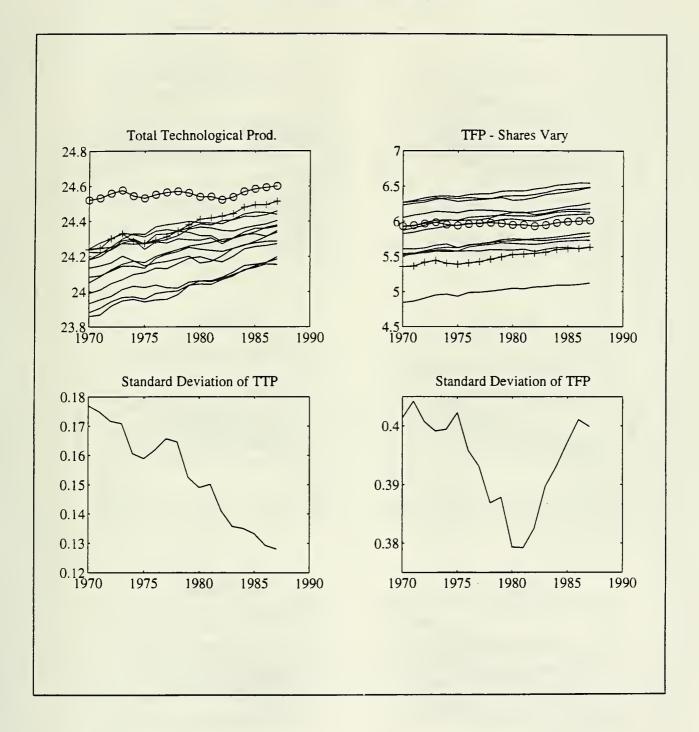


Figure 5 Labor Productivity By Sector (Natural Logs)

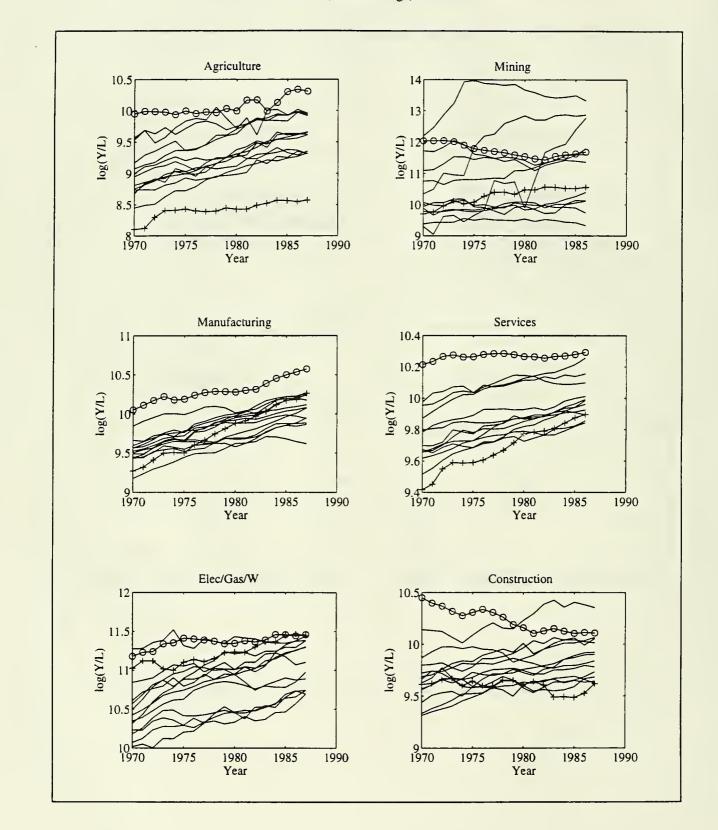


Figure 6 Total Technological Productivity By Sector (Natural Log)

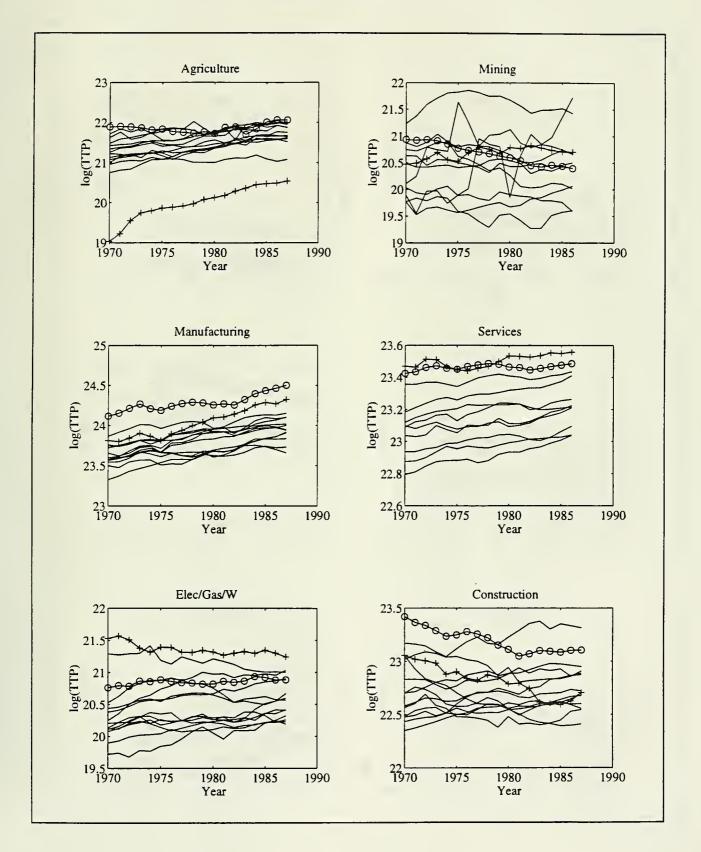


Figure 7 Output Shares By Sector

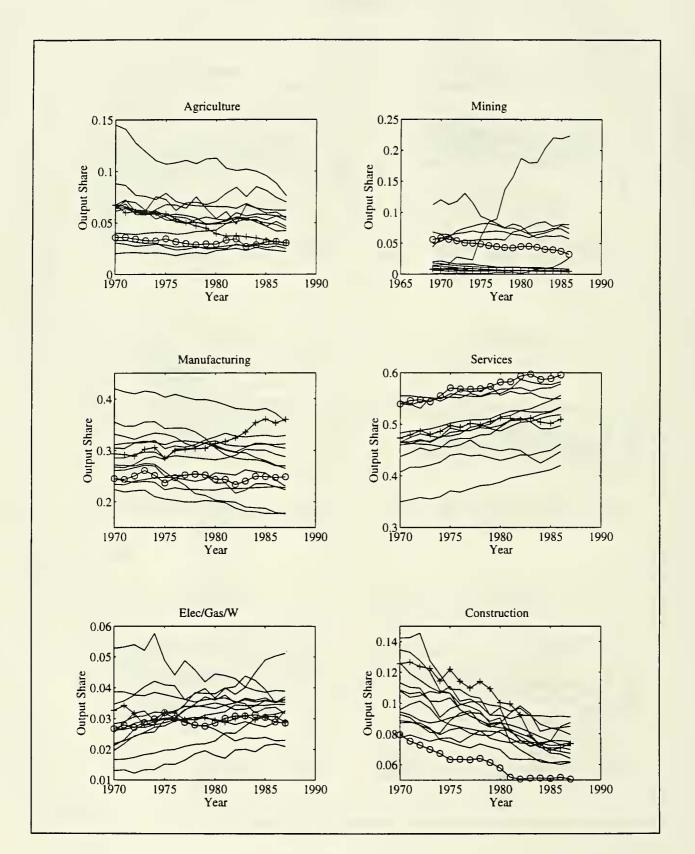


Figure 8 Standard Deviations of (log) Labor Productivity By Sector

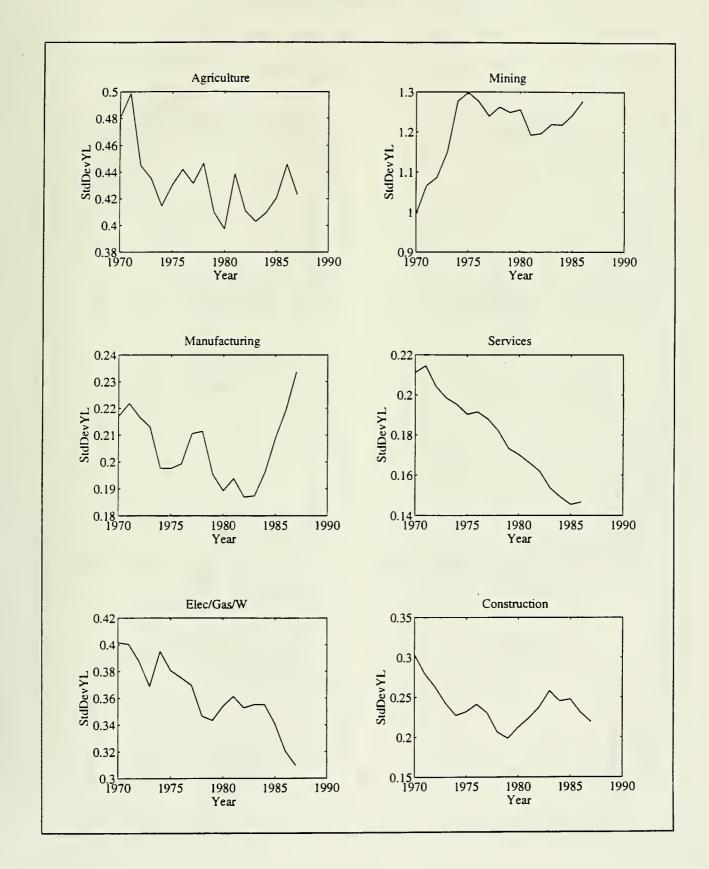


Figure 9 Standard Deviation of (log) Total Technological Productivity By Sector (Evaluated at Median K/L in 1970)



Figure 10 Graphical Analysis of TTP Convergence: Total Industry



$$\ln TTP_{i} = \ln A_{i} + (1 - \alpha_{i}) \ln(\frac{K_{i}}{L_{0}}) + \ln L_{0}$$

Figure 11 Graphical Analysis of TTP Convergence: Manufacturing

(Solid=1970, Dash=1986.U.S.='o', Other='x'.)

$$\ln TTP_{i} = \ln A_{i} + (1 - \alpha_{i}) \ln(\frac{K_{0}}{L_{0}}) + \ln L_{0}$$

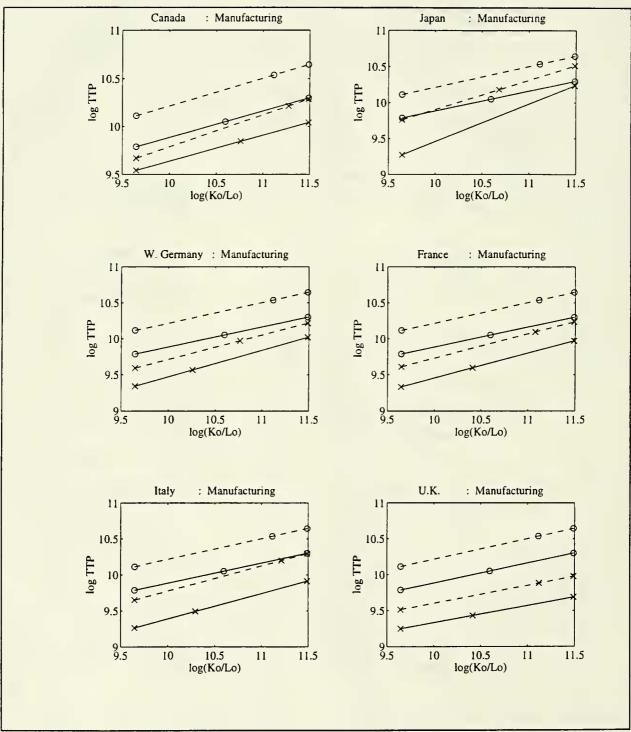
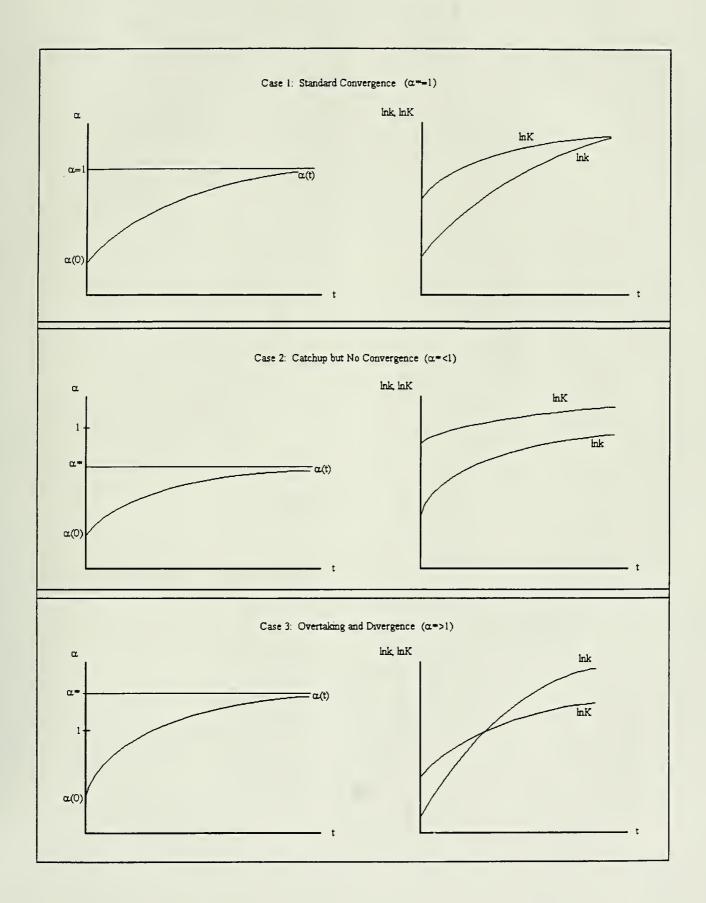
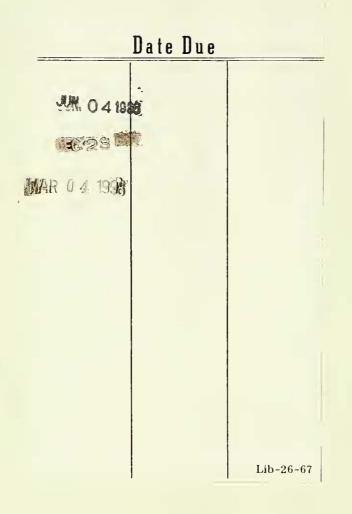


Figure 12 Convergence, Catchup, and Overtaking



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