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Cross-country catch-up in the manufacturing sector: Impacts of heterogeneity on convergence and technology adoption

Patrik T. Hultberg[1], **M. Ishaq Nadiri**[2], **Robin C. Sickles**[3]

[1] Department of Economics and Business, Kalamazoo College, Kalamazoo, MI 49006, USA (e-mail: hultberg@kzoo.edu)
[2] Department of Economics, New York University, 269 Mercer Street, 7th floor, New York, NY 10003, USA
[3] Department of Economics, Rice University, 6100 South Main Street, Houston, Texas 77005, USA

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Abstract. We analyze how technology transfer from a leading economy affects followers' productivity growth in manufacturing sectors and Gross Domestic Product. Allowing for heterogeneous technology levels we explore how this impacts rates of catch-up in labor productivity across manufacturing sectors and GDP for 16 OECD nations. Our results indicate that aggregate studies bias downward the estimated rates of catch-up. These rates of catch-up, as well as efficiency levels, also differ across countries. We find that institutional factors such as bureaucratic efficiency are important determinants of the estimated catch-up rates.

Key words: International comparisons, panel data methods, convergence and catch-up in best-practice technologies

JEL classification: O47, O57, C33, C41

1. Introduction

We analyze econometrically the relationship between labor productivity growth in manufacturing and technology transfer from a leading economy. The

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general literature on convergence, where low per capita income nations catch up with richer nations, often assume identical technology across countries and sectors, an assumption that lacks empirical support.[1] As it is difficult to find a group of countries with identical technologies, a technology gap offers an additional source of growth and may facilitate this catching-up process. In addition, a nation's institutional framework is important when considering productivity growth, both in terms of internal and external sources of growth.[2]

Thus the existence of an external technology gap presents a possible source of growth, but the adoption of best-practice technology is not automatic. Further, if nations differ in their ability to adopt new knowledge then institutional country heterogeneity should be addressed. The influence of technology on productivity growth is therefore ambiguous for a follower nation that exhibits both a technology gap and a low absorption capacity (Abramovitz 1986).

The importance of technology transfer has been explored previously. For example, Hultberg et al. (1999) show that the technology gap to the United States significantly contributes to follower nations' aggregate productivity growth in the postwar period. They also show that growth is influenced by country heterogeneity, which in turn is highly correlated to various institutional variables. Theoretical studies also point to the importance of openness in accelerating the rate of technology transfer or technology adoption (Parente and Prescott 1994).

The empirical work on sector-specific convergence is less extensive. Some of the more compelling studies are Broadberry (1993) and Bernard and Jones (1996a,b). The general result from these papers is that aggregate productivity convergence appears to be quite different from sector-specific results. Broadberry (1993) compares manufacturing data to GDP data and finds the time-series and cross-sectional results to be very different for Britain, Germany and the United States. Although his time series evidence suggest persistent labor productivity gaps between countries in the manufacturing sector, he also indicates that during periods in which one country alters its comparative labor productivity position there are periods of catching-up that restores the long-run comparative position. This is consistent with our study that suggests that a country's catch-up is based on the gap, but productivity may not be at the same level due to an inefficient institutional framework. Bernard and Jones (1996) also find manufacturing to have performed differently compared to GDP and other sectors for 14 OECD countries. They conclude that there is no evidence of convergence for manufacturing in terms of labor productivity, and even less when looking at broader productivity measures. Both of these papers indicate that convergence of GDP per worker must have occurred through trends in other sectors than manufacturing or through compositional effects. Bernard and Jones (1996) differ in their assumption of convergence toward a steady state productivity level, as opposed to a leader nation's productivity, while the results of Broadberry (1993), as mentioned, are in fact not inconsistent with our study. In contrast to these studies, Dollar and Wolff (1988) find convergence in

[1] Studies with aggregate production function differences include Knight et al. (1993) and Islam (1995).

[2] For the importance of institutions, see Knack and Keefer (1995), Barro (1991), and Scully (1988).

virtually all manufacturing-industries and conclude that this is the proximate source of aggregate convergence. Although their study refers to an earlier, but overlapping, time period, their study is quite similar to ours in their sample countries, their focus on manufacturing, and their use of a labor productivity leader.[3]

In the present paper we focus on the manufacturing sector and its two-digit industries. We compare catch-up rates and efficiency estimates across manufacturing sectors and GDP and discuss possible sources for the obtained differences. The focus on the manufacturing industries is interesting for several reasons. It adds to our understanding of convergence of labor productivity at the aggregate level. The answers indicate whether growth is a general phenomenon, or whether it differs across sectors and industries. In fact, if the latter is true then an emphasis on aggregate labor productivity may result in misguided policy evaluations of the growth process of developing economies. Our productivity and catch-up estimates should also expose how institutions impact growth and whether these impacts are neutral or affect industries differently. Again, these results may have significant policy implications.

The paper has the following outline. Section 2 briefly outlines our chosen theoretical model of catch-up. Section 3 discusses the data and our econometric methods. Section 4 explores the empirical results for the aggregate and manufacturing labor productivity of the sixteen OECD countries in our sample. To anticipate some of our results, we find that, in general, manufacturing industries show catch-up and often at rates faster than aggregate productivity. The rates of catch-up also differ across countries. We also analyze a reduced form model that links institutional, political, and economic factors to the time for catch-up using duration modeling techniques with heterogeneity controls based on the Heckman and Singer (1986) estimator. We identify country openness in terms of trade and the level of government oversight in the market place, proxied by an index of bureaucratic efficiency, to be key correlates with time to convergence. Concluding remarks are provided in Sect. 5.

2. Theoretical framework

Our estimation builds on the standard neoclassical model with a constant returns to scale Cobb-Douglas production function

$$Q_{it} = A_{it} K_{it}^{\alpha} L_{it}^{1-\alpha}, \tag{2.1}$$

where output Q, depends on technology A, physical capital K, and employment L. Countries are represented by i, $i = 1,\ldots,N$, in each time period t, $t = 1,\ldots,T$. We use the common specifications of the evolution of exogenous world technology and numbers of workers so that

$$\begin{aligned} A_{it} &= A_{i0} \cdot e^{\gamma t} \\ L_{it} &= L_{i0} \cdot e^{nt}. \end{aligned} \tag{2.2}$$

The only difference from a standard model appears in our equation for the evolution of capital. In order to formalize the dual notion that there exist a technology gap and differing abilities to take advantage of the catch-up

[3] Dollar and Wolff (1988) use a very different econometric approach compared to our study.

potential engendered by these gaps, we argue that capital evolution depends on an exogenous savings rate, the depreciation rate, and a technology catch-up term, $\xi(T, T^w)$, so that

$$\dot{K}_{it} = s \cdot Q_{it} - \delta \cdot K_{it} + \xi(T, T^w) \cdot K_{it} \tag{2.3}$$

The difference with models of purely disembodied technical change is that such models leave out the last term in Eq. (2.3), so that the capital stock may be interpreted as new-machine equivalents implied by the stream of past investments (where δ is the weight that transforms each vintage investment into new-machine equivalents). In contrast, we assume here that new investment might also embody differences in technical design. Thus a new "machine" may be more efficient than an old "machine" even if there is no difference in physical capacity. The standard capital evolution equation would in this case tend to understate the true productivity of the capital stock. In the present set-up, technology from abroad may make the existing and new capital stock more productive and thus increase the capital stock (as measured in efficiency units).

We specify the catch-up term as a logarithmic function of the inverse ratio of labor productivity, $Y_{it} = (Q_{it}/L_{it})$, to the "desired level" of labor productivity, Y_i^*, which may differ between countries: $\xi(T, T^w)_{it} = \theta_i \cdot ln(Y_{i,t-1}{}^*/Y_{i,t-1})$.[4] Thus we assume that countries use last period's technology gap (which is observable) as a possible source of growth.

Log linearizing and differencing the production function and substituting for the growth rate of capital yields the following equation,

$$y_{it} = (\gamma - \alpha \cdot \delta) + \alpha \cdot s \cdot (Q/K)_{it} - \alpha \cdot n + \alpha \cdot \xi(T, T^w)_{it}. \tag{2.4}$$

Assuming that the output per capital ratio remains constant, this implies that the growth rate of per worker output (y) depends on the growth of factor inputs (k, l) as well as the productivity gap,

$$y_{it} = \phi + \alpha \cdot (I/Q)_{it} - \alpha \cdot n_i + \rho_i \cdot (lnY_{i,t-1}{}^* - lnY_{i,t-1}), \tag{2.5}$$

where $\rho_i = \alpha \cdot \theta_i$ is the country-specific technology adoption rate, $\phi = (\gamma - \alpha \cdot \delta)$ is the common rate of exogenous technological change minus capital depreciation, and (I/Q) proxies for the growth of capital.

As mentioned in the introduction, we also want to include the possibility that countries differ in ability to adopt new technology. We have included one factor that measures how economies may differ in their ability to take advantage of the technology gap with the rate of adoption parameter, ρ. However, economies may also differ in their ability to recognize or use the available technology. To incorporate this into the model we include a term that acts to effectively reduce the available technology gap to economies.[5] Since the term used is similar to what frontier production literature refers to as efficiency (Greene 1997) we refer to it in the

[4] Using a "desired" level of labor productivity reflect our belief that countries are not able to obtain the same level of productivity. Naturally it would be better to use relative levels of total factor productivity (Solow residual), but since it is both harder to obtain and is likely to be highly correlated with labor productivity we choose the above approach.

[5] An alternative approach would be to make the adoption rate, ρ, a function of absorption capacity.

same way. This term captures more than mere production slack as it also encompasses the institutional framework.

Adding an efficiency component only slightly modifies our framework, $\xi(T,T^{w})_{it} = \theta_i \cdot ln(Y_{i,t-1}^{*}/(E_i \cdot Y_{i,t-1}))$, where $E > 1$, so that E acts to reduce the available technology gap. Accordingly, an industry may run out of available technology before its labor productivity is equal to that of the leader nation. Incorporating this into our growth Eq. (2.5) yields,

$$y_{it} = \phi - \rho_i \cdot lnE_i + \alpha \cdot (I/Q)_{it} - \alpha \cdot n_i + \rho_i \cdot (lnY_{i,t-1}^{*} - lnY_{i,t-1}). \tag{2.6}$$

The parameter α shows the elasticity of per worker output to a change in the growth in factor inputs while ρ_i is the adoption rate of available technology from abroad and $\rho_i \cdot lnE_i$, the estimated country-specific efficiency (inefficiency) measure, shows the reduction of growth in labor productivity due to political and social factors that reduce the available technology gap.

This model is similar to Bernard and Jones (1996a,b) and Cameron et al. (1999),[6] but differs in that Bernard and Jones use a model of total factor productivity that includes the productivity differential within a sector from that of the most productive country. Their results are, again, that manufacturing has not contributed significantly to the overall convergence in OECD countries. Cameron et al. expand on the Bernard and Jones model to include a term that is comparable to our efficiency term. They look carefully at even more disaggregated data in terms of openness and technology transfers, but only consider the relationship between United Kingdom and the United States. Their results are that the technology gap to the U.S. plays an important role in U.K. technology advancement.

3. Data and estimation

The main data set for the manufacturing industries is STAN (structural analysis database) that is published by the OECD. The STAN data set fills the gap between the detailed data collected through industrial surveys but with limited international comparability, and national accounts data that are more internationally comparable but only available at fairly aggregate levels. Through the use of established estimation techniques, the OECD Secretariat has created a database that is compatible with national accounts for 22 countries. It covers 49 manufacturing industries for six variables with annual data from 1970. The present study is restricted to a subset of 16 countries: Austria (AST), Australia (AUS), Belgium (BEL), Canada (CAN), Denmark (DEN), Finland (FIN), France (FRA), Germany (GER), Italy (ITA), Japan (JAP), The Netherlands (NET), New Zealand (NZ), Norway (NOR), Sweden (SWE), United Kingdom (UK), and the United States (US). The period under study is 1973 to 1990.[7]

[6] Another similarity is that these papers use an earlier version of our data set. The International Sectoral Data Base (ISDB) that has been integrated into the STAN database.

[7] For Australia data was missing for the capital variable for 1989 and 1990. Data points for these years were constructed from the year 1988 value of the capital variable by adding the average growth rate.

The 16 countries are compared across per worker aggregate GDP, total manufacturing, and five 2-digit level industrial sectors: Food and Beverages (FBT), Paper Products (PPP), Non-metallic mineral (NMM), Basic metal (BMI), and Fabricated metal (FMP).[8] Three variables for the countries are used: production (gross output) in current prices, gross fixed capital formation in current prices, and total employment. Before cross-country comparisons are made all expenditures are converted into U.S. prices using the STAN purchasing parity variable for the United States. Per worker GDP estimation uses data from the Summers and Heston data set (PWT5.6). The labor variable is number of workers, where the number of workers is found by multiplying each nation's population by its labor force participation rate. Growth in physical capital is constructed using the share of investment in output as a proxy.[9] The period considered is 1960–1985. For GDP and total manufacturing, the world leader is assumed to be the U.S., for 2-digit manufacturing industries the leader varies.

The estimation uses Eq. (2.6) for the 16 countries and across the different industries (as well as total output). The estimable equation thus takes the form

$$y_{it} = \alpha_1 + \alpha_2 \cdot \rho_i + \alpha_3 \cdot k_i + \alpha_4 \cdot l_i + \rho_i \cdot (lnY^*_{lag} - lnY_{lag}), \tag{3.1}$$

where α_1 estimates the common "industry-specific" technological progress across countries, α_3 and α_4 denote the elasticity of per worker output to growth of capital and labor, respectively, and are constrained by our assumption of constant returns to scale, ρ is used to estimate the catch-up rate and using it we can back out the country-specific inefficiency levels, α_2.

There are several econometric issues with which empirical growth studies must contend. It is common to assume that country-specific effects are uncorrelated with other right-hand side variables, but this assumption is necessarily violated (Caselli et al. 1996). This incorrect treatment of country heterogeneity gives rise to omitted variable bias. In addition, any dynamic relationship that contains a lagged dependent variable among the explanatory variables is subject to endogeneity problems. That is, one explanatory variable will be correlated with the error term.[10] The omitted variable bias is readily removed in panel data estimation by the use of country effects. This method is valid when the effects are fixed rather than random, which is true when the sample of countries is the entire population. A within estimator using fixed effects (Least Squares Dummy Variable) will eliminate the omitted variable bias and deal consistently with

[8] Four other industries, Textiles and Leather, Wood Products and Furniture, Chemical Products, and Other Manufacturing, were studied. The estimation results for the competing model specifications do not identify a statistically significant technological leader. For these industries the overall fit is also very low and several coefficients have theoretically wrong signs. The results for these industries are therefore not reported.

[9] To use investment share (gross capital formation) as a proxy for the growth of capital requires an assumption of constant capital-output ratios, which we impose. The risk is that there might be a systemic relation between capital intensity and level of output, but this is less likely in our sample of relatively similar countries.

[10] That is, $y_{i,t} = \rho y_{i,t-1} + x'_{i,t}\beta + \epsilon_{i,t}$, where $\epsilon_{i,t} = \mu_i + \gamma_{i,t}$ (one-way error component model) ordinary least squares will be both biased and inconsistent. That is, since $y_{i,t}$ is a function of μ_i, $y_{i,t-1}$ must also be a function of μ_i.

Table 1. Ordinary least squares (OLS) estimation

	GDP	Man.	FBT	PPP	NMM	BMI	FMP
Intercept	0.018***	0.063***	0.032***	0.053***	0.040***	0.077***	0.064***
I/Q (labor)	−0.001**	0.132	0.877***	0.124	0.280***	−0.421***	0.223***
Gap	0.055***	0.027*	0.005	0.061***	0.054***	0.044***	0.016
R^2	0.22	0.02	0.21	0.05	0.11	0.07	0.04
Adj. R^2	0.21	0.02	0.21	0.05	0.11	0.06	0.04

*** Denotes significance at < 1%, ** significance at < 5%, * significance at < 10%

the correlation between effects and regressors. However, the within transformation $(y_{i,t}-\bar{y}_{i.-1})$ will still be correlated with $(\upsilon_{i,t}-\bar{\upsilon}_{i.})$ since $y_{i,t}$ is correlated with $\bar{\upsilon}_{i.}$ by construction (see Baltagi 1995). That is, LSDV will still be inconsistent due to this endogeneity problem and instrumental variable (IV) techniques are required.

Our manufacturing sector estimates are based on IV estimation. We also report the (inconsistent) LSDV estimates. These are ordinary least-squares estimates with dummies for all countries, but with a slope coefficient varying across regions. The IV estimates are similar, except that we instrument our technology gap variable with its lagged value. We also attempted to implement the efficient generalized method of moments (GMM) estimator of Ahn and Schmidt (1995). However, the GMM estimates for the manufacturing sectors were highly unstable and economically meaningless. The aggregate results were much less unstable and were reasonable. We have included these latter results in Table 3.

4. Results

Initially the adoption rates are assumed to be the same across all the countries in the sample. The estimation results are given in Tables 2 and 3 for both total productivity and for the manufacturing sectors (Table 1 provides the cross-sectional ordinary least squares results for reference). Parameter estimates for the growth of the I/Q (labor) coefficient vary across industries, suggesting that per capita output responds differently to factor growth across sectors. Catch-up parameter estimates are less variable across sectors. Estimates for the I/Q (labor) coefficient are negative and economically significant for two of the seven sectors, Paper Products (PPP) and Basic Metal (BMI).[11] In contrast, the catch-up parameter estimates are less variable across sectors. These results are true for both LSDV and IV estimations. Estimation of total output indicates a catch-up rate of 0.10 for both estimations, thus a percentage

[11] For example, in light of our finding of one significantly negative coefficient that is also economically significant in Table 5, we can conjecture on the apparently counterintuitive empirical result for this particular sector. Hultberg et al. (1999) have found that the growth of labor contributes to the growth of per capita output for Asian economies. Moreover, current investment shares may not be positively related to the current per capita output growth because of state dependence in investment decisions. This latter interpretation is supported by the results based on five-year intervals. Other explanations include the possibility that the industry is not well-described by the Cobb-Douglas production function, or that imposing constant returns to scale on capital and labor, combined with the possibility of technology adoption, does not describe the industry in question.

Table 2. Least squares dummy variable (LSDV) estimation

	GDP	GDP(5)	Man.	FBT	PPP	NMM	BMI	FMP
Intercept	0.059***	−0.018	0.066***	0.046***	0.070***	0.055***	0.106***	0.067***
I/Q (labor)	−0.002***	0.004	0.099	0.724***	−0.168	0.229***	−0.510***	0.104
Gap	0.099***	0.372***	0.339***	0.136***	0.316***	0.265***	0.101***	0.197***
Canada	−0.07	−0.11	−0.09**	−0.32***			−0.41	
Japan	−0.36***	−0.67***	−0.33***	−0.86***	−0.37***	−0.43***		−0.33***
Austria	−0.25***	−0.34***	−0.51***	−0.73***	−0.35***	−0.34***	−1.04***	−0.50***
Belgium	−0.13*	−0.18**	−0.11**		−0.30***	−0.49***	−0.54	−0.23***
Denmark	−0.27***	−0.40***	−0.66***	−0.66***	−0.58***	−0.68***	−1.39***	−0.88***
Finland	−0.13	−0.50***	−0.47***	−0.62***		−0.47***	−0.53	−0.68***
France	−0.07	−0.23**	−0.37***	−0.54***	−0.29***	−0.25***	−0.74**	−0.42***
Germany	−0.07	−0.25**	−0.43***	−0.64***	−0.44***	−0.27***	−1.20***	−0.43***
Italy	−0.09	−0.25***	−0.42***	−0.39***	−0.18***	−0.33***	−0.07	−0.36***
Netherlands	−0.05	−0.14	−0.07	−0.26***	−0.25***	−0.30***	−0.59*	−0.34***
Norway	−0.02	−0.31***	−0.39***	−0.65***	−0.32***	−0.35***	−0.65*	−0.43***
Sweden	−0.21***	−0.24***	−0.46***	−0.66***	−0.16***	−0.45***	−0.92**	−0.49***
U.K.	−0.50***	−0.37***	−0.53***	−0.69***	−0.47***	−0.35***	−0.85**	−0.61***
Australia	−0.00	−0.23**	−0.49***	−0.75***	−0.59***	−0.24***	−0.50	−0.52***
New Zeal.	−0.20***	−0.29***	−0.53***	−0.86***	−0.21***	−0.17***	−0.37	−0.54***
U.S.							−0.51	
R^2	0.32	0.77	0.19	0.23	0.20	0.26	0.10	0.14
Adj. R^2	0.29	0.71	0.14	0.18	0.16	0.22	0.05	0.09

Empty cells show the "leader" country for that industry. GDP(5) uses 5-year data instead of annual data; the Gap variable refers to 5-year "catch-up".
***, **, * Denote significance at $<1\%$, $<5\%$, and $<10\%$, respectively.

increase in the lagged productivity gap will, on average, lead to 0.10% higher growth of per worker GDP. For the GDP estimation we also conducted GMM estimation. The results were virtually identical (see Table 3).[12] The estimated efficiencies relative to the United States are negative and confirm our leader hypothesis. Of the 15 follower countries' efficiency estimates, seven are significant.[13]

For total manufacturing and five sub-industries some interesting results are obtained. To estimate catch-up we need a leader nation/industry, but the leader may differ across manufacturing industries.[14] The most striking

[12] This estimation entails first differencing the estimable equation for the four available time periods, stacking these four equations and then using all lagged exogenous variables as instruments. See also Caselli et al. (1996). The difference from Caselli et al. (1996) is that we first-difference our growth equation (not levels) so that the equations are actually in second-differences.

[13] In Hultberg et al. (1999), for the sample of European countries using annual data, we also obtain an adoption rate of 0.10. The estimated inefficiencies in our earlier paper for Europe are slightly lower (more negative) than the above estimates.

[14] For FBT, the U.S. and Belgium (1986–1990) share the lead. For PPP, three countries lead the way: the U.S. (1973–1980, 1983), Finland (1981–1982, 1984–1988, 1990) and Canada (1989). The U.S. and Canada (1980, 1982, 1985–1990) lead in the NMP industry. Japan was the sole leader in BMI. Finally, for FMP the U.S and Canada (1982, 1985–1990) share the lead. For total manufacturing, the U.S. lead over the years 1973–1984 and 1987–1988, while the Netherlands and Belgium were in front over the years 1985–1986 and 1989–1990, respectively. However, we assume that the U.S. was the only 'leader' in total manufacturing to compare it to the GDP results.

Table 3. Two-stage least squares (IV) estimation

	GDP	GDP (GMM)	Man.	FBT	PPP	NMM	BMI	FMP
Intercept	0.059***	0.003	0.065***	0.047***	0.073***	0.056***	0.104***	0.065***
I/Q (labor)	−0.002***	0.001	0.047	0.698***	−0.275***	0.183***	−0.481***	0.112
Gap	0.099***	0.495***	0.420***	0.146***	0.392***	0.331***	0.107***	0.253***
Canada	−0.07	−0.06	−0.05***	−0.05***			−0.04	
Japan	−0.36***	−0.35	−0.14***	−0.13***	−0.02***	−0.14***		−0.08***
Austria	−0.25***	−0.18	−0.21***	−0.11***	−0.14***	−0.11***	−0.11***	−0.13***
Belgium	−0.13*	−0.10	−0.04**		−0.11***	−0.16***	−0.06	−0.06***
Denmark	−0.27***	−0.19	−0.27***	−0.10***	−0.23***	−0.22***	−0.15**	−0.22***
Finland	−0.13	−0.22	−0.19***	−0.09***		−0.15***	−0.06	−0.17***
France	−0.07	−0.12	−0.15***	−0.08***	−0.11***	−0.08***	−0.08*	−0.11***
Germany	−0.07	−0.12	−0.18***	−0.09***	−0.17***	−0.09***	−0.13**	−0.11***
Italy	−0.09	−0.14	−0.17***	−0.06***	−0.07***	−0.10***	−0.01	−0.09***
Netherlands	−0.05	−0.07	−0.03	−0.04***	−0.10***	−0.10***	−0.06	−0.09***
Norway	−0.02	−0.14	−0.16***	−0.09***	−0.13***	−0.11***	−0.07	−0.11***
Sweden	−0.21***	−0.12	−0.19***	−0.10***	−0.06***	−0.15***	−0.10*	−0.13***
U.K.	−0.50***	−0.20	−0.22***	−0.10***	−0.18***	−0.11***	−0.09*	−0.15***
Australia	−0.00	−0.09	−0.21***	−0.11***	−0.24***	−0.08***	−0.06	−0.13***
New Zeal.	−0.20***	−0.06	−0.22***	−0.13***	−0.09***	−0.06***	−0.05	−0.14***
U.S.							−0.05	
R^2	0.32	N/A	0.18	0.23	0.20	0.25	0.14	0.09
Adj. R^2	0.29	N/A	0.14	0.18	0.16	0.21	0.09	0.04

Empty cells show the "leader" country for that industry. GDP(GMM) uses Generalized Method of Moments estimation on 5-year data; the Gap variable refers to 5-year "catch-up" and there are no significance levels associated with the country-specific inefficiency levels.
***, **, * Denote significance at $<1\%$, $<5\%$, and $<10\%$, respectively.

result is that the included manufacturing sectors exhibit faster catch-up rates. This supports the study by Dollar and Wolff (1988), as well as Cameron et al. (1999), but is not supportive of Bernard and Jones (1996). In particular, Cameron et al. relate total factor productivity growth in the United Kingdom to the "productivity gap" between UK and the US for several manufacturing industries and find mostly positive values of greater magnitudes than ours. For total manufacturing the catch-up rate is about 0.42 (IV). The two-digit industries display catch-up rates below total manufacturing with Basic Metal Industries, where Japan is the productivity leader, showing the lowest rate at about 0.10 and Paper Products and Printing exhibiting the fastest rate at 0.39 (again using IV). The latter industry is also the sector for which most countries shared the lead over the 20-year period; with very rapid catch-up more countries will be able to be close to the frontier.

In terms of the estimated efficiency levels we note that whereas the total economy results are quite consistent across estimation techniques (a bit lower for GMM estimation), there is some variation for the manufacturing industries. The LSDV estimation produces productivity results that are (in almost all cases) greater than for the GDP results, but with the more consistent IV estimator the productivity results are similar across all industries and comparable to the total economy results. That is, countries that are relatively efficient at the GDP level are, in general, also efficient at the two-digit manufacturing level. However, at the manufacturing level it appears as if the countries are more similar to each other. This is the more intuitive result since it has been argued elsewhere (Hultberg et al. 1999) that the efficiency component of productivity growth is determined by economy wide institutional factors, such as bureaucratic efficiency and political and civil rights.

In the standard convergence literature the parameter in front of initial income (ρ) indicates the implied rate of convergence, through the equation $-(1-e^{-\lambda t}) = \rho$. The λ variable thus shows the convergence rate after controlling for different steady states (or, equivalently, different growth rates of factor inputs). In our model, we can use a similar argument to obtain the rate (and required time) for a follower to close any given productivity gap, holding everything else constant. This isolates one source of catch-up and allows for an investigation into which countries are able to take advantage of this source of growth and perhaps why. As an example, the catch-up parameter from the GDP estimation (0.10) implies a catch-up rate of $\lambda = 0.104$. This in turn suggests that a follower would reduce the gap to the leader by 50% in 6.6 years, holding the other right-hand side variables constant. That is, the rate of catch-up is conditional on the growth of factor inputs in our regression, which is equivalent to the rate of convergence being conditional on the steady state variables. Table 4 presents the calculated times required to both cut half the 'technology gap' and 95% of this gap.

We next turn to non-linear methods to estimate an adoption rate for each country in our sample in an attempt to determine if countries' technology adoption rates exhibit heterogeneity. Table 5 reports that the individual countries and sectors indeed exhibit a wide variation in rates of catch-up and Table 6 reports the associated required times to close 50% of the 'technology gap'. Estimating a separate rate of technology adoption or catch-up naturally asks a lot of our limited data and we only present the LSDV estimation results, but the results are indicative of the varied performances across countries for the different sectors. Total manufacturing show a variety of rates as well, ranging from 0.17 (Australia) to 0.53 (Sweden). Very similar results are found for the 2-digit manufacturing industries, although countries differ in adoption rates across industries. A few countries have negative catch-up rates in these estimations, but in no case are these significantly different from zero. The approximate magnitudes of the catch-up rates across country-sectors mostly match up with the numbers found when using a common adoption rate for each industry.

Table 4. Time to close the technology gap using two-stage least squares estimation

	Estimate (ρ)	Rate (λ)[1]	50% of gap[2]	95% of gap[2]
GDP	0.099	0.104	6.65 years	28.74 years
Man.	0.420	0.545	1.27 years	5.50 years
FBT	0.146	0.158	4.39 years	18.98 years
PPP	0.392	0.498	1.39 years	6.02 years
NMM	0.331	0.402	1.72 years	7.45 years
BMI	0.107	0.113	6.12 years	26.47 years
FMP	0.253	0.292	2.38 years	10.27 years

[1] Calculated from the equation $(1-e^{-\lambda t}) = \rho$.
[2] Calculated from $e^{-\lambda t} = 0.50$ and 0.05, respectively.

Table 5. Heterogeneous catch-up rates across countries and industries (LSDV estimation)

	GDP	Man.	FBT	PPP	NMM	BMI	FMP
Intercept	0.083***	0.070***	0.054***	0.093***	0.059***	0.107***	0.073***
I/Q (labor)	−0.003***	0.115	0.854***	−0.211*	0.249***	−0.541***	0.145***
Canada	0.10	0.48***	0.46***			0.02	
Japan	0.05***	0.44**	0.30**	0.70**	0.45***		0.20
Austria	0.09***	0.37*	0.27	0.28*	0.49**	0.04	0.30*
Belgium	0.16***	0.19*		0.18**	0.12	0.05	0.06
Denmark	0.25***	0.42	0.03	0.57**	0.18	0.32**	−0.01
Finland	0.10***	0.44**	0.26*		0.53***	0.21**	0.34**
France	0.13***	0.28	−0.21	0.20	0.15**	−0.02	0.17
Germany	0.17***	0.44	−0.18	0.41**	0.35	0.04	0.24
Italy	0.13***	0.25	0.09	0.32*	0.30***	0.13	0.19***
Netherlands	0.25***	0.44***	0.31***	0.62	0.36	0.07	0.21
Norway	0.03	0.43***	0.21*	0.77***	0.41***	0.14	0.41***
Sweden	0.33***	0.53***	0.03	0.75***	0.35	0.15	0.35**
U.K.	0.14	0.38**	0.47***	0.31	0.25**	0.09	0.26
Australia	0.33***	0.17	0.22*	0.06	0.19	0.09	0.18
New Zeal.	0.09	0.25	−0.07	0.36***	0.37***	0.03	0.03
U.S.						−0.04	
R^2	0.39	0.22	0.29	0.23	0.30	0.12	0.17
Adj. R^2	0.33	0.13	0.21	0.15	0.23	0.03	0.08

Empty cells show the "leader" country for that industry.
***, **, * Denote significance at $<1\%$, $<5\%$, and $<10\%$, respectively.

Table 6. Time to close 50% of the technology gap (heterogeneous catch-up rates)

	GDP	Man.	FBT	PPP	NMM	BMI	FMP
Canada	6.58	1.06	1.12			34.31	
Japan	13.51	1.20	1.94	0.58	1.16		3.11
Austria	7.35	1.50	2.20	2.11	1.03	16.98	1.94
Belgium	3.98	3.29		3.49	5.42	13.51	11.20
Denmark	2.41	1.27	22.76	0.82	3.49	1.80	0
Finland	6.58	1.20	2.30		0.92	2.94	1.67
France	4.98	2.11	0	3.11	4.27	0	3.72
Germany	3.72	1.20	0	1.31	1.61	16.98	2.53
Italy	4.98	2.41	7.35	1.80	1.94	4.98	3.29
Netherlands	2.41	1.20	1.87	0.72	1.55	9.55	2.94
Norway	22.76	1.23	2.94	0.47	1.31	4.60	1.31
Sweden	1.73	0.92	22.76	0.50	1.61	4.27	1.61
U.K.	4.60	1.45	1.09	1.87	2.41	7.35	2.30
Australia	1.73	3.72	2.79	11.20	3.29	7.35	3.49
New Zeal.	7.35	2.41	0	1.55	1.50	22.76	22.76
U.S.						0	

Empty cells show the "leader" country for that industry.
All numbers represent the number of years required to cut the technology gap in half, negative catch-up rates have been assigned a value of 0 (or infinity).

The result that rates of convergence differ across countries has interesting implications. Consider, as an example, the GDP results for Japan. Japan has a relatively low rate of catch-up at 0.05, which indicates to us that its “miraculous” growth has been the result of high rates of factor accumulation (as argued elsewhere by, in particular Young 1995 and Krugman 1994). In addition, Norway and New Zealand have similar rates of catch-up (0.03 and 0.09, respectively) but the fact that their growth experience has been so different show that our numbers are not good predictors of relative growth performances. However, a possible implication of these numbers exists in regards to future long-term performance. Countries that have caught up without much use of the productivity gap (such as Japan and Norway) may run into diminishing returns earlier than the ones that are catching up without abnormal accumulation rates (i.e., the ones that are increasing output per input rather than the number of inputs). However, these GDP results do not apply to the manufacturing industries. In terms of manufacturing, countries, including Japan and Norway, exhibit much greater ability for productivity catch-up through the use of the available productivity gap.

An additional goal of our study is to investigate whether the different rates of adoption are related to some common institutional variables; that is, whether the institutional framework partially determines how quickly country-sectors can close the gap to the technology leader? We explore this by analyzing the catch-up times from the different sectors in a duration model. For this we use institutional variables from several sources: indices for political and civil rights from Gastil (1985), indices for political stability and bureaucratic efficiency from Mauro (1995), an educational index from Barro and Lee (see Barro and Lee 1993), and an openness variable from Summers and Heston (1991). The Gastil indices are aggregate measures that directly consider the institutional environment. We use both the political rights index and the civil rights index, each of which range from 1 to 7, where 1 represents the most freedom (Gastil 1985). Since the two indices are related we use weighted average of the two and normalize it to be between zero and one. The political and bureaucratic indices, borrowed from Mauro (1985) and originating with Business International (BI), are thought to proxy some general institutional variables. The nine different BI indices range between 0 and 10, where a high value signifies “good” institutions. These nine indicators are grouped into two categories: political stability and bureaucratic efficiency. The political stability index contains the following six indicators: political change–institutional, political stability–social, probability of takeover by opposition group, stability of labor, relationship with neighboring countries, and terrorism. The bureaucratic efficiency index consists of three variables: judiciary system, red tape and bureaucracy, and corruption. The educational variable used represents educational attainment of the total population aged 25 and over. It is an average of the reported five-year intervals between 1960 and 1985. We include openness to international trade mainly because international trade is a leading source of technology diffusion. Cameron et al. (1999) shows evidence of the importance of openness for technology diffusion. Levine and Renelt (1992) find that the relationship between trade and growth is mostly based on enhanced resource accumulation and not as much on improved resource allocation. The measure of openness used is the index compiled by Summers and Heston; the openness variable measures the fraction of imports and exports summed to GDP (Summers and Heston 1991). Table 7 presents these numbers.

Table 7. Institutional variables

	Freedom	Political stability	Bureaucratic efficiency	Openness (Summers-Heston)	Education (Barro-Lee)
US	0.143	9.33	9.75	14.0	10.22
Canada	0.143	9.00	9.58	45.2	9.03
Japan	0.191	9.42	9.08	22.6	7.52
Austria	0.143	9.04	8.25	61.5	5.59
Belgium	0.143	8.00	9.08	107.9	8.05
Denmark	0.143	8.50	9.58	62.4	10.16
Finland	0.286	8.79	9.33	51.5	8.56
France	0.202	8.92	8.25	35.0	5.35
Germany	0.179	8.21	8.67	44.3	8.16
Italy	0.220	7.92	6.33	36.9	5.15
Netherlands	0.143	8.82	10.00	92.2	7.08
Norway	0.143	9.50	9.67	85.8	6.55
Sweden	0.149	9.00	9.25	52.6	8.35
UK	0.143	8.33	9.00	48.4	7.83
Australia	0.143	8.50	9.75	31.1	9.57
New Zeal.	0.143	8.50	10.00	53.0	10.53

Table 8. Determinants of the logarithm of catch-up times (50% of gap)

Variable	Parameter	T-Statistic	Parameter	T-Statistic
(log) Bureaucratic Eff.	−1.425	−1.33	−1.334	−1.97
(log) Openness Index	0.368	2.28	0.361	2.46
(log) Education	0.061	0.11		
GDP	3.182	1.96	3.134	2.02
Manufacturing	2.225	1.37	2.177	1.40
FBT	2.538	1.56	2.489	1.60
PPP	2.091	1.29	2.043	1.31
NMP	2.279	1.40	2.231	1.43
FMP	2.685	1.65	2.636	1.70
θ(t)	0.681	13.5	0.681	13.5
	Pseudo R^2 = 0.682		Pseudo R^2 = 0.682	
	LogL = −94.15		LogL = −94.17	

The natural statistical model in which to examine the effects of institutional factors on particular country-sector catch-up times is a duration model (Huh and Sickles 1994, Kalbfleisch and Prentice 1980, Lancaster 1990). We have utilized the proportional hazard model with unobserved heterogeneity to link these variables to time to convergence (50%) (Heckman and Singer, 1984) and report these results in Table 8. Since the model here is basically descriptive we have included only those variables that have significant explanatory power. These include the Bureaucratic Efficiency (BE) variable, the Summers and Heston measure of openness, and sector specific dummy variables. We also show the results with and without the education variable, which is highly insignificant. We analyze the catch-up times in terms of a closure of 50% of the gap. Estimates indicate substantial sector specific heterogeneity, which suggest that aggregate country studies may distort the empirical record, as well as some play for unobserved country effects. The results validate the important role for "openness" in economic development as well as the role of government oversight in private sector economic allocations. We find these results to be a particularly interesting finding for at least two reasons. First, non-optimal, i.e., inefficient, country specific institutional arrangements and traditions essentially drive the estimates of catch-up times. That percentage changes in these are offset by percentage changes in an independent measure of such country specific institutional constraints in the form of non-market constraints from public sector oversight is consistent with a model that properly measures inefficiency. Second, the estimates point to an empirical basis for the policy prescriptions of such international lenders as the IMF in forcing "structural" changes on the borrower country to mitigate factors which may give rise to bureaucratic inefficiencies.

6. Conclusions

We explore what the effect a productivity gap to a leader nation has on follower nations' growth of labor productivity in manufacturing sectors and Gross Domestic Product. We therefore dispense with the common assumption that countries have similar technology, in favor of an assumption that low productivity nations may be able to adopt foreign best-practice methods and use this as an additional source of growth. This study covers 16 OECD nations in terms of total output, total manufacturing output, and five two-digit manufacturing sectors.

The results are that the technology gap to the leader contributes significantly to growth of labor productivity in all sectors. Its importance appears to be greater for total manufacturing and its two-digit components, compared to the GDP results. Thus our results indicate that aggregate studies bias downward the estimated rates of catch-up and that the manufacturing sector is an important driver of the convergence process. These results clash against previous research in a couple of ways. First, the rates of catch-up estimated by us are significantly greater than the often-quoted two to three percent derived in cross-sectional studies. However, our aggregate GDP result is consistent with more recent panel data studies of convergence, such as Islam (1995). Second, the results for the manufacturing industries are also different. For example, Broadberry (1993) and Bernard and Jones (1996a,b) indicate that convergence of GDP per worker must have occurred through trends in other sectors than manufacturing (such as services) or through compositional effects. Our results dispute these findings, instead supporting Dollar and Wolff (1988) who established convergence in virtually all manufacturing-industries.

We also find that country heterogeneity is important in the growth process, and this is true at all levels of production. Thus both inefficiency levels and rates of catch-up differ across countries. We determine that institutional factors such as bureaucratic efficiency are important sources of these estimated catch-up rates. These results point to the role of openness, both to other nations and within countries. The fact that catch-up results differ across industries and aggregation levels do indicate that policy suggestions need to be targeted to the specific industry. These policies should also be mindful of the fact that the institutional framework influences nations ability to take advantage of foreign sources of growth, in addition to institutions effect on a nation's within border growth potential.

References

Abramovitz M (1986) catching up, forging ahead, and falling behind. Journal of Economic History XLVI(2):385–406

Ahn SC, Schmidt P (1995) Efficient estimation of models for dynamic panel data. Journal of Econometrics 68:5–27

Arrelano M, Bond S (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58:277—297

Baltagi BH (1995) Econometric analysis of panel data. Wiley, England

Barro RJ (1991) Economic growth in a cross section of countries. Quarterly Journal of Economics 106:407–443

Barro RJ, Lee JW (1993) International comparisons of educational attainment. Journal of Monetary Economics 32(2):363–394

Baumol WJ (1986) Productivity growth, convergence and welfare: What the long-term data show. American Economic Review 76:1072–1085

Bernard AB, Jones CI (1996a) Comparing apples to oranges: Productivity convergence and measurement across industries and countries. American Economic Review 86:1216–1238

Bernard AB, Jones CI (1996b) productivity across industries and countries: Time series theory and evidence. Review of Economics and Statistics 78(1):135–146

Broadberry SN (1993) Manufacturing and the convergence hypothesis: What the long-run data shows. Journal of Economic History 53:772–795

Caselli F, Esquivel G, Lefort F (1996) Reopening the convergence debate: A new look at cross-country growth empirics. Journal of Economic Growth 1:363–398

Chamberlain G (1982) Multivariate regression model for panel data. Journal of Econometrics 18:5–46

Chamberlain G (1984) Panel data. In: Griliches Z, Intriligator M (eds) Handbook of econometrics. North-Holland, Amsterdam, pp 1247–1318

Cameron G, Proudman J, Redding S (1999) Productivity convergence and international openness. In: Proudman J, Redding S (eds) Openness and growth. Bank of England, pp 221–260

Dempster A, Laird N, Rubin D (1977) Maximum likelihood from incomplete data via the EM algorithm. Journal of the Royal Statistical Society 39:1–38

Dollar D, Wolff EN (1988) Convergence of industry labor productivity among advanced economies, 1963–1982. Review of Economics and Statistics LXX:549–558

Dowrick S, Nguyen D (1989) OECD comparative economic growth, 1950–85: Catch-up and convergence. American Economic Review 32:365–384

Gastil RD (1985) Freedom in the world: Political and civil liberties. Freedom House, Inc., New York

Greene W (1997) Frontier production functions. In: Paesaran MH, Schmidt P (eds) Handbook of applied economics, vol. II-Microeconometrics. Basil Blackwell, Oxford pp 81–166

Heckman JJ, Singer B (1984) A method for minimizing the impact of distributional assumptions in econometric models for duration data. Econometrica 52:271–320

Huh K, Sickles RC (1994) Estimation of the duration model by nonparametric maximum likelihood, maximum penalized likelihood and probability simulators. Review of Economics and Statistics 75:683–694

Hultberg PT, Nadiri MI, Sickles RC (1999) An international comparison of technology adoption and efficiency: A dynamic panel model. Annales D'Economie et de Statistique 55–56:449–474

Islam N (1995) Growth empirics: A panel data approach. Quarterly Journal of Economics (November): 1127–1170

Kalbfleisch JD, Prentice RL (1980) The statistical analysis of failure time data. Wiley, New York

Knack S, Keefer P (1995) Institutions and economic performance: Cross-country tests using alternative institutional measures. Economics and Politics 7:207–227

Knight M, Loyaza L, Villanueva D (1993) Testing the neoclassical theory of economic growth: A panel data approach. IMF Staff Papers 40:512–541

Krugman P (1994) The myth of Asia's miracle. Foreign Affairs 73(6):62–78

Lancaster T (1990) The Econometric analysis of transition data. Cambridge University Press, New York

Levine R, Renelt D (1992) A sensitivity analysis of cross-country growth regressions. American Economic Review 82(4):942–963

Mauro P (1995) Corruption and growth. Quarterly Journal of Economics (August):681–712

Parente SL, Prescott EC (1993) Changes in the Wealth of Nations. Quarterly Review, Federal Reserve Bank of Minneapolis (Spring):3–16

Sachs JD, Warner A (1995) Economic reform and the process of global integration. Brookings Papers on Economic Activity 1:1–95

Scully GW (1988) The institutional framework and economic development. Journal of Political Economy 96:652–662

Sevestre P, Trognon A (1996) Dynamic linear models. In: Matyas L, Sevestre P (eds) The Econometrics of panel data. Kluwer Academic Publishers, MA, pp 120–144

Sickles RC, Taubman P (1997) Mortality and morbidity among adults and the elderly. In: Rosenzweig MR, Stark O (eds). Handbook of population and family economics. North-Holland, Amsterdam, pp 559–643

Summers R, Heston A (1991) The penn world table (Mark5.0): An expanded set of international comparisons, 1950–1988. Quarterly Journal of Economics 106(2):327–368

Young A (1995) The tyranny of numbers: Confronting the statistical realities of the East Asian growth experience. Quarterly Journal of Economics (August): 641–680