Cross-country Catch-up in the Manufacturing Sector:
Impacts of Heterogeneity On Convergence and Technology Adoption*

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Abstract

This paper analyses econometrically the relationship between productivity growth in manufacturing and technology transfer from the leading economy. The recent convergence literature identifies two processes required for convergence; nations must both attain comparable levels of factor intensity and similar levels of technology. Homogeneity in technologies has neither theoretical nor empirical support. The paper focuses on the manufacturing sector and its two-digit industries while allowing for heterogeneity in technology and in the rate of catch-up. It compares catch-up rates and productivity estimates across manufacturing sectors and GDP and discusses possible sources for the obtained differences. The empirical part of the paper explores the validity of our econometric model for 16 OECD countries for aggregate and manufacturing labor productivity. Our results indicate that aggregate studies bias downward the estimated convergence rates. The rates of catch-up, as well as levels of productivity and sources of its growth in terms of technology and efficiency growth, also differ across countries. Finally, it finds that institutional factors such as bureaucratic efficiency are important determinants of catch-up rates.

Key Words: International comparisons, Panel data methods, convergence and catch-up in best-practice technologies.

JEL Classification Numbers: O47, O57, C33, C41

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1. Introduction

This paper analyses econometrically the relationship between productivity growth in manufacturing and technology transfer from the leading economy. Cross-country convergence of labor productivity in general has been extensively studied.[1] Commonly these studies show that countries do converge to their own steady states as predicted by the standard neoclassical model. Assuming identical technologies across countries, exogenous differences in saving, employment, and education are the proposed causes of all observed differences in levels of income and rates of growth. However, the recent convergence literature explicitly identifies two processes required for convergence. First, nations must attain comparable levels of factor intensity. Second, nations must attain similar levels of technology. This latter assumption has no empirical support.[2] In fact, one is hard pressed to find any group of countries that fit the assumption of identical technologies.

It can also be demonstrated that, in addition to differing accumulation rates and technology, the institutional framework across countries ought to be included when considering productivity growth.[3] In short, the existence of a technology gap may present an additional source of growth, but if nations differ in ability to adopt and absorb new knowledge then country institutional heterogeneity must also be examined. Indeed, if follower nations exhibit both a technology gap and a low absorption capacity, then technology's influence on productivity growth will be ambiguous (Abramovitz, 1986).

The importance of technology transfer has been explored previously. For example, Hultberg, Nadiri and Sickles (1999) show that the technology gap to the United States significantly contributes to follower nations' aggregate productivity growth in the postwar period. It has also been shown that growth is affected 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. Two of the more compelling studies are Broadberry (1993) and Bernard and Jones (1996a,b). The general result

[1] See Abramovitz (1986), Baumol (1986), and Barro (1991).
[2] Studies with aggregate production function differences include Knight et al. (1993) and Islam (1995).
[3] For the importance of institutions, see Knack and Keefer (1995), Barro (1991), and Scully (1988).

from these papers is that aggregate productivity convergence appears to be quite different from sector-specific results. Broadberry 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. Bernard and Jones also find manufacturing to have performed differently compared to GDP and other sectors for 14 OECD countries. Both papers indicate that convergence of GDP per worker must have occurred through trends in other sectors than manufacturing or through compositional effects. In contrast, Dollar and Wolff (1988) find convergence in virtually all manufacturing industries and conclude that this is the proximate source of aggregate convergence. Berman (2000) examines the possibility that factor-biased technological change has acted to constrain international convergence across manufacturing sectors.

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. We 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.

The paper has the following outline. Section 2 briefly outlines our 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, as well as of productivity, also differ across countries. In section 5 we analyze a reduced form model that links institutional, political, and economic factors to the time for catch-up using duration modeling techniques, some of which utilize country-specific heterogeneity controls based on the Heckman and Singer (1986) estimator. An interesting finding from the duration analysis is that the elasticity of catch-up times with respect to an index of bureaucratic efficiency is negative and greater than unity.

2. Theoretical Framework

Building on the standard neoclassical framework, we formalize the dual notion that there exist technology gaps and differing abilities to take advantage of the catch-up potential engendered by these gaps.[4] The inclusion of technology adoption, with and without institutional inefficiency, slightly modifies the standard results for nations' steady states and rates of convergence. Also, more importantly, it allows for quite different convergence paths, but that is not our concern in the present paper (see Hultberg, 2000).

The econometric model introduces the possibility of technology adoption into the Solow-Swan model of a closed economy. We allow for the flow of knowledge, but assume capital and labor to be immobile between countries. We therefore assume that ideas and knowledge can flow across national borders independently of capital and labor migration. The assumption of immobility of physical capital and labor is strong, but it allows us to single out some effects of technology on the growth process. The model is quite similar to the standard neoclassical model that assumes a Cobb-Douglas production function

$$(1) \qquad \ln Q_t = \ln A_t + \alpha \ln K_t + \beta \ln L_t,$$

where population and technological progress are exogenous. The difference from the standard model and ours appears in our equation for the evolution of capital. The capital evolution depends on an exogenous saving rate, the depreciation rate, and a technology catch-up term, $\xi(T,T^w)$, so that

$$(2) \qquad \Delta K_t = sQ_t - \delta K_t + \xi(T,T^w)K_t.$$

We assume that the adoption of technology is a function of an economy's or industry's technology gap relative to the leader, defined as the nation with the highest level of technology. The economy is then able to adopt some fraction of this gap every time period. The simplest definition of the technology adoption function would be $\xi(T,T^w)_t = \theta\ (T^w_t - T_t)$,

[4] We refer to the gap as technology, but it encompasses all things that make a nation more productive.

where θ denotes the technology adoption rate and 'w' represents the leader nation. The measurement of technology is difficult, as no variable captures it perfectly. Possible candidates, such as number of patents or number of Ph.D., are elusive. We therefore make the simplifying assumption that technology is a function of the economy's labor productivity. For example, technology could be a logarithmic function of labor productivity so that $T_t=\ln(Y_t)$ which implies that technology is a positive and diminishing function of labor productivity. From these assumptions we obtain the following §(.) function $§(T,T^w)_t = \theta \ln(Y^w_t/Y_t)$. With this specification we see that the technology adoption function is decreasing in Y, the particular economy's level of productivity, and increasing in Y^w, the leader economy's level of productivity.

We also consider an economy's ability to absorb this new knowledge. 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, θ. 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 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 same way. This term captures more than mere production slack as it encompasses, among other factors, the institutional framework, adjustment costs, international openness.

The above analysis is only slightly modified by the efficiency addition. The difference comes from the technology function which is redefined as

$$(3) \qquad §(T,T^w)_t = \theta \ln(Y^w_t / Y_t E) = \theta (\ln Y^w_t - \ln Y_t - \ln E)$$

where E>1, so that E acts to reduce the available technology gap. Accordingly, the economy may run out of available technology before its labor productivity is equal to the leader nation.

To find an estimable equation, the production function (1) is first-differenced and the growth of capital is substituted in according to the capital evolution equation (2). Thus the growth rate of per worker output depends on the growth of factor inputs as well as the productivity gap to the leader:

(4) $y_t = \varphi - \rho \ln E + \alpha k_t + \beta l_t + \rho(\ln Y^w{}_t - \ln Y_t)$

where $\rho = \alpha\theta$ is the country-specific technology adoption rate and $\phi = (\gamma\text{-}\alpha\delta)$ is net exogenous technology growth. The growth rate of per worker output for a country-sector therefore depends on the rate of growth of factor inputs, the common rate of exogenous technological change minus capital depreciation, country-specific inefficiency, and the productivity gap between the country-sector leader and the follower. The parameters α and β show the elasticity of per worker output to a change in the growth in factor inputs while ρ is the adoption rate of available technology from abroad and the estimated efficiency (inefficiency) measure shows the effect of country-specific characteristics on the growth of per worker output.

This model is very similar to Bernard and Jones (1996a,b) and Cameron et al. (1999). 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. expands 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.

3.0 Data and Estimation

3.1 Data and Variable Construction

The main data set for the manufacturing industries is the STAN data (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 which 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

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

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.[6]

The 16 countries are compared across per worker aggregate GDP, total manufacturing, and initially eight 2-digit level industrial sectors: Food and Beverages (FBT), Paper Products (PPP), Non-metallic mineral (NMM), Basic metal (BMI), and Fabricated metal (FMP).[7] 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 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. The period considered is 1960-85.

Finally, for the duration analysis, institutional variables from several sources are used: indices for political and civil rights from Gastil (1985), indices for political stability and bureaucratic efficiency from Mauro (1995), and an openness variable from Summers and Heston (1991).

3.2 Econometric Issues

There are several possible problems with most existing empirical growth studies. It is usually assumed that country-specific effects are uncorrelated with other right-hand side variables, but as shown by Caselli, Esquivel and Lefort (1996) this assumption is necessarily violated. This incorrect treatment of country heterogeneity due to differences in technology or tastes gives rise to omitted variable bias. In addition, most studies do not deal with the presence of endogeneity problems. In particular, for any dynamic relationship that contains a lagged dependent variable

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[6] 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.

[7] For four of the industries, Textiles and Leather, Wood Products and Furniture, Chemical Products, and Other Manufacturing, estimation results for all of 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 not reported.

among the regressors, so that $y_{i,t} = \rho y_{i,t-1} + x'_{i,t} \beta + \varepsilon_{i,t}$, where $\varepsilon_{i,t} = \mu_i + \nu_{i,t}$ (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. Hence, an explanatory variable is correlated with the error term. The omitted variable bias is readily removed in panel data estimation by the use 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 the correlation between effects and regressors. However, the within transformation ($y_{i,t} - y_{i}$) will still be correlated with ($\nu_{i,t} - \nu_{i}$) since $y_{i,t}$ is correlated with ν_{i} by construction (see Baltagi, 1995). That is, LSDV will still be inconsistent due to this endogeneity problem. This problem is only removed if both N and T go to infinity. Hence, only if the number of periods were very large would LSDV be appropriate. In most panel estimations, however, T will tend to be small.

Several solutions to the endogeneity problem have been suggested in the econometric literature (see Sevestre and Trognon, 1996). The most obvious is to use instrumental variable technique. For example, Arellano and Bond (1991) argue that to get a consistent estimate of the lagged dependent variable for large N but small, fixed T, one needs to (a) first difference to eliminate the individual effects and (b) use lagged differences or levels as instruments. Ahn and Schmidt (1993) point out that there are additional moment conditions that are ignored by the IV estimators suggested by Arellano and Bond (1991). Ahn and Schmidt suggest a generalized methods of moments (GMM) estimator that is asymptotically equivalent to Chamberlain's (1982, 1984) optimal minimum distance estimator. Incidentally, Islam (1995) compares the MD estimator with LSDV in a Monte Carlo study using a similar data set as us. Islam's result is that the LSDV, although it is consistent in the direction of T only, actually performs very well. Caselli et al. (1996) utilize this approach in a GMM framework with the result that estimated rates of convergence increase significantly.

We perform our estimations using LSDV, two-stage least squares (2SLS), and GMM estimators. The LSDV estimation we perform is the standard ordinary least squares estimation with dummies for all countries, but we allow one slope coefficient to vary across regions. The 2SLS is very similar, except that we instrument our technology gap variable with its lagged value. Finally, the GMM estimation is similar to that performed by Caselli et al. (1996) in that we first-difference our estimable equation for all four available (5-year) time periods, stack the four equations and use all lagged exogenous variables as instruments. The difference from Caselli et al. is that we first-difference our growth equation (not levels) so that the equations are actually in second-differences.

Our actual estimation uses the following regression equation:

$$(5) \qquad y_i = \alpha_0 + \alpha_1\rho_i + \alpha_2 k_i + \alpha_3 l_i + \rho_i(\ln Y^W_{t-1} - \ln Y_{t-1})$$

where, for any country i, ρ is the adoption rate or catch-up parameter, α_1 is the estimated efficiency parameter, α_0 is the net exogenous technological progress, and α_2 and α_3 are the elasticity of per worker output to a change in the growth of capital and labor, respectively. For GDP and total manufacturing, the world leader is assumed to be the U.S., for 2-digit manufacturing industries the leader varies.

4. Catch-up results

4.1 Estimation assuming constant and identical adoption rates

Initially the adoption rates are assumed to be the same across all the countries in the sample. The estimation results are given in Tables 1 and 2 for both total productivity and for the manufacturing sectors. The parameter estimates on the growth of capital and labor (α_2 and α_3, respectively) vary substantially across estimations while the catch-up parameter estimates are less variable and more intuitive across sectors. This is true for both LSDV and 2SLS estimations.

Consider first the total output result. The catch-up rate has the value of 0.10 for both estimations; that is, a percentage increase in the lagged productivity gap will, on average, lead to 0.10 percent higher growth of per worker GDP.[8] The estimates of efficiencies relative to the leader, the United States, are all negative and confirm our leader hypothesis. Of the 15 followers' efficiency estimates, eight are highly significant. Three are significant at the 13 (15 for 2SLS) percent level or less, whereas the other four, Canada, Holland, Norway, and Australia

[8] For the GDP estimation we also conducted a General Methods of Moments estimation. The results were virtually identical (see Table 2). This estimation entails first differencing the estimable equation for the four available time periods, stack these four equations and then use all lagged exogenous variables as instruments. See also Caselli et al. (1996).

are insignificant, but still negative. These results may indicate these countries' similarity to the United States.[9]

For the other five industries and total manufacturing some interesting results are obtained. First of all, a characteristic of our estimation procedure is that we need a leader nation/industry to which follower countries catch-up; however, for these five manufacturing industries the leader(s) differ from industry to industry. For FBT the U.S. (1973-85) and Belgium (1986-90) share the leader role. For PPP three countries shared the lead, U.S. (1973-80, 1983), Finland (1981-82, 1984-88, 1990) and Canada (1989). The U.S. (1973-79, 1981, 1983-84) and Canada (1980, 1982, 1985-90) shared the lead in NMP. Japan was the sole leader in BMI. Finally, for FMP the U.S. (1973-81, 1983-84) and Canada (1982, 1985-90) once again shared the lead. For total manufacturing sector the United States is the leader over the years 1973-84 and 1987-88, but the Netherlands and Belgium are also in front over the years 1985-86 and 1989-90, respectively. However, for total manufacturing the U.S. is assumed to be the only 'leader' in order to compare it to the GDP results.

For manufacturing industries, the most striking result is that the included manufacturing sectors exhibit faster catch-up rates.[10] 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 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.[11] For total manufacturing the catch-up rate is about 0.40 (2SLS). The two-digit industries display catch-up rates around total manufacturing with Basic Metal Industries, where Japan is the productivity leader, showing the lowest rate at 0.10 and Paper Products and Printing exhibiting the fastest rate at 0.38 (again using 2SLS). 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 (and thus some leapfrogging is expected).

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[9] 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.

[10] However, this does not imply that the service sectors must be converging at a slower rate.

[11] Cameron et al. (1999) use total factor productivity in their study.

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 2SLS estimator the productivity results are similar across all industries and comparable to the total economy results. That is, countries that are relative efficient at the GDP level are in general more 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.[12]

As is commonly seen in the convergence literature, where growth of per capita income is regressed against initial per capita income, the parameter in front of the initial income or productivity variable can be converted into an implied rate of convergence. That is, after controlling for different steady states (or, which is commonly equivalent, different growth rates of factor inputs) the convergence parameter is converted into a rate of convergence through the following equation: $-(1-e^{-\lambda t})= \rho$, where ρ is the coefficient (negative) in front of initial income. Once the rate of convergence, λ, is obtained the time required to half the distance between the initial level of productivity and the steady state level of productivity can be calculated by simply solving $e^{-\lambda t} = ½$ for t. The same can be done for any desired amount of closure; for example, to obtain the time required to close 95 percent of the gap replace ½ with 0.05 in the above equation.

The present model gives the effect on the growth of per worker output from the technology gap, holding the growth rates of factor inputs constant. Thus the implied rate at which a follower closes the technology/productivity gap to the country/industry leader if everything else is held constant can be calculated. This exercise does not give the unconditional rate at which countries are converging; it does, however, isolate one source of catch-up and may also allow for distinguishing which countries/industries are able to take advantage of this growth source and why. The only real difference in the approach is that the rate of catch-up is found through the equation: $(1-e^{-\lambda t}) = \rho$, where ρ is the coefficient (positive) in front of the productivity gap.

[12] A General Method of Moments estimation was conducted for the manufacturing sectors, but data simply did not allow for any result.

The main difference between this rate of catch-up and the standard rate is the assumption that follower countries are catching up with the economy/industry leader, as opposed to their own steady state. This makes the catching-up process dependent on the leader. Whereas in the traditional model a country's growth is only a function of its own steady state, totally independent of the actions of other nations. The model is thus semi-open. The notion that there exists an economy/industry leader is a fairly common view when one thinks of firms or industries. A firm emulates the technological leader in order to increase its productivity, while the leader (as well as followers) conduct research and development to remain (or become) the industry leader. At the disaggregate level one rarely hears the argument that firms are growing towards their steady state. If so, then the same argument ought to apply to an entire industry or economy as well.

The required time to close any given gap can be found as before, $e^{-\lambda t} = ½$ for half the gap. For example, using the catch-up parameter from the cross-country GDP estimation of 0.10 we find a catch-up rate of $\lambda = 0.108$, which implies that a follower would cut the gap to the leader by 50 percent in 6.4 years. Importantly, for this to hold true the other right-hand side variables cannot change over time. That is, this rate of catch-up is conditional on the growth of factor inputs in our regression. Again, this is equivalent to the rate of convergence being conditional on the steady state variables (such as the growth rates of capital and labor) of countries. Table 3 presents the calculated times required to both cut half the 'technology gap' and 95 percent of this gap.

As a side note, the rate of catch-up is higher than usually predicted by cross-sectional estimations (usually a rate of convergence to steady state of 2-3 percent per year). However, the results do not conflict with more recent panel data estimates of convergence rates that take into account cross-country heterogeneity [e.g. Islam (1995), Hultberg et al. (1999)]. Further, similar results are found in a study by Caselli, Esquivel and Lefort (1996) that considers both heterogeneity and endogeneity problems.[13] In particular, Caselli et al. (1996) using a GMM estimator, find a convergence speed of about 10 percent per year for total GDP. Similarly, Cameron et al. (1999) find high magnitudes on a parameter similar to our manufacturing catch-

[13] Hultberg et al. (1999) also control for the heterogeneity and endogeneity problems.

up estimate, although this paper does not provide any interpretation of that parameter (except for its sign).

4.2 Estimation with different catch-up rates across countries

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 4 reports that the individual countries and sectors indeed exhibit a wide variation in rates of catch-up. 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.

For example, several interesting results appear when looking at the GDP results initially. Japan has a relatively low rate of catch-up at 0.06, indicating 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)). Norway (0.03 and successful) and New Zealand (0.05 and unsuccessful) also show the fact that these numbers are not good predictors of relative growth performances. A possible implication of these numbers exists in regards to future performance. Countries that have caught up without much use of the productivity gap 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). Several countries stand out as clear winners in the game of catch-up: Denmark, Sweden, Australia, and the Netherlands exhibit catch-up rates of over 22 percent.

Total manufacturing show a variety of rates as well, ranging from 0.16 (Belgium) to 0.53 (Germany). 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 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.

Another goal of the paper is to investigate whether the different rates of adoption are related to some common institutional variables: is the institutional framework partially determining how quickly country-sectors can close the gap to the technology leader? To explore this question the rates of adoption are translated into time required to close 50 percent of the productivity gap. As mentioned earlier, this time is conditional on the other right-hand side variables being held constant (see equation 5). These calculations are presented in Table 5. Of course, the lower the technology adoption rate, the longer the required time to close the productivity gap. For GDP the average half-life of the gap to the U.S. is approximately 6.6 years, the same number for total manufacturing is about 1.8 years. So whatever the lead is for the U.S., the representative follower will catch-up by 50 percent in less than 7 years in terms of GDP per capita, and in less than 2 years in terms of manufacturing productivity. Of course, the U.S. is continuously moving the target through its innovations. The 2-digit manufacturing results are similar.

5. Duration Results

The different catch-up times in different sectors can now be analyzed using a duration model. For the institutional variables we use the ones in Hultberg et al. (1999) which are political and civil rights, political stability, bureaucratic efficiency, and openness to international trade (see Table 6). Researchers have used several variables to capture the political and civil right aspect of nations' institutional framework. Barro (1991) used two variables measuring political instability: revolutions and coups, and assassinations. However, as discussed in Knack and Keefer (1995), these variables might not measure what we have in mind since they are only loosely correlated to the more general institutional environment. Instead we explore the impact from the use of the Gastil indices and indices of various institutional variables from Business International. 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 indices from Business International (BI) are thought to proxy some general institutional variables. The numbers are obtained from Mauro (1995) who restricts his attention to nine different indicators of institutional efficiency, which are independent of macroeconomic variables and apply to both domestic and foreign firms. The 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.

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).

The natural statistical model in which to examine the effects of institutional factors on particular country-sector catch-up times is duration modeling. Consider a continuous time duration model where a nonnegative random variable, T (e.g. time until catch-up), has a density, f(t), and a cumulative distribution, F(t) (Kalbfleisch and Prentice, 1980, Lancaster, 1990). The hazard for T is the conditional density of T given T > t | 0 and is given by:

$$\lambda(t) = f(t \mid T > t) = \frac{f(t)}{[1 - F(t)]} \geq 0$$

In terms of the integrated hazard, the density and distribution of T are:

$$f(t) = \lambda(t)\exp\left[-\int_0^t \lambda(\tau)d\tau\right]$$

$$F(t) = 1 - \exp\left[-\int_0^t \lambda(\tau)d\tau\right]$$

Let δ = 1 if the duration is right-censored and δ = 0 otherwise. The distribution associated with realizations on δ is assumed to be independent of the convergence time and is functionally independent of the convergence distribution. The log likelihood function is:

$$\ln \Lambda = \sum_i f(t)(1-\delta) + \sum_i [1 - F(t)]\delta$$

The two most widely used duration specifications are the proportional hazard model and the accelerated time to failure model. The proportional hazard model expresses the natural logarithm of the conditional hazard of converging as a function of time, while the accelerated time to failure model specifies the natural logarithm length of catch-up time as a linear function of covariates, $\ln T = x\beta + \sigma\varepsilon$, where ε is a random disturbance and σ is a scale parameter. Failure time can be written as $T = \exp(x\beta)T_0^{\sigma}$, where T_0 is an event time drawn from a baseline distribution. Different parametric distributions are available to model unobserved country effects [θ(t)]. Intersection of these two specifications occurs when the baseline distribution is assumed to be Weibull. We can also allow for unobserved heterogeneity in country-sector convergence speeds. To see how this statistical treatment can be implemented, consider the Weibull proportional hazard model for country-sector i with log hazard function given by:

$$\ln h(t_i | x_i, \theta_i) = \gamma \ln t_i + x_i \beta + \theta_i$$

Here t_i is the continuous time of a completed spell, x_i is a vector of exogenous time varying or constant covariates, and θ_i is unobserved scalar heterogeneity. Censored observations are given by:

$$T_i = \min(t, t_c), \quad d_i = I(t_i < t_c),$$

where t_c is the censored time of an incomplete spell and I is an indicator function: $d_i = 1$ if $t_i < t_c$ and $d_i = 0$ otherwise.

Assuming independence over duration spells, the joint likelihood of duration times and unobserved heterogeneity is:

$$\Lambda = \prod_i f(t_i, \theta_i | x_i),$$

where

$$f(t_i, \theta_i | x_i) = h(t_i, \theta_i) \exp\left(-\int_0^t h(s_i, \theta_i | x_i)\, ds\right) \quad if\ d_i = 1$$

$$f(t_i, \theta_i | x_i) = \exp\left(-\int_0^t h(s_i, \theta_i | x_i)\, ds\right) \quad if\ d_i = 0$$

The joint density is

$$\Lambda = \prod_i \int g(t_i | x_i, \theta_i)\, d\mu(\theta)$$

and the marginal likelihood of duration times $f(t_i, \theta_I | x_i)$, is given by:

$$f(t_i, \theta_i | x_i) = g(t_i | x_i, \theta_i)\, \mu(\theta_i)$$

Heckman and Singer's Nonparametric Maximum Likelihood Estimator (NPMLE) estimator can be used to avoid the ad hoc specification of the mixing distribution μ(θ). Basically, this method reduces to the use of a finite support histogram to model μ(θ). The EM algorithm (Dempster et al. (1977)) has often been used to solve the likelihood equations. Application to the heterogeneity model is accomplished by treating the sequence of unobservables $\{\theta_i\}$ as missing data. For a more detailed discussion of this and competing duration models with unobservable heterogeneity see Huh and Sickles (1994) and Sickles and Taubman (1997).

We have utilized the Weibull specification with and without the NPMLE of Heckman and Singer and report these results in Table 7. Since the model here is basically descriptive we have included only those variables which have significant explanatory power. These include the Bureaucratic Efficiency (BE) variable, the Summers and Heston measure of openness, and sector specific dummy variables. We analyze the catch-up times in terms of a closure of 50 percent of the gap. Estimates indicate substantial sector specific heterogeneity (suggesting that aggregate country studies may distort the empirical record) as well as some play for unobserved country effects. Moreover, the results indicate a rather robust finding that the elasticity of catch-up times with respect to the constructed index of Bureaucratic Efficiency is greater than unity (-1.663). We find this to be a particularly interesting finding for 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 such as the IMF in forcing “structural” changes on the borrower country to mitigate factors which may give rise to bureaucratic inefficiencies.

6. Conclusion

The paper explores the relationship between the growth of productivity in different country-sectors and the 'technology' gap to the leader nation in that sector. 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 even more important for total manufacturing and its 2-digit components as compared to the GDP results. These results clash against previous research that has concluded that the most important source of convergence is found in either the service sector or in compositional changes of economies (see for example Bernard and Jones, 1996. It is also found that country heterogeneity is important in the growth process, and this is true at all levels of production.

In addition, the catch-up rates not only differ across industries, but also across countries. From these estimates, the time required to close half the productivity gap to the leader is found and a duration model is used to explore its determinants. These results point both to the role of openness to economic trade and to the role of institutional constraints in the growth process of individual OECD industrial sectors.

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Table 1. Parameter Estimates Using Least Squares Dummy Variable Estimation

	GDP	MANUF.	FBT	PPP	NMM	BMI [1]	FMP
ρ	0.10*	0.32*	0.18*	0.28*	0.26*	0.14*	0.17*
	(11.27)	(7.71)	(5.53)	(7.05)	(8.44)	(4.94)	(5.56)
CAN	-0.06	-0.05	-0.28*			-0.42**	
	(-0.96))	(-1.05)	(-3.91)			(-1.74)	
JAP	-0.41*	-0.27*	-0.63*	-0.37*	-0.42*		-0.27*
	(-4.32)	(-5.25)	(-7.60)	(-7.30)	(-7.94)		(-2.85)
AST	-0.30*	-0.46*	-0.54*	-0.34*	-0.31*	-1.11*	-0.48*
	(-3.73)	(-9.35)	(-7.00)	(-6.66)	(-5.78)	(-4.63)	(-6.17)
BEL	-0.17*	-0.09**		-0.31*	-0.48*	-0.71*	-0.24*
	(-2.26)	(-1.93)		(-5.89)	(-9.01)	(-2.95)	(-3.17)
DEN	-0.30*	-0.63*	-0.55*	-0.62*	-0.65*	-1.39*	-0.85*
	(-4.20)	(-12.98)	(-7.51)	(-11.69)	(-11.12)	(-5.81)	(-10.28)
FIN	-0.20*	-0.40*	-0.45*		-0.46*	-0.63*	-0.64*
	(-2.13)	(-7.58)	(-5.97)		(-8.76)	(-2.62)	(-7.69)
FRA	-0.12	-0.32*	-0.31*	-0.30*	-0.20*	-0.82*	-0.37*
	(-1.54)	(-6.30)	(-3.94)	(-5.71)	(-3.34)	(-3.43)	(-4.42)
GER	-0.13	-0.42*	-0.55*	-0.47*	-0.27*	-1.27*	-0.42*
	(-1.53)	(-8.84)	(-7.81)	(-9.04)	(-5.26)	(-5.31)	(-5.44)
ITA	-0.13	-0.34*	-0.23*	-0.19*	-0.31*	-0.14	-0.29*
	(-1.59)	(-6.33)	(-2.97)	(-3.63)	(-5.68)	(-0.55)	(-2.88)
NET	-0.07	-0.02	-0.07	-0.26*	-0.27*	-0.60*	-0.32*
	(-1.10)	(-0.42)	(-0.85)	(-5.09)	(-4.73)	(-2.49)	(-3.91)
NOR	-0.07	-0.34*	-0.41*	-0.35*	-0.32*	-0.73*	-0.42*
	(-0.86)	(-6.49)	(-4.93)	(-6.82)	(-5.86)	(-3.00)	(-5.46)
SWE	-0.22*	-0.43*	-0.54*	-0.17*	-0.46*	-1.04*	-0.49*
	(-3.28)	(-8.79)	(-7.38)	(-3.28)	(-8.80)	(-4.36)	(-6.34)
U.K.	-0.51*	-0.53*	-0.56*	-0.49*	-0.34*	-1.14*	-0.63*
	(-7.02)	(-11.24)	(-7.70)	(-9.12)	(-6.55)	(-4.69)	(-8.33)
AUS	-0.04	-0.46*	-0.53*	-0.62*	-0.25*	-0.51**	-0.56*
	(-0.53)	(-9.30)	(-6.46)	(-11.63)	(-4.60)	(-2.02)	(-7.25)
N.Z.	-0.21*	-0.48*	-0.57*	-0.25*	-0.22*	-0.25	-0.63*
	(-3.15)	(-9.69)	(-3.91)	(-5.01)	(-4.39)	(-0.88)	(-8.24)
U.S.						-0.58**	
						(-2.43)	
R^2	0.36	0.22	0.31	0.21	0.27	0.17	0.14
Adj. R^2	0.33	0.17	0.28	0.16	0.23	0.12	0.10

Note: * and ** imply significantly different from zero at 5 percent and 10 percent, respectively. T-values in parentheses.
The missing cells represent the countries that were considered to be at the technology frontier.
[1] Japan is the 'technology' leader for this industry

Table 2. Parameter Estimates Using Two-Stage Least Squares Estimation

	GDP	GDP_{GMM}[1]	MANUF	FBT	PPP	NMM	BMI[2]	FMP
ρ	0.10*	0.11*	0.40*	0.24*	0.38*	0.35*	0.10*	0.25*
	(10.29)	(7.21)	(7.40)	(5.43)	(7.61)	(8.53)	(2.97)	(5.82)
CAN	-0.06	-0.02	-0.03	-0.07*			-0.04	
	(-0.86)		(-1.52)	(-3.80)			(-0.87)	
JAP	-0.41*	-0.29	-0.12*	-0.16*	-0.14*	-0.15*		-0.07*
	(-4.25)		(-4.51)	(-4.59)	(-6.01)	(-6.56)		(-3.10)
AST	-0.30*	-0.20	-0.19*	-0.13*	-0.13*	-0.11*	-0.11*	-0.12*
	(-3.70)		(-5.84)	(-4.98)	(-5.54)	(-5.85)	(-1.95)	(-4.60)
BEL	-0.17*	-0.12	-0.04*		-0.11*	-0.16*	-0.06	-0.06*
	(-2.26)		(-2.11)		(-4.86)	(-6.84)	(-1.35)	(-3.09)
DEN	-0.31*	-0.18	-0.25*	-0.13*	-0.22*	-0.22*	-0.14*	-0.22*
	(-4.32)		(-6.49)	(-5.21)	(-7.04)	(-7.86)	(-2.40)	(-5.34)
FIN	-0.21*	-0.21	-0.17*	-0.11*		-0.16*	-0.05	-0.16*
	(-2.17)		(-5.29)	(-4.80)		(-6.52)	(-1.19)	(-4.74)
FRA	-0.11	-0.12	-0.13*	-0.08*	-0.11*	-0.07*	-0.08	-0.10*
	(-1.47)		(-4.97)	(-4.07)	(-5.37)	(-3.68)	(-1.63)	(-3.86)
GER	-0.13	-0.15	-0.17*	-0.13*	-0.17*	-0.10*	-0.12*	-0.11*
	(-1.50)		(-5.80)	(-5.17)	(-6.36)	(-5.29)	(-2.29)	(-4.34)
ITA	-0.14	-0.15	-0.15*	-0.05*	-0.07*	-0.10*	0.00	-0.08*
	(-1.67)		(-4.87)	(-3.59)	(-4.01)	(-5.23)	(0.02)	(-3.03)
NET	-0.07	-0.07	-0.01	-0.02	-0.10*	-0.09*	-0.06	-0.08*
	(-1.07)		(-0.86)	(-1.13)	(-5.06)	(-5.04)	(-1.28)	(-3.70)
NOR	-0.07	-0.12	-0.14*	-0.10*	-0.12*	-0.11*	-0.06	-0.11*
	(-0.80)		(-4.93)	(-4.22)	(-5.73)	(-5.69)	(-1.37)	(-4.23)
SWE	-0.24*	-0.12	-0.17*	-0.12*	-0.06*	-0.16*	-0.10**	-0.12*
	(-3.41)		(-5.83)	(-5.35)	(-3.73)	(-6.78)	(-1.90)	(-4.87)
U.K.	-0.51*	-0.21	-0.21*	-0.13*	-0.18*	-0.12*	-0.10**	-0.16*
	(-7.04)		(-6.31)	(-5.09)	(-6.72)	(-5.68)	(-1.83)	(-5.04)
AUS	-0.02	-0.06	-0.19*	-0.13*	-0.23*	-0.08*	-0.04	-0.13*
	(-0.28)		(-5.80)	(-4.64)	(-6.89)	(-4.68)	(-0.92)	(-5.07)
N.Z.	-0.21*	-0.11	-0.20*	-0.14*	-0.08*	-0.07*	-0.02	-0.15*
	(-3.21)		(-5.85)	(-4.61)	(-4.53)	(-4.18)	(-0.35)	(-5.22)
U.S.							-0.06	
							(-1.44)	
R^2	0.33		0.20	0.27	0.21	0.25	0.15	0.10
Adj. R^2	0.30		0.15	0.22	0.16	0.21	0.10	0.04

Note: * and ** imply significantly different from zero at 5 percent and 10 percent, respectively.
The missing cells represent the countries that were considered to be at the technology frontier.
[1] Using a General Methods of Moments estimation technique (5-year data)
[2] Japan is the 'technology' leader for this industry.

Table 3. Time to Close the Technology Gap Using Two-Stage Least Squares Estimation

	Estimate (ρ)	Rate (λ)[1]	50 percent[2]	95 percent[2]
Total GDP	0.10	0.108	6.40	27.66
Manufacturing	0.40	0.506	1.37	5.92
FBT	0.24	0.270	2.57	11.11
PPP	0.38	0.477	1.45	6.28
NMP	0.35	0.434	1.60	6.90
BMI	0.10	0.105	6.60	28.56
FMP	0.25	0.293	2.36	10.21

[1] Calculated from $(1-e^{-\lambda t})=\rho$ [2] Calculated from $e^{-\lambda t}=0.5$ or 0.05, respectively

Table 4. Allowing for Heterogeneous Catch-up Rates Across Countries

	GDP	MANUF	FBT	PPP	NMM	BMI [1]	FMP
CAN	0.11	0.37*	0.26**			0.09	
JAP	0.06*	0.28	0.53*	0.30	0.32*		0.04
AST	0.09*	0.45*	0.29**	0.15	0.45*	0.17	0.14
BEL	0.16*	0.16**		0.09	0.20**	0.09	0.07
DEN	0.35*	0.21	-0.05	0.38	0.17	0.40*	-0.16
FIN	0.10*	0.32*	0.24**		0.39*	0.26*	0.27*
FRA	0.12*	0.27**	-0.16	0.24**	0.14*	0.16	0.09
GER	0.14*	0.53*	-0.04	0.18	0.61**	0.13	0.11
ITA	0.14*	0.39*	0.22*	0.16	0.32*	0.20**	0.18*
NET	0.22*	0.41*	0.25*	0.35	0.29	0.15	0.12
NOR	0.03*	0.35*	0.24*	0.58*	0.42*	0.14	0.42*
SWE	0.33*	0.28	0.11	0.41*	0.39**	0.13	0.11
U.K.	0.15*	0.31**	0.26*	0.18	0.20*	0.07	0.17
AUS	0.28*	0.44*	0.26*	0.38*	0.30*	0.07	0.30*
N.Z.	0.05	0.44*	0.16*	0.81*	0.39*	-0.03	0.40*
U.S.						0.22	

Note: * and ** imply significantly different from zero at 5 percent and 10 percent, respectively.
The missing cells represent the countries that were considered to be at the technology frontier.
[1] Japan is the 'technology' leader for this industry.

Table 5. Catch-up Times for Different Country-Sectors (50 percent of gap)

	GDP	MANUF	FBT	PPP	NMM	BMI [1]	FMP
CAN	5.95	1.50	2.30			7.35	
JAP	11.20	2.11	0.92	1.94	1.80		16.98
AST	7.35	1.16	2.02	4.27	1.16	3.72	4.60
BEL	3.98	3.98		7.35	3.11	7.34	9.55
DEN	1.61	2.94	0	1.45	3.72	1.36	0
FIN	6.58	1.80	2.53		1.40	2.30	2.20
FRA	5.42	2.20	0	2.53	4.60	3.98	7.35
GER	4.60	0.92	0	3.49	0.74	4.98	5.95
ITA	4.60	1.40	2.79	3.98	1.80	3.11	3.49
NET	2.79	1.31	2.41	1.61	2.02	4.27	5.42
NOR	22.76	1.61	2.53	0.80	1.27	4.60	1.27
SWE	1.73	2.11	5.95	1.31	1.40	4.98	5.95
U.K.	4.27	1.87	2.30	3.49	3.11	9.55	3.72
AUS	2.11	1.20	2.30	1.45	1.94	9.55	1.94
N.Z.	13.51	1.20	3.98	0.42	1.40	0	1.36
U.S.						2.79	

The missing cells represent the countries that were considered to be at the technology frontier.
[1] Japan is the 'technology' leader for this industry.

Table 6. Institutional Variables

Country	Freedom	Political Stability	Bureaucratic Efficiency	Openness (S-H)
United States	0.143	9.33	9.75	14.0
Canada	0.143	9.00	9.58	45.2
Japan	0.191	9.42	9.08	22.6
Austria	0.143	9.04	8.25	61.5
Belgium	0.143	8.00	9.08	107.9
Denmark	0.143	8.50	9.58	62.4
Finland	0.286	8.79	9.33	51.5
France	0.202	8.92	8.25	35.0
Germany	0.179	8.21	8.67	44.3
Italy	0.220	7.92	6.33	36.9
Netherlands	0.143	8.82	10.00	92.2
Norway	0.143	9.50	9.67	85.8
Sweden	0.149	9.00	9.25	52.6
United Kingdom	0.143	8.33	9.00	48.4
Australia	0.143	8.50	9.75	31.1
New Zealand	0.143	8.50	10.00	53.0

Table 7. Determinants of Logarithm of Catch-up Times (50 Percent Catch-up).

Variable	Parameter Estimate	T-statistic
(log) Bureaucratic Efficiency	-1.663	-1.98
(log) Summers-Heston Index	0.474	2.59
GDP	3.411	1.77
Manufacturing	2.510	1.31
FBT	3.324	1.73
PPP	2.534	1.32
NMP	2.521	1.31
BMP		
FMP	3.303	1.72
$\theta(t)$	0.856	13.9
Pseudo R^2 = 0.668 LogL = -121.34		