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Diego Comin
Bart Hobijn
Emilie Rovito

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Cambridge, MA 02138
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Correspondence to: Diego Comin, Department of Economics, New York University, 269 Mercer Street, 7th Floor, New York, NY 10003. E-mail: diego.comin@nyu.edu. The views in this paper solely reflect those of the authors and not necessarily those of the Federal Reserve Bank of New York, nor those of the Federal System as a whole. We would like to thank Erick Gong and Ana Maria Santacreu for their execellent research assistance. This project has benefitted from the interaction with Fernando Alvarez, Robert Barro, Jess Benhabib, John Coleman, Boyan Jovanovic, Sam Kortum, Greg Mankiw and Ed Prescott. We also appreciate the financial assistance of the NSF (Grant # SES-0517910) and of the C.V. Starr Center for Applied Economics. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

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ABSTRACT

This paper presents a new data set on the diffusion of about 115 technologies in over 150 countries over the last 200 years. We use this comprehensive data set to uncover general patterns of technology diffusion. Our main 5 findings are as follows: (i) Once the intensive margin is measured, technologies do not diffuse in a logistic way. (ii) Within a typical technology, the dispersion in the adoption levels across countries is about 5 times larger than the cross-country dispersion in income per capita. (iii) The rankings of countries by level of technology adoption are very highly correlated across technologies. (iv) Within a typical technology, there has been convergence at an average rate of 4 percent per year. (v) The speed of convergence for technologies developed since 1925 has been three times higher than the speed of convergence for technologies developed before 1925.

Diego Comin
Department of Economics
New York University
269 Mercer Street, 72
New York, NY 10003
and NBER
diego.comin@nyu.edu

Bart Hobijn
bart.hobijn@ny.frb.org

Emilie Rovito
emilie.rovito@ny.frb.org

Technology plays a central role in macroeconomics and in economic development. Real business cycle theory places technology at the root of economic fluctuations (Kydland and Prescott [1982]). Growth theory has long postulated that improvements in technology are the source of long-run growth (Solow [1956], Romer [1990] and Aghion and Howitt [1992]) and that differences in technology are the main determinant of income per capita differences across countries (Klenow and Rodriguez-Clare [1997] and Hsieh and Klenow [2003]).

To test these and other assertions of macro theory it is quite important to have direct measures of technology; however, current measures of technology are not completely satisfactory.

The Solow residual, the most commonly applied measure of technology, has been criticized because, in addition to technology, it also captures the variation in capacity utilization (Basu [1995]), labor hoarding (Burnside et al. [1995]), and the inefficiencies of the economy (Weil [2005] ch.10).

A more direct way of measuring technology involves measuring the share of potential adopters that have adopted a given technology at a point in time (Griliches [1957], Mansfield [1961], Gort and Klepper [1982], and Skinner and Staiger [2005]). This approach has two drawbacks. First, while this measure captures the extensive margin of technology adoption, it neglects the intensive margin (i.e. how intensively each potential adopter uses the technology). Second, it is complicated to measure the number of potential adopters. As a result, the diffusion of only a limited number of technologies can be documented using such measures.

This paper has two goals. First, it presents a new data set on direct measures of technology adoption. Since technology is often embodied in capital goods, many of our measures correspond to the number of specific capital goods per capita. We measure computers and telephones in this way. Other technologies take the form of new production techniques. In these cases we can measure the diffusion of the technology either by the share of output produced with the technique (i.e. share of steel produced with blast oxygen furnaces) or directly by the technique's level of diffusion (i.e. number of credit and debit card transactions or cheques issued, both on per capita basis).

Our Cross-Country Historical Adoption of Technology (CHAT) data set covers the diffusion of about 115 technologies in over 150 countries during the last 200 years. These technologies cover most sectors of economic activity.

Since we measure technology directly, our measures are not subject to the type of criticisms raised against the Solow residual. Furthermore, as in Comin and Hobijn [2004], our measures of technology capture both the extensive and the intensive margins of diffusion.

Besides presenting the data set, the second goal of this paper is to uncover general characteristics of technology adoption patterns both across countries and over time. We start this search by providing a number of illustrative examples taken from the CHAT data set. However, because of the large number of technologies and countries in the dataset, merely presenting the data does not allow us to extract common patterns more formally. We overcome this complication by using simple summary statistics to document a set of general patterns in the international diffusion of technology.

Five facts emerge from this exploration.

First, once the intensive margin is taken into account, the evolution of the level of the technology in the country does not typically follow an S-shaped pattern.

Second, the cross-country dispersion of the level of technology is much larger than the dispersion of income per capita. On average, the dispersion of technology per capita is between *3* and *5* times larger than the dispersion of income per capita, and for *68* percent of the technologies the cross-country dispersion of the technology level is larger than the dispersion of income per capita.

Third, there are universal leaders and universal followers in technology among the countries in the world. That is, the rankings of countries according to the technology adoption level in a given year are highly correlated across technologies. The median correlation is *0.78*. Among OECD countries, the universality of technological leadership is weaker. The median correlation of country rankings across technologies within the OECD is *0.54*.

Fourth, there is absolute convergence in *91* percent of the technologies of our CHAT data set. The average speed of convergence is *3.7* percent per year. Thus, half of the distance to the steady state is covered in *19* years.

Fifth, the speed of convergence of technology across countries has accelerated over time. The median speed of convergence for technologies invented before 1925 has been about *2* percent per year. The median speed of convergence for technologies invented between 1925 and 1950 has been *5.5* percent per year, and, for the technologies invented since 1950, the median speed of convergence has been about *6* percent per year.

The rest of the paper is structured as follows. The next section discusses the various conceptual and practical issues of measuring technology. Section 2 presents the illustrative examples of several diffusion curves that we use to point out the general patterns documented in the subsequent sections. Section 3 explores the shape of diffusion curves for each country-technology pair and shows that S-shaped diffusion is only applicable for a limited set of technologies. Section 4 studies the cross-country dispersion of technology levels and compares it to the cross-country dispersion of income per capita. Section 5 examines the rankings of countries by level of adoption to see whether some countries tend to lead in all technologies or lead in some and trail in others. Section 6 looks at the cross-country convergence of technology and the evolution of the speed of convergence over time. Section 7 concludes.

1. Measurement

According to the Merriam-Webster's Collegiate Dictionary, technology is

"a manner of accomplishing a task especially using technical processes, methods, or knowledge"

Next we discuss various conceptual and practical issues that arise when attempting to measure technology levels.

1.a Conceptual issues

One approach to measuring technology diffusion, used in Griliches [1957] and Mansfield [1961], assumes that the adoption of technologies is a binary decision; producers or consumers can either adopt a technology or not adopt it. The ratio of the number of users of the technology to the number of potential users measures this extensive margin.

For some technologies, however, the intensive margin may be as relevant as the extensive. For example, in transportation technologies, the improvement in productivity is proportional to the frequency of use, not to whether the technology is used at all; for computers and cars it is not unreasonable to think that, in the long run, each potential adopter may adopt more than one unit of the good. Similarly, technological change in cotton spinning has been directed toward increasing the number of spindles that each worker can operate simultaneously. Thus, we consider it necessary to incorporate the intensive margin into measurement of technology diffusion. By doing that, we may be studying a different phenomenon than what the diffusion literature has previously explored, and some new terminology might be necessary. Conversely, one may think that technologies also diffuse along the intensive margin and employing the traditional terminology to refer to more comprehensive measures of the adoption of technologies may be appropriate. This latter opinion is our view on the matter, and, in the rest of the paper, we continue to talk about technology diffusion as encompassing both the intensive and the extensive margins.

To capture the intensive margin, we use measures of technology for which the numerator depends on the intensity with which each producer or consumer adopts the technology. For example, the diffusion of credit and debit cards is measured by the number of credit and debit card transactions per capita or by the number of points of service per capita, instead of by the share of people that has at least one credit card. This latter measure would capture only the extensive margin.

A second important issue concerns the heterogeneity of units in our multiple measures of technology. We remove units from our measures either by taking logs (i.e. log of number of MRI units per capita) or by looking at shares (i.e. share of farmland that uses high yield varieties).

The problem of units, however, does not fully address the larger question of how to measure technology, which can enter the economy in many forms and often cannot be separated from other inputs to production. Many new technologies are embodied in new capital. Their degree of adoption is therefore proportional to the amount of the existent capital in which they are embodied. Thus, it can be difficult to determine if cross-country differences in these technologies are due to cross-country variation in aggregate capital per capita or in the degree of adoption of technologies. We answer this question by comparing the cross-country dispersion in our measures of embodied technology to the cross-country dispersion in aggregate capital per capita. The differential in the dispersion of embodied technologies over the dispersion in aggregate capital per capita is due to the dispersion in technology.

One of the well-known Kaldor facts is that the capital-output ratio is roughly constant across countries. This implies that the cross-country dispersion in aggregate capital per capita is similar to the cross-country dispersion in income per capita. Based on this, we take the dispersion in income per capita as the benchmark for the embodied measures of technologies.

Not all of our technologies are measured with capital per capita; some are measured by the capital or output share associated to a new technology. These measures capture the diffusion of a particular production process or technique. Since the diffusion of these technologies typically involves capital substitution, it should not lead to capital deepening. The share of spindles that are ring or the share of steel produced with open hearth furnaces should thus be immune to variation in capital per worker. For these technological measures, the observed cross-country variation reflect only cross-country differences in technology.

Another potentially interesting distinction is between technologies exclusively used for production and those also used by consumers. It may be argued that the latter are less interesting because home production output and consumer's utility are left largely outside national accounting. Many technologies described as consumer technologies, however, including cell phones and cars, are important in the production of some services. In addition, since we have only about 13 technologies that are used primarily by consumers in our data set, the effect of their inclusion in our analysis will be small.

Finally, after analyzing each individual technology, we need to aggregate the results. One way to aggregate over technologies is to use the GDP share of each technology's sector. However, this approach presents two problems. First, we do not have a time series on sectoral shares for all countries in the data set. Second, these weights will depend on the level of aggregation used when assigning technologies to sectors. To avoid these complications, we restrict our analysis to technologies that have a significant effect in the sector and report both means and medians of the distribution of statistics by technology.

1.b Practical issues

To make cross-country and time-series comparisons of the level of technology, the objects measured must be as homogenous as possible. We try to mitigate this problem by measuring precisely defined technologies. In some cases, such as credit and debit card transactions or tons of steel produced with Bessemer furnaces, the measure of technology is relatively homogenous both over time and across countries. In others, such as cars, there are important differences in the quality of the object measured over time and across countries. One factor that moderates in part the differences in quality is the positive correlation between demand and the quality of a technology. As a result, our quantity measures of technology partially reflect the cross-country and time-series variation in the quality of technologies.

In order to be useful for inferring general patterns of technology diffusion, the data set must be comprehensive in at least three dimensions. First, it must contain information on technologies that span the most relevant sectors of economic activity. Second, it is important that the list of technologies covers production activities within sectors densely. Given the micro nature of our technologies, individual technologies may not be representative of the technological state of the sector; we have thus included multiple measures of technology for each sector. Third, the data set must cover both advanced and developing countries in significant numbers. This diversity overcomes the sample selection bias that may arise when focusing on a sample of developed countries (DeLong [1988]).

The final practical concern is that the measures of technology sought must be easy to find. One of the main drawbacks of the traditional measures of the diffusion literature is that, in the last 50 years, researchers have been able to document the diffusion of a relatively small number of technologies in a few countries; measuring the number of producers that use a particular technology or the number of producers that potentially could requires micro-level data that is difficult to find. It is therefore important that we are able to compute our measures of diffusion using aggregate national data instead of information at the plant or producer level.

1.c The CHAT Data Set

The Cross-Country Historical Adoption of Technology data set is an unbalanced panel with information on the diffusion of about 115 technologies in over 150 countries during the last 200 years. Table A1 (in the appendix) describes for each country the number of technologies for which we have data that span at least three five-year periods. The average number of technologies per country is about *34*, while the median is *28*. Table 1 describes the geographic distribution of the countries in our sample and the distribution of the number of technologies (that span at least three consecutive five-year periods) for countries in each continent. One interesting feature of the data set is that even in continents that have predominantly low income countries, such as Africa, the number of technologies in the typical country is fairly large. In this respect, the CHAT data set improves on previous data sets on technology diffusion, including the HCCTAD, which was presented in Comin and Hobijn [2004] and covered the diffusion of 25 technologies in 23 developed economies.

In addition to covering the countries in the world evenly, a comprehensive data set on technology diffusion must also represent the various sectors in the economy. Table 2 describes the number of technologies covered by the CHAT data set in each of 8 major sectors in which the technologies are primarily used. These are agriculture, finance, health, steel, telecommunications, textiles, tourism, and transportation. Three of our technologies, namely electricity production, the number of computers, and the number of internet users, are used across the economy. They represent general purpose technologies and thus defy categorization by sector; we place them in a separate group.

The first observation from Table 2 is that the data set covers eight sectors that represent a majority of GDP in most of the countries. In the U.S., for example, the sectors covered by the data set represented approximately 55 percent of the value added in the private sector in 2000.

In addition, the data set covers a substantial number of technologies in each of the sectors. These range from 2 technologies in tourism to 49 in health. Along this dimension, the CHAT data set also constitutes a substantial improvement over the HCCTAD, which does not contain information on the technologies in agriculture, finance, health, and tourism and has only 25 technologies, instead of about 115.

2. Illustrative examples

Before exploring the general patterns of technology diffusion, it is useful to consider some specific examples. This will enable us to illustrate the general patterns uncovered in the sections that follow.

One of the main conclusions from the empirical literature on technology diffusion has been that S-shaped curves, such as the logistic, provide a good approximation to the diffusion of technologies. In Figure 1 we present one technology, the share of modern varieties in the total area cultivated, that diffuses approximately in an S-shaped manner. It reflects the extensive margin with which modern variety agricultural technologies are used.

However, for technologies for which the intensive margin is more relevant, S-shaped curves do not appear to provide a good fit for diffusion patterns. This is the case, for example, in Figures 2 and 3, which cover the diffusion of planes and cars, respectively. More specifically, Figure 2 plots the (log of the) passenger-kilometers traveled by plane per capita, while Figure 3 plots the (log of) cars per capita.

Another a striking feature of these figures is the large cross-country dispersion present in diffusion. The number of per capita aviation passenger-kilometers traveled in the U.S. in 1960 was *400* times larger than in China and almost *150* times larger than in India in the same year. The number of cars per capita in the U.S. in 1960 was *400* times larger than in India and, as late as 2000, it was about *50* times larger than in China or India. These disparities are very big when compared to the large gap in income per capita between the U.S. and China and India (a factor of about 20). Moreover, they do not reflect the quality differential between cars in the U.S. and cars in China or India.

The large disparity in technology diffusion across countries is ubiquitous across sectors. Figure 4 illustrates this point with the (log of) kilowatts of electricity produced per capita.

A complementary way to address this issue is to measure how many years it took country B to reach the level country A had in year Y. Answering this question is only possible with a long time series. Data this extensive is often not available. For the case of telephones, however, we have sufficient data to measure the cross-country technological distance in time. As illustrated in Figure 5, the distances are fairly large and vary substantially across countries. For example, the level of phones per capita in the U.S. had in 1910 was reached by France *45* years later, by South Africa *55* years later, by Brazil *65* years later, by China more than *80* years later, and by India *90* years later; Tanzania still has fewer phones per capita than the U.S. in 1910.

Interestingly, this enormous dispersion in technology diffusion is also present within advanced economies. Figures 6, 7 and 8 display the diffusion of technologies in the service sector. Figures 6 and 7 depict the diffusion of magnetic resonance imaging (MRI) and computer-assisted tomography (CAT) scanners, respectively, by looking at the log of units per capita. Figure 8 covers the diffusion of a technology in the financial sector, namely the log of the number of credit and debit card payments per capita.

The multidimensional nature of technology implies that for the large cross-country differences in technology adoption to lead to large cross-country differences in the overall technological level, the relative position of countries in technology adoption must be highly correlated across technologies. In other words, there must be universal technology leaders and universal followers across technologies. Figures 2 through 5 support the consistency in technological leadership from a worldwide perspective.

Figures 6 through 8 demonstrate that, within the OECD, country rankings in technology adoption are less correlated across technologies.

After studying the distribution of technology adoption levels in the cross-section, it is interesting to explore its dynamics. In particular, we can investigate whether the differences in the speed of technology adoption across countries decline over time. Figure 9 presents the diffusion of cell phones. The gap between the U.S. and China in the number of cell phones per capita has reduced from a factor of about 1100 in 1990 to about 7 in 2000. This convergence in the technology adoption levels is also evident in most of the other technologies whose diffusion curves we have presented so far.

Because of the multidimensional nature of technology, however, we can look for a new notion of convergence that does not arise in one-dimensional variables such as income per capita. We can examine whether the speed with which followers catch up to the technological leaders has accelerated for recent technologies relative to technologies that were invented earlier. Figures 10 and 11 represent the diffusion of computers and the internet, respectively. The diffusion of these technologies in the U.S. in 1990 was, respectively, 490 and 13,000 times more extensive than in China, while in 2000 the gap was reduced by a factor of 14 for computers and to a factor of 480 for the internet. In earlier technologies, such as automobiles or electricity, the diffusion of these technologies in the U.S. in 1990 was 20 and 400 times more extensive than in China. By 2000, this gap was reduced by a factor of 7 and 8, respectively. These illustrative examples suggest that the convergence within newer technologies is faster than within older technologies.

Next, we go beyond these illustrative examples to show that the basic observations presented in this section constitute robust facts about the general diffusion patterns of the CHAT data set.

3. Diffusion Curves are not Logistic

At least since Griliches [1957], economists have acknowledged the good approximation that S-shaped curves, such as the logistic, provide to the process of technology diffusion as measured by the extensive margin. The logistic curve is defined by

$$Y_t = \frac{\delta_1}{\left[1 - e^{-(\delta_2 + \delta_3 t)}\right]} \tag{1}$$

where *t* represents time, in our case measured in years, δ_3 reflects the speed of adoption, δ_2 is a constant of integration that positions the curve on the time scale, and δ_1 is the long-run outcome, i.e. the limit of Y_t for *t* going to infinity.

Several features of this curve are relevant. First of all, it asymptotes to *0* when *t* goes to minus infinity and to δ_1 when *t* goes to infinity. Secondly, it is symmetric around the inflection point of $Y_t=0.5\delta_1$ which occurs at $t=-\delta_2/\delta_3$. Finally, the one percent diffusion point (i.e. the time in which $Y_t=0.01\delta_1$) is given by $t=(-ln(0.99)-\delta_2)/\delta_3$. On account of its good fit when the extensive margin of adoption is measured, the logistic has often been used to reduce the process of technology diffusion to the three parameters that define it, namely δ_1, δ_2, and δ_3.

The first question that we investigate is whether this approximation of a country's technology diffusion still provides a reasonable approximation once the measure of technology diffusion incorporates the intensive margin. To answer this question we fit a logistic curve to each of the 5700 technology-country pairs and explore the implications of the estimates. Specifically, let Y_{ijt} be the level of technology *i* in country *j* at time *t*. The curve we fit is as follows:

$$Y_{ijt} = \delta_{1ij} / [1 + e^{(-\delta_{2ij} - \delta_{3ij} t)}] + \varepsilon_{ijt} \text{ where } \varepsilon_{ijt} \sim N\left(0, \sigma_{ij}^2\right) \tag{2}$$

We first find that, for *23* percent of the technology-country combinations, it is not possible to fit logistic to the diffusion curves, likely because of the data's lack of curvature. When the diffusion line does not have sufficient curvature, the log-likelihood function is flat for many parameter configurations, and it is therefore not possible to determine the parameter configuration that maximizes the log-likelihood function. In these circumstances, we cannot identify the parameters that govern the curvature of the logistic. We take this as an indication that the logistic provides a poor approximation to the diffusion of technology i in country j.

When the estimation converges, the R^2 tends to be very high. In particular, conditional on obtaining an estimate, the R^2 is above *.90* for *92* percent of the technology-country pairs.

The R^2 is not a good measure of fit for logistic curves. It is well known that, since both the fitted logistic curves and the data contain trends, the high R^2s reflect the fit of this trend and not of the fluctuations around it. Therefore, for a better sense of the appropriateness of the logistic approximation, we have to go beyond the R^2.

In particular, we explore how the data conforms to three properties of the logistic. First, logistic curves increase monotonically from the introduction of the technology to a ceiling. This implies that the estimate of δ_{3ij} should be positive. This is the case for a majority of technology-country pairs, but a substantial number of pairs (*929* out of *4381*) have a negative estimate of δ_{3ij}. In some instances, such as open hearth steel production or the number of mule spindles, the negative estimate of δ_{3ij} results from the partial or complete replacement of the technology by a better technology. The replacement of a dominated technology may, of course, be consistent with a logistic diffusion.

In other cases, however, the negative estimate of δ_{3ij} does not result from the replacement of the technology but simply from the fact that the use of technology is growing at a lower rate than the population. The example of cars in Tanzania illustrated in Figure 3 provides a good example of this phenomenon. These cases contradict the hypothesis of logistic diffusion.

In order to precisely identify cases that violate this property of logistic diffusion, we would have to examine each of the *929* pairs individually. This would involve an, in large part, arbitrary classification of our results. However, we can make a conservative estimate of the number of technology-country pairs for which the negative estimate of δ_{3ij} does not result from the substitution by a superior technology. Since the relative productivity of two competing technologies is likely to be similar across countries, the introduction of a superior technology will likely induce the eventual replacement of the original technology in all countries and will thus produce negative estimates of δ_{3ij} for a majority of countries. Therefore, we can use the fraction of negative estimates of δ_{3ij} to guide our judgments.

For *17* out of *116* technologies in CHAT, at least *50* percent of the countries have negative estimates for δ_{3ij}. As expected, the technologies include measures such as open hearth and Bessemer steel production and the number of sail ships, hospital beds, and cheques, all of which have been recently dominated by another technology. In addition, only a few technologies with a high prevalence of countries with negative estimates of δ_{3ij}., such as pesticide usage and the number of varicose vein correction procedures, clearly have no superior technology. Meanwhile, the list of technologies that do not have a majority of negative estimates of δ_{3ij} includes a few technologies, such as the number of telegrams sent, that have been dominated in some countries. Using the *50* percent cutoff as a general guide for selecting non-dominated technologies, we find that *462* of the *929* technology-country pairs with a negative estimate of δ_{3ij} violate one of the assumptions of logistic diffusion by not increasing monotonically to a ceiling (Table 3, row 4).[1]

[1] From this point forward, we consider only technologies with positive curvature parameters.

Next, we explore the predicted initial adoption dates to detect further issues with the logistic approach. To determine predicted initial adoption dates, we use our estimates of equation (2) to find the predicted time at which *1* percent of the estimated ceiling adoption level was reached. Then, we compare these to each technology's invention date. Figures 12 and 13 plot these predicted adoption dates and actual invention dates for every technology-country pair[2]. Figure 13 zooms in Figure 12 and only shows the technologies invented during the last 200 years.

Two types of red flags emerge from these figures. For *210* of the technology-country pairs for which we have a positive estimate of the slope, the predicted initial date of diffusion is prior to the invention date of the technology. For some technologies for which we do not have an invention date, such as hospital beds or irrigation, it is harder to determine precisely when a predicted initial adoption date is too early to be reasonable. Even after taking this fact into consideration, however, the estimated initial adoption dates are still implausibly early for some countries. Taking a conservative invention date of 1000BC, we find an additional *14* technology-country pairs with implausibly early predicted adoption dates.

These implausible estimates reflect the fact that the diffusion of the technology does not follow a logistic pattern in these countries. More precisely, it likely happens because the identified diffusion curves are concave. When fitting a logistic to a curve that is concave, the steeper region of the curve will be fit near to inflexion point of the logistic, and, as a result, the predicted *1* percent adoption level will occur much earlier than the actual one. This can be seen in Figure 14, which presents the actual diffusion of televisions in Sweden (in solid) and the diffusion predicted by fitting a logistic (in dash).

The opposite situation, an unrealistically late predicted initial adoption date, also suggests the failure of the logistic approximation. Technically, this may occur for two different reasons. First, the diffusion

[2] For clarity we have not included in the plots the technologies already available in 1500. The invention date of these technologies is more difficult to establish.

data for the technology may be relatively flat initially with a slight acceleration at the end of the sample. The logistic interprets this acceleration as indication that the inflexion point has not yet been reached and places the predicted initial adoption date close to the first available observation; in some cases, the first observation in our data set may correspond to a date posterior to the invention. Figure 15 illustrates this argument with the diffusion of cars in Taiwan. Second, the logistic may predict an unrealistically late initial adoption date if the first observation in sample is significantly later than the invention date and if the slope of the diffusion data's curve is initially steep before flattening. As illustrated with the diffusion of newspapers in Germany in Figure 16, the logistic fits the first observation near to the inflexion point. Since the curve is initially very steep, the predicted initial adoption date is close to the first observation. In reality, however, diffusion has not occurred symmetrically, and it has taken many years to reach the level at which our sample starts. In addition, the initial level in sample is substantially higher than one percent of the "estimated ceiling". As a result, the logistic predicts that the one percent adoption level is reached close to the beginning of sample, while, in reality, that level was reached long before.

The identification of these cases is a bit arbitrary since, as we have seen in Figure 5, some countries tend to lag the technological leaders for as long as a century. Given that the existence of data for a technology implies that diffusion has begun, we assume that the *1* percent level must be reached soon after our initial observation. We will assume that the initial adoption date predicted by the logistic is unreasonably late if either it is at least *150* years after the invention date or at least *20* years after the first observation we have in sample for the pair.[3] We find *294* additional technology-country pairs are poorly approximated by the logistic in this respect (Table 3, row 5).

[3] We omit the technologies without precise invention dates when identifying cases in which initial adoption falls more than 150 years after the invention date.

One final, critical property of S-shaped diffusion curves is that their convergence to a fixed ceiling. Once the intensive margin is included, this condition no longer necessarily holds. Indeed, based on the plots in Figures 2, 4, 5, 8, and 9, we can see that technological measures such as aviation passenger-kilometers, electricity, telephones, credit and debit card payments, and cell phones violate this property. However, as with the share of negative estimates of δ_{3ij}, it is not trivial to determine exactly how many of our technology-country pairs have a moving ceiling. However, it seems reasonable to attempt to identify technologies that clearly fit this profile. To the list above we can conservatively add steam and motor ship tonnage; rail passengers-kilometers; railway freight tonnage; tons of blast-oxygen furnace, electric-arc furnace, and stainless steel produced; cars; trucks; aviation freight ton-kilometers; TVs; PCs; credit and debit card points of service; ATMs; and cheques, all in per capita terms. The variable ceiling that characterizes a priori the diffusion of these technologies generates *1171* additional deviations from the logistic pattern (row 6 in Table 3). This brings the total number of technology-country pairs for which the diffusion is not well characterized by the logistic to *3507* out of the *5700* technology-country pairs in our sample. Hence, we conclude with the first finding of our analysis.

> *Fact 1: Once the intensive margin is included in the measure of technology diffusion, the S-shaped curves, and in particular the logistic, provide a poor description of the diffusion process.*

4. Cross-country Dispersion in Technology

One important rationale for looking directly at technology is to assess the role of technological differences as a determinant of the cross-country dispersion in income per capita. If technology is an important driving force of differences in standards of living, observed cross-country disparities in technology must be large. To explore whether this is the case, for each technology and year, we compute the dispersion of the technology levels across countries and compare it to the dispersion of income per capita for the same groups of countries.

This analysis requires that our dispersion statistics are unaffected by the units of the technology measures. We achieve this in two ways. First, we express the differences in technology adoption levels in log per capita terms, which do not depend on units of measurement; therefore, we measure their dispersion with the cross-country variance. For the technologies measured as shares, we compute dispersion with the coefficient of variation. Then we compare the cross-country dispersion of each technology with the cross-country dispersion of either the log of income per capita (for log per capita technologies) or income per capita (for shares) across the same set of countries. This results in one ratio of dispersion measure for each technology for each five-year period. We aggregate all this information across technologies both weighted by the length of our time series (measured by the number of five-year periods for which we have data) and un-weighted.

Table 4 reports the average ratio of cross-country dispersion of technology over the cross-country dispersion of income per capita. To have a better sense of the distribution of these ratios, Table 4 also reports the percentage of cases in which the cross-country dispersion in technology is larger than the cross-country dispersion in income per capita.

The main conclusion from this analysis is that cross-country differences in the adoption of technologies are much larger than income per capita differences. The ratio of the variances is on average *5* when we weight technologies by the length of their time series and *3* when we do not weight. It is not merely a few outliers driving this large dispersion; for *76* percent of the technology-periods the cross-country dispersion in technology adoption is larger than the dispersion in income per capita. When giving equal weights to the technologies, we still find that the cross-country dispersion is larger than the dispersion in income per capita in 68 percent of the technologies.

We do observe that the cross-country dispersion in the *13* consumer technologies in CHAT is larger than for the rest of log-per capita technologies. In particular, the un-weighted average of the ratio of the dispersion of consumer technologies to the dispersion in log income per capita is slightly below *7*; when weighted by the length of series, the ratio is *9.8*.

Finally, the cross-country dispersion of technology relative to income per capita seems to be smaller for technologies measured as shares than for technologies measured in log per capita terms. However, even in the former, cross-country dispersion in technology adoption is comparable to the cross-country dispersion in income per capita.

Based on these facts, we summarize the main conclusion from our exploration of the cross-country variation in technology adoption and income.

> *Fact 2: The cross-country dispersion in technology adoption for individual technologies is 3 to 5 times larger than cross-country dispersion in income per capita.*

5. Universal Technology Leaders

The multidimensional nature of technology makes it possible to understand the correlation of relative positions of countries across technologies. This is relevant for two reasons. First, given the large observed cross-country dispersion in individual technology adoption (Fact 2), a high correlation of rankings across technologies implies that there are big cross-country differences in aggregate technology levels. Second, as we shall see in the next section, the persistence of country rankings across technologies in the initial stages of adoption may have important consequences for the dynamics of the cross-country distribution of overall technology levels.

One practical problem with considering a country's percentile at a point in time stems from the way that relative position depends on the country coverage of the data set for that technology and period; variation in the country coverage may significantly distort the rankings of countries. We mitigate this potential problem in two ways. First, we conduct two separate analyses, one using only OECD countries and the other using only technologies that cover both OECD and non-OECD countries.. With this strategy, we lessen the effect of variation in the mix of rich and poor countries in the sample when assigning rankings. In addition, we also remove from our analysis the technology-periods for which we have very few countries in sample. This reduces the volatility of rankings of countries in the initial stages of diffusion when the data set includes only a few countries.[4]

To compute the correlations between country rankings in a technology and country rankings across technologies we proceed as follows: First, we assign each country (*j*) to a percentile for each technology (*i*) and 5-year period (*t*). Let's denote this percentile by r_{ijt}. Then, we compute the average ranking across technologies for each country and year, r_{jt}. Formally,

$$r_{jt} = \frac{\sum_{i=1}^{N_{jt}} r_{ijt}}{N_{jt}} , \tag{3}$$

where N_{jt} denotes the number of technologies for country *j* in period *t*. Finally, we compute the cross-country correlation between the vector of rankings in the technology (r_{ijt}) and the vector of average country rankings across technologies (r_{jt}) for year *t*. This generates a correlation for each technology and (5-year) time period. To aggregate this information we compute the average and median of these cross-country correlations. These are reported in Table 5 both for the sub-sample of technologies that have an even coverage of the countries in the world and for the OECD sub-sample.

[4] For OECD technologies we require at least 3 countries in sample to consider the correlation. For technologies that cover both OECD and non-OECD countries we require a minimum of 6 countries.

The correlations of rankings across technologies are fairly high. For the technologies that cover both OECD and non-OECD countries the average correlation is *67* percent, while the median is *78* percent. When we restrict attention to the OECD, the correlations remain high but are significantly lower than when all the countries are included. Within the OECD sample, the average correlation of technology rankings is *45* percent, while the median is *54* percent. Therefore, we conclude that, from a global perspective, there are universal technological leaders and universal followers.

> *Fact 3: The relative position of countries according to the degree of technology adoption is very highly correlated across technologies. This correlation declines significantly within the OECD.*

6. Convergence

After exploring the properties of the cross-sectional distribution of technologies, we turn our attention to the dynamics of the distribution. More specifically, we address the issue of convergence in technology levels across countries. The convergence of income per capita levels across countries has attracted much attention (Baumol [1986], DeLong [1988], Mankiw et al. [1992], Barro and Sala-i-Martin [1992]).[5] Because technology is an important determinant of income per capita differences, the issue of technological convergence is of equal interest.

One important difference from the literature on the convergence of income per capita stems from the multidimensional nature of technology. This introduces the distinction between convergence within a technology and convergence across technologies. That is, even if countries that start behind catch up with leaders within each technology, the overall technology level of less advanced countries may not be converging if less advanced countries similarly start behind in the new technologies. We proceed next to explore the convergence first within and then across technologies.

6.a Within Technologies

We follow the example of the convergence of income per capita literature and estimate both measures of absolute *β*-convergence and *σ*-convergence. We estimate the speed of *β*-convergence of technology *i* by running the following regression for technologies measured in log-per-capita terms:

$$\ln(Y_{ij,t}) - \ln(Y_{ij,t-1}) = \alpha - (1 - e^{-\beta_j})\ln(Y_{ij,t-1}) + u_{ij,t} \tag{4}$$

while for technologies measured as shares we estimate *β*-convergence from:

$$y_{ij,t} - y_{ij,t-1} = \alpha - (1 - e^{-\beta_j})y_{ij,t-1} + u_{ij,t} \tag{5}$$

Figures 17 and 18 display the distributions of *β* separately for the technologies measured in logs per capita and those measured as shares. Table 6 reports the mean and median speed of convergence for each type of technology. For both types of technologies combined, the average speed of convergence has been *3.8* percent per year, while the median has been *2.6* percent per year. We observe *β*-convergence in *93* percent of the log-per-capita measures and *83* percent of the technologies measured as shares. The distributions of speeds of convergence are fairly similar for each type of measure. The average speed of convergence is slightly higher for log-per-capita than for share variables, but the way the technology adoption level is measured does not seem to be relevant when studying the convergence properties of technology. For the small subset of consumer technologies, meanwhile, the average speed of convergence is slightly smaller than for the overall group of log-per-capita technologies (2.7 vs. 4.1 percent per year).

The absolute convergence within technologies contrasts with the established lack of convergence in income per capita on the global level. Within the OECD, however, it is well established that income per capita levels converge. The dichotomy in income per capita level convergence makes one wonder if the

[5] Furthermore, in principle, one can explore the convergence of any variable. Comin [1997] and Hobijn and Franses [2001], for example, explore whether there is convergence in alternative indicators of standards of living, like life expectancy and mortality.

within-technology convergence comes only from OECD countries converging to the technological leader. To answer this question we analyze the technologies for which we have data for both OECD and non-OECD countries. For these technologies we estimate the speed of convergence within the OECD and compare it to the speed of convergence worldwide. In Table 7 we observe that, for these technologies, the worldwide speed of convergence is on average *2.9* percent per year while within the OECD the average speed of convergence for these technologies is *1.9* percent per year. Hence, contrary to what we observe in income per capita, non-OECD countries converge to the adoption level of technological leaders faster than the technological laggards within the OECD.

σ-convergence provides an alternative way to describe the evolution of the cross-country distribution of technology over time. We estimate the speed of *σ*-convergence in technology *i*, $\beta_{\sigma i}$, by running the following regression:

$$\sigma_{j,t}^{2} = \alpha + e^{-2\beta_j} \sigma_{j,t-1}^{2} + u_{j,t} \qquad (6)$$

where σ^2_{jt} is the cross-country standard deviation of technology *j* at year *t*. To avoid the bias produced by the gradual inclusion of countries to the sample, we make sure that every year the cross-country measures of technology used as left and right-hand-side variables in regression (3) are computed over the same sample of countries. Columns 4 through 6 of Table 6 report the mean and median speeds of *σ*-convergence. The average of the technology speeds of convergence estimated from equation (3) is *7* percent per year, and the median speed of convergence is *4.1* percent per year. These estimates are *80* and *60* percent higher than the estimates obtained from the *β* speeds of convergence regression (2). Qualitatively, the *β* and *σ* estimates of the speed of convergence within a technology are consistent. Not only is the fraction of convergent technologies similar (*89* percent for *β* vs. *80* percent for *σ*), but also the *β* and *σ*-speeds of convergence are positively correlated across technologies (*42* percent for the *109* technologies for which *β* is smaller than *.5*).

The disparity in the average speed of β and σ convergence may be an indication that the system that governs the dynamics of technology diffusion has multiple state variables. In this case, the dynamics of the system would not be well approximated by only the current state of the specific technology. Our goal here, however, is to provide a statistical description of the dynamics of technology diffusion and not to interpret these estimates in a structural way.

Based on these results we reach the following conclusion.

> *Fact 4: There is convergence within technologies. The average speed of convergence is between 4 and 7 percent per year.*

6.b Across Technologies

The presence of cross-country convergence within technologies may not be sufficient to guarantee the convergence of overall technology levels. If new technologies arrive continuously and laggard countries tend to start behind in most new technologies, that effect will counterbalance the catch up that takes place within existing technologies. As a result, follower countries will not catch up in the overall technological level unless the speed of convergence within technologies accelerates over time. This situation is represented in Figures 19 and 20 in which we see the trajectories for a continuum of technologies in two countries (A, the leader, and B, the laggard). In Figure 19, the speed of convergence within each technology is constant, and, in this stationary world, the overall technological gap between A and B is also constant (see bottom panel). In Figure 20, the speed of diffusion of technologies in country B accelerates over time, which increases the speed of convergence within technologies and reduces the technological gap between A and B (see bottom panel).

To consider which of these situations provides a better characterization of global technology diffusion, we order the technologies in the CHAT data set by their date of invention and explore how the speed of convergence has evolved over time. For the purposes of brevity, we only report the results from this exercise using the β speed of convergence. The results for σ convergence are qualitatively very similar. Figure 21 presents the scatter plot of the speeds of convergence of our technologies and the evolution of the median speed of convergence for the technologies invented in each 25 year period. Table 8 reports the evolution of the average and median speed of convergence.

The first striking observation is that there has been a significant increase in the speed of convergence for technologies developed after 1925.[6] The average speed of convergence for technologies developed before 1925 is *2.4* percent per year, and the median speed of convergence is *2* percent. For the technologies developed after 1925 the mean and median speeds of convergence are, respectively, *6.7* and *5.9* percent per year. The average speed of convergence within technologies developed after 1925 has almost tripled in comparison to those developed before 1925.

By looking at the evolution of the average and median speed of convergence within technologies, it is also evident that the increase in the speed of convergence of post-1925 technologies resembles more a structural break than a smooth transition.[7] The average speed of convergence of technologies developed in the period 1900-1925 is approximately *1.5* percent per year, while the average speeds of convergence for technologies developed in the periods 1925-1950 and 1950-1975 are *5.8* and *7.8* percent per year, respectively.

However, before concluding that cross-country technology levels have converged faster for new than for old technologies, we must determine whether the acceleration of the speed of convergence is uniform across technologies or whether it is driven by the technologies that cover only OECD countries. Figure 22 answers this question by plotting the evolution of the median speed of

[6] Table A3 in the appendix details the speed of convergence for each technology together with the technology invention dates.

[7] The high average speed of convergence during the period 1850-1875 is driven entirely by acid Bessemer steel. If that technology is removed from the sample, the average speed of convergence for the technologies developed between 1850 and 1875 becomes *2.6* percent per year.

convergence for each 25-year period separating the technologies that cover only OECD economies from the rest. The increase in the median speed of convergence is evident for both groups of technologies; therefore, this suggests that the increase in the speed of convergence is present across OECD and non-OECD countries.

Thus, we conclude our analysis by stating the last finding.

> *Fact 5: The cross-country speed of convergence within technologies developed after 1925 is about three times higher than for the technologies developed before 1925.*

A corollary of Fact 4 and Fact 5 is that there seems to be evidence of absolute convergence in the overall technology levels across countries. This finding may seem to be at odds with the observed lack of absolute convergence in income per capita. However, it is consistent with the evolution of existing aggregate measures of technology. In particular, we have estimated a standard convergence regression (with no controls) on the productivity residuals that emerge from the development accounting exercise conducted by Klenow and Rodriguez-Clare [1997]. Using this very different measure of aggregate technology we also estimate a rapid speed of convergence (7 percent per year).

7. Conclusion

This paper has presented and begun to analyze a new data set that provides the most comprehensive coverage to date of technology diffusion over the last 200 years. Five facts emerge from this analysis. First, once the intensive margin is measured, technologies do not diffuse in a logistic way. Second, within a typical technology, the dispersion in the adoption levels across countries is about 5 times larger than the cross-country dispersion in income per capita. Third, there is a high correlation across technologies in the rankings of countries by technology adoption. Fourth, within a typical technology, there has been convergence at an average rate of 4 percent per year. Fifth, the speed of convergence for technologies developed since 1925 has been almost three times higher than the speed of convergence for technologies developed before 1925.

These facts are important in themselves. Our CHAT data set allows us to uncover direct evidence on relevant patterns in technology adoption that could not be explored using other data sets. In addition, these stylized facts provide guidance for the development of future theories on determinants of technology adoption.

We leave for future research the search for correlates of our technology measures that should provide a second set of binding constraints in the effort to uncover the determinants of the large cross-country differences in technology adoption. Candidate correlates are not only variables that have been suggested as determinants of income per capita, but also the intensity of other technologies that may complement or substitute the relevant technology.

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A. Underlying details

This appendix contains more detailed information about the CHAT data set and about the estimated rates of convergence presented in the main text. Tables A1, A2 and Figure A1 provide detailed information about the coverage of the data that we use, while table A3 contains details about the estimated rates of convergence.

Table A1 lists the number of technologies we have for each of the countries in the data set. In our analysis we have to deal both with country fragmentations and reunification processes. When a majority of the territory remains after the fragmentation or a majority of the unified territory corresponds to just one of the pre-unification countries we identify the unified country with the big part. In cases of country fragmentation, we have identified a successor country in cases where a large portion of the territory remains as a single country; in cases of unification, we have identified a precursor country in a similar manner. Thus, Russia and the U.S.S.R have been treated as one national entity, as have Germany and West Germany. In cases where a country divides into or merges from a number of more equal pieces, we have chosen to treat the whole and the parts as different countries. Examples of this approach include Yugoslavia, Czechoslovakia, and Korea.

Table A2 describes for each technology the number of countries, the type of economies, and the time period covered.

Table A3 presents the annual speed of β-convergence for each technology together with its invention date. Technologies invented prior to 1500 are usually difficult to date precisely, and we list them as pre-1500 technologies.

Table 1: Geographic Distribution of Sample Countries and Technologies

Region	Mean Technologies Per Country	Median Technologies Per Country	Standard Deviation of Technologies Per Country	Number of Countries
Total	34.2	28.0	20.37	159
Africa	24.9	26.0	9.00	48
Asia	28.9	26.5	12.51	44
Europe	49.3	41.5	28.23	38
North America	34.0	27.5	22.64	12
Oceania	43.3	44.0	21.09	4
South America	40.0	44.0	20.94	13

Table 2: Technology Sector Coverage

	Technologies Per Sector
Agriculture	8
Finance	5
General Purpose	3
Health	49
Steel	14
Telecommunications	8
Textiles	6
Tourism	2
Transportation	21

Table 3: Deviations from Logistic Diffusion

	Number of Technology-Country Pairs	Cumulative Failure of Logistic
Total Country -Technology Pairs	5700	
Flatness of Likelihood Surface	1319	1319
Negative Estimate of δ_3	462	1781
Too Early Predicted Adoption	224	2005
Too Late Predicted Adoption	331	2336
Growing Ceiling	1171	3507

Table 4: Dispersion in Technology Adoption Relative to Dispersion in Income per Capita

	Average Dispersion			Percentage of Instances with Ratios>1		
	Log Per Capita	Share	All	Log Per Capita	Share	All
Weighted by # of 5-Year Intervals	6.02	1.03	5.2	84	33	76
Un-Weighted	3.68	0.95	3.17	75	42	68

Table 5: Correlations Between Country Rankings in a Technology and Average Country Rankings across Technologies

	Technologies Covering All Countries	Technologies Covering OECD countries
Average Correlation	0.67	0.45
Median Correlation	0.78	0.54
Number of Technologies	51	115

Table 6: Speed of Convergence Within Technologies.

	β-convergence			σ-convergence		
	Log Per Capita	Shares	All	Log Per Capita	Shares	All
Average	0.041	0.027	0.038	0.071	0.068	0.07
Median	0.03	0.015	0.026	0.043	0.019	0.041
Number of technologies	89	23	112	91	24	115

Table 7: Speed of Convergence Worldwide and Within the OECD.

	β-convergence	
	All Countries	OECD
Average	0.029	0.019
Median	0.02	0.01

Note: Average and median speed of convergence over 55 technologies that cover both OECD and non-OECD countries

Table 8: Evolution of Speed of Convergence by Invention Date.

Inverval	Median	Mean
Up to 1800	0.020	0.025
		(0.015, 0.034)
1801-1825	0.004	0.011
		(-0.004, 0.026)
1826-1850	0.020	0.018
		(0.005, 0.03)
1851-1875	0.025	0.061
		(0.005, 0.118)
1876-1900	0.030	0.024
		(-0.005, 0.052)
1901-1925	0.015	0.002
		(-0.039, 0.042)
1926-1950	0.055	0.055
		(0.03, 0.079)
1951-1975	0.087	0.087
		(0.059, 0.115)
1976-2000	0.037	0.038
		(0.017, 0.06)

Table A1: Technologies Per Country

Afghanistan	16	Egypt	43	Lebanon	39	Saudi Arabia	34
Albania	21	El Salvador	34	Lesotho	16	Senegal	28
Algeria	44	Equatorial Guinea	9	Liberia	17	Serbia and Montenegro	18
Angola	26	Eritrea	3	Libya	28	Sierra Leone	21
Argentina	48	Estonia	20	Lithuania	19	Singapore	27
Armenia	14	Ethiopia	29	Luxembourg	10	Slovak Republic	39
Australia	68	Finland	95	Macedonia	16	Slovenia	22
Austria	70	France	82	Madagascar	29	Somalia	20
Azerbaijan	15	Gabon	20	Malawi	5	South Africa	44
Bangladesh	32	Gambia	18	Malaysia	37	South Korea	44
Belarus	16	Georgia	15	Mali	26	Spain	77
Belgium	78	Germany	87	Mauritania	22	Sri Lanka	37
Belize	4	Ghana	36	Mauritius	26	Sudan	29
Benin	26	Greece	61	Mexico	78	Suriname	4
Bolivia	29	Guatemala	27	Moldova	21	Swaziland	17
Bosnia-Herzegovina	17	Guinea	26	Mongolia	20	Sweden	83
Botswana	21	Guinea-Bissau	13	Morocco	36	Switzerland	59
Brazil	49	Guyana	20	Mozambique	24	Syria	33
Bulgaria	34	Haiti	17	Namibia	16	Taiwan	28
Burkina Faso	18	Honduras	29	Nepal	18	Tajikistan	13
Burma	34	Hong Kong	19	Netherlands	77	Tanzania	27
Burundi	20	Hungary	66	New Zealand	48	Thailand	40
Cambodia	27	Iceland	5	Nicaragua	28	Togo	27
Cameroon	29	India	50	Niger	19	Tunisia	34
Canada	77	Indonesia	39	Nigeria	37	Turkey	57
Central African Republic	20	Iran	41	North Korea	23	Turkmenistan	12
Chad	21	Iraq	34	Norway	65	Uganda	27
Chile	50	Ireland	81	Oman	21	Ukraine	24
China	49	Israel	38	Pakistan	42	United Arab Emirates	24
Colombia	45	Italy	75	Panama	27	United Kingdom	94
Costa Rica	26	Ivory Coast	31	Papua New Guinea	17	United States	80
Croatia	20	Japan	59	Paraguay	27	Uruguay	44
Cuba	40	Jordan	26	Peru	44	Uzbekistan	17
Czech Republic	39	Kazakhstan	17	Philippines	40	Venezuela	41
Czechoslovakia	36	Kenya	33	Poland	62	Vietnam	22
Dem. Rep. of the Congo	35	Korea	18	Portugal	82	Yemen	21
Denmark	84	Kuwait	25	Republic of the Congo	26	Yugoslavia	44
Dominican Republic	19	Kyrgyzstan	14	Romania	39	Zambia	28
East Germany	30	Laos	19	Russia	44	Zimbabwe	31
Ecuador	41	Latvia	22	Rwanda	16		

Table A2: Description of Technologies and their Coverage

Category	Variable Description	Number of Countries	Country Coverage	Date Range
Agriculture	Fertilizer consumed, total	149	all	1965 - 2005
	Harvesters	116	all	1965 - 2005
	Irrigated area	144	all	1965 - 2005
	Milking machines	53	all	1965 - 2005
	Percent of cultivated land using modern variety crops	85	developing	1960 - 2000
	Percent of irigated land out of cultivated land	148	all	1965 - 2005
	Pesticide consumed, total	120	all	1990 - 2000
	Tractors	149	all	1965 - 2005
Financial	ATMs	33	mostly OECD	1990 - 2005
	Cheques issued	39	mostly OECD	1990 - 2005
	Debit and credit card transactions	37	mostly OECD	1990 - 2005
	Electronic funds transfers	34	mostly OECD	1990 - 2005
	Points of service for debit/credit cards	35	mostly OECD	1990 - 2005
General	Electricity production	149	all	1895 - 2005
	Internet users	146	all	1990 - 2005
	Personal computers	129	all	1980 - 2005
Health	Appendectomies	19	OECD	1990 - 2005
	Beds: in-patient acute care	26	OECD	1960 - 2005
	Beds: in-patient long-term care	20	OECD	1960 - 2005
	Beds: total hospital	145	all	1960 - 2005
	Bone marrow transplants	25	OECD	1975 - 2005
	Breast conservation surgeries	13	OECD	1995 - 2005
	Caesarean sections	19	OECD	1990 - 2005
	Cardiac catheterisations	17	OECD	1990 - 2005
	Cataract surgeries	17	OECD	1980 - 2005
	Cholecystectomies	16	OECD	1980 - 2005
	Cholecystectomies, laparoscopic	10	OECD	1995 - 2005
	Computed tomography (CAT) scanners	27	OECD	1980 - 2005
	Coronary bypass procedures, in-patient	20	OECD	1980 - 2005
	Coronary bypasses	23	OECD	1990 - 2005
	Coronary interventions, percutaneous (PTCA and stenting)	24	OECD	1990 - 2005

Table A2 (continued): Description of Technologies and their Coverage

Category	Variable Description	Number of Countries	Country Coverage	Date Range
Health (ctd.)	Coronary stenting procedures	10	OECD	1995 - 2005
	Dialysis patients	27	OECD	1970 - 2005
	Dialysis patients, home	24	OECD	1970 - 2005
	Heart transplants	25	OECD	1980 - 2005
	Hernia procedures, inguinal and femoral	17	OECD	1980 - 2005
	Hip replacement surgeries	20	OECD	1990 - 2005
	Hysterectomies (vaginal only)	20	OECD	1990 - 2005
	Kidney transplants	27	OECD	1965 - 2005
	Kidney transplants, functioning	25	OECD	1970 - 2005
	Knee replacement surgeries	15	OECD	1990 - 2005
	Lithotriptors	23	OECD	1985 - 2005
	Liver transplants	27	OECD	1980 - 2005
	Lung transplants	22	OECD	1985 - 2005
	Mammographs	15	OECD	1970 - 2005
	Mastectomies	18	OECD	1990 - 2005
	MRI units	26	OECD	1985 - 2005
	Pacemaker surgical procedures	11	OECD	1990 - 2005
	Percent immunized for DPT, children 12-23 months	153	all	1980 - 2005
	Percent immunized for measles, children 12-23 months	153	all	1980 - 2005
	Percent of beds for acute care	21	OECD	1960 - 2005
	Percent of cataract surgeries done as day cases	14	OECD	1990 - 2005
	Percent of cholecystectomies (laparoscopic) done as day cases	9	OECD	1995 - 2005
	Percent of cholecystectomies done as day cases	11	OECD	1995 - 2005
	Percent of dialysis patients at home	25	OECD	1970 - 2005
	Percent of hernia procedures (inguinal and femoral) done as day cases	14	OECD	1995 - 2005
	Percent of renal failure patients, end stage	28	OECD	1970 - 2005
	Percent of tonsillectomies done as day cases	12	OECD	1995 - 2005
	Percent of varicose veins procedures done as day cases	14	OECD	1995 - 2005
	Prostatectomies (excluding transurethral)	14	OECD	1990 - 2005
	Prostatectomies (transurethral)	17	OECD	1990 - 2005

Table A2 (continued): Description of Technologies and their Coverage

Category	Variable Description	Number of Countries	Country Coverage	Date Range
Health (ctd.)	Radiation therapy equipment	24	OECD	1960 - 2005
	Renal failure patients, end stage	25	OECD	1970 - 2005
	Tonsillectomies	13	OECD	1980 - 2005
	Varicose vein procedures	12	OECD	1995 - 2005
Steel	Percent of steel production by other methods	23	all	1930 - 2005
	Percent of steel production by the acid bessemer method	11	all	1930 - 1975
	Percent of steel production by the basic bessemer method	9	all	1930 - 1980
	Percent of steel production in BOFs	58	all	1960 - 2005
	Percent of steel production in EAFs	95	all	1930 - 2005
	Percent of steel production in OHFs	53	all	1930 - 2005
	Percent of steel production that is stainless	24	all	1985 - 1990
	Stainless steel production	24	all	1985 - 1990
	Steel production by other methods	23	all	1930 - 2005
	Steel production by the acid bessemer method	11	all	1930 - 1975
	Steel production by the basic bessemer method	8	all	1930 - 1980
	Steel production in blast oxygen furnaces	56	all	1960 - 2005
	Steel production in electric arc furnaces	93	all	1930 - 2005
	Steel production in open hearth furnances	51	all	1930 - 2005
Telecommunications	Cable television subscribers	95	all	1975 - 2005
	Cell phones	146	all	1980 - 2005
	Mail items	79	all	1830 - 1995
	Newspaper circulation (daily)	153	all	1950 - 2000
	Radios	149	all	1925 - 2000
	Telegrams	78	all	1850 - 1995
	Telephones	152	all	1880 - 2005
	TVs	152	all	1950 - 2005
Textiles	Automatic looms	96	all	1965 - 1980
	Percent of automatic textile looms	98	all	1965 - 1980

Table A2 (continued): Description of Technologies and their Coverage

Category	Variable Description	Number of Countries	Country Coverage	Date Range
Textiles (ctd.)	Percent of spindles that are ring spindles	31	all	1905 - 1955
	Percent of textile raw materials that are unnatural	79	all	1965 - 1980
	Spindles: mule	31	all	1905 - 1955
	Spindles: ring	52	all	1905 - 1955
Tourism	Hotel and other visitor beds	144	all	1980 - 2005
	Hotel and other visitor rooms	145	all	1980 - 2005
Transportation	Aviation passenger kilometers	109	all	1920 - 1995
	Aviation ton-km of cargo	103	all	1930 - 1995
	Percent of ships that are steam and motor	71	all	1790 - 1995
	Percent of the tonnage of ships that are steam and motor	71	all	1790 - 1995
	Railroads: freight ton-kilometers	100	all	1850 - 1995
	Railroads: freight tons	116	all	1850 - 1995
	Railroads: length of line open	126	all	1830 - 1995
	Railroads: passenger journeys	112	all	1835 - 1995
	Railroads: passenger-journey kilometers	94	all	1840 - 1995
	Ships: motor	8	all	1910 - 1995
	Ships: sail	31	all	1820 - 1995
	Ships: steam	20	all	1820 - 1995
	Ships: steam and motor	57	all	1870 - 1995
	Ships: total	13	all	1830 - 1995
	Tonnage of motor ships	8	all	1910 - 1995
	Tonnage of sail ships	32	all	1790 - 1995
	Tonnage of steam and motor ships	59	all	1870 - 1995
	Tonnage of steam ships	21	all	1810 - 1995
	Tonnage of total ships	13	all	1830 - 1995
	Vehicles: commercial	121	all	1905 - 1995
	Vehicles: passenger cars	149	all	1895 - 2005

Table A3: Annual speed of β Convergence by Variable

Variable Description	Invention Date	Speed of Convergence	Variable Description	Invention Date	Speed of Convergence
Beds: in-patient acute care	pre-1500	0.035	Ships: steam	1788	-0.002
Beds: in-patient long-term care	pre-1500	0.011	Ships: steam and motor	1788	0.002
Beds: total hospital	pre-1500	0.082	Tonnage of steam and motor ships	1788	0.020
Breast conservation surgeries	pre-1500	0.022	Tonnage of steam ships	1788	0.001
Caesarean sections	pre-1500	0.030	Automatic looms	1801	0.001
Cheques issued	pre-1500	0.059	Percent of automatic textile looms	1801	0.063
Hernia procedures, inguinal and femoral	pre-1500	0.122	Fertilizer consumed, total	1815	0.004
Hotel and other visitor beds	pre-1500	0.011	Railroads: freight ton-kilometers	1825	0.008
Hotel and other visitor rooms	pre-1500	0.035	Railroads: freight tons	1825	-0.001
Irrigated area	pre-1500	0.012	Railroads: length of line open	1825	0.004
Mail items	pre-1500	0.020	Railroads: passenger journeys	1825	0.013
Mastectomies	pre-1500	-0.002	Railroads: passenger-journey kilometers	1825	-0.002
Percent of beds for acute care	pre-1500	0.007	Percent of spindles that are ring spindles	1828	0.025
Percent of hernia procedures done as day cases	pre-1500	0.009	Spindles: ring	1828	0.015
Percent of irigated land out of cultivated land	pre-1500	-0.005	Telegrams	1835	0.001
Percent of tonsillectomies done as day cases	pre-1500	0.001	Hysterectomies (vaginal only)	1843	0.028
Percent of varicose veins procedures done as day cases	pre-1500	0.007	Harvesters	1850	0.008
Ships: sail	pre-1500	0.020	Percent of steel production by the acid bessemer method	1855	0.276
Ships: total	pre-1500	0.033	Percent of steel production by the basic bessemer method	1855	0.023
Tonnage of sail ships	pre-1500	0.027	Percent of steel production in OHFs	1855	0.014
Tonnage of total ships	pre-1500	0.009	Steel production by other methods	1855	0.040
Tonsillectomies	pre-1500	0.023	Steel production by the acid bessemer method	1855	0.080
Varicose vein procedures	pre-1500	0.033	Steel production by the basic bessemer method	1855	0.082
Newspaper circulation (daily)	1606	0.041	Steel production in open hearth furnances	1867	0.025
Cataract surgeries	1748	0.072	Tractors	1868	0.007
Percent of cataract surgeries done as day cases	1748	0.039	Milking machines	1870	0.006
Percent of ships that are steam and motor	1788	0.004	Telephones	1876	0.041
Percent of the tonnage of ships that are steam and motor	1788	0.007	Cholecystectomies	1882	0.002

Note: Speed of convergence estimated using equation (4) or (5).

Table A3 (continued): Annual speed of β Convergence by Variable

Variable Description	Invention Date	Speed of Convergence	Variable Description	Invention Date	Speed of Convergence
Electricity production	1882	0.010	Percent of dialysis patients at home	1943	0.021
Percent of cholecystectomies done as day cases	1882	-0.145	Percent of renal failure patients, end stage	1943	0.063
Prostatectomies (excluding transurethral)	1883	0.024	Cell phones	1947	0.033
Percent of textile raw materials that are unnatural	1884	0.073	Cable television subscribers	1949	0.015
Appendectomies	1885	0.037	Debit and credit card transactions	1950	-0.002
Vehicles: commercial	1885	0.024	Percent of steel production in BOFs	1950	0.061
Vehicles: passenger cars	1885	0.055	Points of service for debit/credit cards	1950	0.148
Ships: motor	1897	0.024	Steel production in blast oxygen furnaces	1950	-0.027
Tonnage of motor ships	1897	0.039	Kidney transplants, functioning	1951	0.115
Percent of steel production in EAFs	1900	0.015	Kidney transplants	1951	0.229
Radiation therapy equipment	1900	0.083	Pacemaker surgical procedures	1952	0.028
Steel production in electric arc furnaces	1900	0.048	Coronary bypasses	1953	0.036
Cholecystectomies, laparoscopic	1901	0.039	Coronary bypass procedures, in-patient	1953	0.033
Percent of cholecystectomies done as day cases	1901	-0.133	Bone marrow transplants	1956	0.043
Radios	1901	0.004	Lung transplants	1963	0.118
Aviation passenger kilometers	1903	0.047	Percent immunized for measles, children 12-23 months	1964	0.119
Aviation ton-km of cargo	1903	0.033	Mammographs	1966	0.104
Percent of steel production that is stainless	1913	-0.005	ATMs	1967	0.148
Stainless steel production	1913	0.022	Heart transplants	1967	0.093
TVs	1924	0.009	Liver transplants	1967	0.112
Percent immunized for DPT, children 12-23 months	1927	0.086	Knee replacement surgeries	1970	0.016
Prostatectomies (transurethral)	1931	0.051	Computed tomography (CAT) scanners	1972	0.037
Hip replacement surgeries	1938	0.025	Internet users	1973	0.078
Pesticide consumed, total	1939	0.164	Personal computers	1973	0.082
Cardiac catheterisations	1941	0.044	Electronic funds transfers	1979	0.020
Dialysis patients	1943	0.065	Coronary stenting procedures	1980	0.059
Renal failure patients, end stage	1943	0.060	Lithotriptors	1980	0.020
Dialysis patients, home	1943	0.069	MRI units	1981	0.054

Note: Speed of convergence estimated using equation (4) or (5).

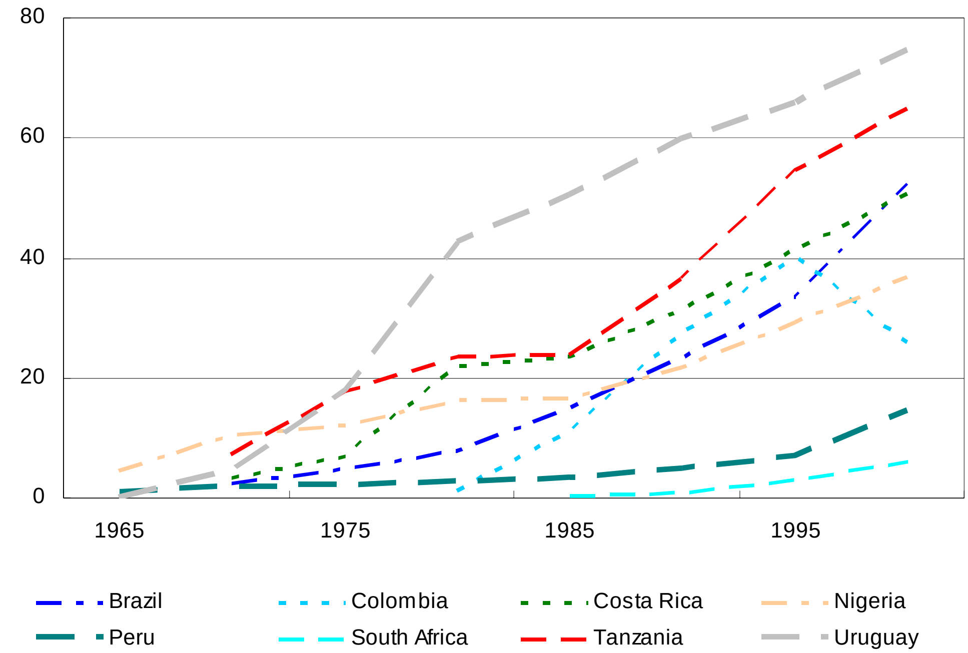

Figure 1: Percent of agricultural area using modern varieties in various developing countries.

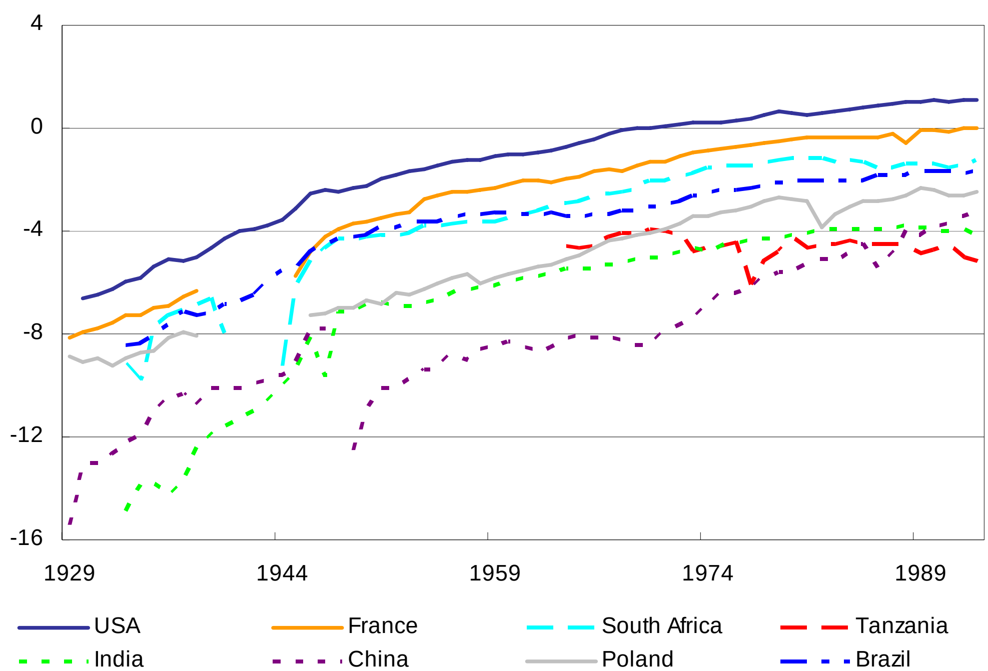

Figure 2: Log of per capita aviation passenger-kilometers.

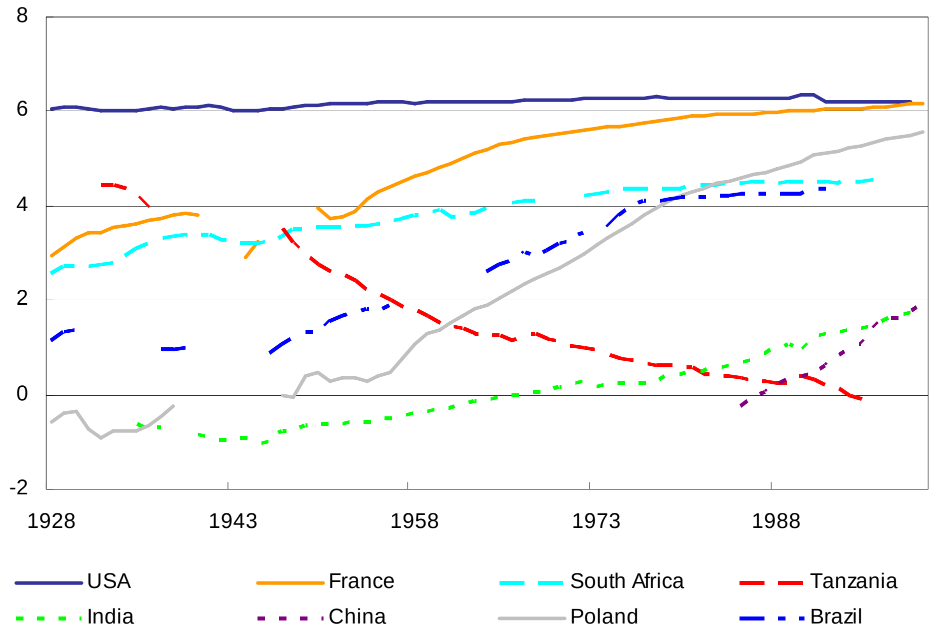

Figure 3: Log of cars per capita.

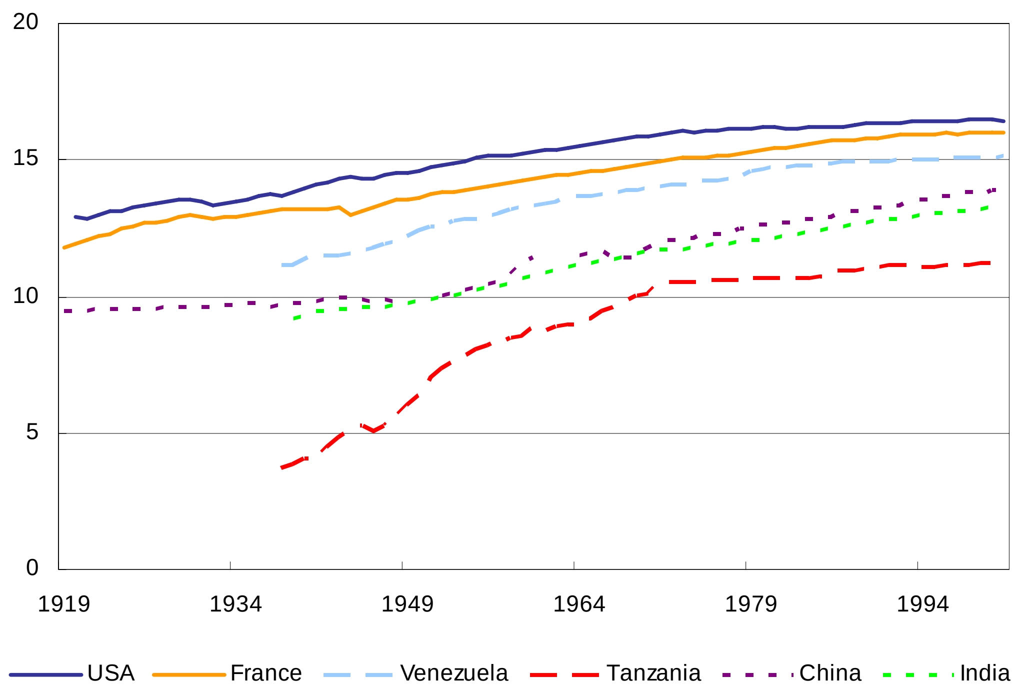

Figure 4: Log of kilowatts of electricity produced per capita.

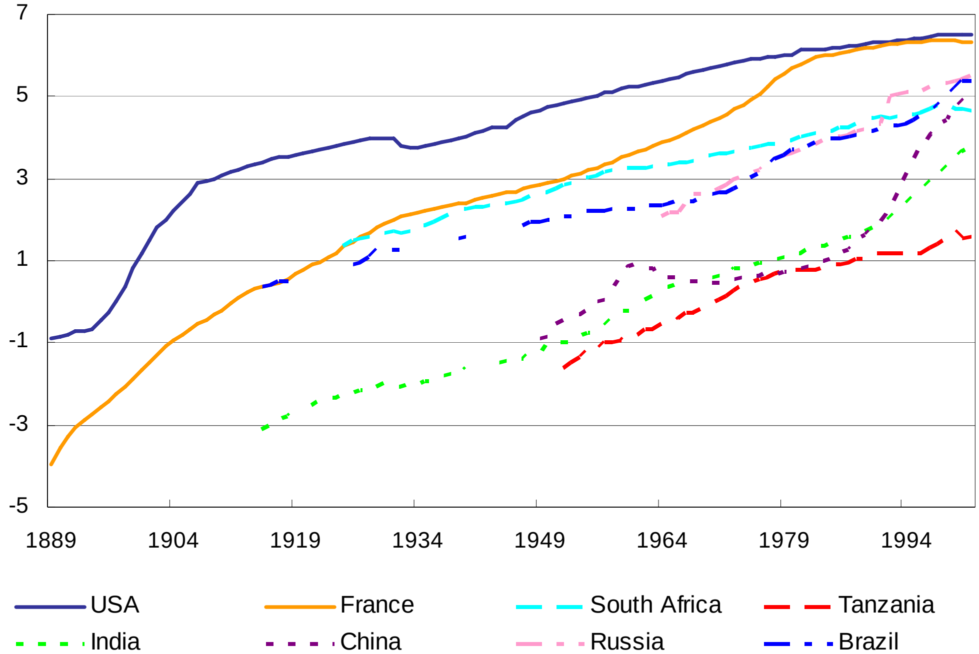

Figure 5: Log of telephones per capita.

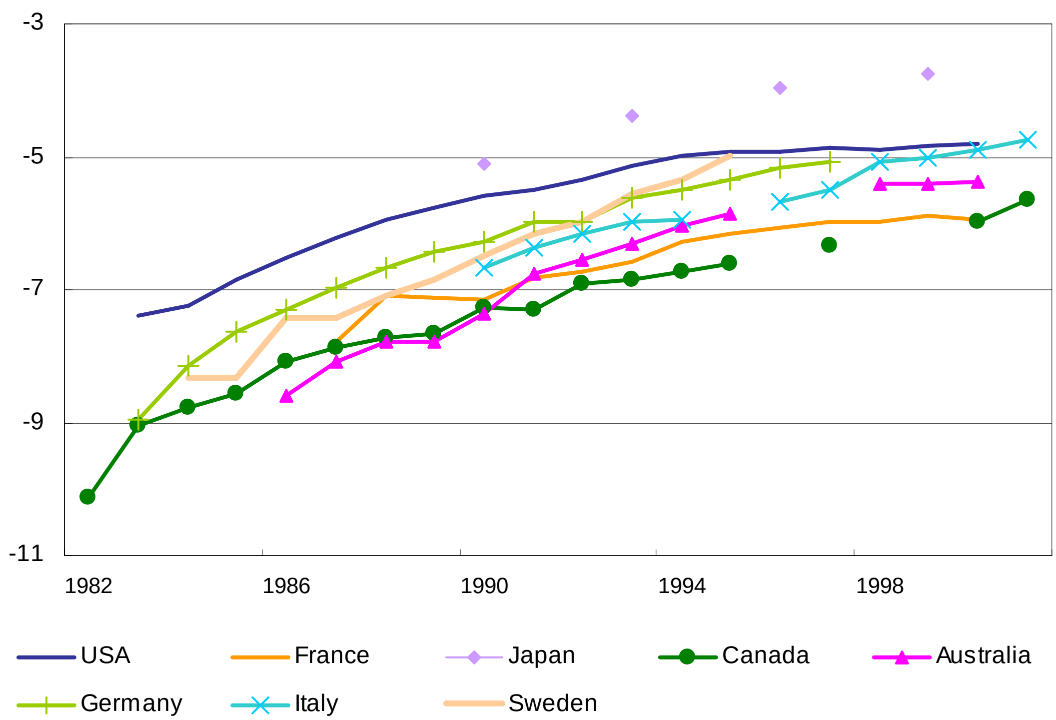

Figure 6: Log of MRI scanner units per capita.

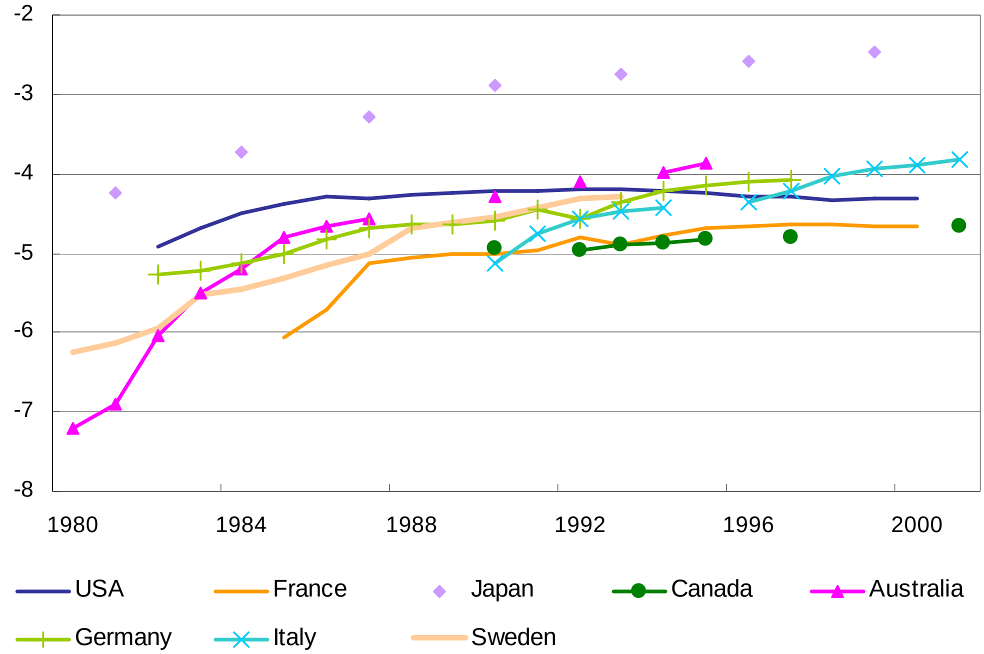

Figure 7: Log of CAT scanner units per capita.

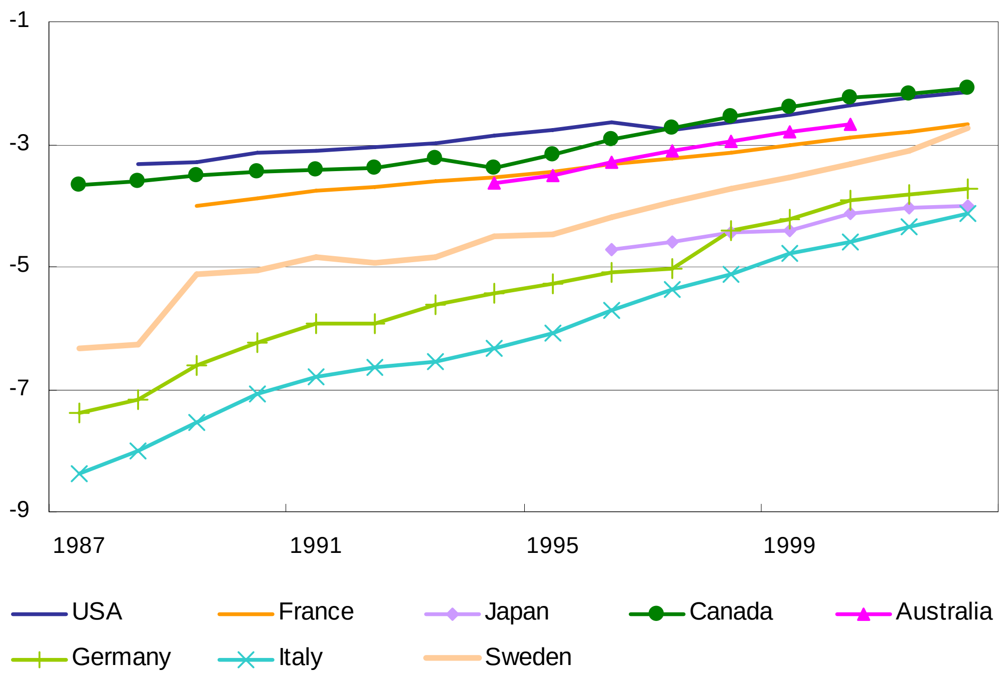

Figure 8: Log of credit and debit card payments per capita.

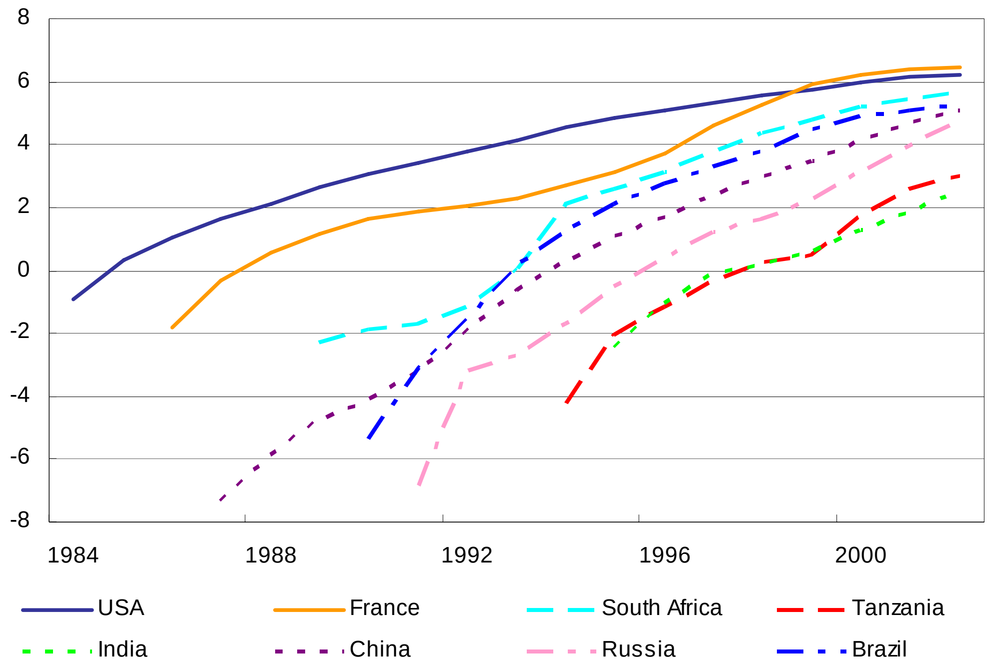

Figure 9: Log of cell phones per capita.

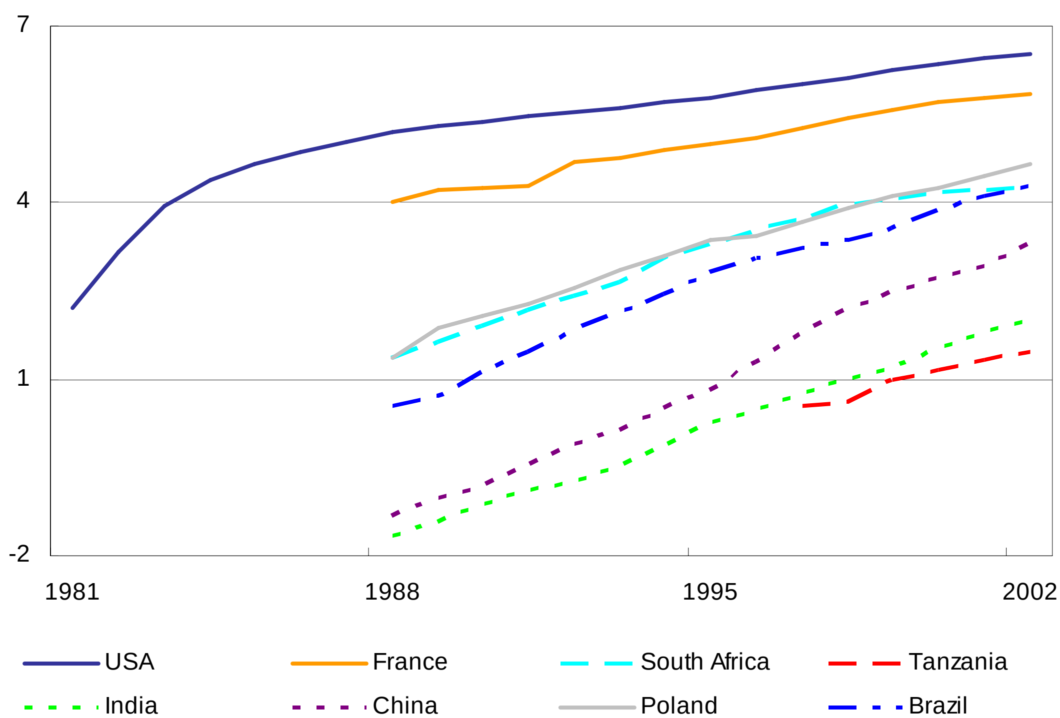

Figure 10: Log of personal computers per capita.

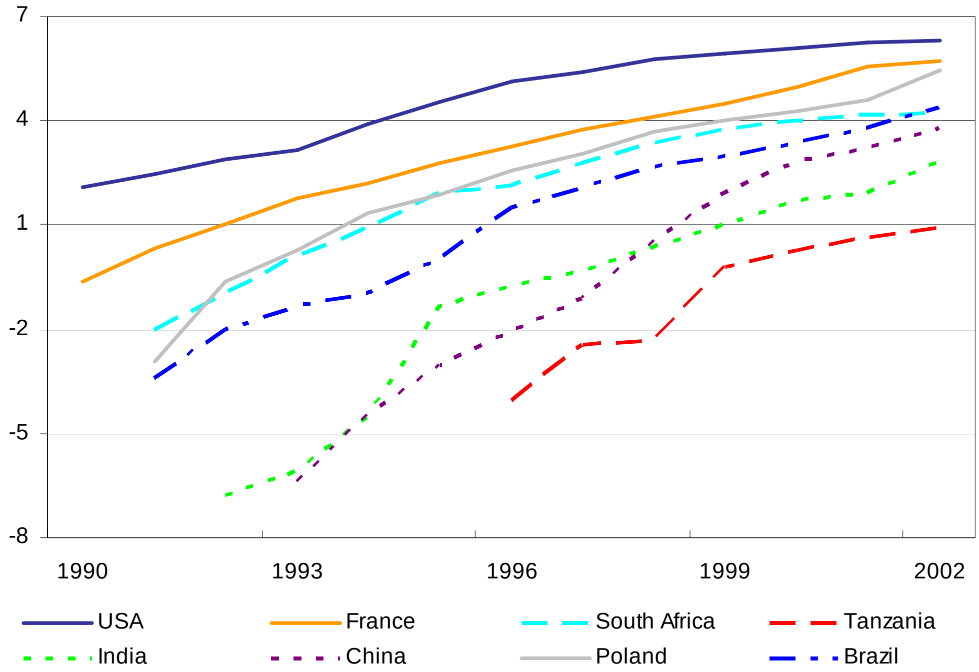

Figure 11: Log of internet users per capita.

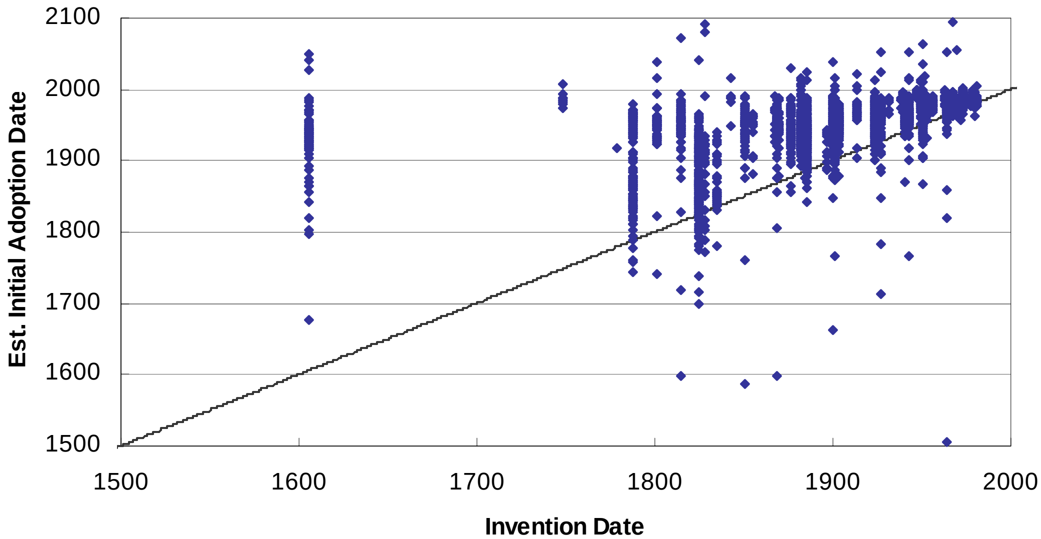

Figure 12: Predicted initial adoption under logistic vs. invention dates for technology-country pairs

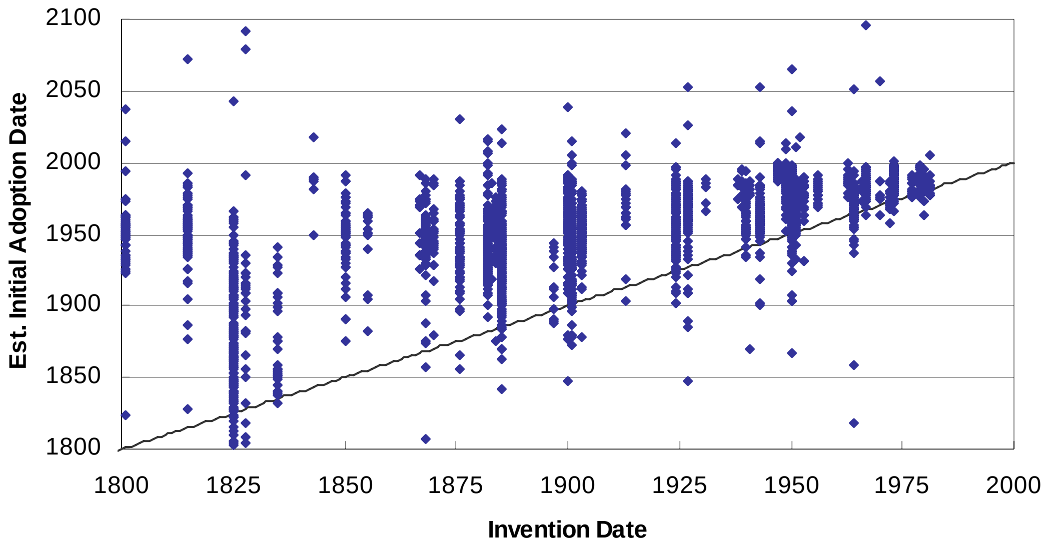

Figure 13: Predicted initial adoption under logistic vs. invention dates (1800-2000).

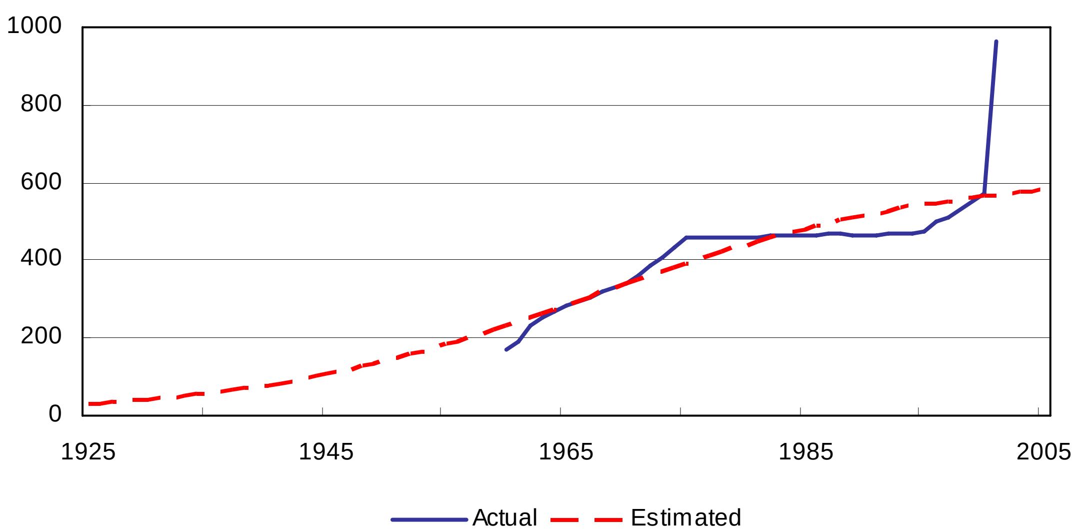

Figure 14: Actual adoption curve of TVs in Sweden and fitted logistic function.

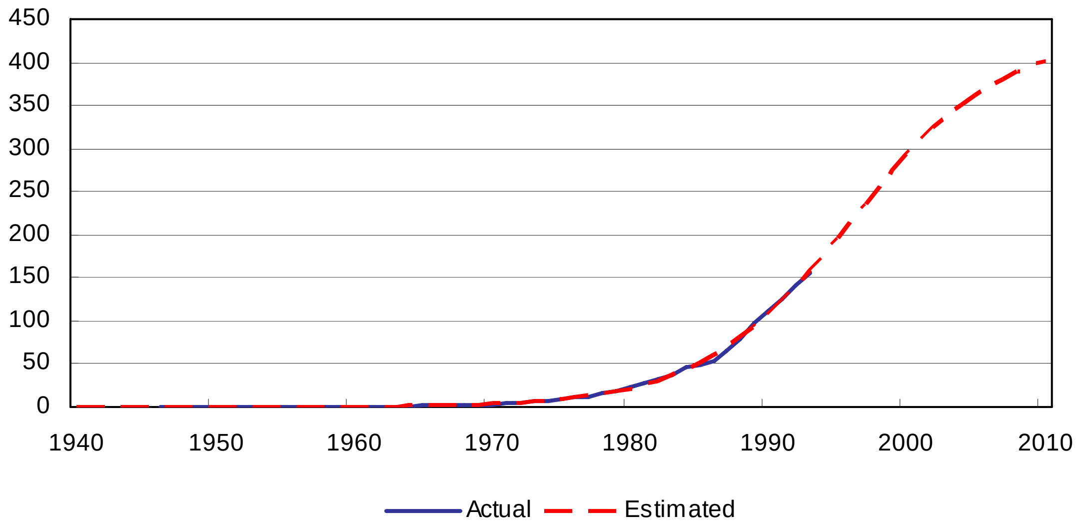

Figure 15: Actual adoption curve of cars in Taiwan and fitted logistic function.

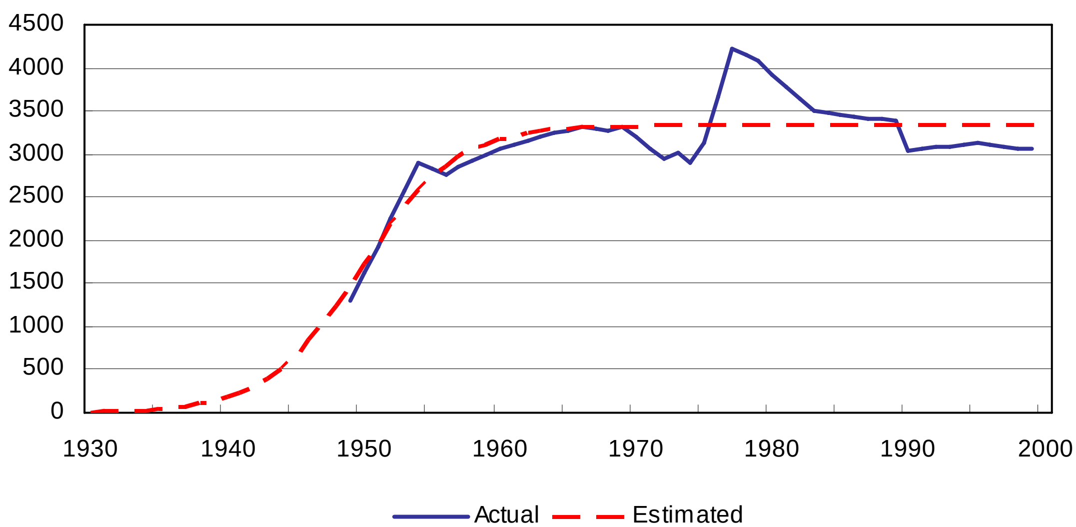

Figure 16: Actual adoption curve of newspapers in Germany and fitted logistic function.

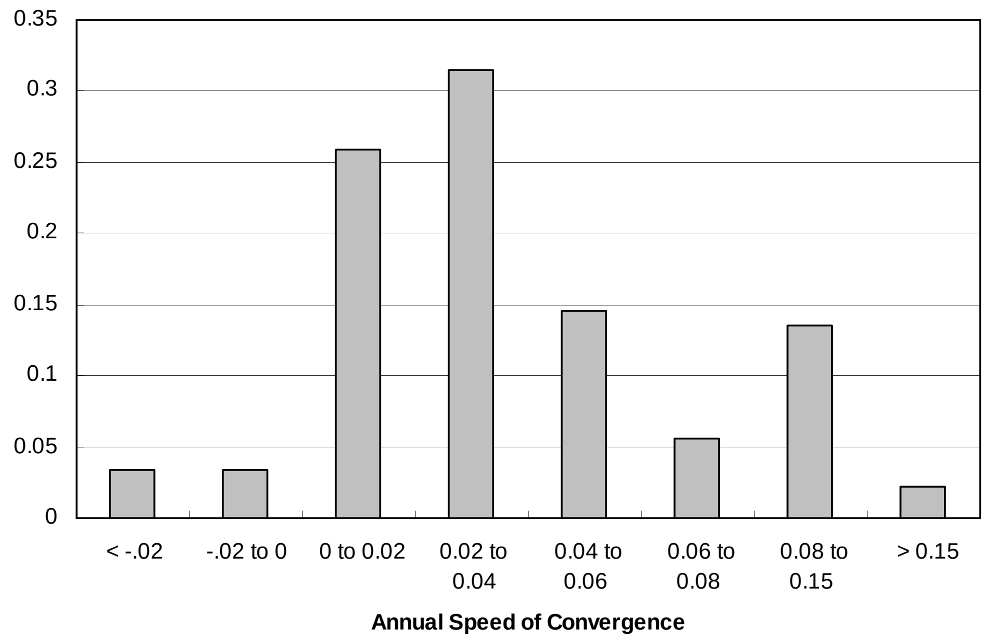

Figure 17: Distribution of estimates of β-speed of convergence: log-per capita technologies.

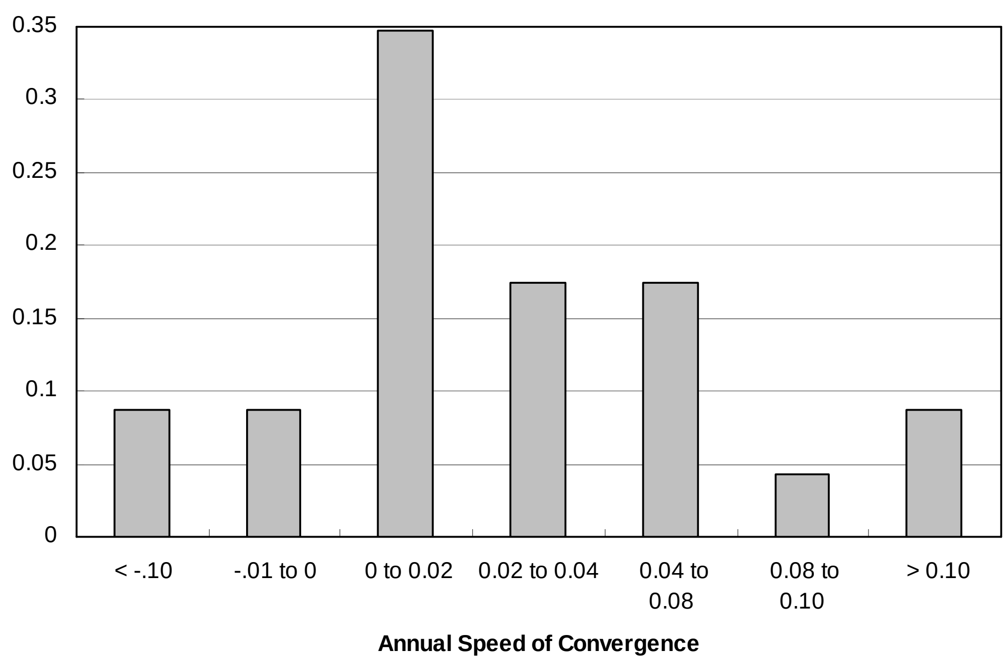

Figure 18: Distribution of estimates of β-speed of convergence: share technologies.

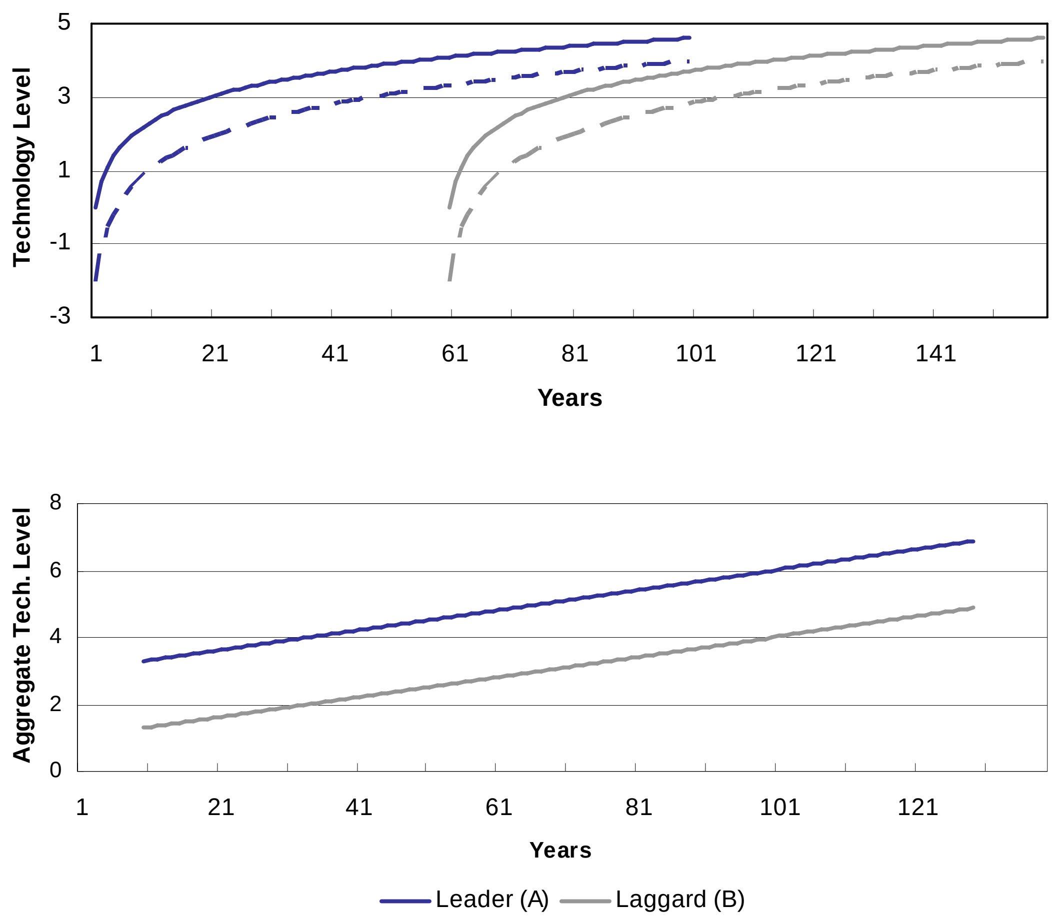

Figure 19: Convergence within technologies does not imply convergence across technologies.

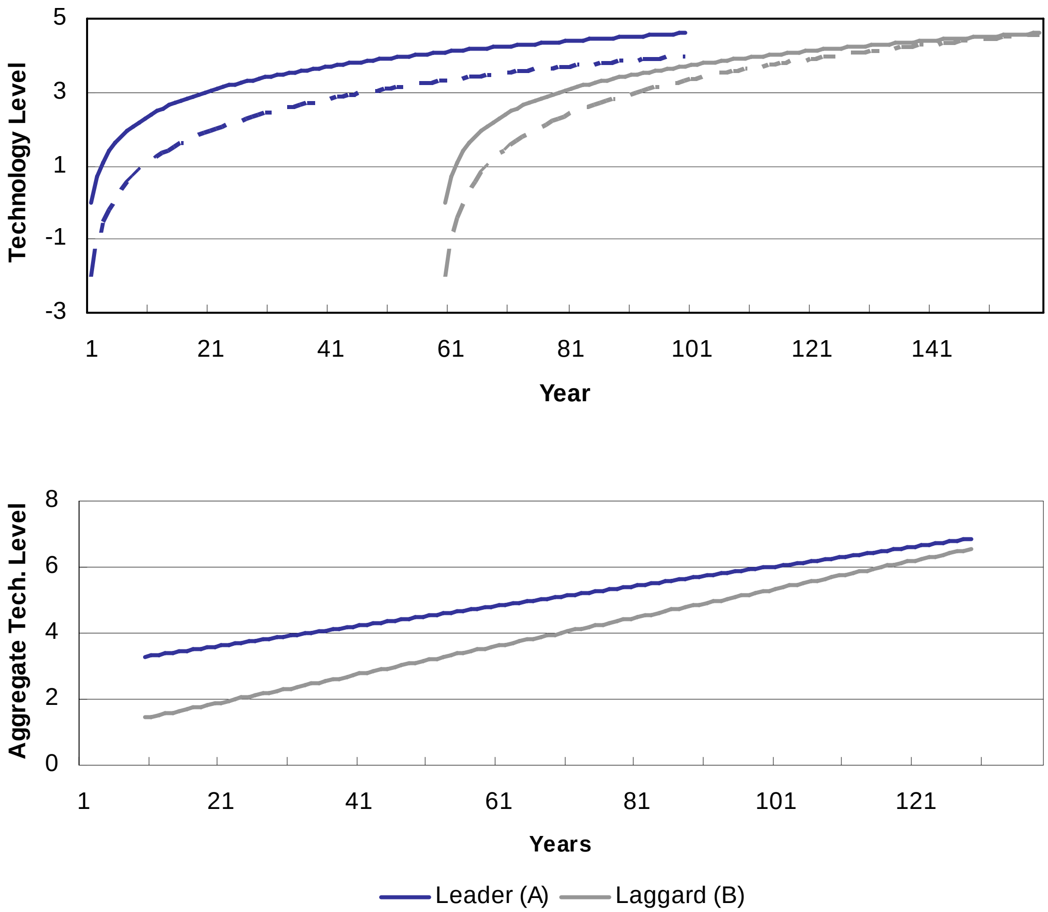

Figure 20: Convergence within technologies could imply convergence across technologies.

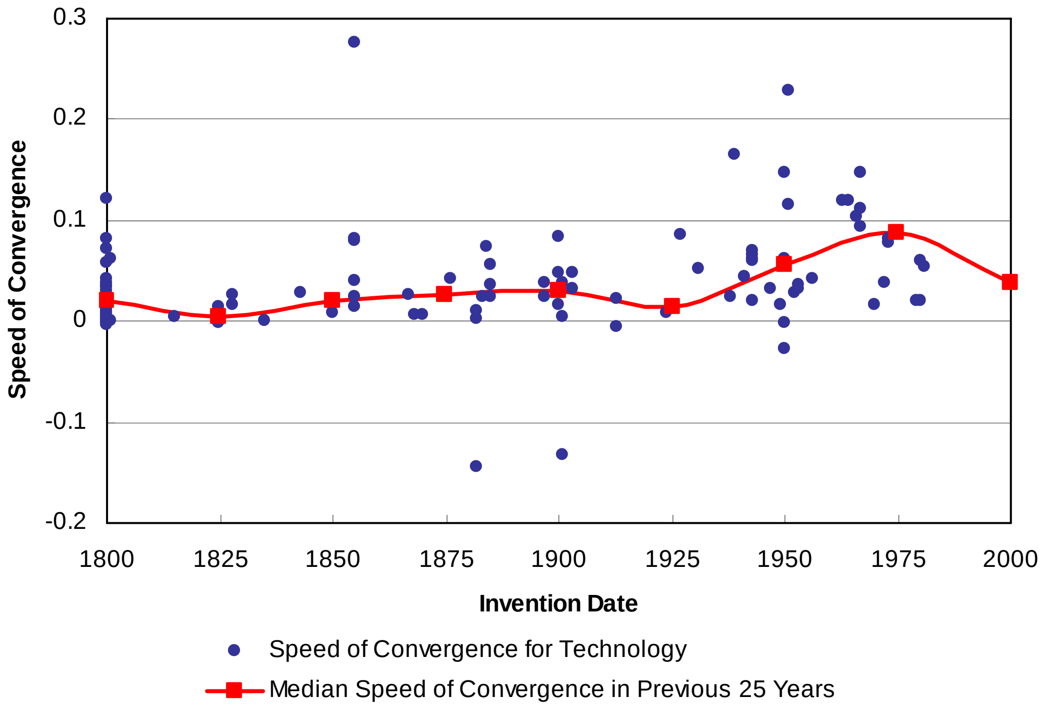

Figure 21: Evolution of the speed of technology by invention date.

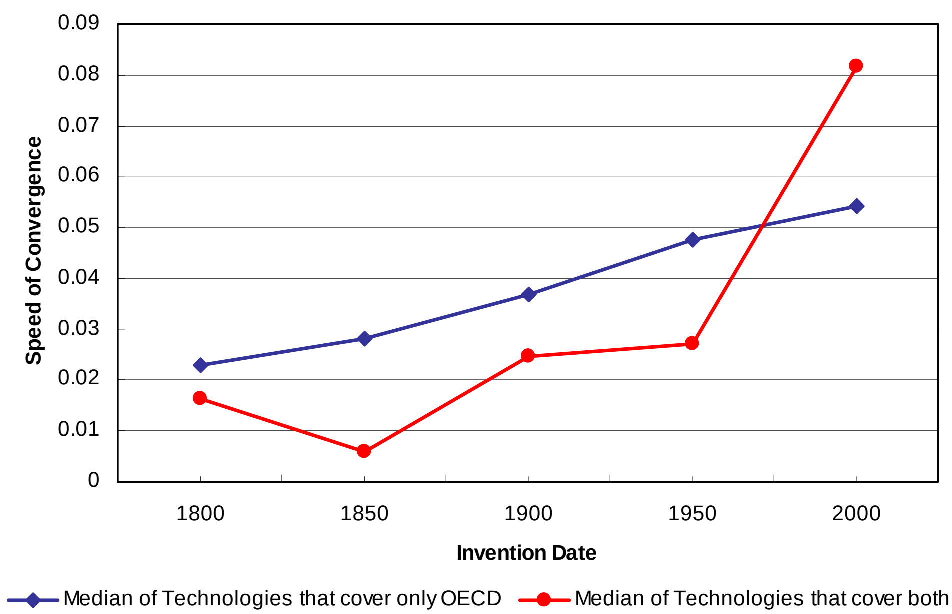

Figure 22: Evolution of median speed of convergence for technologies according to country coverage.