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# Technology usage lags

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**Abstract** We present evidence on the differences in the intensity with which ten major technologies are used in 185 countries across the world. We do so by calculating how many years ago these technologies were used in the U.S. with the same intensity as they are used in the countries in our sample. We denote these time lags as technology usage lags and compare them with lags in real GDP per capita. We find that (i) technology usage lags are large, often comparable to lags in real GDP per capita, (ii) usage lags are highly correlated with lags in per-capita income, and (iii) usage lags are highly correlated across technologies. The productivity differentials between the state-of-the-art technologies that we consider and the ones they replace, combined with the usage lags that we document, lead us to infer that differences in the intensity of usage of technologies might account for a large part of cross-country TFP differentials.

**Keywords** Technology adoption · Cross-country studies

**JEL Classification** O33 · O47 · O57

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## 1 Introduction

How large are cross-country differences in technology? Are they comparable to cross-country differences in income per capita?

A substantial literature[1] has tried to answer these two questions by constructing indirect measures of technology based on the Solow residual. This approach, however, suffers from the problem that the Solow residual captures not only differences in technology, but also variation in capacity utilization (Basu 1996), labor hoarding (Burnside et al. 1995), and the inefficiencies of the economy (Weil 2005, Ch. 10).

Concerning the second question, Weil (2005, Ch. 15) argues that technology adoption lags are most likely much smaller than per-capita income lags; if technology were responsible for the cross-country variation in income per capita and grew at an annual rate of 2% a year,[2] India would currently be using technologies that the U.S. employed 100 years ago. This is obviously not the case, since producers in India also use recent technologies such as computers and cell phones.

Weil correctly highlights the importance of using direct measures of technology to answer the questions that motivate this paper. However, his argument ignores the importance of cross-country variation in the intensity of adoption of new technologies.

That is, most discussions of technology adoption differentials, including Weil's, focus on whether or not, or what fraction of, users have adopted a technology. This is the extensive margin of adoption. This ignores, however, at what intensity the adopters use the technology, i.e., the intensive margin. It is not only relevant whether computers and cell phones are being used in India, but also how many of them are used (per user).

An older literature initiated by Griliches (1957) and Mansfield (1961) directly measures technology adoption by considering the fraction of the potential adopters using a technology. Calculating this type of measure requires micro-level data at the producer level that is not available for a broad sample of countries and technologies.[3] Just like Weil's argument, this approach also does not capture the intensity with which each adopter uses the technology. As shown by Clark (1987), this margin may be critical to explain cross-country differences in labor productivity.

In this paper, we explore the questions posed above by constructing per-capita usage intensity measures of technology, like kWh of annual electricity production per capita and personal computers per capita. These measures include both the extensive and the intensive margins of technology adoption. Furthermore, their construction only requires aggregate data that is available for a wide sample of countries and technologies.

We consider 10 technologies that share three properties: (i) They are major production technologies, (ii) they represent the state-of-the-art technology available to produce a good or service at the point in time we consider them, and (iii) they are technologies for which we have data for a wide range of countries.[4]

[1] Klenow and Rodríguez-Clare (1997), Hall and Jones (1999), and Benhabib (2005), among others.

[2] This is the rate necessary to sustain the growth rate in labor productivity observed during the last 120 years in the U.S.

[3] Federal Reserve Bank of Dallas (1996) has an informative description of the historical diffusion patterns of consumer technologies in the U.S.

[4] The technologies we consider are a subset of those introduced in Comin et al. (2006b).

Rather than analyzing the level of the technology usage measures, we analyze time lags with respect to the U.S. The usage lag of technology $x$ in country $c$ at year $t$ is defined as the answer to the following question: How many years before year $t$ did the United States last have a usage intensity of technology $x$ that country $c$ has in year $t$?

For example, the quantity of kWh of electricity produced per capita in Uruguay in 1990 was last observed in the United States in 1949. Thus, the electricity usage lag in Uruguay in 1990 is 41 years. Similarly, the number of personal computers per capita in Spain in 2002 was comparable to that in the United States in 1989. Hence, the 2002 PC usage lag of Spain is 13 years.

Usage lags make measures of technology adoption comparable across technologies and also with income per capita. In addition, by considering the intensive margin of adoption, they enable us to shed light on Weil's claim.

The purpose of our analysis is not to establish any causality, but rather to uncover facts that shed a light on the extent to which technology usage disparities might account for the observed cross-country TFP differentials. From this point of view, we uncover three main facts: (i) Technology usage lags are large, often comparable to lags in real GDP per capita, (ii) usage lags are highly correlated across countries with (lags in) per-capita income, and (iii) usage lags are highly correlated across technologies.

## 2 The concept of time lags

We further explain the concept of time lags with an additional example. Consider Fig. 1. It plots real GDP per capita as a percentage of the 2003 U.S. level (in log-scale) for the U.S. as well as China, France, Japan, and Mexico. Using this figure, we can answer the following question: how many years before the year 2000 did the United States last have the real GDP per capita that China had in 2000?

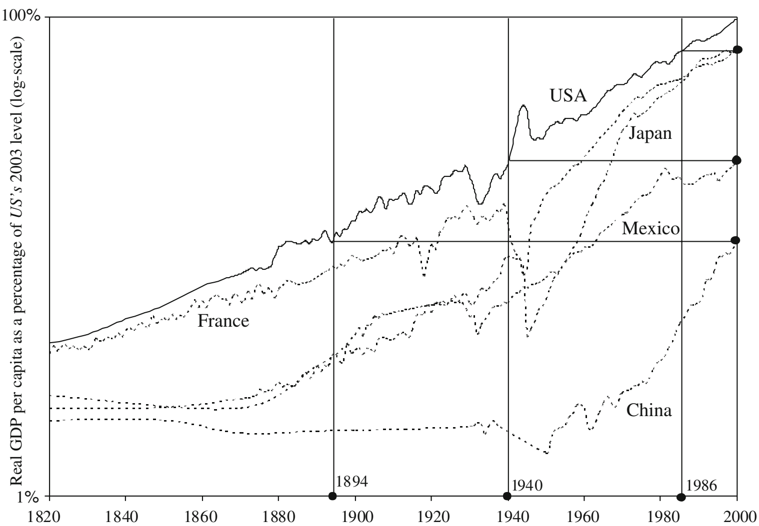


**Fig. 1** Real GDP per capita lags, examples for 2000

When we look at Fig. 1, we see that the U.S. last passed China's 2000 level of GDP per capita in 1894, 106 years before 2000. Similarly, in 2000 the U.S. led Mexico by 60 years and France and Japan by 14.[5]

More formally, let $X_{j,t}$ be the usage level of a given technology in country $j$ at time $t$. We compare this observation with the historical time series for the United States. Let this series be given by $\{X_{US,s}\}$ where $s$ indexes the observations. These are not necessarily consecutive observations because of missing data in the U.S. historical time series. Let $S$ denote the set of observations available in the historical time series for the United States.

We define the following two observations in the time series for the U.S. The first is the last time the U.S. passed level $X_{j,t}$. That is,

$$\bar{s} = \arg\min_{s \in S} \left\{ s \mid X_{US,s'} \geq X_{j,t} \text{ for all } s' \in S \text{ and } s' \geq s \right\} \tag{1}$$

The second observation we define is the last time the U.S. recorded a technology usage level lower than or equal to $X_{j,t}$. That is,

$$\underline{s} = \arg\max_{s \in S} \left\{ s \mid X_{US,s} \leq X_{j,t} \right\} \tag{2}$$

Because of these definitions, we know that observation $\bar{s}$ is the one after observation $\underline{s}$ in the U.S. historical time series.

We impute the time that the U.S. last had the technology usage level $X_{j,t}$, say $\tau$, by linear interpolation. That is, we calculate

$$\tau = \left( \frac{X_{j,t} - X_{US,\underline{s}}}{X_{US,\bar{s}} - X_{US,\underline{s}}} \right) \left( \bar{s} - \underline{s} \right) \tag{3}$$

The technology usage lag between the U.S. and country $j$ at time $t$ is then given by $t - \tau$. Hence, we thus interpolate the U.S. time series when the observation for country $j$ is not exactly equal to one observed for the U.S.

For the interpretation of the results, especially those for real GDP per capita, it is important to realize that we define $\tau$ as the *last* time the U.S. had level $X_{j,t}$. Hence, if technology usage, or real GDP per capita for that matter, exhibits a dip, then we consider $\tau$ the last time the usage level passed $X_{j,t}$ after the trough. In terms of real GDP per capita, the biggest such 'dip' is the Great Depression. U.S. real GDP per capita in 1933, at the trough of the Great Depression, was at a level not seen in the U.S. since 1908. As a result, our imputed $\tau$ for real GDP per capita does not include any years between 1908 and 1933.

The analysis of time lags has two major advantages over that of disparities in technology usage levels across countries.

First, time lags are independent of the units of measurement of the variables considered. This flexibility is important when one aims to consider a broad range of statistics and compare them across countries and technologies, as we do for measures of technology usage here.

Second, the calculation of these lags does not require a very long time series for countries other than the U.S. It only requires a long historical time series for the U.S.[6]

A couple of practical details are relevant for the calculation of the time lags. Sometimes, the U.S. historical time series does not go back so far as to include the invention date of the

[5] Jovanovic (2007) also considers this type of time lags in a theoretical model of endogenous growth and technology adoption.

[6] In principle, we could consider the lag relative to the technological leader rather than the U.S. The U.S. is, however the leader in the use of the bulk of the technologies in the years that we consider. Using the U.S. as a base has the advantage that the U.S. has the longest historical time series for all the technologies we consider.

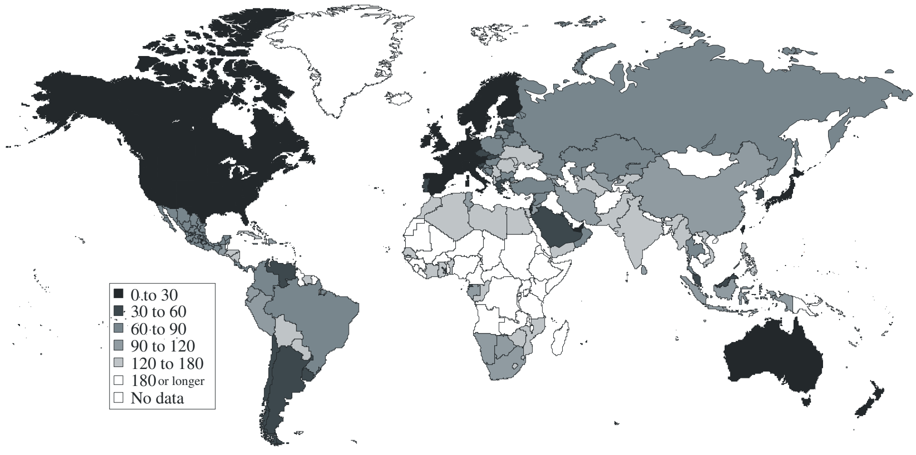


**Fig. 2** Real GDP per capita lags, 2000

technology. We initialize the U.S. historical time series by setting $X_{US,inventionyear} = 0$. The invention years that we use are described in Appendix 1. GDP, however, does not have an invention date. For GDP we use Maddison (2007) historical time series of U.S. GDP per capita, which goes back to 1600, and measure $X_{j,t}$ as the logarithm of real GDP per capita.

For some countries, we find right-truncated lags in GDP per capita because they have GDP per capita levels lower than that of the U.S. in 1600. We have this problem for only a very limited number of Sub-Saharan African countries, including Guinea-Bissau and Botswana in 1950 and Zaire in 1990 and 2000. We also find some cases in which our technology usage lags are censored because the U.S. never achieves the level $X_{j,t}$. In this case the U.S. is not the technological leader.[7]

The number of censored technology usage lags in our sample is so small, though, that these censored observations do not affect the gist of our results.

## 3 Real GDP per capita lags

### 3.1 Size of real GDP lags

Differences in standards of living across the world are very large. For example, U.S. real GDP per capita in 2000 was almost 19 times higher than the average over the continent of Africa. For the poorest country in the world, which in 2000 was Zaire, this ratio is almost 130! By comparison, U.S. real GDP per capita in 2000 was 23 times higher than it was in 1820.

Our time lag measures allow us to translate these differences across countries into years behind the United States. Figure 2 shows the time lags in real GDP per capita for all countries in the world in 2000. As can be seen from the figure, most of the world population is living in countries with real GDP per capita levels that have not been observed in the United States in the post World War II era. Moreover, most of Sub-Saharan Africa, as well as Afghanistan

[7] This is particularly relevant for our results for cell phones in 2002, as can be seen from the many zero lags depicted in Fig. 10. These lags are zero because 2002 is the last year for which we have data for the U.S, and the U.S. is not the global leader in cell phone adoption.

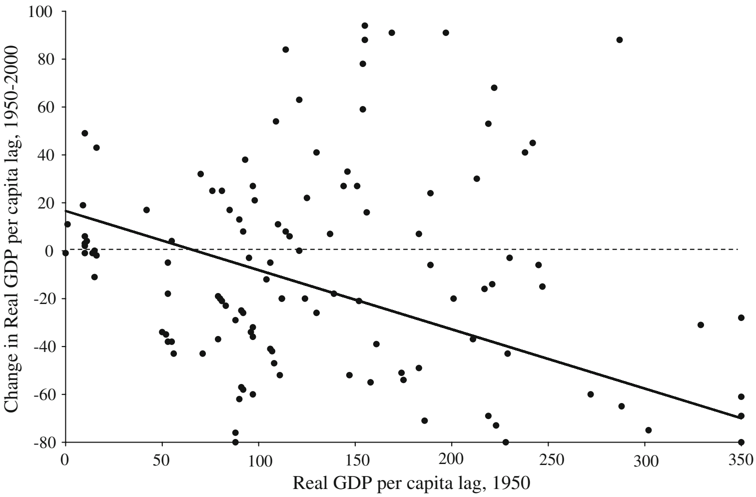


**Fig. 3** Change in real GDP per capita lags between 1950 and 2000

and Mongolia, have per-capita income levels that have not been observed in the United States since 1820.

### 3.2 Catch-up in GDP lags

After documenting the magnitude of the per-capita income lags, it is natural to explore their dynamics. One way to do this is by studying the relationship between the change in the per-capita GDP lag between 1950 and 2000 and the initial lag in 1950. Figure 3 shows this relationship.

As can be seen from the figure, the countries that started off lagging the U.S. by the most years tended to have a bigger decrease (negative change) in their lags, suggesting that, on average, they caught up with the U.S. more quickly than the countries that were relatively richer in 1950.

For example, Ireland's GDP per capita lag was 56 years in 1950 and 13 years in 2000. Thus, its change was −43 years. This suggests that over the period 1950 through 2000, Ireland's GDP per capita increased by the same amount as the U.S.'s GDP per capita over the period 1894 through 1987. Some additional countries with big leaps forward during the last five decades of the last century include Botswana, from more than 350 to 100 years; China, from 316 to 106 years; South Korea, from 183 to 34 years; and Taiwan, from 172 to 24 years.

Not all countries saw their GDP lags decrease over the 1950 to 2000 period. Some countries, including some of the poorer nations, like Zimbabwe, Mozambique, and Ecuador, saw their distance from the U.S. increase by two decades or more. Argentina is also an interesting case, with its GDP lag relative to the U.S. increasing from 16 years in 1950 to 59 years in 2000.

To formalize this analysis, we estimate a regression of the 1950–2000 change in the real GDP lag of a country on its initial 1950 real GDP lag for a sample of 138 countries. The regression results are

$$\Delta\text{GDP lag}_{j,1950-2000} = \underset{(9.95)}{16.61} - \underset{(0.06)}{0.25}\,\text{GDP lag}_{j,1950}, \quad R^2 = 0.12, \quad j = 1, \ldots, 138$$

and show that the GDP lags became significantly smaller for countries that started off more years behind the U.S. than for countries that started closer. The initial (1950) GDP lags explain 12% of the cross-country variation in the reduction in GDP lags relative to the U.S. over the second half of the 20th century.[8]

This result may seem to be in sharp contrast with standard cross-country convergence analyses that do not find unconditional convergence in per-capita income, such as Barro and Sala-i-Martin (1992). However, we are asking a different question than the convergence literature.

The convergence literature considers whether countries that had relatively low per-capita GDP levels in 1950 grew faster than countries with higher levels of per-capita GDP. Our convergence analysis considers whether countries with relatively low per-capita GDP levels in 1950 grew faster in the 1950–2000 period than the U.S. did in the 50 years after it had the same per-capita GDP level as the countries in 1950.

This somewhat subtle, but important, difference means that our regression does not compare the countries over the same period in history but, instead, compares the countries at similar points in their per-capita GDP paths. This analysis offers a new perspective on the development process that allows us to understand whether it takes longer, on average, for currently developing economies to become developed and enjoy a sustained growth rate in per-capita income than that it took for the U.S. during its development period.

Hence, the convergence regression presented here compares the growth patterns of economies at a similar development stage rather than during a similar time period. Our analysis from this point of view offers an illuminating conclusion: on average, it takes less time for currently developing economies to achieve development than that it took for the U.S.

If the U.S. had grown at the same rate over the 380 years for which we have its historical GDP per capita data, then a country's real GDP lag would be a linear transformation of its log real GDP level and our regression would be the same as an unconditional convergence regression. U.S. real GDP per capita has not grown at a constant rate, however: growth accelerated during the second Industrial Revolution in the second half of the nineteenth century and again at the beginning of the twentieth century.

Hence, real GDP per capita lags are not a linear function of the log real GDP per capita levels. This can be seen from Fig. 4, which plots log levels of real GDP against the real GDP lags used in our analysis. The two big jumps in real GDP lags reflect the Great Depression and the Depression of 1893. As can be seen from the figure, lags decrease faster in log GDP per capita levels for poorer countries. This is because the U.S. grew slower when it had similar levels of GDP per capita than it grew afterwards.

This different perspective on the convergence question allows us to reconsider the predictions of different growth models. In particular, existence of the type of catch-up in real GDP lags documented here and the absence of unconditional convergence in conventional growth regressions suggest that real GDP dynamics are more consistent with the model presented in Lucas (2000) than with the dynamics implied by the neoclassical growth model, on which Barro and Sala-i-Martin (1992) base their analysis.

Lucas (2000) provides a model, based on Tamura (1996), of take off where countries are in stagnation; there is a random variable that determines when each country will start growing. When they start growing, they catch up with the countries that started the growth process

[8] The negative correlation between initial lags and the subsequent change in lags is robust to conditioning on the subsample of countries with lags smaller than 130 in 1950. These are countries with real GDP levels higher than that of the U.S. in 1820, which is the first year of the most commonly used subsample of the Maddison (2007) time series.

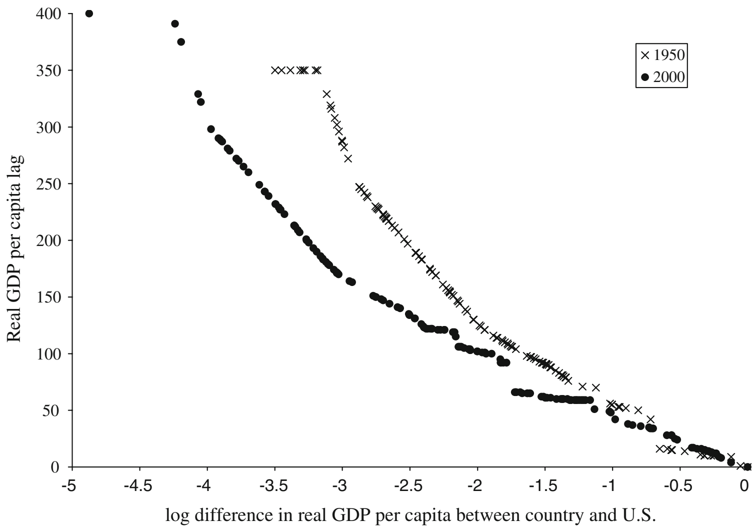


**Fig. 4** Real GDP per capita lags and levels 1950 and 2000

earlier. To explain the lack of (traditional) absolute convergence in the post-war period, the Lucas model should be modified to allow for different steady states across countries.

### 3.3 From GDP lags to technology usage lags

There is an extensive literature that tries to find the main sources of the cross-country differences in per-capita GDP levels. This literature is mainly based on the assumption that GDP is produced with two factors of production, namely capital and labor, and that these production factors are used with a particular level of efficiency, called total factor productivity (TFP), that varies across countries. Much of the evidence, as in Lucas (1990), Klenow and Rodríguez-Clare (1997), and Hall and Jones (1999), suggests that the majority of per-capita GDP differences come from differences in TFP, rather than from differences in the capital per worker used in production.

What causes cross-country disparities in TFP levels is a controversial topic in economics.[9] One potential source of cross-country TFP differentials is differences in the intensity of use of cutting-edge technologies that embody a higher level of productivity than older technologies. Such differences could be due to, among others, cross-country differences in adoption costs that prevent modern technologies from being used, as in Parente and Prescott (1994, 1999) and Chari and Hopenhayn (1991), or from differences in the costs of implementing technologies that result in newer technologies being used below their potential productivity level, as in Jovanovic (2007) and Comin and Hobijn (2007).

In what follows, we present evidence that suggests that a significant part of cross-country differentials in TFP and per-capita income may be accounted for by cross-country differences in the intensity of adoption and usage of new technologies.

[9] See Prescott (1997) for a discussion of why a theory that explains such differences is crucial to explaining cross-country differences in per-capita income levels.

## 4 Technology usage lags

For our analysis of technology usage lags we use data on 10 major technologies from the Cross-country Historical Adoption of Technology (CHAT) data set introduced in Comin et al. (2006b). The technologies we consider are all technologies that satisfy the following three criteria. First, they are mainly production technologies. Second, at the point in time for which we perform our analysis, they are cutting-edge technologies; that is, they are much more productive than other existing technologies that might be used to produce a similar good or service. Third, for the reference year for which we do our analysis, data on technology usage is available for a large sample of countries (at least 95). This requirement results in more meaningful global cross-country comparisons.

### 4.1 Technologies in our sample

The 10 technologies can be classified in five broad categories (technologies in parentheses): (i) electricity (electricity production), (ii) information technologies (internet and PCs), (iii) communication technologies (telephones and cell phones), (iv) transportation technologies (cars, trucks, plane passenger kilometers, and plane cargo kilometers), and (v) agricultural technologies (tractors). Appendix 1 contains a description of these technologies, our data sources and their years, and the invention dates we use for the calculation of the usage lags. Just as for real GDP, we measure the intensity of usage of these technologies in per-capita terms.

There is a wealth of evidence that suggests that the productivity of each of these technologies is significantly higher than their predecessors. For example, Comin and Hobijn (2009) document the large productivity gains associated with the use of PCs, cell phones, telephones, cars, trucks, and planes. These productivity increments range from 1/3 for cell phones to many orders of magnitude for PCs.

The use of electricity as a power source led to significant increases in productivity. David (1990) estimates that "approximately half of the 5 percentage point acceleration recorded in the aggregate TFP growth rate of the U.S. manufacturing sector during 1919–1929 (compared with 1909–1919) is accounted for…by the growth in manufacturing secondary electric motor capacity during that decade."

Many growth accounting studies, including Oliner and Sichel (2000), suggest that information technology, in large part driven by the internet, has led to a surge in U.S. productivity growth in the second half of the 1990s.

For tractors, Easter et al. (1977) estimate the marginal product of various factors of production using the value of wheat produced and the extent to which each input was used in 73 Indian districts. During the period 1967–1969 they find that the marginal product of tractors is over 1000 times larger than the marginal product of work animals and over 2200 times larger than the marginal product of labor.

### 4.2 Usage lags versus usage levels

The lag concept that we consider here translates differences in technology usage between countries into years it took the U.S. to bridge this usage gap. The major advantage of this concept is that these years are comparable across technologies, whereas the units of measurement are different for the usage measures of different technologies. This makes the usage

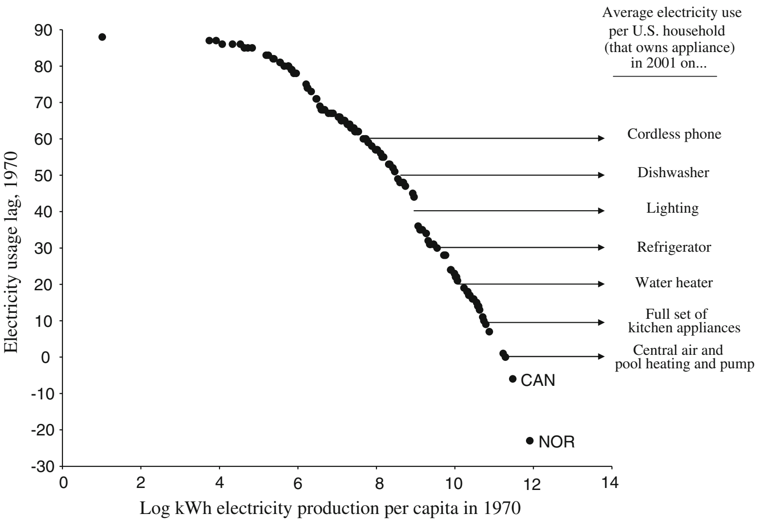


**Fig. 5** Electricity production lags versus levels, 1970

lags more easily comparable across technologies than the usage levels. To illustrate this, we provide two examples in which we compare usage levels with lags.

The first example is that of technology usage lags for electricity production in 1970. Figure 5 plots the levels of electricity production in 1970, measured in log kWh per capita, for the countries in our sample versus the corresponding electricity usage lags. Just as for real GDP per capita in Fig. 4, there is a notable non-linear relationship between the lags and the levels. This non-linearity is not particular to electricity. Since usage levels start, by definition, at zero at the time a technology is first adopted, this non-linearity reflects the rapid growth in usage shortly after adoption. In the case of electricity production, this rapid growth period occurred during the last decade of the nineteenth century and the first two decades of the twentieth century.

Usage lags are relatively easy to interpret. For example, electricity production in China in 1970 was 131 kWh per capita. That level of electricity production per capita was last passed in the U.S. in 1905. Hence, China's usage lag in electricity in 1970 was 65 years. The problem with the usage level of 131 kWh is that it is hard to interpret on its own, while the usage lag is directly interpretable and comparable to that for other technologies.

Electricity usage per color TV in the U.S. is estimated to be 137 kWh annually.[10] This means that energy production in China in 1970 was not enough to provide everyone with a color TV. To put the kWh levels underlying the electricity lags in perspective, we include a list of appliances in Fig. 5. Out of the 122 countries in our sample for the year 1970, 56 had electricity production levels lower than that in the U.S. in 1910 and below the equivalent of having one cordless phone per person. Only 19 out of these 122 countries had an electricity production level per capita sufficient to run one refrigerator per person. Note that two countries, namely Canada and Norway, had per-capita electricity production levels higher than the U.S. in 1970; Canada's electricity production level in 1970 was last observed in 1976 in the U.S., while that of Norway was last seen in 1993.

[10] These data are for 2001 and are taken from the Energy Information Agency's Household Electricity Report (2005).

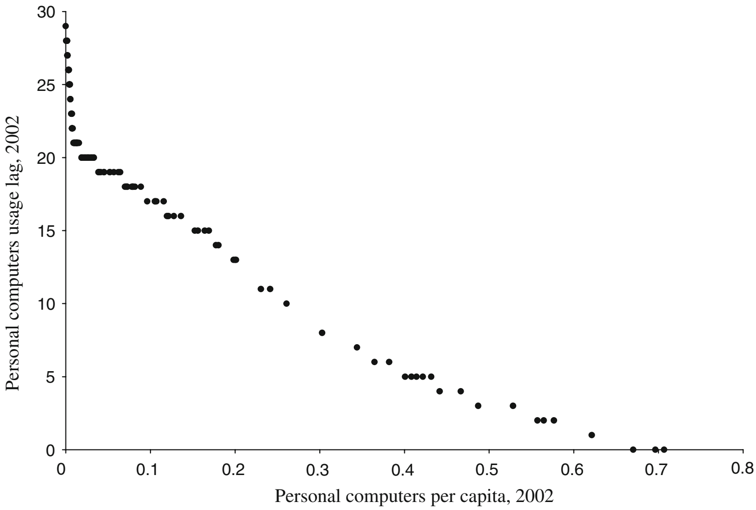


**Fig. 6** Personal computer lags versus levels, 2002

The second example is personal computers. Figure 6 shows personal computers per capita in 2002 versus the corresponding technology usage lags. Again, we observe a notable non-linear relationship. Because we did not take a logarithmic transformation, however, it is convex rather than concave in this case.

We find that, in 2002, PCs are used at an intensity level in most countries that predates the U.S. 1990 level. In fact, one-third of the countries in our sample have an intensity of PC usage that is less than that in the United States in 1981, the year that IBM introduced its first PC and the year for which we have the first data on U.S. PC usage.

### 4.3 Cross-country disparities in usage lags

For the presentation of the technology usage lags, we divide the technologies into four groups. The first two groups consist of technologies invented in the nineteenth century: electricity, tractors, and telephones are in the first group, while the road transportation technologies (i.e., cars and trucks) are in the second. The third group consists of cargo and passenger aviation kilometers, while the final group represents the digital age of personal computers, cell phones, and the internet.

Figures 7, 8, 9, and 10 depict the real GDP per capita lags versus technology usage lags for these four respective groups of technologies. The diagonal line in each of these figures represents the 45-degree line. The main summary statistics for all technologies, and a broader set of years than depicted in the figures, are reported in Table 1.

The first three groups of technologies exhibit a very similar pattern in terms of their technology lags. For richer countries, the technology lags were generally at least as large as their GDP lags. Countries with real GDP lags smaller than 50 years have technology usage lags that are similar in magnitude to the GDP lags and thus are plotted close to the dashed line in the figures. In fact, most of these countries have technology lags that are slightly bigger than their GDP lags.

In the standard neoclassical growth model under unconditional convergence, real GDP per capita lags and capital per capita lags should be equal to each other. Our analysis includes

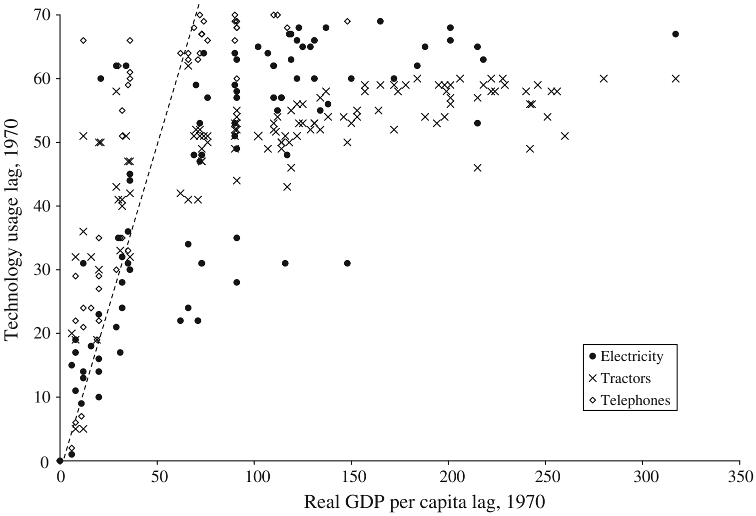


**Fig. 7** Real GDP per capita lags in 1970 versus lags in electricity, tractors, and telephone usage

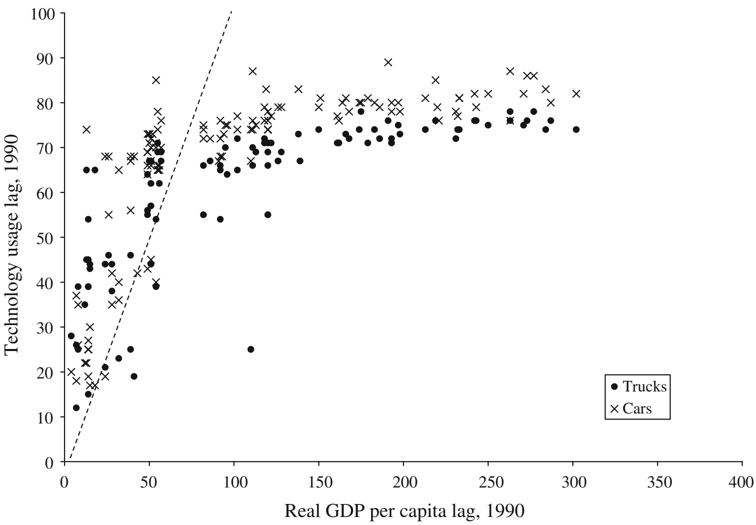


**Fig. 8** Real GDP per capita lags in 1990 versus lags in road transportation

technology usage measures for various technology-specific capital stocks, such as tractors, telephones, trucks, and cars. The fact that for developed countries the technology usage lags for these capital measures tend to be larger than real GDP lags implies that cross-country technology usage patterns and dynamics cannot be fully understood using the standard neoclassical theory of capital accumulation. Instead, a theory that satisfactorily explains these cross-country patterns has to include an explanation of the shift in the composition of the aggregate capital stock and the non-linear dynamics that such a shift entails; it has to be a theory of technology adoption rather than capital accumulation.

Because technologies cannot be adopted before they are invented, we find that for most poor countries technology adoption lags are much smaller than real GDP lags. However,

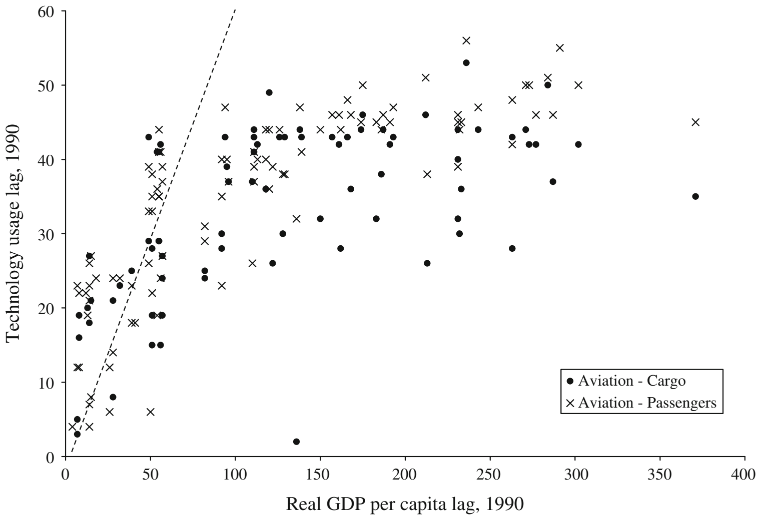


**Fig. 9** Real GDP per capita lags in 1990 versus lags in aviation transportation

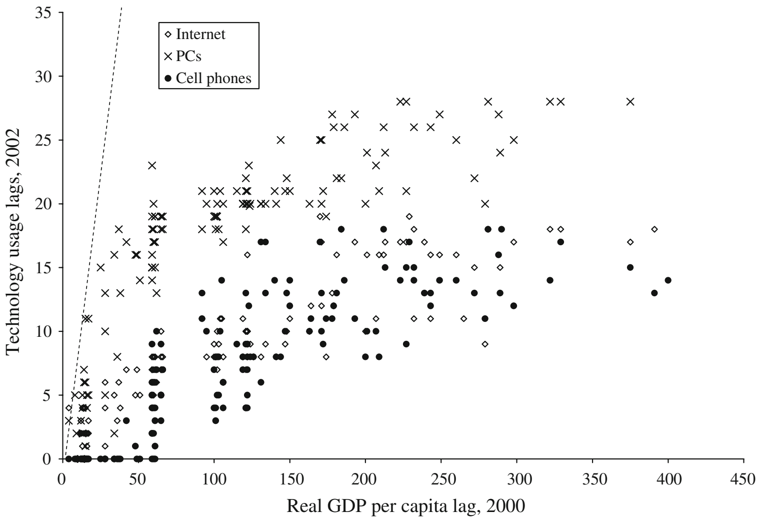


**Fig. 10** Real GDP per capita lags in 2000 versus lags in internet, PC, and cell phone usage

countries with 1970 real GDP per capita levels comparable to those in the pre-World War I U.S. also largely had pre-World War I levels of technology usage in electricity, tractors, telephones, and road transportation. For example, for cars in 1990 10 out of the 112 countries in our sample had usage lags of at least 82 years. That is, for these 10 countries the number of cars per capita was lower than the U.S. in 1908, the year in which Henry Ford sold his first Model T. There are 50 countries in which both the number of trucks and the number of cars are lower than that of the U.S. in 1924, when the U.S. highway system was established.

Figure 9 shows that, for aviation, we find slightly smaller technology lags, especially for non-industrialized economies. This difference largely reflects the fact that, although modern airplanes were invented by the Wright brothers in 1903, it was only after 1945 that civil aviation really took off, even in the U.S.

**Table 1** Summary statistics of technology usage lags for all technologies in particular years

| | Technology | Invention date | Year | Sample size | Mean | Median | St. dev. | IQR | Correlations and joint sample sizes 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Real GDP | | 1950 | 138 | 149 | 128 | 93 | 128 | | 0.93 | 0.82 | 0.75 | 0.77 | 0.75 | 0.75 | 0.77 | 0.71 | 0.71 | 0.75 | 0.61 | 0.70 | 0.63 | 0.71 | 0.63 |
| 2 | Real GDP | | 1970 | 138 | 118 | 114 | 79 | 114 | 138 | | 0.90 | 0.82 | 0.78 | 0.83 | 0.86 | 0.82 | 0.77 | 0.79 | 0.80 | 0.65 | 0.76 | 0.75 | 0.76 | 0.66 |
| 3 | Real GDP | | 1990 | 164 | 113 | 94 | 82 | 119 | 138 | 138 | | 0.94 | 0.74 | 0.80 | 0.89 | 0.86 | 0.80 | 0.81 | 0.75 | 0.66 | 0.77 | 0.73 | 0.68 | 0.61 |
| 4 | Real GDP | | 2000 | 164 | 122 | 105 | 89 | 119 | 138 | 138 | 164 | | 0.69 | 0.75 | 0.83 | 0.87 | 0.80 | 0.82 | 0.70 | 0.65 | 0.75 | 0.68 | 0.65 | 0.58 |
| 5 | Electricity | 1882 | 1950 | 99 | 46 | 48 | 20 | 29 | 96 | 96 | 97 | 97 | | 0.94 | 0.89 | 0.81 | 0.82 | 0.72 | 0.90 | 0.66 | 0.75 | 0.80 | 0.88 | 0.81 |
| 6 | Electricity | 1882 | 1970 | 124 | 52 | 59 | 25 | 37 | 119 | 119 | 121 | 121 | 99 | | 0.94 | 0.84 | 0.85 | 0.80 | 0.89 | 0.67 | 0.77 | 0.79 | 0.87 | 0.77 |
| 7 | Electricity | 1882 | 1990 | 127 | 58 | 57 | 28 | 46 | 120 | 120 | 126 | 126 | 97 | 121 | | 0.86 | 0.86 | 0.82 | 0.85 | 0.68 | 0.80 | 0.82 | 0.80 | 0.70 |
| 8 | Internet | 1983 | 2002 | 123 | 9 | 8 | 5 | 6 | 101 | 101 | 120 | 120 | 81 | 99 | 103 | | 0.89 | 0.86 | 0.81 | 0.74 | 0.81 | 0.74 | 0.78 | 0.69 |
| 9 | PCs | 1973 | 2002 | 127 | 18 | 20 | 7 | 6 | 108 | 108 | 124 | 124 | 86 | 107 | 111 | 110 | | 0.80 | 0.89 | 0.76 | 0.84 | 0.75 | 0.83 | 0.74 |
| 10 | Cell phones | 1973 | 2002 | 145 | 8 | 8 | 6 | 11 | 118 | 118 | 142 | 142 | 93 | 116 | 120 | 122 | 127 | | 0.76 | 0.77 | 0.79 | 0.69 | 0.72 | 0.58 |
| 11 | Telephones | 1876 | 1970 | 108 | 63 | 70 | 23 | 15 | 104 | 104 | 106 | 106 | 90 | 106 | 105 | 90 | 95 | 102 | | 0.70 | 0.79 | 0.83 | 0.93 | 0.84 |
| 12 | Aviation —cargo | 1903 | 1990 | 96 | 27 | 30 | 16 | 23 | 92 | 92 | 95 | 95 | 76 | 93 | 95 | 79 | 88 | 92 | 83 | | 0.89 | 0.68 | 0.69 | 0.51 |
| 13 | Aviation —passengers | 1903 | 1990 | 102 | 34 | 38 | 14 | 21 | 98 | 98 | 101 | 101 | 81 | 99 | 101 | 83 | 92 | 97 | 88 | 96 | | 0.83 | 0.75 | 0.60 |
| 14 | Trucks | 1885 | 1990 | 98 | 59 | 67 | 18 | 26 | 97 | 97 | 98 | 98 | 78 | 96 | 96 | 81 | 84 | 94 | 86 | 78 | 83 | | 0.82 | 0.66 |
| 15 | Cars | 1885 | 1990 | 127 | 66 | 74 | 20 | 14 | 106 | 106 | 127 | 127 | 81 | 100 | 105 | 102 | 103 | 119 | 92 | 81 | 86 | 97 | | 0.84 |
| 16 | Tractors | 1894 | 1970 | 130 | 47 | 52 | 16 | 11 | 124 | 124 | 128 | 128 | 97 | 121 | 123 | 105 | 113 | 123 | 105 | 95 | 101 | 96 | 107 | |

*Note*: 'st. dev.' is standard deviation. 'IQR' is the interquartile range. In the correlations and joint samples sizes part, the numbers above the diagonal are the correlations and the numbers below the diagonal are the sample size on which the correlations are based

The results for the three 'digital age' technologies that were invented after 1970 are remarkably different from the early ones. In 2002, the U.S. was not the leader in internet and cell phone usage. In 2002, Australia, Canada, Denmark, Singapore, and Sweden had more internet users per capita than the U.S. As for cell phones, cell phone usage in 32 out of the 145 countries in our sample in 2002 exceeded that in the U.S. in the same year. These countries include, among others, almost all of Western Europe, Australia, New Zealand, Japan, Singapore, South Korea, as well as the Czech Republic and Slovenia.

Cell phones and PCs were invented at the same time. However, technology usage lags in PCs are substantially large than that of cell phones. This can be seen from the column labeled 'mean' in Table 1; the average usage lag of PCs is 18 years versus 8 for cell phones. Although the internet usage lags that we find are relatively small, many countries have internet usage levels that were last seen in the U.S. during the early stages of adoption of the internet; 51 out of the 123 countries for which we have data had internet usage levels in 2002 that have not been observed in the U.S. since the introduction of web browsers in 1993.

Our results reveal that many developing countries lag the U.S. much less in the use of recent technologies such as the internet or cell-phones than in older technologies such as electricity or cars. This indicates an increase in the rate of international technology diffusion.

### 4.4 Implications for cross-country differences in TFP

In Sect. 4.1 we reviewed micro-level evidence on the very large productivity gains associated with the use of the technologies in our data set over their predecessor technologies. We documented in Sect. 4.2 that there are also large cross-country differences in technology usage lags, indicating the large differences in the intensity of use of state-of-the-art technologies. It follows from these two facts that cross-country differences in the intensity of use of state-of-the-art technologies contribute significantly to large cross-country differences in labor productivity. If all embodied quality improvements in the state-of-the-art technologies would be fully captured in capital stock measures, then these labor productivity differences due to technology usage would be fully attributed to capital deepening. However, because not all the embodied productivity gains are captured in the capital stock measures, technology usage lags are also likely to affect measured cross-country TFP disparities.

### 4.5 Analysis of technology lags

The results plotted in Figs. 7, 8, 9, and 10 already suggest that technology usage lags are highly correlated for the technologies in the four groups depicted in these figures.

For all the technologies depicted in Figs. 7, 8, 9, and 10, technology usage lags are positively correlated with real GDP lags. The actual correlations between technology and income lags are listed in the "correlations and joint sample sizes" part of Table 1. The first four rows of this part of the table list the correlations of the technology usage lags with real GDP lags in 1950, 1970, 1990, and 2000. The average correlation of technology usage lags with GDP lags is 0.76. The minimum is cargo aviation kilometers at 0.66. The maximum is the internet with 0.87. These correlations are high, in spite of the non-linear relationship between GDP lags and technology lags, which is evident from Figs. 7, 8, 9, and 10.[11]

[11] This observation is consistent with (1) a positive correlation between levels of per-capita GDP and technology usage documented in Comin and Hobijn (2008) and Comin et al. (2006b), (2) the positive partial correlations of per-capita GDP and PC usage found by Caselli and Coleman (2001), and (3) per-capita GDP and the timing of adoption of real time gross settlement systems for interbank payments found by Bech and Hobijn (2007).

**Table 2** Income lags do not fully account for technology usage lags

| Explanatory variable: | Dependent variable: Technology lag$_t$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | I | II | III | IV | V | VI | VII |
| Technology lag$_{t-k}$ | 1.11 | 1.00 | 0.93 | 0.96 | 0.85 | 0.88 | 0.88 |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.03) | (0.03) | (0.03) |
| Income lag$_{t-k}$ | | 0.04 | | −0.02 | | −0.02 | −0.03 |
| | | (0.00) | | (0.01) | | (0.01) | (0.01) |
| Income lag$_t$ | | | 0.06 | 0.08 | | | 0.05 |
| | | | (0.00) | (0.01) | | | (0.01) |
| $N$ | 1439 | 1392 | 1413 | 1392 | 1439 | 1392 | 1392 |
| $R^2$ | 0.90 | 0.92 | 0.92 | 0.92 | 0.89 | 0.88 | 0.91 |
| Country fixed effects | No | No | No | No | Yes | Yes | Yes |

*Note*: All regressions include a full set of technology dummies. Robust standard errors in parenthesis

Moreover, the correlations across technologies, which can be found in the "correlations and joint sample sizes" part of Table 1, are also very high. The average correlation across technology lags is 0.79, while the minimum is 0.51 for cargo aviation kilometers and tractors, and the maximum is 0.93 for electricity in 1970 and 1990. Considering only correlations between different technologies, the maximum is also 0.93, between cars in 1990 and telephones in 1970.

One interesting implication of this analysis is that the positive correlation in usage lags is not only observed contemporaneously but also between lags for different technologies decades apart. Skinner and Staiger (2007) document similar correlations in cross-state adoption patterns of several, seemingly unrelated, technologies over time for U.S. states. Hence, it seems that there are country-specific factors, which have relative effects that are relatively constant over time, that affect the usage levels of all technologies in a similar manner.

If these factors are fully captured by cross-country per capita GDP differences, then the study of the dynamics of technology adoption does not add much in terms of the identification of these factors above and beyond more aggregate development accounting methods. To investigate the relative importance of earlier technology lags and per capita income lags in explaining current technology usage lags, we build a panel of technology adoption lags[12] and estimate Eq. 4.

$$tech_{cit} = \alpha_i + \beta tech_{cit-k} + \gamma y_{ct-s} + \varepsilon_{cit} \tag{4}$$

where $c$ indexes country, $i$ technology and $t$ year, *tech* denotes the technology usage lag, $y$ denotes the per-capita income lag, $k$ depends on data availability but is typically 20 years[13] and we set $s$ both equal to $k$ and to 0.

Table 2 reports our estimates. Column I does not include the income lag. It shows that technology usage lags are highly persistent. The technology lag $k$ (i.e., 20) years earlier explains almost 90% of the variance in the panel of technology lags.

The rest of the columns show that this finding is robust to controlling for various income lags and for country fixed effects. Specifically, Column II shows that the association between

[12] Specifically, the dependent variables are lags in electricity in 1970 and 1990, in internet users in 2002, in telephones in 1970 and 1980, in aviation cargo and passengers in 1970 and 1990, trucks in 1970 and 1990, cars in 1950, 1970 and 1990 and tractors in 1970.

[13] It is set to 10 for telephones in 1980, and for computers and internet users in 2002.

the technology lags at $t$ and $t-k$ is unaffected by the inclusion of income lag at $t-k$ in the regression. The income lag has a positive effect on the technology lag, but its coefficient is much smaller than the coefficient of the technology lag at $t-k$. Including the income lag at $t$, instead of at $t-k$, as a control, as in Column III, does not much affect this conclusion.

Similarly, when a country has done well in terms of the reduction of its income lag between $t-k$ and $t$ it tends to have shorter technology lags at $t$. This effect however, is small relative to the effect of lagged technology intensity on current technology intensity as shown in column IV of Table 2. This leads us to conclude that, for technology usage lags, the past in terms of usage lags matters much more than the present and the past in real GDP lags.

Columns V through VII show the robustness of these findings to including country fixed effects. A few results are worth noting. First, the effect of lagged technology intensity (measured by the lag at $t-k$) on current intensity (measured by the technology lag at $t$) remains virtually unchanged after the country fixed effects as shown in Column 5. This is interesting because, though 40% of the variance in the panel is driven by the country fixed effects, there is sufficient heterogeneity across technologies within countries to identify that the effect of lagged technology intensity on current technology intensity operates at the technology level rather than at the country level.

Second, the effect of income lag at $t-k$ on technology lag at $t$ becomes negative once the country effects are included. Finally, after including both the income lags at $t$ and $t-k$, it seems that the change in the income lag is positively associated with the technology lag at $t$. As in column IV, however, this effect seems small indicating that the technology adoption dynamics are much more important than the overall dynamics of per-capita income in explaining the intensity of technology adoption.

Interestingly, Skinner and Staiger (2007) and Comin et al. (2006a) reach similar conclusions using different methodologies, sets of technologies, geographical units, and time periods.

## 5 Conclusion

The U.S. leads the world in the intensity of use of a broad range of technologies. For many countries, the degree to which they use various technologies, including electricity, cars, trucks, and phones, lags the technology usage level in the U.S. by several decades.

The evidence on usage lags, which measure how many years ago the 10 technologies that we consider were used in the U.S. at the same intensity as they are used in the countries in our sample, that we presented in this paper uncovers three main generalizations.

First, usage lags are sizeable. Second, usage lags are highly correlated across technologies. Third, technology usage lags are also highly correlated with the level of economic development of a country, as measured by per-capita income.

The productivity differentials between the state-of-the-art technologies that we consider and the ones they replace, combined with the usage lags that are documented at the micro level, lead us to infer that technology usage disparities might account for a large part of cross-country TFP differentials. If so, then (the intensity of) adoption of new technologies is a key mechanism for understanding the development process.

With this in mind, we began to explore the dynamics of technology intensity. In particular, we showed that the technology adoption dynamics are more important than the overall dynamics of per-capita income in explaining the intensity of technology adoption. Moreover, our analysis of real GDP per capita and technology usage lags uncovers a type of catch-up in GDP and technology usage that suggests that cross-country dynamics are more consistent with those described in Lucas (2000) than with the neoclassical growth model analyzed by Barro and Sala-i-Martin (1992).

## Appendix 1. Data: sources and definitions

*Countries* Our sample consists of 185 countries. Unfortunately, we do not have data for all countries for all years. Because of this we have chosen the years for which we present our results to make the coverage of our sample as broad as possible.

*Description of technologies* The particular technologies that we use are measured and classified as follows. For those technologies for which we use more than one source, we use the merged time series from Comin et al. (2006b).

Standard of living

*Real GDP per capita* Gross domestic product measured in 1990 International Geary–Khamis dollars. *Source*: Maddison (2007).

Electricity

*Electricity* Gross output of electric energy (inclusive of electricity consumed in power stations) in kWh per capita. *Invention date*: 1882, when Edison built first DC generator and used the electricity it produced to illuminate Pearl St. in New York City. *Source*: World Bank (2007) and Mitchell (1998a, b, c).

Information technologies (IT)

*Internet users* Number of people with access to the worldwide network per capita. *Invention date*: 1983, when TCP-IP is introduced as the standardized internet protocol. *Source*: World Bank (2007).

*Personal computers* Number of self-contained computers, designed for use by one person, per capita. *Invention date*: 1973, with the first application of Intel microprocessors in computers. *Source*: World Bank (2007).

Communication technologies (CT)

*Cell phones* Number of portable cell phones per capita. *Invention date*: 1973, when Martin Cooper of Motorola placed first public telephone call on a portable cellular phone. *Source*: World Bank (2007).

*Telephones* Number of mainline telephone lines connecting a customer's equipment to the public telephone network, as of year end, per capita. *Invention date*: 1876, when the telephone invented by Alexander Graham Bell. *Source*: World Bank (2007) and Mitchell (1998a, b, c).

Transportation technologies

*Aviation—cargo* Civil aviation ton-KM of cargo carried on scheduled services by companies registered in the country concerned per capita. *Invention date:* 1903, with the Wright brothers' first controlled, powered, heavier-than-air human flight. *Source*: Mitchell (1998a, b, c).

*Aviation—passengers* Civil aviation passenger-KM traveled on scheduled services by companies registered in the country concerned per capita. *Invention date*: 1903, see 'Aviation—cargo'. *Source*: Mitchell (1998a, b, c).

*Commercial vehicles* Number of commercial vehicles, including trucks, buses and taxis (excluding tractors), in use per capita. *Invention date*: 1885, when Karl Benz built the world's first practical automobile to be powered by an internal-combustion engine. *Source*: World Bank (2007) and Mitchell (1998a, b, c).

*Passenger cars* Number of passenger cars (excluding tractors and similar vehicles) in use per capita. *Invention date*: 1885, see 'Commercial vehicles'. *Source*: World Bank (2007) and Mitchell (1998a, b, c).

### Agricultural technologies

*Tractors* Number of wheel and crawler tractors (excluding garden tractors) used per capita. *Invention date*: 1894, when Paterson patented his gas-traction engine. *Source*: FAO (2008).

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