The role of production factor quality and technology diffusion in 20th century productivity growth[1]

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Abstract:

The 20th century was a period of exceptional growth, driven mainly by the increase in total factor productivity (*TFP*). Using a database of 17 OECD countries over the 1890-2013 period, this paper integrates production factor quality into the measure of TFP, namely by factoring the level of education of the working-age population into the measure of labor and the age of equipment in the measure of capital stock. We then estimate how the diffusion of technology impacts the growth of this newly measured *TFP* through two emblematic general purpose technologies, electricity and information and communication technologies (ICT). Using growth decomposition methodology from instrumental variable estimates, this paper finds that education levels contribute most significantly to growth, while the age of capital makes a limited, although significant, contribution. Quality-adjusted production factors explain less than half of labor productivity growth in the largest countries except for Japan, where capital deepening posted a very large contribution. As a consequence, the "one big wave" of productivity growth (Gordon, 1999), as well as the ICT productivity wave for the countries which experienced it, remains only partially explained by quality-adjusted factors, although education and technology diffusion contribute to explain the earlier wave in the US in the 1930s-1940s. Finally, technology diffusion, as captured through our two general purpose technologies, leaves unexplained between 0.6 and 1 percentage point of yearly growth, as well as a large proportion of the two 20th century technology waves. These results support both a significant lag in the diffusion of general purpose technologies and raise further questions on a wider view on growth factors, including changes in the production process, management techniques and financing practices. Measurement problems may also contribute to the unexplained share of growth.

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1. Introduction

Growth in the 20th century was characterized by three stylized facts, which the growth literature has tried to explain in recent decades. First, the period starting with the second industrial revolution was a period of exceptional growth compared with the history of mankind including the first industrial revolution. World GDP per capita growth averaged 1.5% per year from 1870 to 2000, as compared with less than 0.1% during the pre-industrial era and 0.3% during the first industrial revolution (Maddison, 2001). Second, this take-off was uneven across countries, leading to a "Great Divergence" (Galor, 2005) between emerging and advanced economies, and was staggered across advanced countries (see for example Baumol, 1986, Barro, 1991 and Bergeaud *et al.*, 2015). The subperiod 1913-1950 thus witnessed the largest growth rate for total factor productivity in the US, with an average 2.4% per year, while it amounted to 1.1% in European countries. The subsequent subperiod 1950-1974 was exceptional, with an average 3.6% growth per year. Finally, GDP per capita has slowed markedly since the 1970s in advanced countries, except during the 1995-2005 period in the US and the UK, where productivity accelerated thanks to the ICT technology revolution, raising questions about the durability of the pace of growth in the 21st century (Gordon, 2012, 2013 and 2014). Which factors drove this strong but heterogeneous productivity growth in the 20th century? When considering the average number of years of education in the population over 15, the US and the current euro area countries were at a comparable level in 1920, while in 1940 every American had spent on average 1.5 more years in school, and 2.2 more years in 1950.[2] What is the role of education in explaining the US's advance in terms of productivity in the 1940s and 1950s? Regarding technology adoption and diffusion, the US was the first country to massively integrate electricity into its economy at the beginning of the 20th century and was one of the most ICT-capital intensive countries at the end of that century. How can the use of such fundamental technologies explain the heterogeneous growth rates of productivity in developed countries?

Growth accounting exercises presented in Solow (1957) were a first attempt to analyze the respective roles of production factors (capital and labor), yet they failed to explain the bulk of 20th century growth. As reported by Bakker *et al.* (2015), Solow finds that more than 85% of US productivity growth between 1909 and 1949 can be attributed to total factor productivity (*TFP*), defined as the residual of the decomposition of production over capital stock and labor. *TFP* improvements are then attributed to technical change, which remains more or less a "black box". This is partly related to the difficulty of capturing the role of general purpose technologies (GPTs), due to their diffusion lag (see for instance David, 1990), their pervasiveness and dynamic technological effects (Bresnahan and Trajtenberg, 1995). Indeed, GPTs' contribution goes beyond factors included in the growth accounting approach such as capital deepening in GPT-related equipment and *TFP* improvement in GPT-producing sectors. First, GPTs lead to fundamental changes in the production process of GPT-using industries. These changes may be poorly accounted for in growth accounting exercises as they require the accumulation of complementary organizational capital (Basu and Fernald, 2007). Second, GPTs may generate spillovers to seemingly far-away sectors (Helpman and Trajtenberg, 1998). In fact, Lipsey *et al.* (2005) define a GPT as "*a single generic (…) that initially has much scope for improvement and eventually comes to be widely used, to have many uses, and to have many spillover effects*".

In spite of these difficulties, several papers have attempted to distinguish growth factors over the long run on a large panel of countries (see Crafts and O'Rourke, 2013, for a survey). In particular, Madsen develops a long-term database on OECD countries and examines the respective roles of capital deepening and *TFP* (Madsen, 2010a), production factors and *TFP* determinants (Madsen, 2010b) and human capital (Madsen, 2014). He emphasizes the major role of *TFP* in growth dynamics. In amongst the vast convergence literature, Barro (2015) emphasizes the role of education and democracy in conditioning β-convergence for a country panel starting in 1870; Bergeaud *et al.* (2016) show that the bulk of 20th century σ-convergence depends on *TFP* and capital deepening. Cervellati *et al.* (2013) find that, since 1880, income gaps between rich and poor countries have related to the health

[2] All these figures come from sources that will be detailed below and are used throughout the paper.

environment, the occurrence of wars and geographical remoteness. They derive their analysis from unified growth theory (Galor, 2005), which provides microfunded and macrodynamic models that attempt to highlight the causal relationship between human capital, technology and growth,

In this paper we estimate the role of quality-adjusted production factors and technology diffusion in the GDP per capita growth of 17 OECD countries over the period 1890-2013. First, we draw on a previously built long-run dataset (see Bergeaud *et al.*, 2016) on a large number of countries, with data reconstructed in purchasing power parity and based on consistent assumptions. With these data, we decompose GDP growth between the contribution of production factors, capital and labor, to obtain *TFP* as a residual. Second, we adjust these production factors for quality, taking into account levels of education and the age of capital stock. Third, we estimate the contribution of technology diffusion to *TFP* growth, focusing on two general purpose technologies, namely electricity and ICT, which are often considered as characteristic of different technology diffusion periods during the 20th century (see among others Comin *et al.*, 2006a and 2006b and Lipsey *et al.*, 2005). The originality of our approach is twofold: the empirics are realized on an original large dataset for countries over a long period and we try to assess the impact on GDP per capita growth of the two indicators of factor quality (education and age of capital) and the two GPTs (electricity and ICT use). This assessment is carried out through the estimation of elasticities which are, for each of these four aspects (two concerning factor quality and two concerning GPTs), assumed to be the same for all countries of the dataset and over the whole of the 1890-2013 period. This choice seems sensible for two reasons. First, to be consistent with the way our database is constructed, we make common hypotheses across time and countries as much as possible: for example, we use the same permanent inventory methodology to build the capital stock and we use the same capital elasticity to compute the *TFP* indicator (see Bergeaud *et al.*, 2015). Second, this choice has been made in the existing literature (*e.g.* Madsen, 2008a and 2008b; Barro and Lee, 2013); hence, it yields deriving elasticities that can be compared with the estimates of these articles.

Numerous papers have attempted to characterize the role of technology diffusion in productivity growth using growth accounting approaches. Among others, Jorgenson and Stiroh (2000), Oliner and Sichel (2000) and Oliner, Sichel and Stiroh (2007) have focused on the contribution of ICT in the US at the end of the 20th Century. Regarding the comparison of industrial revolutions, Crafts (2002) studied the contribution of steam engines in the UK during 1780-1860, and electricity and ICT in the US during 1899-1929 and 1974-2000 respectively. Jalava and Pohjola (2008) compared the contribution of electricity during 1920-1938 and ICT during 1990-2004 in Finland. In the latter paper, electricity is believed to have accounted for 26.7% of total growth between 1920 and 1938, while the effect of ICT capital is considered lower, with a contribution to total growth of 16%. These numbers are consistent with the findings of Bakker *et al.* (2015) who revisited the idea that electricity was the main factor of growth in the US in the 1920s and found that electrification explained 28% of manufacturing *TFP* growth during this period. An abundant literature has emphasized the role of innovation and innovation diffusion in interaction with education and institutions. For countries at the technological frontier, growth relies on improved human capital through education (see Krueger and Lindahl, 2001, for a survey) and increasing *TFP* through innovation. The innovation process hinges on education levels and suitable institutions (labor and product market regulations, quality of the legal system, political system, etc.) as well as relative factor endowment and market size ("Directed technical change", see Acemoglu, 1998, 2002).[3] For countries not at the frontier, even those conducting significant R&D activity such as France, Germany and the United Kingdom, adoption of new technologies from abroad is the main source of technological progress (Eaton and Kortum, 1999). Heterogeneity in the adoption and diffusion of new technologies is large and explains a significant

[3] Basu and Fernald (2002) show that imperfections and frictions in output and factor markets matter in the relation between aggregate technology and aggregate productivity. For example, with heterogeneous firm mark-ups, the same resources may be valued differently in different uses. Then "reallocating resources towards more socially valued uses raises aggregate productivity, without necessarily reflecting changes in technology." Citation from page 964 of Basu and Fernald (2002). Edquist (2001) raises the question of the role of innovation policy with respect to technology diffusion.

share of the "Great Divergence" (Comin and Mestieri, 2013). Comin and Hobijn (2010) provide evidence that those countries that caught up the most with the US in the postwar period are those that also saw an acceleration in the adoption of new technologies. But adoption of new technologies requires both "social capability", relying on a minimum level of education within the population and appropriate institutions, and "technological congruence" making it cost effective to adopt the leader's technology (Abramovitz and David, 1995). These conditions that enable one to benefit as much as possible from new innovations could play a growing role in the future if the rate of innovation accelerates, as observed for example by Fernald and Jones (2014), who suggest that such an acceleration could happen within the next decade due to the rise of emerging countries like China and India which will generate rapid growth in the number of researchers.[4] One of our most significant contributions to this literature consists in the systematic comparison our study makes possible of a fairly large number of developed countries throughout the 20th century, including technological leaders and laggards. As stressed by van Ark and Smits (2002), most of the literature on technology diffusion, adoption and on estimating the impact of GPTs over the long-run has focused on the UK and the US, because of better data availability and coverage. However, little is known about other countries that were not necessarily at the productivity frontier and that might have reacted differently to the development of GPTs.

Beyond our manifold results, the three main contributions to the literature are the following: (i) among factor quality, education levels contribute to growth the most, while the age of capital makes a significant, although limited, contribution; (ii) quality-adjusted production factors explain less than half of labor productivity growth in the largest countries, except for Japan, where capital deepening accounts for a large share of the growth. As a consequence, the "one big wave" of productivity growth (Gordon, 1999), as well as the ICT productivity wave for the countries which experienced it, remain unexplained by quality-adjusted factors, although the early access of the masses to higher education partly explains the US's lead before World War II; (iii) we estimate the contribution of general purpose technologies to long-term growth. Technology diffusion, as captured through our two GPTs, electricity production and ICT intensity, also contributes to explaining the US's lead in the 1930s-1940s and ICT productivity waves but leaves unexplained between 0.6 and 1 percentage point of yearly growth, as well as a large share of the two 20th century technology waves. These results support both a significant lag in the diffusion of general purpose technologies and a wider view on growth factors including changes in the production process, financing techniques, etc., as emphasized by Ferguson and Wascher (2004). Finally, and this aspect will be developed below, some measurement errors bearing on all the variables of interest may also contribute to the unexplained share of growth.

In what follows, Section 2 presents the data sources and construction methods. Section 3 focuses on the contribution of factor quality. Section 4 addresses the impact of the spread of technologies. Section 5 concludes.

2. Data: sources, method and construction

The original dataset used in this study comes from Bergeaud *et al.* (2015), updated and enlarged to include more countries (2.1.). We have completed this dataset with data on levels of education (2.2.), age of capital (2.3.) and the spread of some generic technologies (2.4.).

2.1. The original dataset

Our main dataset is the one used in Bergeaud *et al.* (2015) and based on the works of Cette *et al.* (2009) and Bergeaud *et al.* (2016) consisting of data for 17 OECD countries over the period 1890-

[4] "[T]he rise of China, India and other emerging economy countries, [is] likely [to] impl[y] rapid growth in world researchers for at least several decades." Citation from page 48 of Jones and Fernald (2014).

2013. These countries have been chosen for their economic relevance: the G7 (the United States, Japan, Germany, France, the United Kingdom, Italy and Canada), five other euro area countries (Spain, the Netherlands, Belgium, Portugal and Finland) and five other countries which are of specific interest in terms of productivity (Australia, Switzerland, Denmark, Sweden and Norway). In addition, a euro area has been reconstituted, aggregating Germany, France, Italy, Spain, the Netherlands, Belgium, Portugal and Finland. This approximation seems acceptable as, in 2010, these eight countries together accounted for 93.2% of the euro area's GDP (16 countries in 2010). The starting date, 1890, has been chosen so as to have sufficiently long time series to initialize our capital stock.

A detailed description of the construction of this dataset is given in Bergeaud *et al.* (2016), in particular its appendix A which presents the source of the data. To compute GDP over this long 1890-2013 period, we have drawn mostly on Maddison (2001), whose series have recently been updated and improved by Bolt and Van Zanden (2014). Maddison provides data for GDP and population, mainly from 1820. We have supplemented these data with national accounts data. For other series and in particular to compute capital intensity and labor productivity, three basic series are needed for each country: employment, average hours worked per worker and capital. The capital indicator is constructed by the perpetual inventory method (PIM) applied to each of the two components (equipment and buildings) using the corresponding investment data. The yearly depreciation rates used to construct the capital series by the PIM are 10% for equipment and 2.5% for buildings, following Cette *et al.* (2009) and are assumed to be constant across time and space. Finally, the damage that occurred during the World Wars, earthquakes in Japan and the civil war in Spain are, as far as information is available for these, taken into account to build the capital series.

For long aggregate historical data, we have used series built by economists and historians on consistent assumptions. Many of these data are subject to uncertainty and inaccuracy, not only for the most distant periods but also for recent ones. The data are built at the country level assuming constant borders in their latest state. It should be noted that, however talented economists and historians are, strong assumptions are required to reconstitute some countries, and in addition retropolating series on a different year basis may bias the estimated growth rates, as argued in Prados de la Escosura (2015). We may nevertheless consider that the orders of magnitude of our estimates and the ensuing large differentials in productivity levels and growth rates are fairly reliable and meaningful. Series for GDP and capital are given in 2010 constant national currencies and converted to US dollars at 2010 purchasing power parity with a conversion rate from the Penn World Tables.

For this study, we have improved and completed the Bergeaud *et al.* (2015) database, including or building series for education, age of capital and the spread of technology as described below.

2.2. Levels of education

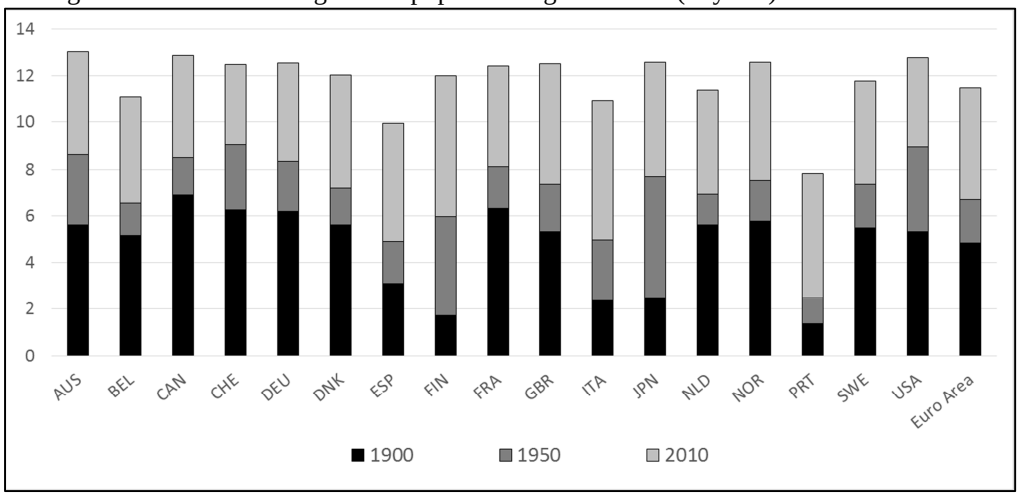
Since the development of new growth accounting frameworks based on the addition of the stock of human capital in the production function, many attempts have been made to compute series of educational attainment. First, figures for school and university enrollment have been used. For example, Mankiw *et al.* (1992) proxied the rate of human capital accumulation by the share of the total population that is currently attending secondary school, while Barro (1991) used the same measure to proxy for the stock of human capital. However, comparing different education systems can be cumbersome and macroeconomic studies have struggled to find convincing experimental results that match theories. In addition, these approaches have been widely criticized because they focus on a flow which only makes sense if we are at the steady state. Since these first developments, many studies have chosen to focus on educational attainment as defined by the average time spent studying in the total population over the age of 15 or 25,[5] taking advantage of newly improved datasets. Kyriacou (1991) was one of the first to compute and share such data. Since then, further improvements have

[5] The calculation starts with primary school and does not include kindergarten or any other type of education received before 6.

been made and educational attainment is available every five years for a large set of countries from 1950 to 2010 in the Barro and Lee (1993, 2010) dataset, or alternatively every 10 years from 1960 to 2020 in Cohen and Soto (2007). These series can be extended back to 1870, with one observation every decade, using data from Morrisson and Murtin (2009). Finally, Barro and Lee have recently updated their series and cover the time period 1870-2010, with one point every 5 years. Once again, this measure is not perfect. First, several economists (*e.g.* De la Fuente, 2011; Krueger and Lindahl, 2000; and Soto, 2002) suggest that, while they are regularly improved, these data suffer from measurement errors due to differences in education law across countries, which may lead to a bias in growth regression. Others (see in particular Pritchet, 2001) argue that the average number of years of education cannot be expected to be correlated with economic growth if the quality of education is not taken into account. For this reason, some studies have used literacy rates or exam results to capture the quality of education (see Hanushek and Ludger, 2012, for example). Unfortunately, such data are available for a very limited time period and cannot be incorporated in our study.

Because we wanted to take advantage of our long time perspective, and to use on yearly data as much as possible, we have updated our dataset with new series of educational attainment provided by van Leeuwen and van Leeuwen-Li (2014) and available from 1870 to 2010, except for Denmark, for which before 1900, only 1890, 1880 and 1870 are given (we have linearly interpolated these data). At the beginning of the 20th century, Canada, France, Germany and Switzerland were the countries with the highest level of educational attainment with over 6 years in education, while Finland, Portugal and Japan recorded less than 2 years of education. At the end of our dataset, in 2010, Portugal is by far the country with the lowest level of education in its population, with an average duration of 7.8 years, far behind Australia, Canada and the US with around 13 years. Other countries stand at around 12 years, except for Spain (9.9), Italy (11) and Belgium (11.1), as seen in Chart 1.

Chart 1
Educational attainment in 1900, 1950 and 2010
Average duration of schooling for the population aged over 15 (in years)



Source: van Leeuwen and van Leeuwen-Li (2014).

Strikingly from Chart 1, we see that the average level of education was roughly the same for the euro area and the US in 1900, whereas the latter had a more educated population by an average of 2.2 years in 1950. Educational attainment in the working-age population is a stock that is very slow to adjust to an increase in the average years of schooling of a new generation. Therefore, this difference cannot be attributed to World War II as children who were affected by the war in their curriculum during the early 1940s account for only a very small share of the population over 15 in 1950. This is rather the result of the "high school movement" in the US resulting in a large increase in secondary attainment in the US from 1910 to 1940 (Goldin and Katz, 1998), namely due to the building of new public schools. Hence, according to Sydner (1993), secondary enrollment doubled between 1920 and 1930, while it did not increase much in Europe in addition to being at a lower level (Goldin and Katz, 1997; Morisson and Murtin, 2009; Barro and Lee, 2015). At the same time, there was not much difference in

tertiary enrollment between the two regions according to data from Mitchell (1998a, 1998b). At the end of the period, the US still had a significant advance over the euro area. This difference was mostly driven by differences in tertiary education which emerged during the 1950s along with mass investment in research during the Space Race.

2.3. The age of capital

We have calculated the average age of the equipment capital stock, which is an indicator of the quality of this factor and should therefore be incorporated into the production function. This simply translates the intuitive idea of a vintage effect: older capital should be less productive than newer capital, as suggested by Solow (1959, 1962) and developed subsequently in numerous papers, such as for example Nelson (1964) and more recently Gittleman *et al.* (2003).

With our yearly series on investment in volume terms, it is possible to compute an estimate of the average age of capital stock. To do so, we have used the fact that capital stock is computed by the PIM and therefore:

$$K_t = K_{t-1}(1-\delta) + I_t = \sum_{k=1}^{t} I_k(1-\delta)^{t-k} + K_0(1-\delta)^t$$

Where K_t and I_t stand respectively for the capital stock installed at the end of year t and the investment realized during year t, and δ is a depreciation rate.[6]

The average age of the capital installed at the end of year t, A_t, is computed using the relation:

$$A_t = \frac{(1+A_{t-1})(1-\delta)K_{t-1}}{K_t} = (1-\frac{I_t}{K_t})(1+A_{t-1}) \quad \textbf{(1)}$$

To use relation 1, we need the value of A_0, the average age of capital at the starting year of our investment series. Assuming that before this starting year investment grew at a constant rate G, then A_0 is computed by the relation:[7]

$$A_0 = \frac{1-\delta}{\delta+G} \quad \textbf{(2)}$$

One must also consider the case of exceptional destruction due to wars or natural disasters such as earthquakes. We have taken this exceptional destruction into account in our capital evaluation (see Bergeaud *et al*., 2016, for details). However, their effect on age is not trivial as it would require knowing exactly what type of capital was destroyed. We have considered that the destruction was homogenous in the age distribution of capital stock and that it therefore has no effect on the average age of capital.

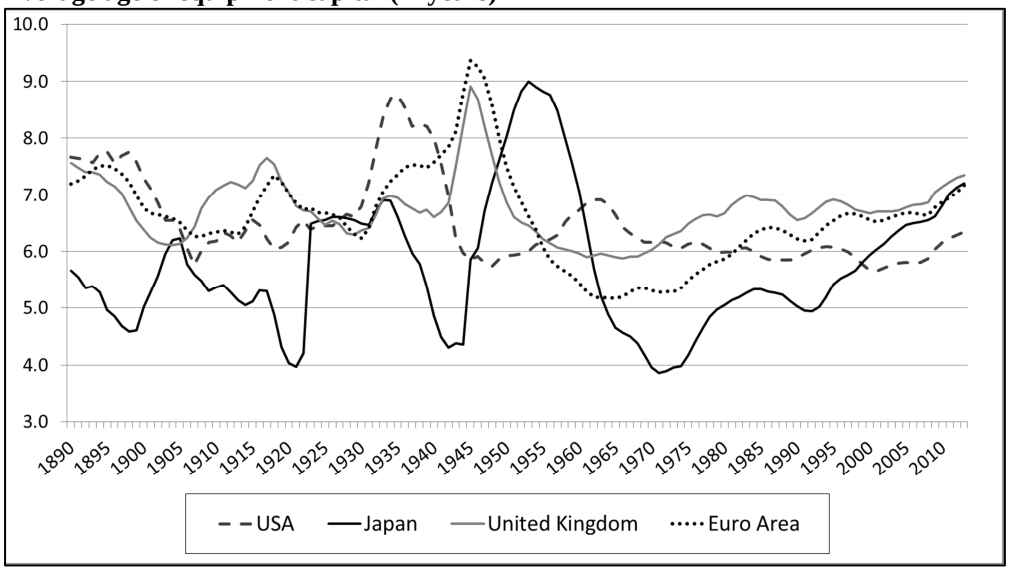
Results from these calculations are presented in Chart 2 for the US, Japan, the United Kingdom and the euro area for equipment capital stock. The average age varies from 4 to 8 years depending on the period. It increased strongly during the Great Depression in the US, which weighed strongly on investment; it decreased strongly during World War II due to the war effort, and more modestly during

[6] In our model, depreciation of each element of capital follows a geometric distribution where the probability of depreciation is δ. This distribution is memoryless, that is, the probability of depreciation is independent of the age of capital, and the average life expectancy of capital is then equal to $\frac{1}{\delta}$.

[7] In practice, we compute G by taking the average of the growth rate of GDP over 10 years. This relationship makes a strong assumption, but the initial stock of capital is computed years before 1890, which is the first year in this study. The empirical impact of this simplification is then of minor importance in the age of capital evaluation.

the ICT wave as new investment was needed to incorporate the new technology. In the euro area and the United Kingdom, it increased strongly during World War II as the conflict depressed investment and decreased in the post-war reconstruction period. It has been on an increasing trend since 1990 in Japan due to the banking crisis and since the financial crisis in other areas, as credit constraints and low demand prospects weigh on investment. Smaller contra-cyclical fluctuations can be observed.

Chart 2
Average age of equipment capital (in years)



Source: Authors' calculations – see text. The depreciation rate is assumed to be equal to 10%.

2.4. Spread of technology

To measure the diffusion of technology over the whole period, we have drawn on the CHAT database constructed by Comin and Hobijn (2009). This database provides annual estimates of the diffusion of more than 100 technologies for a large set of countries. We have selected one technology which is often considered to be representative of the development of technologies during the 20th century, the production of electricity in kWh (see Comin *et al.*, 2006a and 2006b). Data have been completed with series using the World Development Indicators of the World Bank up to 2013 and have been standardized by total population. To measure the diffusion of technology in the more recent time period, we have drawn on the work of Cette *et al.* (2015), which provides estimates of the stock of capital of three ICT from 1950 to 2012 for most of our countries. More details on data construction will be given in section 4. An alternative measure of innovation would have used the stock of patents, both domestic and foreign. However, using patents as a technological indicator can be very tricky when it comes to cross-country comparisons with different intellectual property regulations. In addition, as shown in Sanchis *et al.*, (2015), the stock of patents has a heterogeneous impact on *TFP* from one country to another, which may depend on differences in education levels and domestic knowledge accumulation. By using measures of electricity and ICT capital, we are directly measuring technology diffusion at the closest level to what actually impacts *TFP*.

3. Education and age of capital in a growth accounting framework

The purpose of this section is to evaluate the contributions of changes in education and age of capital on *TFP* growth. To do that, we successively specify how the productivity impact of education (3.1.) and age of capital (3.2.) can be empirically taken into account and what the main results of the literature are on these aspects. We then propose some estimates of these impacts (3.3.) and an

evaluation of them on productivity growth over the long period of our analysis, using a growth accounting approach for this purpose (3.4.).

3.1. Education and productivity

We have used the endogenous growth model of Lucas (1988), formalized, *inter alia*, in Hall and Jones (1999) to expand the approach we adopted in Bergeaud *et al.* (2015, 2016). Lucas updated the neoclassical growth model by considering the stock of human capital (denoted *C*) as an input in a Cobb-Douglas production function. This stock accumulates according to the equation:

$$\frac{dC}{dt} = \varphi(1-u)C$$

Where u is the fraction of time spent working and φ is a parameter representing the maximum reachable human capital for someone who spent his whole life studying (that is, when $u = 0$), also sometimes called the productivity of schooling (the productivity level of an individual who spends his whole life studying). The stock of physical capital *K* increases following a permanent inventory method and, from a Cobb-Douglas constant return to scale relation, the production function becomes:

$$Y = TFP.K^{\alpha}(u.C.L)^{1-\alpha}$$

Where Y is the production, *L* the number of hours worked, with $L = N.H$, *N* being the number of workers and *H* the average working hours per worker. The idea is that individuals invest in education through the choice of a fraction $1 - u$ of life spent studying and accumulating knowledge in order to increase their productivity. This model is a microfoundation of the way education can enter the production function.

In Bergeaud *et al.* (2015, 2016), we used a classical Solow Model in which the production function was a Cobb-Douglas constant return to scale relation: $Y = TFP.K^{\alpha}.L^{1-\alpha}$. Here we aim to understand what share of *TFP* can be attributed to human capital and we therefore consider that $Y = TFP'.K^{\alpha}.(LC)^{1-\alpha}$ where *C* is the human capital stock. To calculate the stock of human capital *C*, we have followed a Mincerian approach developed in Mincer (1974) and assumed that:

$$C = e^{g(S)} \qquad \textbf{(3)}$$

With *S* representing the number of years spent studying and g being an increasing function verifying $g(0) = 0$. When $g = 0$, we are back to the Solow model and human capital is no longer an input. Otherwise, the derivative of g is called the return to education. Usually, g is assumed linear, or at least piecewise linear (see Psacharopoulos, 1994, for a review), but more complex formula have also been tested in the literature, namely by Temple (2001). In this study, we have supposed that $g(S) = \theta.S$ where θ is a constant and homogenous term that we shall estimate.

Many studies have focused on estimating the returns to education, using micro or macro approaches. In the former, the return to one year of education is defined as the average increase in wage associated with an additional year of schooling. Even if a large number of individual datasets are available for a large range of countries, estimating the private return to education is not straightforward because the effect of schooling on wages is highly endogenous (Klein and Vella, 2009; Card, 1999; Bills and Klenow 2000). Indeed, the choice of the duration of schooling is likely to be correlated with unobserved ability that would also be positively correlated with wages. The OLS coefficient would then be biased upwards. Most studies use different strategies to address this issue: for example, some use natural experiments, among which reforms raising the minimum school leaving age to generate exogenous discontinuities in educational attainment (see Devereux and Wen, 2011 or Dickson and Smith, 2011). Angrist and Krueger (1991) use a different school age start policy for individuals born at the beginning of the year to instrument education by the quarter of birth while other studies look at

parents' or spouse' education as an instrument (Trostel *et al.*, 2002). There is a broad empirical consensus in most micro studies on a private return to education of between 6% and 8% in developed countries, which means that each additional year of education raises the wage by 6% to 8%. For example, Dickson and Smith (2011) find a value of 8% for males in the UK, exploiting the reform raising the minimum leaving age from 15 to 16 in 1972. Trostel *et al.* (2002) look at 28 countries and find similar values when family education is taken as an instrument. Finally, Psacharopoulos (1994) surveys many studies and concludes that the average private return to education in the literature in OECD countries is 6.8%.[8]

In macro analyses, the return to education is defined by taking the national mean of every variable from the Mincer wage equation to obtain the "Macro-Mincer" equation. It is thus the productivity gains associated with an average increase of one year in educational attainment. Due to social externalities, the productivity impact of education is expected to be higher at macro than at micro level. But unlike the relative micro literature consensus, results are subject to more uncertainty in macro approaches and economists find contradictory results. Some studies, among which Benhabib and Spiegel (1994) and Pritchett (2001), have found a non-significant coefficient on education when physical capital stock is also included in the regressions. This result led Pritchett to develop the idea that the absence of correlation between education and growth is the result of low quality education in developing countries in line with the idea that human capital should take into account the quality of education in addition to the quantity. Krueger and Lindahl (2000) suggest that measurement errors in education data is the main reason for these negative results and show that when capital stock in not included as a regressor, human capital becomes significantly positive. Since then, other studies have tried to solve this puzzle by using updated and improved figures of educational attainment (Soto, 2002; Cohen and Soto, 2007; and Barro and Lee, 2010).

In Barro and Lee (2010), a very similar framework as the one presented in this study is used and the return to education is estimated at around 4% for developed countries, using the twenty year lag in the education series as an instrument to proxy parental educational background. Similarly, Soto (2002) uses data from Cohen and Soto (2007) and finds values from 6.7% to 10% using a GMM estimator and after dealing with collinearity by changing the growth accounting framework. Finally, Topel (1999) finds a return of 6% with the Barro Lee dataset but chooses to set the coefficient of capital intensity. All in all, results from the macro literature suggest that the value of θ should stand between 4% and 15%. However, every study cited above focuses on a large range of countries (the Barro-Lee database contains 146 countries) and on a shorter time period. Our dataset enables us to extend the time period from 1890 with yearly data on GDP, human capital and physical capital but in turns limits the number of countries to 17 developed countries, which may lead to different estimates of return to education.

Finally, it is important to understand what a given value of θ implies for productivity. From the neoclassical framework, we indeed have:

$$Y = TFP'.K^{\alpha}.L^{1-\alpha}e^{(1-\alpha)\theta.S} \quad \textbf{(4)}$$

Which yields:

$$\frac{Y}{L} = TFP'.\left(\frac{K}{L}\right)^{\alpha}.e^{(1-\alpha)\theta.S}$$

But another transformation can also yield:

$$\frac{Y}{L} = TFP'\left(\frac{K}{Y}\right)^{\frac{\alpha}{1-\alpha}}e^{\theta.S}$$

[8] As raised in Psacharopoulos (1994), this return can be higher in other regions of the world (12.4% in Latin America, 13.4% in Sub-Saharan Africa and 9.6% in Asia).

Hence, conditionally on the fact that $\frac{K}{L}$ is constant, an increase of one year in educational attainment leads to an increase of productivity of $(1-\alpha).\theta$ points and conditionally on the fact that $\frac{K}{Y}$ remains constant, a similar increase in education leads to an increase in productivity of θ points. Soto (2002) calls $(1-\alpha).\theta$ the "short-time" return to education and θ the "long-time" return to education.[9]

3.2. Age of capital and productivity

It is very intuitive that older investment is less productive than newer investment as technical progress is partly embodied in capital.[10] Constant-quality price indexes attempt to take productive performance improvements in investment into account. For a stable value of investment spending over two years, an embodied productive performance improvement would correspond to an increase in the investment volume and to a decrease in the investment price index. The embodied technical change is, from this point of view, a determinant of the price of investment (see the survey by Gordon, 1990, on this debate). From a broader point of view, and as raised by different papers, for example Jorgenson and Griliches (1967), if the production function is perfectly specified and if all the productive factors are well measured and taken into account, the *TFP* measurement using the Solow residual approach would be small and would mostly correspond to the impact of externalities.

Nevertheless, the measurement of investment price indexes takes only partly into account the improvements in investment productive performance for several reasons, and at least for the two following ones: (i) these improvements are taken into account only for some products, mainly automobiles and, within ICT, hardware, prepackaged and partly custom software, and some communication equipment. For other investment products, there is almost no impact of an investment quality change on the measurement of investment prices. This partial approach is explained by the cost of the methods (hedonic or matching approaches, mainly) used to take into account changes in quality in investment price indexes; (ii) whatever the efforts of national accountants and their degree of sophistication, these methods remain imperfect and take only partially into account the embodied technical progress in investment price indexes. For these reasons, an unknown part of the embodied technical progress is not included in the increase in investment volume and a decrease in investment prices. From this mismeasurement channel, the vintage composition of capital should influence the productivity level.

A large amount of literature takes into account the vintage composition of capital in production functions through a synthetic capital age variable. In this approach, a negative impact of capital age on productivity is expected. To take account of this idea, we define effective productive capital stock (*KP*) as the productive capital stock (*K*) times an exponentially decreasing function of the average age of capital (*A*):

$$KP_t = K_t e^{-\varepsilon . A_t}$$

Where ε is the elasticity of the age of capital. This representation was suggested by Solow (1959, 1962) and developed later by Nelson (1964) among others. So far, we have considered two types of assets to construct our series of capital: equipment and buildings. The vintage effect of capital is not necessarily relevant for this latter type, or at least, it is negligible when compared to the vintage effect of equipment. An older piece of machinery is likely to be less productive than a newer one, either because of technological obsolescence or because of physical depreciation. This is not necessarily the

[9] Over the long run, the ratio of capital to output is very stable, as seen in Madsen (2010). Such stability is consistent with the idea that the saving rate results from aggregated individual preferences that are quite constant over time.

[10] A reverse impact could come from a learning by doing effect: firms may manage to use a capital vintage better as it ages. Our estimates encompass this effect, which appears not to be predominant.

case for a building. For this reason, in what follows, we have only considered the average age of equipment capital stock. Numerous papers have estimated an empirical impact of the capital vintage structure on productivity, both on macro and micro data. On industry level data, Gittleman *et al.* (2003) survey the literature and show that the capital vintage productivity impact can vary a lot across industries.

On macroeconomic data, some papers assume a vintage effect without estimates. For example, Jorgenson (1966) assumes, for the US, a value of the elasticity of the average age of capital to productive capital (which correspond to our parameter ε) of 0.13, which would mean, if we suppose a value of the capital elasticity α of 0.3, an impact of the age of capital on productivity of nearly 4% ($\alpha.\varepsilon = 0.039$).[11] Clark (1979) directly assumes an impact of the average age of capital on productivity of 1% using US macro data ($\alpha.\varepsilon = 0.01$), which corresponds to a low value compared to estimate results. For example, Wolf (1991, 1996) proposes some estimates of the impact of the average capital age on productivity on a country level dataset panel composed of the G7 countries over the 1950-1989 period. His results are within a range of 3% to 6.5% ($0.03 \leq \alpha.\varepsilon \leq 0.065$), and for his growth accounting exercise, Wolf later assumes a value of 4.1% ($\alpha.\varepsilon = 0.041$).

Other analyses have proposed estimates of the impact of the average age of capital on productivity based on firm level data. To the best of our knowledge, these studies mostly focus on French firms. Using a sample of 124 to 195 manufacturing firms over the period 1966 to 1975 and a dataset of 16,885 manufacturing firms in 1962 and 275 manufacturing firms in 1972, Mairesse (1977, 1978) and Mairesse and Pescheux (1980) estimate a capital age productivity impact of about 4% ($\alpha.\varepsilon = 0.04$). On a panel of 3,200 French manufacturing firms over the period 1972-1984, Cette and Szpiro (1989) also estimate a capital age productivity impact of about 4% ($\alpha.\varepsilon = 0.04$).

3.3. Estimation strategy and results

Taking into account these considerations, we have included education and age of capital into the production function:

$$Y = TFP'.(K.e^{-\varepsilon.A})^{\alpha}(Le^{\theta.S})^{1-\alpha} \quad \textbf{(5)}$$

Where *TFP'* is the new measurement of total factor productivity (taken as a Solow residual), from which the effects of embodied technical progress and human capital (education) are removed.

Dividing equation (5) by *L*, the total number of hours worked, yields the following breakdown:

$$\frac{Y}{L} = TFP'.\left(\frac{K}{L}\right)^{\alpha}.e^{-\varepsilon.\alpha.A}.e^{(1-\alpha)\theta.S} \quad \textbf{(6)}$$

Finally, taking relation (6) in log form gives:

$$lp = \mathrm{tfp}' + \alpha.ik - \varepsilon.\alpha.A + (1-\alpha)\theta.S \quad \textbf{(7)}$$

Where *lp* and *ik* are the logarithms of labor productivity and capital intensity ($IK = \frac{K}{L}$), and *tfp'* is the logarithm of total factor productivity excluding the effects of the age of physical capital and of human capital. With our data, we want to estimate the values of θ and ε using equation (6). To do so, we first

[11] The effect of the age of the capital stock on productivity is of course negative. We will however present the effect in absolute value terms in the following paragraphs to better relate it to the value of ε, which is positive.

assume that the value of α is 0.3, which is equivalent to setting the dependent variable in the regression to $lp_{i,t} - 0.3.ik_{i,t}$ for a country i, $1 \leq i \leq 17$ and a year t. On the right-hand side of the equation, we use the average years of education $S_{i,t}$ and the average age of equipment capital stock $A_{i,t}$ as regressors. The induced values of θ and ε can then be obtained after division of the estimated coefficients of these two explaining variables by *1* - α and α respectively. In a second step, we generally estimate α, θ and ε by including capital intensity on the right-hand side, the dependent variable now only being the logarithm of labor productivity.

Results from these two OLS regressions are presented in Table 1, columns 1 and 2.[12] [13] Because the data are highly volatile between 1890 and 1895, we remove these first five years from the regressions. We find a coefficient of education that is highly significant and positive in both cases, equal to 0.037 and 0.031, and a negative coefficient for the age of capital equal to -0.010. When the coefficient α is estimated, its value can be directly read from the coefficient on the log of capital intensity which is equal to 0.323 in column 2. These results in turn imply a value of ε of around 3% while θ is estimated at around 5% which are both lower than expected, although still acceptable as far as macro returns to education are concerned. Remarkably, at odds with results from Barro and Lee (2013), Soto (2002) and Krueger and Lindahl (2000), we find a convincing and standard value for α in column 2. In the latter studies, when physical capital intensity is included in the regressions, the implicit value of α is always larger than expected. This led Soto (2002) to argue in favor of an endogeneity issue stemming both from measurement errors in education and capital stock[14] and simultaneity between education and growth: when people anticipate future growth, they are likely to spend more time studying. Bils and Klenow (2000) also suggest that better enforcement of property rights may explain both higher levels of schooling and an increase in productivity and is therefore a potential omitted variable.

To better compare our results with those already mentioned in the literature, we have restricted the time period to 1950-2010 and run the same regressions. The results are presented in columns 3 and 4 of Table 1, from which we see that when α is set to 0.3 the value of θ is 9.14%, which is within the expected range, whereas ε is still lower than expected but higher than previously (7.67%). From column 4 however, the estimated value of α is very large (0.638) and the education coefficient loses its significance. These results are common across the literature and can for example be found in Barro and Lee (2013). This could be due to the high correlation between capital intensity and education in this 1950-2010 period over our set of countries, the correlation being lower over the longer 1890-2010 period as increases in education were mostly driven by compulsory attendance at the primary and secondary levels during the first half of the century. Finally, going back to our whole 1895-2010 period, we have followed Barro and Lee (2013) and instrumented school attainment by its 20-year lagged value to proxy for parental education, which is likely to be less endogenous. In addition, physical capital intensity is instrumented by its 1-year lag value to correct for correlation in measurement error with the current value of the left-hand side variable. These results are presented in columns 5 and 6 and imply a value for θ of around 7%, suggesting that our OLS estimators were biased downward.

We then reproduce the exact same regressions, but after deleting average working time per worker, that is, by defining labor productivity as the ratio of GDP to employment, and capital intensity as the ratio of physical capital to employment. Removing average working time per worker is a way of reducing the inaccuracy in our measures as it is by far the trickiest series to measure. In addition, this would enable us to derive the elasticity of education with regard to labor productivity per employee which is most in line with the existing literature. As shown in Table 2, the value of θ remains stable

[12] The dependent variable shows very strong autocorrelation of degree one which disappears when looking at longer lags. We thus check that our results are still valid when autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator are implemented (of course this does not affect the coefficients).

[13] For these columns and for all the others, we include time and country fixed effects and remove war periods.

[14] Capital stock is constructed from investment which is included in GDP, so any measurement error in investment would impact both labor productivity and capital intensity.

and around its expected value. The coefficient on capital intensity is still too high between 1950 and 2010, but this time education has a positive and significant effect on productivity. The other changes are for ε which is now higher and much closer to its 10%-13% expected value.

All in all, these results suggest that over the whole period, and for the set of 17 countries under study, the coefficient of education in the Macro-Mincer equation θ is roughly equal to 8%, which implies a short-term return to education of 5.6% (assuming the elasticity of capital to be equal to 0.3). Note that, in this study, we have followed the growth literature on a relatively long period and measure the elasticity of the average years of education in the population aged over 15 to *TFP*. For this reason, the results presented in Table 3 might differ from other estimates on the most recent period. For example, the Bureau of Labor Statistics uses a more detailed and sophisticated measure of human capital by estimating a Mincer equation from microdata, taking into account many parameters such as gender, type of education, etc. Of course, over such a long period as the one considered in this study, it is impossible to conduct a similarly detailed analysis.

3.4. The impact of education and age of capital on *TFP* growth

We can now evaluate *TFP'* corrected by the impact of education and age of capital and compare its evolution to that of *TFP* not excluding these two factors. To do this, we have used the growth accounting approach corresponding to equation (5) and set parameter values to $\alpha = 0.3$ for the share of capital, $\theta = 7\%$ for the impact of education and $\varepsilon = 10\%$ for the impact of the age of capital.

We can see from Table 3[15] that changes in human capital and the age of capital contribute significantly to *TFP* growth. Over the whole 1890-2010 period, human capital and the age of physical capital account together for 21% of the US's TFP growth, 17% for the euro area, 25% for the UK and 26% for Japan. However, it appears that the amplitude of *TFP'* growth does not differ a lot from that of *TFP*.

In particular, the "one big wave" that occurred during the 20th century is still persistent as shown in Chart 3[16] concerning the US and this is also the case for the mid-1990s wave. The same result is obtained for different values of θ and ε within the ranges which seem reasonable from previous developments ($5\% < \theta < 10\%$ and $5\% < \varepsilon < 15\%$). Our results for the contribution of education closely compares to that of Madsen (2010) but, as his methodological approach tries to identify *TFP*-induced capital deepening and attributes its contribution to *TFP*, the contribution of capital stock growth is smaller than in our estimates, the bulk of growth being attributed to *TFP*. Hence, Madsen's results leave an even greater share of the productivity waves unexplained by his growth accounting estimates. These results are important: they indicate that even if education (mainly) and the age of capital have a strong impact on productivity levels and growth, they do not explain the productivity waves observed during the 20th century. Interestingly, the one big wave is the one most affected by the exclusion of education and age of capital: for the US, the peak is reduced by 25%. This is not surprising as this wave is associated with an acceleration in educational attainment. In the US, the average duration of schooling increased by more than 2 years between 1935 and 1955. Other contributions have to be found among numerous candidates. We try, in the following section, to evaluate the impact of some generic technologies on *TFP* growth.

Nevertheless, we see from Table 3 that education significantly contributed to the first productivity wave in the United States, with a contribution of 0.42 percentage point (pp) during the 1913-1950 period, only slightly decreasing in the following periods (0.38 pp in 1950-1974 and 0.34 pp in 1974-1990). Hence, the early opening up of education to the masses in the US yielded a lasting contribution

[15] Periods in Table 3 are based on productivity breaks from Bergeaud *et al.* (2016).

[16] The waves presented in Charts 3 and 6 have been computed by removing the cyclical component of our time series using a HP filter with a coefficient of 500. The choice of this coefficient has been made to better capture 30-year-long business cycles, consistent with Norbert (2006). On these aspects, see Bergeaud *et al.* (2015).

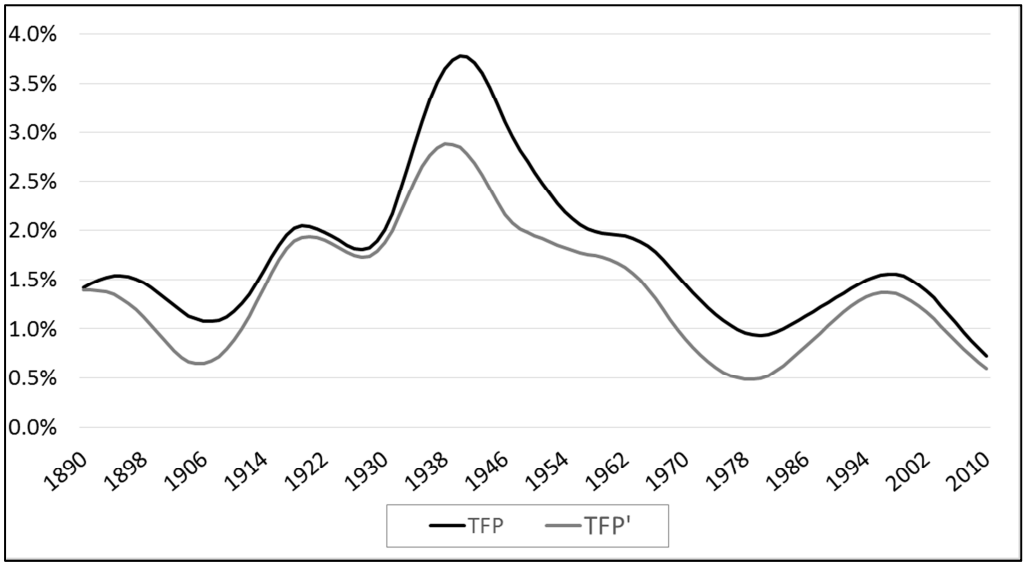
to productivity and partly explains the US advance. Indeed, the increase in the contribution of education appears one period later, in the 1950s, in the other areas (euro area, the United Kingdom). In Japan, education posts a significant contribution throughout the century due to the initial very low level of education. The age of capital makes a significant contribution mainly during the reconstruction period after World War II in the euro area and Japan.

Conversely, education and capital age barely contribute to explaining the ICT wave in the US, as education reached a plateau and the age of capital only slightly decreased during the 1990s and increased when the financial crisis struck. In other areas, the contribution of education is lower than before, although it posted a significant contribution in the euro area and Japan, where the opening-up of college education to the masses was delayed compared to the US. Equipment has aged since 1990 in Japan due to the banking crisis and since the 2000s in the euro area.

Chart 3

Filtered growth rate of *TFP* for the US including (*TFP*) and excluding (*TFP'*) the impact of age of capital and human capital

The series have been computed using a HP filter with coefficient 500 (λ = 500) over the period 1870-2010 to address the issue of initial values.



Source: See text (human capital has been computed with a value of 7% for θ and age of capital with a value of 10% for ε). α is set to 0.3.

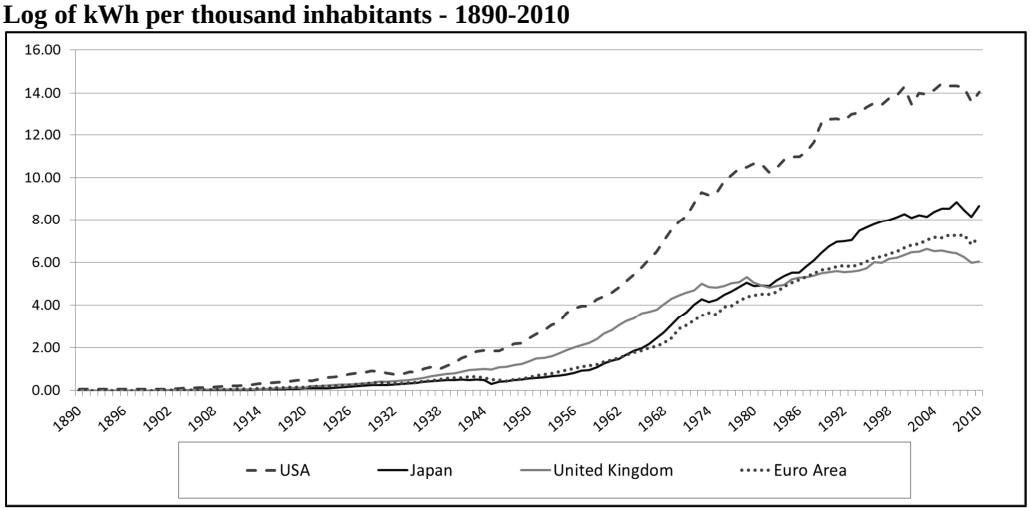
4. <u>The spread of technologies</u>

As shown in numerous papers, notably Comin and Hobijn (2010), the speed of adoption of new technologies plays a key role in productivity developments and growth. We have identified two technologies often considered to be characteristic of different technology diffusion periods across the 20th century (see Comin *et al.*, 2006a and 2006b). First, electricity which, in addition to being a good indicator of global technology development, is the major characteristic GPT of the mid-20th century. Second, information and communication technologies (ICT) to try to capture the most recent productivity growth wave starting at the end of the 20th century. These two technologies were selected because, as general purpose technologies, they may yield network effects and externalities beyond their direct capital intensity impact in the using sectors. We successively describe the measurement of the spread of the two technologies (4.1.), the channels of the productivity impact of the spread of the new technologies (4.2.), the estimation strategy of these channels and the results (4.3.) and, using these estimates, an evaluation of the impact of the spread of technologies on TFP growth (4.4.).

4.1. Measurement of the spread of the two new technologies

For our first measure of technology, we have taken the production of electricity per capita. This measure has increased over time for all countries, but this increase slowed from the 1970s onwards (see Chart 4).[17] In line with the literature that focuses on the impact of electricity on US productivity growth (Bakker *et al.*, 2015, among others), we can clearly see from Chart 4 that the take-off of electricity in the US started at the beginning of the 20th century and accelerated during the 1920s. The United Kingdom just lags behind with a take-off that started in the 1930s, while euro area countries and Japan started to massively adopt electricity after World War II. The take-off date depends on both the decline in electricity prices and on a reorganization of the production process to fully benefit from electricity (David, 1990)

Chart 4
Production of electricity per inhabitant for the four main areas
Log of kWh per thousand inhabitants - 1890-2010



Source: See text.

Concerning the second measure of technology, we have taken the ratio of the stock of ICT capital to GDP in current value. To compute this ratio, we have drawn on the work of Cette *et al.* (2015) based on investment data provided by the OECD. ICT is split into three products: hardware, software and communication equipment, and capital stock is computed using a permanent inventory method. Because such data were not available for Norway, Portugal, Denmark and Switzerland, we have conducted all the following estimates on the remaining 14 countries.[18] Chart 5 shows the evolution of this ratio for the US, the euro area, Japan and the UK. Note that for ICT, we have used a measure of stock and for electricity we have used a measure of production. However, electricity production should reflect productive capacity, as electricity cannot be stored, electricity imports and exports are low compared to country production, and utilization of productive capacities should not create a systematic bias.

ICT capital stock took off in the 1980s in the US, with a peak at the end of the 1990s. This early diffusion of ICT in the US can be explained by education levels and low market rigidities in the US (Cette and Lopez, 2012). ICT diffusion accelerated at the end of the 1990s in Japan and the UK, while the euro area lagged behind due to its stringent employment protection legislation and product market regulation.

[17] When data were missing, we have interpolated them with the production of CO2 emissions from the Global Carbon Project.

[18] When all countries are included (and when we only estimate the effect on electricity), the coefficients remain extremely stable.

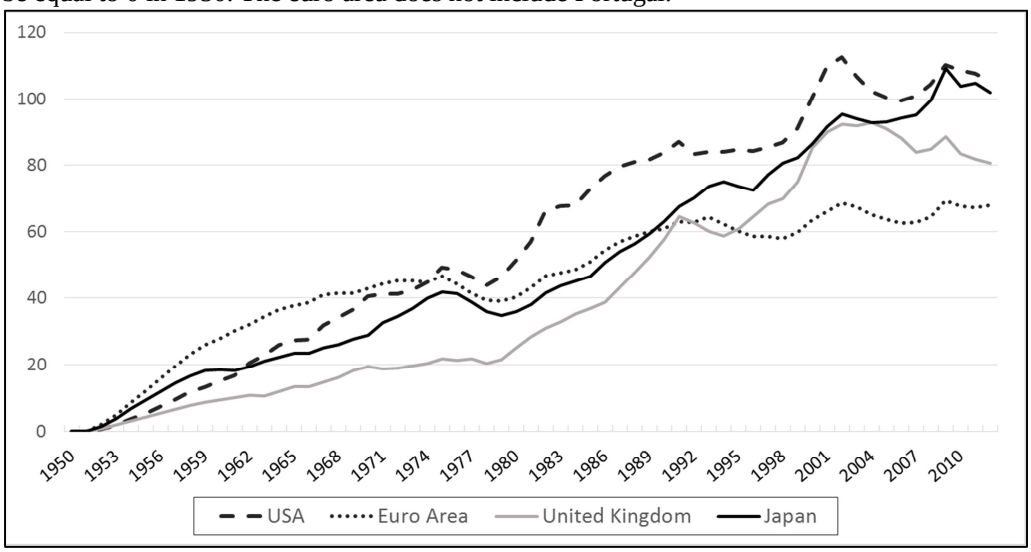
We assume that both electricity and ICT enters linearly into the production function. Our new baseline equation thus becomes:

$$\frac{Y}{L} = TFP''(ELEC)^{\eta} e^{\mu.ICT} \left(\frac{K}{L}\right)^{\alpha} e^{-\varepsilon.\alpha.A} e^{(1-\alpha)\theta.S} \quad \textbf{(8)}$$

Where η and μ are the two new coefficients corresponding to the effect of electricity per inhabitant (denoted *ELEC*) and ICT to GDP ratio (denoted *ICT*) on productivity and *TFP''* is the new residual and therefore our new TFP excluding the effects of education, age of capital and these two characteristic technologies.

As our series start in 1890, we do not capture the whole of the first industrial revolution which was already tailing off at the end of the 19th century in many countries. For example, in an attempt to capture the effect of GPTs during the first industrial revolution, van Ark and Smits (2002) selected the period 1800-1913 in the Netherlands. In what follows, we have chosen to start our series in 1905, and we do so for our subsequent estimations.[19] With longer series and fewer countries, we could have chosen other General Purpose Technologies such as the steam engine or railways to focus on the second half of the 19th century and measure their effect on 19th century growth.

Chart 5
Ratio of ICT capital stock to GDP in value terms (multiplied by 1000)
1950-2010
ICT capital stock is the sum of communication equipment, software and computers capital stock, all assumed to be equal to 0 in 1950. The euro area does not include Portugal.



Source: Authors' calculation based on Cette *et al.* (2015).

Equation 8 makes the assumption that electricity enters log linearly in the production function, which in turn implies the underlying assumption that the elasticity of electricity was constant over time. Therefore, the measured effect is probably a lower bound of the elasticity of electricity during some periods. For example, if we assume that a technological shock makes the use of electricity more efficient, then this quality improvement will not be captured in our regression and due to this effect we will underestimate the impact of electricity over *TFP*. An alternative would be to allow non-linearity in the effect of technology on growth, for example by fitting a logistic function with three parameters, the first one determining the speed of diffusion, the second the maximum possible effect and the third

[19] Small variations in this starting date do not affect our results; we do however believe that 1905 is a good starting point at the end of the first industrial revolution since from Chart 4 we can see that it is the beginning of the surge in electricity production in the US. Results are also robust to starting the estimations in 1895 or 1913.

the date at which the marginal effect of electricity is the largest. However, the fitting of this function would necessarily be arbitrary. The constant elasticity assumption, as it has been chosen for the productivity impact of education and although it is a strong one, appears preferable to an *ad hoc* rule.

4.2. Channels of the productivity impact of the spread of new technologies

New technologies may have three distinct types of effects on productivity (see Jorgenson, 2001; Cette *et al.*, 2005; or Cette, 2014, for more details).

- First, sectors producing new technologies benefit from a fast pace of technological progress, leading to a rapid increase in their *TFP*. In ICT-producing sectors, according to Moore's law, the number of transistors in a dense integrated circuit has doubled approximately every two years, leading to a fast decrease in the ICT production deflator and a fast increase in ICT production volume.

- Second, due to the price decrease of investment including the new technology, this technological progress can accelerate the capital deepening process in the new technology-using industries, leading to an increase in capital intensity and hence in labor productivity, but not necessarily in *TFP*. But as mentioned earlier, national accounts only take partially into account in investment price indexes embodied technical progress, which is not fully included in increases in investment volume and decreases in investment prices. Consequently, the accounting split between capital deepening and *TFP* within labor productivity growth is biased, the role of the capital deepening component being undervalued and, conversely, the role of *TFP* growth being overvalued. The usual methodology adopted to evaluate this capital deepening effect for ICT is described in Appendix 1.

- Finally, the two selected technologies can be considered to be general purpose technologies (see Lipsey *et al.*, 2005, for possible examples of GPT from the invention of writing and Jovanovic and Rousseau, 2005, for a comparison between ICT and electricity and Kander *et al.* (2007) for arguments in favor of considering electricity as a GPT) and their joint utilization across firms may lead to *TFP* gains through spillovers, which means externalities or network effects at the macroeconomic level, this impact being "*manna from heaven*", to use the expression from Hulten (2000).

Usual growth accounting approaches are able to characterize empirically the role of the first two channels (with nevertheless, for reasons mentioned above regarding the second channel, an undervaluation of the capital deepening impact and an overvaluation of TFP growth) but not of the third. Concerning these studies, among numerous others, Jorgenson and Stiroh (2000), Oliner and Sichel (2000) and Oliner *et al.* (2007) evaluate the contribution of ICT in the US at the end of the 20th Century. For industrial revolution comparisons, among others also, Crafts (2002) compares the contributions of steam engines in the UK during 1780-1860, electricity and ICT in the US during 1899-1929 and 1974-2000 respectively, and Jalava and Pohjola (2008) compare the contributions of electricity during 1920-1938 and ICT during 1990-2004 in Finland.

Our approach goes one step further by trying to decompose *TFP* growth into the impact of the different technologies, taken into account as explained below through these three channels, and an unexplained component which corresponds to a residual.

- Concerning electricity, the three channels are empirically taken into account simultaneously in the estimates using the electricity production elasticity. Concerning the first channel, as mentioned above, production and use of electricity are very similar for all countries (there is no storage of electricity and electricity imports and exports are low compared to production), and spillovers can realistically be considered as highly correlated to production and use. The second channel is characterized only for the share that is not already taken into account through electric

equipment and consequently through capital deepening or the age of equipment. Due to the measurement problems mentioned above, the impact of electricity production on *TFP* growth may be undervalued. And the third channel is implicitly taken into account in our evaluation, externalities being realistically considered as highly correlated to electricity use.

- Concerning ICT, the first channel is not taken into account as a large and variable share of ICT investment goods are imported and not produced domestically. Even in the US, the share of ICT production in GDP has decreased in the last 15 years (Byrne *et al.*, 2013) due to the delocalization of some parts of ICT production and conversely, chip production, which benefits most from technological progress, mainly remained in the US. Unfortunately, we do not have enough detailed data to characterize this first channel for all countries. The second channel (ICT diffusion) is, as for electricity, explicitly considered for the share that is not already taken into account through ICT equipment and consequently through capital deepening. But here again, due to the measurement problems mentioned before, the impact of ICT on *TFP* growth may be undervalued. And the third channel (externalities) can realistically be considered as highly correlated to ICT use (as for electricity), which means that we take it into account.

4.3. Estimation strategy and results

The technology *TFP* effects are included in our *TFP* and *TFP'* measures. To evaluate them for each of the two technologies, we have regressed tfp', the logarithm of *TFP'*, on the two technology indicators (in log form), each of them assumed to correspond to the spread of a specific general purpose technology.

Table 4 columns 1, 2 and 3 display the results from OLS regressions when we use as regressors the logarithm of the production of electricity per capita (column 1), the ratio of ICT capital stock to GDP in value terms (column 2, over 1950-2010, as 1950 is the starting date of the ICT series and the starting date of a significant use of ICT in the economy) or the two jointly (column 3). Coefficients for the two technologies are positive and significant in each case. From 1905 to 2010, when electricity is the only regressor the estimated coefficient value is 0.077, while it increases to 0.096 when ICT intensity is added as a regressor. In the same specification, the effect of ICT is equal to 1.46. These results suggest that in the long run, a 1% increase in the production of electricity per capita increases productivity by almost 0.1% while a one standard deviation (0.049) increase in the ratio of ICT to GDP in value terms generates an increase of 7.4% in productivity.

Of course, it is likely that the effect of electricity is not constant over time. Many economists consider for instance that electrification had a massive effect in the US during the 1920s and 1930s (see for example David, 1990 and Field, 2003) which is much larger than today. To take this into account, one could look at the effect of electricity using different sub-periods. We conduct the same regression as in column 1 of Table 1 over the periods 1895-1930, 1895-1940, 1905-1940, 1905-1974 and 1950-2010. The coefficient on electricity is estimated respectively at 0.043, 0.044, 0.064, 0.138 and a non-significant coefficient of 0.027. These results suggest that the effect of electricity was indeed less after 1974, and the strongest from 1905 to 1974, but not particularly during the interwar period. This is probably due to the fact that most of the countries in our dataset did not benefit from electrification before the end of World War II. Nevertheless, in this study we seek to estimate the average long-run effect of electricity over our time period and for many different OECD countries. For this reason, just as we did for the return to education and age of capital, and consistent with the growth accounting literature, we consider a constant coefficient from our baseline regressions presented in Table 4.

All the previous results are based on an OLS estimator. However, in such growth accounting regressions, endogeneity and reverse causality effects are likely for both electricity and ICT. Indeed, the demand for new technologies increases with standards of living and other *TFP*-improving changes in areas such as management, financing and production processes (Ferguson and Wascher, 2004) can take place along with the diffusion of the three technologies. We therefore utilize a new strategy based

on instrumental variables. In columns 4, 5 and 6 of Table 4, we have run the same regressions as in columns 1, 2 and 3 but we instrumented these technologies with the sum of the other countries' technological diffusion measures, weighted by the logarithm of distance. Indeed, trade is one vector of technological diffusion and is closely related to distance, which in turn is a good indicator of the intensity of technology diffusion (Madsen, 2016). Of course, reflection effects may lead our instruments to include the improvement in the country's technological diffusion themselves. To limit this effect, we have lagged our indicator by one year.

In the IV regressions, the coefficients of the two technologies are positive. The ICT one is highly significant while electricity is no longer significant. However, when estimated together, the coefficients are both significant. This regression presented in column 6 is our preferred one and we therefore use the corresponding coefficients. A 1% increase in electricity production would lead to a 7.9% increase in *TFP'*. A 1 standard deviation increase in the ratio of ICT capital stock to GDP would lead to an increase of 8.1% in *TFP'*. Instrumentation reduces the electricity coefficient, which may be the most prone to reverse causality as it is a production measure (the wealthier a country, the more it will consume electricity).

One could question the choice of population to standardize the production of electricity. The production of electricity per capita could be considered as a demand variable inserted in the production function (the average consumption of electricity). Our instrumentation strategy is designed to address this potential endogeneity problem. However, ideally, we would like to proceed as in some country-specific articles (see for example Jalava and Pohjola, 2008) and to measure the capital deepening due to highly electricity intensive sectors. Since such data are unfortunately not available for our set of countries and for the whole of the 20th century, an alternative would be to standardize the production of electricity by GDP. But doing so would lead to a specification problem as the log of GDP intervenes in the left-hand side variable of the equation, leading to a negative coefficient on electricity per unit of output.

4.4. The impact of technology diffusion on *TFP* growth

From our previous estimation, we can now look at the shape of our new estimate of *TFP* (denoted *TFP''*). To do this, we have used the values η = 0.079 for electricity and μ = 1.56 for ICT, corresponding of Table 4 column 6 estimate results, which seem to us the most interesting.

Chart 7 plots the three waves from 1905 to 2010 for the US for *TFP*, *TFP'* and *TFP''* growth rates. We can see that the general evolution is still persistent, especially as far as the one big wave is concerned. However, the amplitude of this one big wave has been reduced and is almost 40% lower for *TFP''* than for *TFP'*. This result seems comparable to that of David (1990), who estimates for example that "… *approximately half of the 5 percentage point acceleration recorded in the aggregate TFP growth rate of the US manufacturing sector during 1919-29 (compared with 1909-19) is accounted for … by the growth in manufacturing secondary electric motor capacity during that decade.*" The ICT wave is also significantly explained. However, the impact of ICT diffusion may seem low as only about 35% of the corresponding productivity wave is explained by education, age of capital and the inclusion of ICT diffusion in our regressions.

Table 5 gives more detail about the share of *TFP* growth that is attributed to electricity and ICT. Because of data restrictions, we have started this decomposition in 1913: the period 1905-1913 would be of poor statistical interest with only 9 years. We also mention the whole 1913-2010 period. In addition, because we have removed four countries from our dataset, we do not plot results for "the World". Looking for instance at the euro area, we can see that electricity explains a large share of *TFP* growth (23%), and accounts for 20% in the US on average over the whole period. ICT appears especially important in the US and the UK.

Although the difference in contribution is not very large across areas, the spread of electricity contributed significantly to the US advance on the euro area, as its contribution peaked in the 1913-1950, while it increased during the 1950-1974 period in the euro area. The UK appears not to lag in terms of electricity diffusion, with a very large contribution in the 1913-1950 period. Broadberry and Crafts (1990) trace the productivity lead that the US took over the UK during this period rather to barriers to competition allowing high cost producers to remain in business.

The contribution of ICT to *TFP* growth appears to be smaller than that of electricity in all areas. This result seems consistent with, for example, those from Crafts (2002) or Jalava and Pohjola (2008) mentioned above, which find that in the US and Finland ICT's contribution to growth is lower than the electricity's. And their approaches differ from ours. As explained previously, their growth accounting methodologies characterize two channels of the growth impact of technology shocks: TFP gains in the producing sectors and capital deepening in using sectors. Conversely, our approach partly characterizes the capital deepening channel, more precisely the share not already taken into account in our capital measurement and consequently in the explicit capital deepening channel, and the spillover channel which cannot be measured through growth accounting approaches. For these reasons, our results cannot strictly be compared to these previous ones.

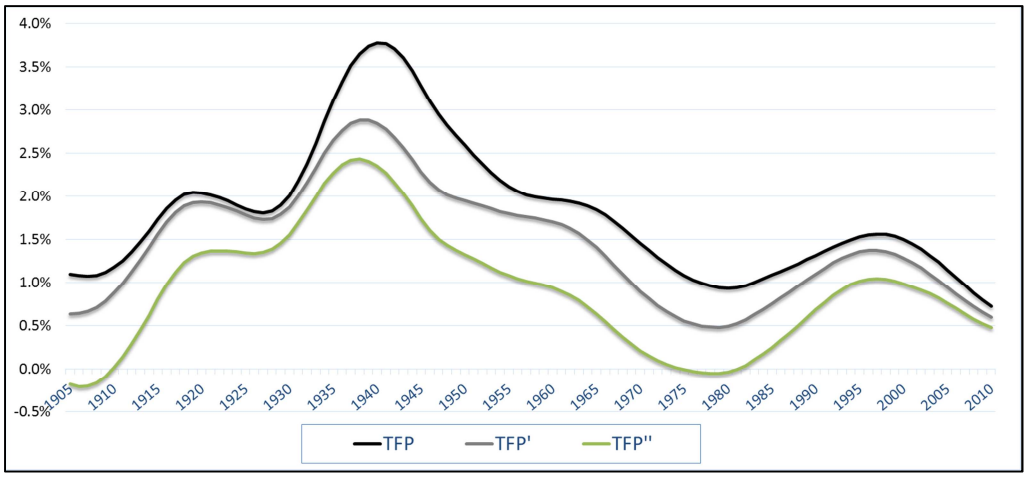
One other reason for the low contribution of ICT diffusion to explaining the second productivity wave could come from the fact that ICT investment data compiled by national accountants (and taken into account here as ICT investment) underestimate productive ICT expenditure. Indeed, spending on ICT is regarded as investment only when the corresponding products are physically isolated. Therefore, generally speaking, ICT that is included in productive investment (for example machine tools or robots) is not counted as ICT investment but as intermediate consumption of companies producing these capital goods. Beretti and Cette (2009) have tried to correct French ICT investment data in 2000 by considering intermediate consumption ICT components integrated in non-ICT productive investment as ICT investment. Their main result is that the amount of ‘indirect ICT investment’ appears to be small compared with ‘direct ICT investment’, and that considering them as ICT investment changes numbers only slightly. But we cannot rule out that this result could differ for other countries and on more recent periods. Another reason could stem from the fact that ICT had not yet yielded their full productivity benefits. Previous GPTs took a very long time to be fully profitable: between the first practical design of a dynamo in 1867 and the actual conversion of industrial processes to electricity in the US, which only took off in 1914-1917, 50 years elapsed and the full productivity benefits were only felt 70 years afterwards (David, 1990). Part of the current productivity debate hinges on whether a second productivity wave could be expected from ICT, with Gordon (2014) on the pessimistic side and, among others, Brynjolfsson and McAfee (2014) on the optimistic side.

Chart 7

Filtered growth rate of different *TFP* measurements for the US, 1905-2010

TFP is the residual including education, age of capital, electricity and ICT. *TFP'* excludes the impact of education and age of capital and *TFP''* also excludes the impact of electricity and ICT.

The series have been computed using a HP filter with coefficient 500 (λ = 500) over the period 1890-2010 to address the issue of initial values.



Source: See text (human capital has been computed with a value of 7% for θ and age of capital with a value of 10% for ε). α is set to 0.3. The coefficients for electricity and ICT are 0.079 and 1.557 respectively.

5. Conclusion

This paper examines the contributions to increases in productivity of quality-adjusted factor growth and technology diffusion. Accordingly, to explain the main stylized facts of 20th century growth, a long-term view is required. First, after centuries of "Malthusian stagnation", growth took off in the 19th century and accelerated further in the 20th century, leading to questions about the timing and reasons for this take-off. Second, growth has been highly heterogeneous, with both a "Great Divergence" splitting the world between advanced and emerging countries and a staggered take-off among advanced countries. Finally, growth has slowed down since the 1970s in advanced countries, leading economists to question the durability of 20th century growth.

We address these questions by looking at productivity growth factors in the 20th century. First, productivity, and more precisely total factor productivity (*TFP*), was indeed the main contributor to 20th century growth (Madsen, 2010a; Bergeaud *et al.*, 2015). As *TFP* is computed as a residual of a growth decomposition equation, there is always the suspicion that production factors have been improperly measured, which contributes to ascribing too much weight to *TFP* in growth dynamics. In this paper, production factors are adjusted for quality: education for labor and the age of equipment for capital. Second, technology diffusion appears to be a large contributor to *TFP* growth (Comin and Mestieri, 2013), even in innovating countries such as France, Germany and the United Kingdom (Eaton and Kortum, 1999). This paper assesses the contribution of technology diffusion by means of two 20th century general purpose technologies, electricity and information and communication technologies (ICT).

To do this, we use an original capital, labor and GDP database built over 1890-2013 for seventeen advanced countries. We completed this database with data on education, age of capital and technology so that we were able to decompose GDP growth.

GDP growth was then decomposed into the contribution of production factors, capital and labor, to obtain *TFP* as a residual. In a second step, the quality of production factors, education and the age of capital, was introduced through an estimation of their contribution to this gross *TFP*, taking into account their potential endogeneity through instrumental variables regressions. In a third step, the

contribution of technology diffusion was estimated, endogeneity being treated with a similar estimation procedure.

The main results are the following: (i) among factor quality, levels of education have contributed the most to growth, while the age of capital has a significant, although limited, contribution; (ii) quality-adjusted production factors explain less than half of labor productivity growth in the largest countries, except for Japan, where capital deepening posted a very large contribution. Although the US's "one big wave" of productivity growth, which took place some two decades before other advanced countries (Gordon, 1999) is partially explained by earlier access to higher education by the masses, this wave, as well as the ICT productivity wave for the countries which experienced it, remains partly unexplained by quality-adjusted factors; (iii) technology diffusion, as captured through our two general purpose technologies, also constitutes a partial explanation for the earlier US "one big wave" and for the ICT productivity wave, but leaves between 0.6 and 1 percentage point yearly growth, as well as a large share of the two 20th century technology waves, unaccounted for.

These results are consistent with previous ones on the role of education and *TFP* in a standard growth accounting approach. Education posted a very significant contribution to productivity growth throughout the period, explaining part of the US's lead in the first productivity wave, but not the extent of the wave itself. Our analysis goes further by taking into account the quality of the capital stock using the age of equipment, which posts a significant contribution mostly in the post-World War II reconstruction period. But another major contribution consists in trying to estimate the role of general purpose technologies beyond their capital-deepening impact and TFP growth in GPT-producing sectors. While ICT contribution remains limited at this point, both in duration and extent, the diffusion of electricity explains a significant share of 20th century growth and part of the US's advance in the first productivity wave. However, it still cannot account for the whole extent of the productivity waves, which points to a major role of factors beyond technology diffusion and production factors in 20th century growth. Candidates are numerous: among them, improvement in the production process such as assembly lines in large manufacturing firms (implemented for example for the Ford Model T in the Ford Motor Company in 1913), enhanced management practices (Bloom *et al.*, 2014) and new financing techniques (Ferguson and Wascher, 2004). Interactions between these different growth factors are large and further research appears necessary to disentangle their respective roles. Another limitation of our analysis is that we have assumed a linear (in log form) impact of education, capital age, electricity or ICT capital on *TFP*. We cannot rule out that in reality, these impacts might be non-linear. But more detailed data would be necessary to go further in these directions. A final limitation which has been highlighted in the paper corresponds to measurement problems. Two examples of these measurement problems deserve to be underlined. First, concerning labor quality, we have used information only on the average years of education in the working-age population, without any information concerning the quality of this education or the average years of education among the employed population. Second, concerning ICT, for the reasons detailed in the previous section, available numbers underestimate the value of ICT investment and, within this value, overestimate growth in prices and consequently underestimate growth in volume.

This study has empirically given some partial explanations for the sources of *TFP's* contribution to growth over the 20th century. That is its main contribution. But a large part of this contribution remains unexplained, and, as a consequence, remains "*manna from heaven*"…

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Appendix 1: Methodology for the evaluation of the contribution of ICT to labor productivity growth through capital deepening

The evaluation of the contribution of ICT to hourly labor productivity growth, through capital deepening, is calculated by applying the growth accounting methodology set out by Solow (1956, 1957). This contribution in year *t*, noted as CO_t^{ICT}, is evaluated using the following relation:

$$CO_t^{ICT} = \alpha_t^{ICT} \left(\Delta k_{t-1}^{ICT} - \Delta n_t - \Delta h_t\right)$$

Where K_{t-1}^{ICT} corresponds to the ICT capital installed at the end of year *t-1*, N_t refers to total employment in year *t*, and H_t designates the average annual hours worked per person per year *t*. The notation of the variables in lowercase corresponds to their natural log ($x = ln(X)$), and the growth rate of a variable is approximated by the variation of its logarithm. The Δ symbol refers to the variation of a variable ($\Delta X_t = X_t - X_{t-1}$).

The coefficient $\alpha_{t,2}^{ICT}$ is the Törnquist index of the coefficient α_t:

$$\alpha_{t,2}^{ICT} = \frac{1}{2}\left(\alpha_t^{ICT} + \alpha_{t-1}^{ICT}\right)$$

The coefficient α_t^{ICT} corresponds to the share of capital remuneration in GDP:

$$\alpha_t^{ICT} = \frac{C_t^{ICT}\, K_{t-1}^{ICT}}{P_{Y_t} \,.\, Y_t}$$

Where C_t^{ICT} corresponds to the user cost of capital, P_{Y_t} corresponds to the GDP deflator, and Y_t refers to GDP in volume.

The user cost of ICT capital C is calculated employing the relation proposed by Jorgenson (1963):

$$C_t^{ICT} = P_t^{ICT} \left(i_t + \delta^{ICT} + \Delta p_t^{ICT}\right)$$

Where P^{ICT} corresponds to the investment price of ICT, *i* refers to the nominal interest rate, and δ^{ICT} designates the assumed invariant depreciation rate of ICT.

We have considered two alternative options for the nominal interest rate: 10-year government bond yields and a fixed rate of 10%. The evaluation of both approaches is close to one another in the growth contribution calculation. In this study, we have used the 10-year government bond yields taken from the OECD's main economic indicators.

The overall share of capital, *α*, is assumed to be invariant and the same for all countries, with *α = 0.3*. This means that to evaluate the overall capital deepening effect, we have assumed that α_t^{NICT}, the non-ICT capital share, is obtained, for each year *t* and country *i* observation, from the relation:

$$\alpha_t = \alpha_t^{ICT} + \alpha_t^{NICT} = 0.3 \text{ and then } \alpha_t^{NICT} = 0.3 - \alpha_t^{ICT}$$

Appendix 2: Tables

Table 1
Results from estimates of labor productivity (*lp*) or *tfp* (*lp – 0.3.ik*) in log form, on school attainment and age of equipment capital stock. Labor input is measured by total hours worked.
Time and country fixed effects included. Heteroskedasticity robust standard errors are in brackets. Estimations start in 1895 because GDP is highly volatile during the first five years.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	$lp - 0.3.ik$	lp	$lp - 0.3.ik$	lp	$lp - 0.3.ik$	lp
Estimator	**OLS**	**OLS**	**OLS**	**OLS**	**IV**	**IV**
School	0.037***	0.031***	0.064***	0.007	0.050***	0.047***
	(0.005)	(0.006)	(0.009)	(0.009)	(0.006)	(0.008)
Age of equipment	-0.010**	-0.010**	-0.023***	-0.022***	-0.012**	-0.011**
	(0.005)	(0.005)	(0.007)	(0.005)	(0.005)	(0.005)
Log of capital intensity	-	0.323***	-	0.638***	-	0.315***
		(0.011)		(0.016)		(0.012)
Implicit θ	**5.29%**	**4.58%**	**9.14%**	**1.93%**	**7.14%**	**6.86%**
Implicit ε	**3.33%**	**3.10%**	**7.67%**	**3.45%**	**4.00%**	**3.49%**
Implicit α	Set to 0.3	0.323	Set to 0.3	0.638	Set to 0.3	0.315
Time period	1895-2010	1895-2010	1950-2010	1950-2010	1895-2010	1895-2010
Number of Obs.	1,714	1,714	1,037	1,037	1,714	1,714
Adjusted R^2	0.961	0.983	0.920	0.981	0.983	0.982

Notes: **** p value < 1%, ** p value < 5%, * p value < 10%*

Table 2
Results from estimates of labor productivity (*lp*) or *tfp* (*lp – 0.3.ik*) in log form, on school attainment and age of equipment capital stock. Labor input is measured by number of workers.
Time and country fixed effects included. Heteroskedasticity robust standard errors are in brackets. Estimations start in 1895 because GDP is highly volatile during the first five years.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	$lp - 0.3.ik$	lp	$lp - 0.3.ik$	lp	$lp - 0.3.ik$	lp
Estimator	**OLS**	**OLS**	**OLS**	**OLS**	**IV**	**IV**
School	0.060***	0.053***	0.074***	0.018**	0.076***	0.074***
	(0.004)	(0.006)	(0.010)	(0.009)	(0.006)	(0.008)
Age of equipment	-0.017***	-0.016***	-0.035***	-0.029***	-0.019**	-0.018**
	(0.005)	(0.005)	(0.007)	(0.004)	(0.005)	(0.005)
Log of capital intensity	-	0.323***	-	0.605***	-	0.312***
		(0.010)		(0.015)		(0.011)
Implicit θ	**8.57%**	**7.83%**	**10.6%**	**4.56%**	**10.9%**	**10.8%**
Implicit ε	**5.67%**	**4.95%**	**11.7%**	**3.08%**	**6.33%**	**5.77%**
Implicit α	Set to 0.3	0.323	Set to 0.3	0.638	Set to 0.3	0.315
Time period	1895-2010	1895-2010	1950-2010	1950-2010	1895-2010	1895-2010
Number of Obs.	1,714	1,714	1,037	1,037	1,714	1,714
Adjusted R^2	0.948	0.977	0.898	0.975	0.948	0.978

Notes: **** p value < 1%, ** p value < 5%, * p value < 10%*

Table 3

Average growth rates for various subperiods for labor productivity (col. 1) and some of its contributors: capital intensity (col. 2), *TFP* (col 3= col 1 - col 2), education (col 4), age of capital (col 5) and *TFP'* (col 6 = col 3 - col 4 - col 5)

Subperiods	(1) Δlp	(2) $\alpha.\Delta ik$	(3) Δtfp	(4) $(1-\alpha).\theta.\Delta S$	(5) $-\alpha\varepsilon\Delta A$	(6) $\Delta tfp'$
	The United States					
1890-1913	1.76%	0.57%	1.19%	0.14%	0.18%	0.87%
1913-1950	2.85%	0.45%	2.41%	0.42%	0.03%	1.96%
1950-1974	2.25%	0.57%	1.68%	0.38%	-0.02%	1.32%
1974-1990	1.27%	0.29%	0.98%	0.34%	0.04%	0.60%
1990-2010	1.83%	0.58%	1.25%	0.17%	-0.03%	1.11%
1890-2010	2.21%	0.51%	1.70%	0.31%	0.04%	1.34%
	Euro area					
1890-1913	1.82%	0.49%	1.34%	0.23%	0.11%	1.22%
1913-1950	1.49%	0.39%	1.10%	0.15%	-0.13%	1.08%
1950-1974	5.19%	1.58%	3.62%	0.48%	0.33%	2.81%
1974-1990	2.77%	1.02%	1.74%	0.34%	-0.18%	1.58%
1990-2010	1.28%	0.59%	0.69%	0.26%	-0.06%	0.48%
1890-2010	2.52%	0.80%	1.72%	0.29%	0.01%	1.43%
	United Kingdom					
1891-1913	0.72%	0.16%	0.55%	0.22%	0.04%	0.29%
1913-1950	1.51%	0.34%	1.17%	0.19%	0.00%	0.98%
1950-1974	2.97%	1.43%	1.55%	0.62%	0.11%	0.82%
1974-1990	2.22%	0.74%	1.48%	0.49%	-0.06%	1.05%
1990-2010	2.18%	0.70%	1.48%	0.07%	-0.06%	1.47%
1890-2013	1.93%	0.66%	1.27%	0.31%	0.01%	0.94%
	Japan					
1890-1913	2.35%	1.59%	0.76%	0.53%	0.05%	0.18%
1913-1950	1.78%	1.08%	0.70%	0.47%	-0.19%	0.42%
1950-1974	6.58%	2.20%	4.38%	0.50%	0.44%	3.44%
1974-1990	3.61%	1.62%	1.99%	0.31%	-0.21%	1.88%
1990-2010	1.70%	1.06%	0.64%	0.29%	-0.21%	0.56%
1890-2010	3.20%	1.52%	1.67%	0.45%	-0.02%	1.25%
	World					
1890-1913	1.84%	0.64%	1.19%	0.25%	0.14%	0.80%
1913-1950	2.15%	0.48%	1.68%	0.28%	-0.03%	1.43%
1950-1974	3.75%	1.11%	2.64%	0.48%	0.13%	2.03%
1974-1990	2.24%	0.78%	1.46%	0.36%	-0.06%	1.16%
1990-2010	1.68%	0.65%	1.03%	0.22%	-0.09%	0.90%
1890-2010	2.42%	0.73%	1.70%	0.32%	0.02%	1.35%

Source: See text. World includes all of the 17 countries: Australia, Belgium, Canada, Denmark, Germany, Finland, France, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom and the United States of America.

Table 4

Results from estimates of labor productivity (in log form and corrected for capital intensity, school attainment, age of equipment capital stock and hours worked) on the production of electricity per inhabitant (in log form) and the ratio of ICT capital stock to GDP in value terms

Time and country fixed effects included. Heteroskedasticity robust standard errors are under brackets.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent variable:			**tfp' with ICT capital deepening**			
Estimator	OLS	OLS	OLS	IV	IV	IV
Log(electricity/pop)	0.077*** (0.022)	-	0.096*** (0.021)	0.039 (0.038)	-	0.079** (0.039)
ICT		0.938*** (0.142)	1.459*** (0.162)	-	1.585 *** (0.210)	1.557*** (0.247)
Time period	1905-2010	1950-2010	1905-2010	1905-2010	1950-2010	1905-2010
First stage F stat	-	-	-	271.63	140.86	109.95
Number of Obs.	1180	732	1180	1180	732	1180
Adjusted R^2	0.968	0.963	0.968	0.963	0.962	0.965

**** p value < 1%, ** p value < 5%, * p value < 10%*

Table 5

Average growth rates for various subperiods for *TFP* (col. 1), *TFP'* (col. 2), electricity per capita (col. 3), ICT capital stock ratio (col. 4) and *TFP''* (col. 5= col. 2 - col. 3 - col. 4).

Subperiods	(1) Δtfp	(2) Δtfp'	(3) ηΔelec	(4) μΔICT	(5) Δtfp''
	The United States				
1913-1950	2.41%	1.96%	0.46%	0.00%	1.49%
1950-1974	1.68%	1.32%	0.43%	0.27%	0.62%
1974-1990	0.98%	0.60%	0.16%	0.35%	0.09%
1990-2010	1.25%	1.11%	0.04%	0.18%	0.89%
1913-2010	1.70%	1.34%	0.32%	0.14%	0.88%
	Euro area				
1913-1950	1.10%	1.08%	0.42%	0.00%	0.67%
1950-1974	3.62%	2.81%	0.56%	0.27%	1.97%
1974-1990	1.74%	1.58%	0.21%	0.15%	1.22%
1990-2010	0.69%	0.48%	0.08%	0.05%	0.35%
1913-2010	1.72%	1.43%	0.36%	0.09%	0.98%
	United Kingdom				
1913-1950	1.17%	0.98%	0.67%	0.00%	0.31%
1950-1974	1.55%	0.82%	0.41%	0.13%	0.28%
1974-1990	1.48%	1.05%	0.07%	0.34%	0.65%
1990-2010	1.48%	1.47%	0.03%	0.19%	1.25%
1913-2010	1.27%	0.94%	0.38%	0.11%	0.45%
	Japan				
1913-1950	0.70%	0.42%	0.63%	0.00%	-0.21%
1950-1974	4.38%	3.44%	0.64%	0.24%	2.55%
1974-1990	1.99%	1.88%	0.23%	0.21%	1.44%
1990-2010	0.64%	0.56%	0.10%	0.30%	0.17%
1913-2010	1.67%	1.25%	0.47%	0.13%	0.65%

Source: See text. The euro area does not include Portugal.