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Benjamin David *

Abstract: This paper investigates the relationship between Information and Communication Technologies (ICT) and productivity within 240 industries from 8 OECD countries. Specifically, it aims at providing explanations for the coexistence of this strong technological evolution together with the absence of break in the productivity trend during the last decades. We calculate the total factor productivity changes and their components (technical progress and pure efficiency changes) over the period 1973-2005 using the Malmquist productivity index and we then relate these measures with data on ICT diffusion using regression trees. Our results suggest that ICT diffusion is accompanied by opposite movements that conceal the potential of these technologies. Indeed, we find evidence of a clearly identifiable positive relationship between computerization and technical progress, while ICT diffusion negatively affects pure efficiency changes. Our findings support the existence of an adjustment period and are consistent with the fact that the economies under consideration are still in a phase of adaptation.

Keywords: Information and Communication Technologies, General Purpose Technologies, Malmquist productivity index, Data envelopment analysis, regression tree

JEL Classification: C14, D24, O33

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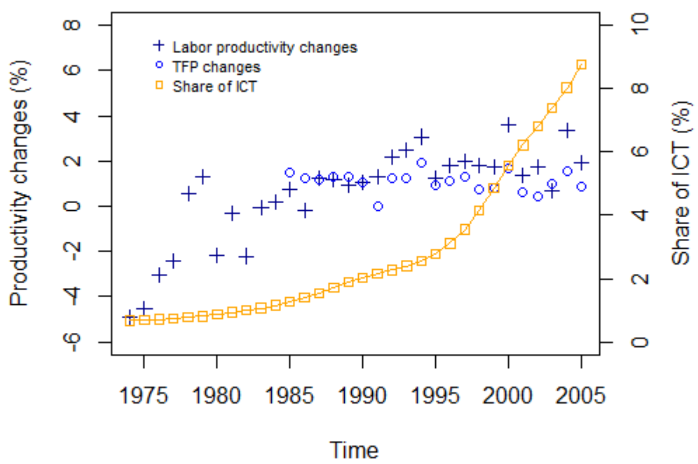
1 Introduction

In 1987, Solow coined his famous paradox: « You can see the computer age everywhere but in the productivity statistics. » This statement referred to the introduction of ICT tools in the economy without any apparent improvement in productivity. Since this observation, a large literature about the impact of computerization on productivity has been produced. After inconclusive or contradictory results, a consensus in favor of a positive impact of ICT on productivity has emerged (see e.g. OCDE (2012) and Cardona et al. (2013)). However, productivity gains seem to have a limited magnitude although ICT are traditionally accompanied by many promises in terms of performance improvements. Even if we acknowledge the possibility of methodological issues which prevent the accurate measurement of ICT impact (David (1990) and Cardona et al. (2013)), there is no doubt that the pace of productivity growth in the computer era (from 1970s to now) is not « miraculous » (OECD data[1], Jorgenson et al. (2008), Timmer et al. (2011)). There is no paradigm shift, and there is to some extent a persistence of the Solow paradox. This fact is illustrated in Figure 1 displaying productivity changes together with the evolution of the share of ICT in the total capital stock for eight industrialized countries.

Figure 1: Average trends of productivity and share of ICT in total capital stock in eight industrialized countries[2]



[1] http://stats.oecd.org/Index.aspx?DataSetCode=MFP

Indeed, between 1973 and 1995 –a period which corresponds to the beginning of ICT diffusion– labour productivity and Total Factor Productivity (TFP) growth clearly slowed down in the EU and the US, while during the second part of the 1990s, only the US had a limited « resurgence of productivity growth » (Timmer et al. (2008)). According to Jorgenson et al. (2008), this dynamic originates in the industries producing ICT equipment. Companies belonging to this sector experienced a strong growth in productivity contributing to a relative fall in prices, associated with massive investment in ICT facilities and capital deepening. This period ended with the burst of the internet bubble in 2001. From the mid-2000s growth rates in labour productivity and TFP have slowed down (Fernald (2012), Byrne et al. (2013)).

The gap between the expected improvement in productivity and the levels of productivity actually observed has prompted some authors to develop a pessimistic viewpoint about the capacity of ICT to profoundly reshape production performance positively. Gordon (2012) establishes a chronology where the computer and internet revolution begins in the 1960s and reaches its maximum at the end of the 1990s in the US. According to him, the US is now facing up to « six headwinds »[3] which are « the end of "demographic dividend" », rising inequality, factor price equalization, educational problems, consequences of environmental regulations and consumer and government debt. Gordon considers that the technological advance including the field of ICT is too weak to offset these problems. This pessimistic analysis is consistent with the work of Cowen (2011) who argues that the US economy has reached a « technological plateau » that severely limits the perspective of productivity growth.

Falling into this strand of the literature, this paper aims at contributing to the analysis of the link between ICT and productivity. Specifically, we argue that such pessimistic analyses may lead to hasty conclusions. Indeed, this representation does not match the data and literature on technological improvement and ICT diffusion, and the idea of a decrease in technological advance is not empirically supported. On the contrary, as shown by Nagy et al. (2013), technological progress is often rapid and can be mostly approximated by exponential laws, while the evolution of ICT performances is

[2]The eight countries considered in this paper are: Australia, Denmark, Finland, Italy, Japan, the Netherlands, the UK and the US. Labor productivity is defined by the ratio value added/number of hours worked. This series and share of ICT data are from EUKlems database. TFP changes data correspond to OECD estimations.

[3]Gordon asserts that these problems are US specific and that other countries are subject to different mix of headwinds.

possibly faster. By analyzing data on storage,transportation and transformation of information in terms of volume and cost in a long-term perspective, Nagy et al. (2011) suggest that they may follow a « superexponential » growth. Moreover, the massive decrease in the cost of ICT is accompanied by the apparition of many tools capable of improving productivity to a large extent in firms: computers and means of communication with increasing capacities, software which has dramatically facilitated information processing. The chronology exposed by Gordon merits comment. He dates the beginning of the computer revolution from the 1960s, although key inventions such as microprocessors or personal computers (PC) did not exist at that time. Similarly, he locates the climax of this era at the end of the 1990s. This hypothesis seems too strong with regard to the US situation in 2000: only 43% of the population used Internet and only 39% had a mobile phone,[4] whilst the share of ICT capital in the total capital stock was roughly equal to 9.5% although it has doubled since.[5]

To explain the absence of a break in the productivity path despite ICT diffusion, we follow a different approach based on the hypothesis that the ICT effects can appear after an extended adjustment period (David, (1990)). David (1990) draws a parallel with the electrification period and argues that the emergence of this new technology has produced large effects in production activities but after many years of adaptation. The key elements of the « electric age » date from around the 1880s and the positive impact on the US productivity growth is mainly visible towards 1920s[6] suggesting that, in 1900, economists could certainly formulate a first productivity paradox. This delay can be attributed to the slow pace of electrification in factories due to the necessity of large organizational changes. Indeed, appropriation of a new technology is a difficult task requiring massive material and human reorganization. It is necessary to reshape production units, firms, sectors, distribution chains and mobilise new abilities. It involves the hiring of people with specific skills and learning-by-doing processes. Transition is complicated by the presence of a previous technology which should be profitable but causes detrimental overlay of new and old technologies. Surprisingly, Gordon (2012) himself suggests that the two first industrial revolutions (the steam engine and electricity) reached their full potential at the end of, respectively, 150 and 100 years.

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[4]http://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx

[5]EUKlems database

[6]See also Devine (1983).

This approach proposed by David (1990) is connected with the nature of ICT that can be viewed as a General Purpose Technology (GPT) characterized by « binary logic » (Bresnahan and Trajenberg, (1995)). Each GPT is defined by « pervasiveness » that refers to the idea that this technology diffuses in all economic sectors,by increasing capacities and by creating complementarities. This definition suggests a diffusion process with different steps and gradual effects. In the same way, Helpman and Trajtenberg (1998a) propose a GPT-based growth model with a first phase marked by a « productivity slowdown » and a second stage where development of complementary inputs and the diffusion of new technology produce positive effects. This model is summarized by the title of their paper: « A Time to Sow and a Time to Reap ». From this point of view, ICT could have a strong effect on productivity performances but only after the economy has realized a costly transition. This approach is a natural explanation to the actual situation and constitutes our working hypothesis.
Some authors, such as Sichel (1997) or Hempell (2005b), have suggested that the absence of ICT impact in the 1970s or 1980s on productivity performances arises simply because at this time the size of ICT capital stock is too limited to have significant effects. We do not consider this point of view as a competing explanation but just as a symptom of the adjustment hypothesis. Indeed, the low levels of ICT stock in firms that prevailed over several years can be interpreted as being due to the difficulty of incorporating these technologies.

To investigate the link between ICT and productivity and assess the relevance of the existence of an adjustment period, we rely on the following empirical strategy. Firstly, we study the productivity performances in 240 industries from eight industrialized countries. To this end, we calculate the Malmquist productivity index relying on Data Envelopment Analysis (DEA). This enables us to obtain the changes in TFP and its decomposition into Technical Changes (TC), Efficiency Changes (EC) and Scale Changes (SC). This method had the added advantage of not making strong assumptions in terms of returns to scale or functional form. Secondly, we relate these estimations to data on ICT through regression trees. This nonparametric methodology allows us to take into account the particular form of ICT data characterized by nonlinear trends. Our results suggest that while the effect of ICT on TFP variations is not clear-cut, it impacts its components by positively affecting TC and by reducing EC. These opposing movements corroborate the existence of the adaptation process postulated by David (1990).

The rest of the paper is organized as follows. Section 2 presents arguments in favour of an ongoing adaptation phase. Section 3 contains the productivity analysis and section 4 assesses the link between ICT and productivity performances. Section 5 concludes the paper.

2 The relevance of an adaptation period

In line with David's hypothesis, we can find in the literature about ICT the probable signs of the adaptation process that may explain the expected delayed effect. Indeed, the electrification episode has shown that changes in organization are a key element for incorporating new technology into the economy. Bresnahan et al. (2002) found complementarities between ICT investments, the hiring of high-skilled workers, new work organization, product and service innovations. In particular, ICT reshape the modality of information diffusion in firms because these technologies substantially increase the amount of available data and their flows (« Information overload »). In response, firms need a more flexible and horizontal organization where high-skilled workers operate. Using data from 379 US firms for the period from 1987 to 1994, the authors obtain results in line with their assumptions. Tambe et al. (2011) enrich this approach by arguing that the positive impact of ICT productivity depends on a combination of decentralization, ICT investments and external focus.[7]
However, the phase of reorganization is not necessarily easy and some initiatives of this kind may fail. An illustration of this trial and error process is given by Aral et al. (2006). Their work enables the observation of a microeconomic foundation for ICT productivity gains and details about the dynamics of the link between ICT investment and performance growth. Using panel data from 623 US firms over the 1998-2005 period, they show that ICT investments are carefully implemented and their success (productivity growth) provides an incentive to the achievement of other specific expenses. This forms a feedback process that gradually strengthens productivity gains. Inversely, when investment is not conclusive (no additional productivity gains), firms reduce their propensity to make new ICT investment.

Another way to support the assumption that ICT need an adjustment period is to consider that they are deployed in part in the form of network because ICT cover technologies such as mobile phones, the Internet or any computer network. Observations and theory (Curien (2000)) suggest that their diffu-

[7]Authors define external focus « to be a set of practices firms use to detect changes in their external operating environment ».

sion displays specific trajectories mainly characterized by nonlinear dynamics on both the demand and supply sides. Networks are characterized by a positive externality called « club effect » that corresponds to the situation where when the number of network users grows, individual satisfaction increases. On the other hand, on the supply side, networks are characterized by the fact that investments are concentrated in the deployment phase of the physical structure. These high fixed costs are independent of the production volume but the use of the network is virtually cost-free due to very low variable costs. Then, firms that develop networks benefit from increasing returns to scale (IRS) (until a threshold where complexity costs could become important). Gains in profitability constitute an incentive to improve the quality of the service offered. Due to « club effects » and the specific costs structure, networks produce nonlinear dynamics. During the first phase, the size of a network is limited and the costs are important for producers and users (due to learning costs). After achieving a critical mass of users, a new phase begins with a strong growth of the network sustained by retroactions. The increasing number of users attracts new customers while the producer could improve the service offered which attracts new users. This kind of dynamics produces an increase in both the capacity and the quality of the network.
On the basis of these theoretical precisions, it seems to be logical that the network goods used in the production process by firms (they constitute a part of capital stock) do not immediately cause productivity gains. For a time, networks generate mainly costs for users and producers. A certain level of maturity is necessary before a potential improvement is realized. For example, at the beginning of the Internet, the first users have no possibility to contact in this way with their suppliers or customers due to the low adhesion and technical level. This argumentation concerns many networks used for economic activities (fax machines, mobile phones and, specifically the Internet) from the middle of the 1990s, and all other computer networks used internally by firms (Intranet).

From an empirical point of view, the hypothesis of the delayed and increasing effects of ICT on productivity performances has been studied by several authors for example Jovanovic and Rousseau (2005). Considering the Hodrick-Prescott filtered annual growth in output per man-hour data for US over the 1874–2004 period, they show that, at the beginning of the electricity diffusion, the US economy suffered from a productivity slowdown and that this situation was reflected again in the first years of the ICT diffusion.[8]

[8] Jovanovic and Rousseau (2005) point out that it is just a correlation and that a debate towards a possible causality relation is still open.

Brynjolfsson and Hitt (2003) use panel data from US firms between 1987 and 1994, and regress TFP variations on computer capital growth using varying differences (from one to seven years). Their results suggest that in the short term (one-year difference), the contribution of computers is approximately equal to its factor share but as the time horizon grows, the effect becomes increasingly important. These results are similar when time and industry controls are taken into account. Basu et al. (2004) study the differential productivity path in the US and the UK during the 1990s. They estimate the impact of contemporaneous and lagged variations in computer and software capital stock on TFP changes. Their results for the US are in line with the hypothesis of a delayed effect. Indeed, the shareweighted computer and software capital growth over the 1995-2000 period are positively associated with ICT capital growth for the 1980-1990 period while it is negatively associated with contemporaneous ICT capital growth. On the other hand, Basu et al. (2004) do not obtain similar results for the UK.

3 Productivity analysis

3.1 Malmquist productivity index

We consider the Malmquist Productivity index to grasp productivity variations. It is constructed on the basis of distance functions estimated by DEA (Fare et al., 1994). The starting-point of this approach is the concept of production technology frontier that is a function based on inputs used (x^t and outputs (y^t) produced by the Decision Making Unit (DMU) considered.[9] For a given period, the most efficient DMU(s) define(s) this frontier and a production possibility set (S^t) that give the possibility to assess the level of efficiency of the other DMUs compared to this benchmark. The concept of distance function (D_o)[10] can be used for measuring productivity growth through the Malmquist productivity index. This index was introduced by Caves et al. (1982), building upon the work of Malmquist (1953). It is constructed on the basis of four distance functions differentiated by time horizon (see details in Appendix 1):

$$M_o\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \underbrace{\frac{D_o^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_o^t\left(x^t, y^t\right)}}_{EC} \underbrace{\left[\left(\frac{D_o^t\left(x^{t+1}, y^{t+1}\right)}{D_o^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right)\left(\frac{D_o^t\left(x^t, y^t\right)}{D_o^{t+1}\left(x^t, y^t\right)}\right)\right]^{1/2}}_{TC} \tag{1}$$

[9]DMU is a general formulation. It can be firm, sector, country...or any component of a panel.

[10]Subscript "o" indicates the output orientation of the distance function.

As shown in equation (1), the Malmquist index measures productivity changes as the geometric mean of efficiency change (EC) and technical change (TC). A variation in efficiency change refers to the movement of a DMU over the best practice frontier. Therefore, an improvement (or a decrease) in efficiency corresponds to the diminution (or an augmentation) of the distance over the most efficient DMU –this kind of movement is called « catching up » by Färe et al. (1994)– whilst technical change reflects shifts in the frontier of S^t. When Variable Returns to Scale (VRS) are considered, EC can be decomposed into « pure efficiency change » (PEC) and scale change (SC) by using the difference between estimates under the two hypotheses. Formally, we have:[11]

$$SC = \left[\left(\frac{D_{ov}^{t+1}\left(x^{t+1}, y^{t+1}\right) / D_{oc}^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_{ov}^{t+1}\left(x^{t}, y^{t}\right) / D_{oc}^{t+1}\left(x^{t}, y^{t}\right)} \right) \left(\frac{D_{ov}^{t}\left(x^{t+1}, y^{t+1}\right) / D_{oc}^{t}\left(x^{t+1}, y^{t+1}\right)}{D_{ov}^{t}\left(x^{t}, y^{t}\right) / D_{oc}^{t}\left(x^{t}, y^{t}\right)} \right) \right]^{1/2} \tag{2}$$

$$PEC = \frac{EC}{SC} \tag{3}$$

Numerical interpretation of the Malmquist index is simple. When its values are greater than unity, this indicates an increase in TFP between t and t+1, while a decrease is observed when values are inferior to unity. The same interpretation holds for its components (TC, EC, SC and PEC). The estimations of the distance functions are realized by DEA analysis. This is a linear programming method for constructing a nonparametric envelopment frontier that contains all data points. Details on the calculation procedure are given in Appendix 1.

In our case, using the Malmquist index and DEA analysis is very convenient because it is a nonparametric approach. It does not assume any specific functional identity for the production frontier described above. The form and the location of the combination output(s)/input(s) are just deduced from the data of the DMUs considered.
Moreover, this method allows us to make a minimum of arbitrary hypotheses because it does not require classical and strong assumptions regarding constant returns to scale and perfect market used in growth accounting approach (Solow, 1957). This last restrictive assumption can be problematic to take into account the influence of the technological change since it is located in an

[11]Subscripts "v" and "c" refer respectively to VRS and CRS.

equilibrium framework. On the contrary, as stressed by OECD (2001), some evolutionist economists (Nelson and Winter (1982), Dosi (1988)) argue that the notion of « disequilibrium » is fundamental to understanding innovation and productivity changes. Another drawback of the growth accounting approach avoided by the Malmquist index estimated by DEA analysis is to consider only TFP changes. Indeed, the Malmquist index provides a more precise view on productivity changes, since it allows decomposition between TC, EC and SC.

3.2 Data

Our analysis of the productivity changes relies on data from the EU Klems database (2009 release). Data are available for 30 sectors[12] for 8 countries (Australia, Denmark, Finland, Italy, Japan, the Netherlands, the UK and the USA) during the 1973-2005 period. We therefore have 240 DMUs observed over a 33 year period. We calculate the Malmquist productivity index in a standard way by considering one output, Value Added (VA), and two inputs, total capital stock (K) and labor expressed as the number of hours worked (LAB). To have the same unit of measurement for the variables VA and K, we divide the real values of the variables by the purchasing power parity data provided by OECD.[13] The size of our sample is the result of the tradeoff between the need for a « long » interval, and the maximum of industries in a harmonized framework. This delimitation is convenient because we have, in our balanced panel, a sufficient number of observations for implementing DEA analysis (7920 observations for each variable and 240 observations for each period).[14]

3.3 Results of productivity estimates

Due to the number of DMUs considered and the length of the time interval, we obtain a lot of results,[15] and we will only comment the main features here. We present the geometric mean results.[16]
At the country level, we can compare these results with the TFP estimations realized by the OECD using the growth accounting method (Table 1). Our comparisons concern the period 1985-2005 because older estimations are not

[12]The complete list of sectors is given in Table 3.
[13]http://stats.oecd.org/Index.aspx?DataSetCode=PPPGDP#
[14]DEA analysis may be biased when the number of observations is insufficient.
[15]All results are available from author upon request.
[16]Indeed, since the Malmquist index is a multiplicative index, the mean is also multiplicative.

Table 1: Correlation between DEA results and OECD estimations

Country	Correlation
Australia	0.628
Denmark	0.531
Finland	0.715
Italy	0.852
Japan	0.483
Netherlands	0.726
UK	0.608
US	0.190
Mean	0.591

available. We found that the Malmquist index is well correlated with OECD data because we obtain, on average, a correlation of 0.591. One exception is the US which displays a positive, but low correlation coefficient. Japan has a slightly lower value than the mean, while Australia, Denmark and the UK have values above the average. Finland, the Netherlands and, in particular, Italy have the strongest correlation with the OECD data. This comparison is interesting because it assures the plausibility of our results, and emphasizes that using different methods does not lead to similar results. The productivity changes in the countries studied are clearly heterogeneous (Table 2). Indeed, half of them have experienced on average a decline in TFP (Australia, Denmark, Italy and the UK) while four other countries have witnessed positive variations (Finland, Japan, the Netherlands and the US). The magnitudes are also distinctly differenced. For example, Italy displays a strong negative variation but the Netherlands has large gains in TFP.

Table 2: Geometric mean by country

Country	EC	TC	PEC	SC	TFP
Australia	0.9890	1.0044	0.9884	1.0006	0.9934
Denmark	0.9924	1.0052	0.9934	0.9989	0.9975
Finland	0.9995	1.0048	0.9991	1.0004	1.0043
Italy	0.9773	1.0049	0.9681	1.0094	0.9820
Japan	1.0029	1.0064	1.0025	1.0003	1.0093
Netherlands	1.0098	1.0033	1.0077	1.0020	1.0131
UK	0.9868	1.0040	0.9826	1.0042	0.9908
USA	1.0014	1.0045	0.9986	1.0028	1.0059

Regarding the TFP components, we observe that all countries have, on average, benefited from a positive technical change while the pure efficiency performances are more nuanced. Only three countries (Japan, the Netherlands and the USA) display a growth in efficiency. Low values are obtained in Australia and in the UK, and especially in Italy with a mean of 0.9820.

At the sectoral level, results are also contrasted (Table 3). Some sectors such as agriculture, hunting, forestry and fishing; chemicals and chemical products; basic metals and fabricated metal; electricity, gas and water supply; post and telecommunications; the electrical and optical sectors, all display large gains in productivity. Other sectors like Coke, refined petroleum and nuclear fuel; construction; hotels and restaurants; public administration and defense; compulsory social security sectors, have strong negative evolutions. Furthermore, the coexistence of technical progress accompanied by losses in efficiency observed at the country level is also discernable at the sectoral level. This observation will be commented on further.

Table 3: Geometric mean by industry

Sector	EC	TC	PEC	SC	TFP
Agriculture, hunting, forestry and fishing	1.008	1.008	0.996	1.011	1.015
Mining and Quarrying	0.992	1.001	0.987	1.004	0.993
Food, beverages and tobacco	0.987	1.012	0.984	1.003	0.999
Textiles, textile, leather and footwear	0.990	1.007	0.995	0.995	0.997
Wood and of wood cork	0.992	1.008	0.984	1.009	1.001
Pulp, paper, printing and publishing	0.986	1.011	0.984	1.002	0.997
Coke, refined petroleum and nuclear fuel	0.987	0.993	0.994	0.994	0.981
Chemicals and chemical products	1.020	1.001	1.015	1.005	1.021
Rubber and plastics	0.994	1.012	0.987	1.008	1.006
Other non-metallic metals	0.990	1.011	0.989	1.001	1.001
Basic metals and fabricated metal	0.998	1.010	0.992	1.006	1.009
Machinery NEC	0.991	1.009	0.987	1.004	0.999
Electrical and optical equipment	1.025	1.012	1.020	1.005	1.038
Transport equipment	0.990	1.010	0.989	1.001	1.000
Manufacturing NEC; recycling	0.984	1.007	0.985	1.000	0.991
Electricity, gas and water supply	1.013	0.996	1.011	1.003	1.009
Construction	0.983	1.000	0.983	1.000	0.983
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel	0.985	1.006	0.986	0.999	0.991
Wholesale trade and commission trade, except of motor vehicles and motorcycles	0.994	1.010	0.996	0.998	1.004
Retail trade, except of motor vehicles and motorcycles; repair of household goods	0.993	1.003	0.993	1.000	0.996
Hotels and restaurants	0.975	1.005	0.974	1.001	0.980
Transport and storage	1.000	1.002	0.989	1.011	1.002
Post and telecommunications	1.026	0.995	1.022	1.004	1.020
Financial intermediation	0.997	1.010	0.998	0.999	1.007
Real estate activities	1.020	0.976	1.014	1.005	0.995
Renting of machinery and equipment and other business activities	0.979	1.005	0.982	0.997	0.984
Public admonistration and defence; compulsory social security	0.987	1.001	0.978	1.008	0.988
Education	0.984	1.009	0.984	1.000	0.992
Health and social work	0.984	1.006	0.989	0.995	0.990
Other community, social and personal services	0.976	1.010	0.975	1.001	0.986

Note: NEC = Not Elsewhere Classified

As suggested by Färe et al. (1994), it may be interesting to identify which DMU(s) shift the frontier over time. Formally, DMU that shift the frontier have the following characteristics:

- $TC > 1$
- $D_o^t\left(x^{t+1}, y^{t+1}\right) > 1$
- $D_o^{t+1}\left(x^{t+1}, y^{t+1}\right) = 1$

Table 4 summarizes the evolution of the contributions to the frontier in our analysis.

Table 4: Industries contributing to the evolution of the frontier

Year	Industry	Country	Year	Industry	Country
1974	Coke. refined petroleum and nuclear fuel	Italy	1994	Construction	UK
1975	Coke. refined petroleum and nuclear fuel	Italy	1995	Financial intermediation	Finland
1976	Manufacturing NEC; recycling	UK	1995	Real estate activities	Italy
1977	Coke. refined petroleum and nuclear fuel	Italy	1995	Financial intermediation	Japan
1977	Mining and Quarrying	Netherlands	1996	Financial intermediation	Finland
1979	Mining and Quarrying	Netherlands	1996	Coke. refined petroleum and nuclear fuel	Japan
1980	Coke. refined petroleum and nuclear fuel	Italy	1996	Construction	UK
1980	Renting of machinery and equipment and other business activities	USA	1997	Financial intermediation	Finland
1981	Renting of machinery and equipment and other business activities	USA	1997	Real estate activities	Italy
1983	Construction	UK	1997	Coke. refined petroleum and nuclear fuel	Japan
1983	Construction	USA	1998	Financial intermediation	Finland
1983	Renting of machinery and equipment and other business activities	USA	1998	Real estate activities	Italy
1984	Education	Italy	1998	Electrical and optical equipment	USA
1984	Coke. refined petroleum and nuclear fuel	Japan	1999	Electrical and optical equipment	Finland
1984	Construction	UK	1999	Financial intermediation	Finland
1984	Construction	USA	1999	Electrical and optical equipment	USA
1984	Renting of machinery and equipment and other business activities	USA	2000	Electrical and optical equipment	Finland
1985	Coke. refined petroleum and nuclear fuel	Japan	2000	Real estate activities	Italy
1985	Construction	UK	2000	Electrical and optical equipment	USA
1985	Construction	USA	2001	Real estate activities	Italy
1986	Construction	UK	2001	Electrical and optical equipment	USA
1986	Construction	USA	2002	Electrical and optical equipment	Finland
1987	Coke. refined petroleum and nuclear fuel	Japan	2002	Electrical and optical equipment	USA
1987	Construction	UK	2003	Electrical and optical equipment	Finland
1988	Renting of machinery and equipment and other business activities	USA	2003	Electrical and optical equipment	USA
1989	Coke. refined petroleum and nuclear fuel	Japan	2004	Electrical and optical equipment	Finland
1989	Renting of machinery and equipment and other business activities	USA	2004	Electrical and optical equipment	USA
1992	Construction	UK	2005	Electrical and optical equipment	Finland
1992	Construction	USA	2005	Real estate activities	Italy
1993	Real estate activities	Italy	2005	Electrical and optical equipment	USA
1994	Real estate activities	Italy			

The country whose industries have the best contribution, is the US with construction; renting of machinery and equipment and other business activities, and the electrical and optical equipment sectors. A more surprising contribution is that of Italian industries because the Coke, refined petroleum, nuclear fuel sector and the real estate activities sector successively sharply modify the technological frontier during the period studied. Traditionally, Italy is not seen as a technological leader. However, these results are plausible since there are only two specific industries which contribute to the shifting of the frontier. Indeed, we can suppose that the importance of tourism to the Italian economy may have a positive influence on productivity performances in real estate and the very significant weight of the petroleum company ENI (the largest company in Italy) in the energy sector explains this contribution to the evolution of the efficient frontier. Other countries have industries that significantly move technological frontiers such as Finland, Japan and the UK. In the Netherlands, only two industries have influence; whilst Australia and Denmark do not have any industry that shifts the frontier.
Now let us provide some comment about the sectoral level. We found that from the beginning of our interval until the end of the 1990s, the best frontier practice is defined mainly by Coke, refined petroleum, nuclear fuel; construction and the renting of machinery equipment and other activities sectors. From the end of the 1990s, we note a contribution of financial intermediation and the real estate activities sectors but especially of the electrical and optical equipment sector. In this category are included many products that constitute ICT.[17] Otherwise, the most efficient DMUs at the end of the period studied (last eight years) are DMU producing ICT. This point emphasizes the fact that ICT have an important and increasing role in the productivity path, at least in terms of technical change.

4 On the link between diffusion of ICT and productivity changes

4.1 Methodology: regression trees

Our aim is to check if ICT diffusion has an impact on productivity changes and its components. The methodological challenge concerns the unit root

[17] These subsectors are office, accounting and computing machinery; electrical engineering; electrical machinery and apparatus, NEC; insulated wire; other electrical machinery and apparatus nec, radio, television and communication equipment; electronic valves and tubes; telecommunication equipment; radio and television receivers; medical, precision and optical instruments; scientific instruments; other instruments.

property of our series, and the potential nonlinearities in their interaction. Specifically, 240 series are characterized by polynomial trends but their order is difficult to identify (probably degree three or four) and there is no reason to consider that interactions between our variables are linear. These characteristics prevent us to use classical panel data methods. We rely on the regression tree approach, a methodology most used in machine learning but which may be very fruitful in economics as suggested by Varian (2014).[18]

Regression trees model the response of a continuous dependent variable to explicative variable(s) by partitioning « the space of all joint predictor variable values into disjoint regions ... as represented by the terminal nodes of the tree (Hastie et al (2009)). »[19] In each region R_m for m=1,... M, the response is mostly modelled as a constant (c_m). Formally, the model can be expressed as follow:

$$f(x) = \sum_{1}^{M} c_m I(x \in R_m) \tag{4}$$

We identify the dependent variable (f(x)) with, successively, the Malmquist index or its components (TC and PEC). We consider only one predictor (x), the share of ICT in the total capital stock (%), that proxies ICT diffusion in the economy.[20] Thus, we expect that there is a link between the Malmquist index (or TC and PEC) and the importance of ICT used by industries.[21]

In order to construct our regression tree, we use the popular CART algorithm[22] defined by Breiman et al. (1984) which proceeds by binary partition. At each non terminal node, there are necessarily only two leaves where j is the splitting variable and s the split point:

$$R_1(j,s) = X|X_j \leq s \ and \ R_2(j,s) = X|X_j > s \tag{5}$$

[18]Breiman et al. (1984) underline that the first work on tree method was co-written by economist James N. Morgan in the context of Automatic Interaction Detection program (AID) (see Morgan and Sonquist (1963)).

[19]Our brief presentation is based on Hastie et al. (2009).

[20]ICT capital contains hardware, software and communication equipment.

[21]Note that we do not include control variables given the lack of relevant data at the fine level used in our analysis since it would be necessary to have data for the 240 industries. Furthermore, in several studies, authors consider TFP as the dependent variable with only one ICT variable as predictor (for example Brynjolfsson and Hitt (2003); Basu et al. (2003)).

[22]CART = Classification And Regression Trees.

In our case, there is just one splitting variable because we have one explicative variable. The search of the best partition consists in solving the following expression:

$$min \left[min_{c1} \sum_{x_i \in R_1(s)} (y_i - c_1)^2 + min_{c2} \sum_{x_i \in R_2(s)} (y_i - c_2)^2 \right] \tag{6}$$

For any s, the best $\hat{c}_m$ is equal to ave$(y_i|x_i \in R_m)$. Determination of s is realized by comparing residuals obtained in all partitions computable with input data. In the two regions obtained, we repeat the same procedure to construct the regression tree. The size of the tree (i.e. number of terminal nodes) has crucial implications. The problem consists in arbitrating between grasping informative structure in data and the risk of overfitting. In CART framework, the idea is to construct a large tree and to prune it by using cost-complexity pruning criterion. More detailed explanations regarding this procedure are provided in Appendix 2. We apply CART algorithm at different levels with all sample, by aggregating sectors and by country.[23]

4.2 Regression trees results

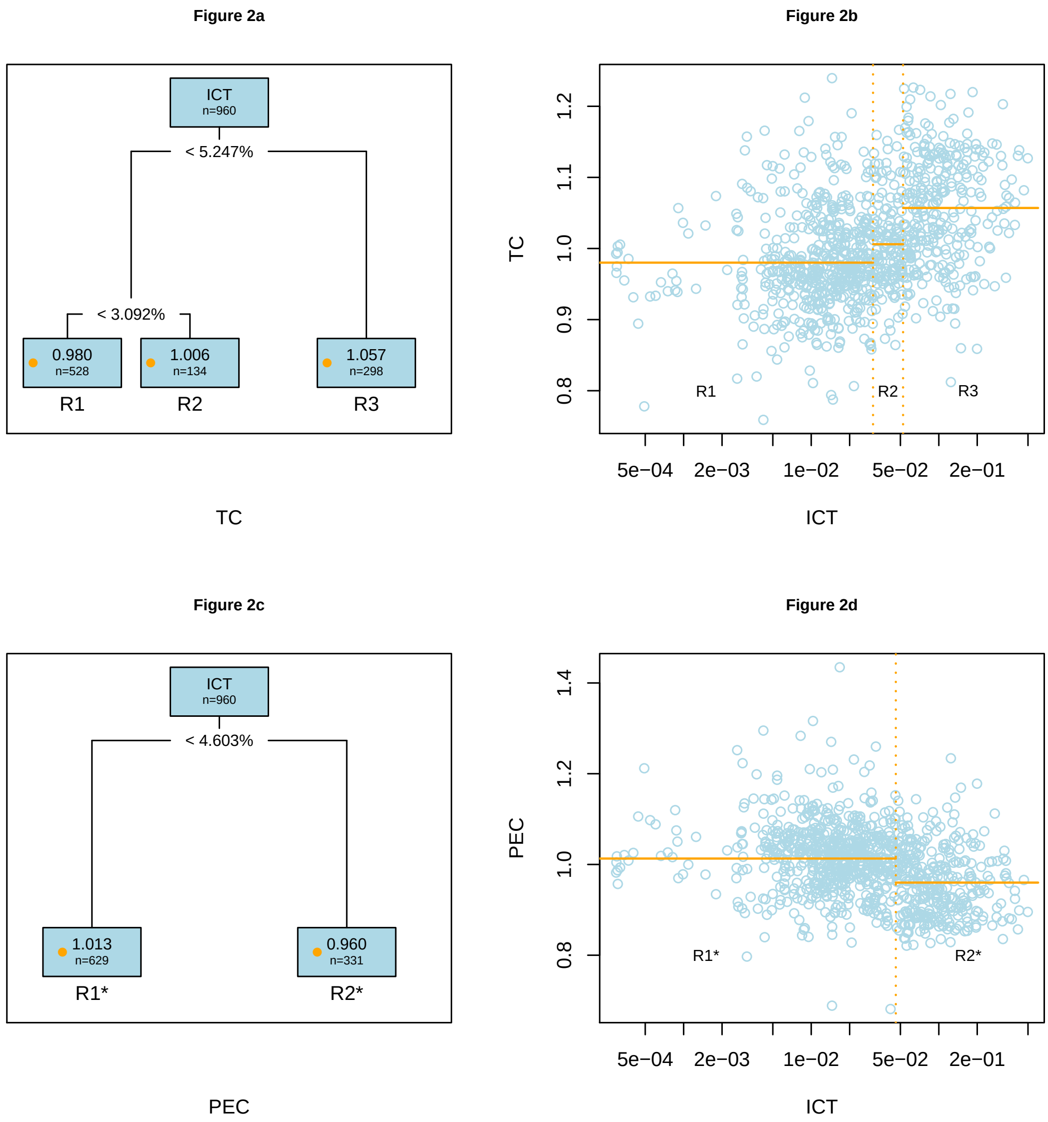
Results of regression trees are displayed in Figure 2. The presented results apply only to variables aggregated at the sectoral level because this level corresponds to the format of the data source. Application of the CART algorithm does not provide interesting results when TFP changes are considered as the dependent variable. In fact, any partition is realized in the final tree (i.e. there is only one region after the pruning procedure). This means that we do not identify any relation between the share of ICT in capital stock and the TFP changes. Inversely, when we consider the variables TC and PEC as dependent variables in the regression, we obtain very interesting findings (Figures 2 a,b,c,d). Indeed, in the case of TC, we obtain a tree with three leaves delimited by two split points equal to 3.092% and 5.247%. Constants $(\hat{c}_1, \hat{c}_2, \hat{c}_3)$ in each region are clearly different because in the first region (R1), the value is equal to 0.980, in R2 to 1.006 and in R3 to 1.057. This means that in our sample, the higher the share of ICT in capital stock the more important are the gains in technical progress. Regarding to PEC, we have a tree with two terminal nodes delimited by a split point equal to 4.603%. In region R1*, the constant is equal to 1.013 and in region R2*, there is a value of 96.02. These results suggest a negative relation between

[23] We use the R software with tree package version 1.0-35 designed by Ripley (2014): http://cran.r-project.org/web/packages/tree/.

share of ICT and efficiency growth. We plot respectively on Figure 2 the trees obtained and the observations partitioned. Note that even if we apply the same methodology by country or by considering all observations not pooled by sector, we obtain the same kind of results (Table 6 in Appendix). TC increases and PEC decreases with the share of ICT in capital stock. The number of terminal nodes is ranged from two and four.
The absence of clear relation between our ICT variable and TFP changes and the fact that the share of ICT in total capital stock is statistically associated with different levels of technical progress and efficiency changes highlight that ICT require an adjustment period before expressing their full potential. From this point of view, the positive link between ICT and the contribution of TC to TFP indicates the capacity of new technologies to strongly improve production capacity. Indeed, regression trees show that, on average, when the level of ICT reaches a threshold value, very large gains in TC are observable (for example, 5.7% by year when data are pooled by sector). This result is in line with promises of paradigm shift due to the introduction of computer tools in the economy.
On the other hand, performances in PEC seem to be negatively affected by ICT diffusion. We view this relation as « the cost of the introduction » of these technologies in the economic area. Behind these statistical results, there are probably obsolescence of machines, of skills, overlapping of technologies, groping in research of efficient organization into firms, lack of anticipation of managers or psychological barriers (resistance to change)... that affect efficiency performances.

The coexistence of these two contradictory relations can be interpreted as the sign of the adjustment period postulated by David (1990). This hypothesis explains why any structural change is observable in productivity path in the ICT era. This means that from this perspective, productive systems in the countries studied are submitted to deep and ongoing adaptation which creates temporary losses in efficiency. Logically, this situation should end and large productivity gains should appear in the following years or decades. The existence of important growth in TC and a decrease in efficiency has also been identified by Färe et al. (2006) who report a similar evolution in sixteen European countries mainly from the 1990s. They propose that these trends can be explained by the costs, in the short run, of regulatory reforms operated in these economies. This argument seems to be plausible and probably explains a part of these observations but it is also limited by the fact that all the countries studied have not simultaneously carried out this

Figure 2: Regression trees results



Note 1: Data are plotted on semi-log graphs.

Note 2: The number of observations in each region is mentioned under the constant (Figures 2a, 2c).

Note 3: The solid lines in Figures 2b an 2d represent the fitted models and the dotted lines demarcate each region.

kind of reform.[24] The advantage of our approach is to refer to ICT diffusion as a uniform process (even if there are differences in timing) to explain the broader movement identified by Färe et al. (2006) and in our analysis.

4.3 Robustness checks

We assess the robustness of our results using other statistical approaches. We compute the correlation coefficient and the Kendall's tau coefficient (1938) between each variable TFP, TC, PEC and our ICT variable. The first method allows us to identify linear dependence for each pair of series, whereas Kendall's tau coefficient is a measure of the rank correlation. It can detect potential dependence between the ranks of the two series considered.

Table 5: Correlation tests between productivity variables and ICT

Test	Dependent Variable		
	TFP	TC	PEC
Pearson	0.004	0.278	-0.177
p-value	(0.7376)	(<2.22e-16)	(<2.22e-16)
Tau Kendall	0.0246	0.234	-0.178
p-value	(0.0012)	(<2.22e-16)	(<2.22e-16)

As shown in Table 5, we observe that the positive link between the diffusion of ICT and the growth of technical progress previously identified is visible with the two correlation measures. Results show positive and highly significant correlations. Values for PEC are also consistent with the previous analysis since we observe a negative and strongly significant correlation between the variables. When we consider TFP and ICT, results are less compelling because correlations are very low even if significant in the case of Kendall test. These observations coincide with our previous findings presented in part 4-2.

5 Conclusion

We study the coexistence of the massive spread of ICT in the economy and the absence of paradigm shift in the productivity path. Although a contribution of ICT to productivity variations has been observed since the 1990s, it does not correspond to the « revolution » expected. We suggest that this situation is linked to the hypothesis formulated by David (1990) stating that

[24]The panel considered is heterogeneous, including countries as Sweden, Portugal, the Netherlands, Greece...

new technology needs a relatively long period to adapt a productive system before it achieves its potential. To assess the relevance of this hypothesis, we measure the evolution of productivity performances in 240 industries from eight industrialized countries. We use the Malmquist productivity index estimated by DEA analysis in order to have estimations of TFP changes and its components. Then, we explore the link between these measures and ICT diffusion by using regression trees. Our results are consistent with the adjustment period hypothesis: no clear relation between TFP changes and ICT diffusion can be observed, while as the share of ICT in total capital stock increases, the performances in technical progress improve. Inversely, we find evidence of a negative association between ICT and pure efficiency changes. On the whole, our findings are consistent with the existence of a delay between ICT diffusion and an improvement in productivity, and with the fact that the considered economies are still in their adaptation phase.

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Appendix 1: Malmquist productivity index estimated by DEA analysis

The following presentation is broadly based on Färe et al. (1994) and Coelli et al. (2005).

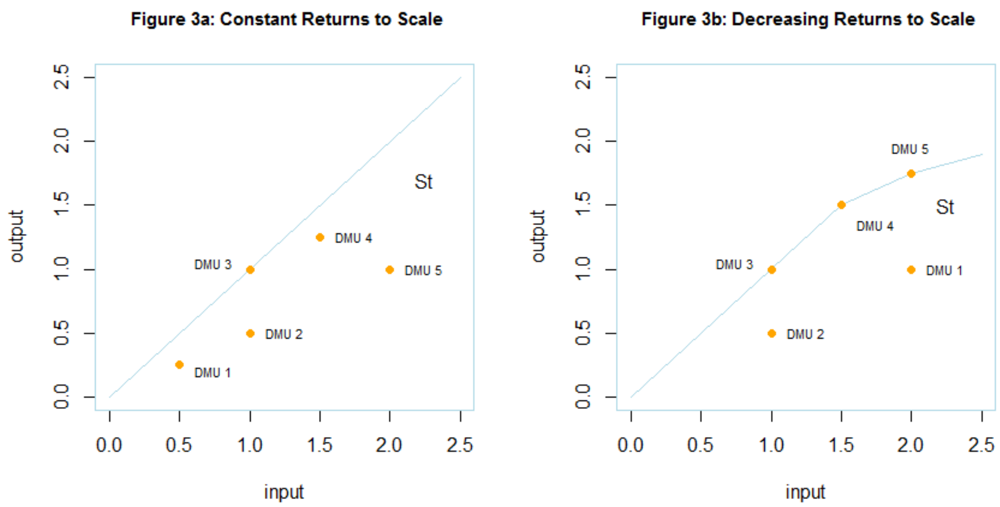
Distance function
We consider DMUs that realize the transformation of input(s) (x^t) in outputs (y^t). A production possibility set $S^t = \{(x^t, y^t) : x^t \text{ can produce } y^t\}$ models, at each period t, this process and the frontier of S^t is defined by the fully efficient DMU. The distances of the other DMUs over this limit allow to assessing their level of inefficiency. In a formal way, Shepard (1970) defines the output distance function[25] as follows:

[25] Distance functions can be constructed with input orientation.

$$D^t(x^t, y^t) = inf\left\{\theta : (x^t, y^t/\theta) \in S^t\right\} = \left(sup\left\{\theta : (x^t, y^t\theta) \in S^t\right\}\right)^{-1} \quad (7)$$

According to Färe et al. (1994), « the distance function is defined as the reciprocal of the maximum proportional expansion of the output vector y^t, given input x^t. » If $D_o^t(x^t, y^t) = 1$, (x^t, y^t) are situated on the boundary of the production possibility set. This corresponds to the maximum level of efficiency that can be reached by a DMU at t. Inversely, when $D_o^t(x^t, y^t) < 1$, this situation reflects inefficiency. Figures 3a and 3b show an example with five DMUs and only one input and one output. We consider the CRS case and VRS with Decreasing Returns to Scale (DRS).

Figure 3: production possibility sets



In Figure 3a, DMU 3 is the most efficient DMU, therefore it defines the frontier of the production possibility set. All other DMUs (1, 2, 4, 5) are situated below this frontier, meaning they are inefficient. When VRS is considered (Figure 3b), the shape of the frontier is piecewise because it is constructed by several DMUs (3, 4, 5). Again, inefficient DMUs are located under the limit of the production possibility set.

Malmquist index

In order to compute the Malmquist productivity index, several distance functions are used as shown in Equation (1). Some distance functions are defined in t, t+1 or with mixed period.

Figure 4: production possibility sets

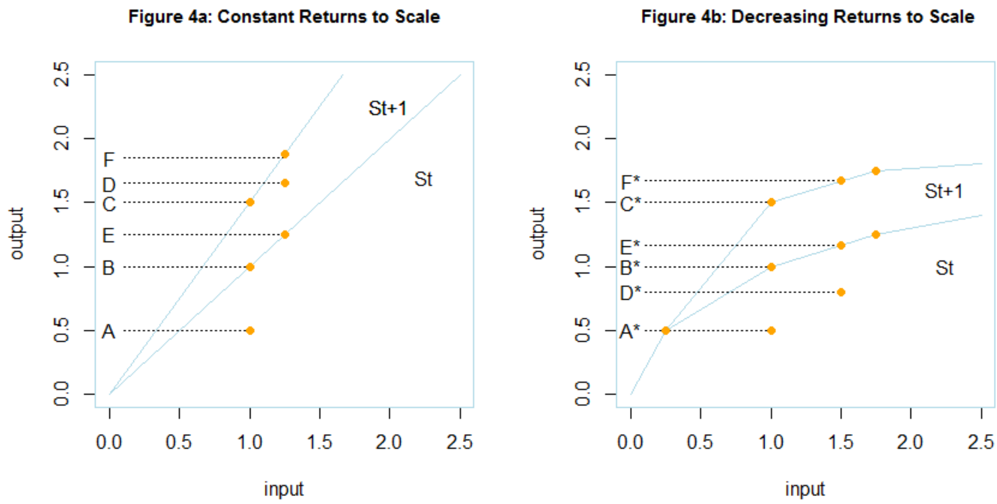


Figure 4a represents two production possibility sets in t and t+1 when CRS and DRS are considered. In t, DMU which defines the frontier of this set has a ratio input/output located at point $(1; 1)$. If we consider another DMU which has the ratio $(1; 0.5)$, its distance function in t, $D_o^t(x^t, y^t)$, is equal to $(0A)/(0B)$. Since the ratio input/output of this DMU is under the limit of the production possibility set, it is inefficient and therefore the value of $(0A)/(0B)$ is lower than one. In t+1, the frontier has positively moved because the DMU that defines this frontier has improved its own performance. That means technical progress has occurred. It is possible to have distance function in t+1. If we consider that the inefficient DMU has the ratio input/output equal to $(1.25, 1.65)$ the distance function $D_o^{t+1}(x^{t+1}, y^{t+1})$ is $(0D)/(0F)$. Furthermore, we can define mixed period distance functions evaluating (x^t, y^t) in relation to technology in t+1 $D_o^{t+1}(x^t, y^t) = (0A)/(0C)$ and evaluating (x^{t+1}, y^{t+1}) in relation to technology in t $D_o^t(x^{t+1}, y^{t+1}) = (0D)/(0E)$. Figure 4b is similar except for the shape of the frontier of the possibility production set because DRS are considered. In the same way, we can define the precedent distance functions. All distance functions combined permit to construct the Malmquist productivity index.

The general formulation is:

$$M_o\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \underbrace{\frac{D_o^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_o^t\left(x^t, y^t\right)}}_{EC} \underbrace{\left[\left(\frac{D_o^t\left(x^{t+1}, y^{t+1}\right)}{D_o^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right)\left(\frac{D_o^t\left(x^t, y^t\right)}{D_o^{t+1}\left(x^t, y^t\right)}\right)\right]^{1/2}}_{TC} \tag{1}$$

By inserting the distance functions of Figures 4a and 4b, the Malmquist index becomes:

$$M_o\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \underbrace{\left(\frac{0D}{0F}\right)\left(\frac{0B}{0A}\right)}_{EC} \underbrace{\left[\left(\left(\frac{0D}{0E}\right)/\left(\frac{0D}{0F}\right)\right)\left(\left(\frac{0A}{0B}\right)/\left(\frac{0C}{0A}\right)\right)\right]^{1/2}}_{TC} \tag{8}$$

In our application, we prefer to use VRS that is why we decompose EC into PEC and SC. The last two terms can be expressed as follows:

$$SC = \left[\left(\frac{D_{ov}^{t+1}\left(x^{t+1}, y^{t+1}\right)/D_{oc}^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_{ov}^{t+1}\left(x^t, y^t\right)/D_{oc}^{t+1}\left(x^t, y^t\right)}\right)\left(\frac{D_{ov}^t\left(x^{t+1}, y^{t+1}\right)/D_{oc}^t\left(x^{t+1}, y^{t+1}\right)}{D_{ov}^t\left(x^t, y^t\right)/D_{oc}^t\left(x^t, y^t\right)}\right)\right]^{1/2} \tag{2}$$

$$PEC = \frac{EC}{SC} \tag{3}$$

It should be noted that there exist other types of decompositions (see Coelli et al. (2005) p293).

Data envelopment analysis

There are many methods for calculating the Malmquist productivity index,[26] among which the DEA approach that has been coined and defined by Charnes et al. (1978). The distance functions are obtained by linear programming to establish a nonparametric envelopment frontier that contains all data points. These data must be located under or on the frontier.

By considering k=1, ..., K DMUs (here industry), n=1, ..., N inputs and m=1,..., M outputs, $\lambda = \lambda^1, ..., \lambda^r$ a vector of weights, the purpose is to get for each DMU four distance functions.

[26] See Färe et al. (1994) p73.

This corresponds to solving the following maximization programs:

$$\begin{aligned} \left[D_o^t(x^t, y^t)\right]^{-1} &= \text{Max}_{\theta,\lambda}\theta \\ \text{s.t. } -\theta y_i^t + Y^t\lambda &\geq 0 \\ x_i^t - X^t\lambda &\geq 0 \\ \lambda &\geq 0 \end{aligned} \qquad \begin{aligned} \left[D_o^{t+1}(x^{t+1}, y^{t+1})\right]^{-1} &= \text{Max}_{\theta,\lambda}\theta \\ \text{s.t. } -\theta y_i^{t+1} + Y^{t+1}\lambda &\geq 0 \\ x_i^{t+1} - X^{t+1}\lambda &\geq 0 \\ \lambda &\geq 0 \end{aligned}$$

$$\begin{aligned} \left[D_o^t(x^{t+1}, y^{t+1})\right]^{-1} &= \text{Max}_{\theta,\lambda}\theta \\ \text{s.t. } -\theta y_i^{t+1} + Y^t\lambda &\geq 0 \\ x_i^{t+1} - X^t\lambda &\geq 0 \\ \lambda &\geq 0 \end{aligned} \qquad \begin{aligned} \left[D_o^{t+1}(x^t, y^t)\right]^{-1} &= \text{Max}_{\theta,\lambda}\theta \\ \text{s.t. } -\theta y_i^t + Y^{t+1}\lambda &\geq 0 \\ x_i^t - X^{t+1}\lambda &\geq 0 \\ \lambda &\geq 0 \end{aligned}$$

Two additional programs are necessary for taking into account the possibility of VRS. We insert in the program a convexity restriction ($N1'\lambda = 1$) where N1 is a vector of one.

$$\begin{aligned} \left[D_o^t(x^t, y^t)\right]^{-1} &= \text{Max}_{\theta,\lambda}\theta \\ \text{s.t. } -\theta y_i^t + Y^t\lambda &\geq 0 \\ x_i^t - X^t\lambda &\geq 0 \\ N1'\lambda &= 1 \\ \lambda &\geq 0 \end{aligned} \qquad \begin{aligned} \left[D_o^{t+1}(x^{t+1}, y^{t+1})\right]^{-1} &= \text{Max}_{\theta,\lambda}\theta \\ \text{s.t. } -\theta y_i^{t+1} + Y^{t+1}\lambda &\geq 0 \\ x_i^{t+1} - X^{t+1}\lambda &\geq 0 \\ N1'\lambda &= 1 \\ \lambda &\geq 0 \end{aligned}$$

The number of problems to solve is equal to $N \times (4T - 2)$. Thus, in our application, the calculation of the Malmquist productivity index for all industries needs to solve $240 \times (4 \times 33 - 2) = 31200$ linear-programming problems. To achieve this task, we use the DEAP Version 2.1 computer program designed by Coelli (1996).

Appendix 2: Pruning algorithm in CART

The way for building a regression tree in CART framework is, in a first step, to construct a large tree T_0 and then apply it «weakest link pruning algorithm». One has to successively collapse the internal node identified as « weakest link » and continue until we produce the root tree. In this sequence, we would like to identify T_α, the tree that minimizes the cost complexity criterion $C_\alpha(T)$. This criterion is defined as follows:

$$C_\alpha(T) = \sum_{1}^{|T|} N_m Q_m(T) + \alpha|T| \tag{9}$$

with $Q_m = \frac{1}{N_m} \sum_{x_i \in R_m} (y_i - \hat{c}_m)^2$, $T =$ subtree of T_0 , $\alpha|T|$ is the number of nodes in T, a real number $\alpha \geq 0$. α is the parameter that sets the size of the tree. If $\alpha = 0$, the final tree is T_0 because any penalty is defined for any new node. If T_0 is large enough, each observation is contained in one specific region. Inversely, large values of α produce small trees since growth tree is costly.

We can also define the contribution of node (t) to total cost after pruning:

$$C_\alpha(\{t\}) = N_m Q_m(T) + \alpha \tag{10}$$

Pruning becomes interesting at threshold $C_\alpha(\{t\}) = C_\alpha(T_t)$ where $C_\alpha(T_t)$ is the cost of the branch T_t, α is deduced from this equality.

By collapsing successively internal nodes, we obtain a sequence of subtrees of $T_0 : T_0 \gg T_1 \gg T_2 \gg T_3 \gg T_k$ where T_k is the root node of the tree and a sequence of α as $0 = \alpha \gg \alpha_1 \gg \alpha_2 \gg \alpha_3 \gg \alpha_k$. For each α there is one subtree which minimizes the squared error.
In order to find the best tree in the sequence, it is necessary to identify the best α. Several methods may be used but generally cross-validation is preferred.
We consider a learning sample $L^v = L - L_v$ where $v = 1, \ldots, V$ are subsets of the same size from data. Mostly, $v = 10$ therefore L^v contains 90% of observations. The pruning procedure is repeated with the ten learning samples L^v. We compute at each time the sum of squared errors on test sample L_v that allows finding the best α (in terms of minimization of squared error).

Appendix 3: Additional results

Table 6: Additional regression trees results

Dependent variable = TFP	Split point(s)			constants			
	$\hat{s}_1$	$\hat{s}_2$	$\hat{s}_3$	$\hat{c}_1$	$\hat{c}_2$	$\hat{c}_3$	$\hat{c}_4$
Australia	20.646%			0.9987	0.9584		
Denmark	No partition						
Finland	0.384%			0.9802	1.0120		
Italy	20.610%			0.9831	1.0410		
Japan	No partition						
Netherlands	0.377%	0.442%		1.024	1.170	1.013	
UK	No partition						
USA	No partition						
All sample	No partition						

Dependent variable = TC	Split point(s)			constants			
	$\hat{s}_1$	$\hat{s}_2$	$\hat{s}_3$	$\hat{c}_1$	$\hat{c}_2$	$\hat{c}_3$	$\hat{c}_4$
Australia	3.481%	5.501%	10.060%	0.9812	1.0070	1.0370	1.0840
Denmark	0.041%	2.879%	7.129%	0.9043	0.9787	1.0250	1.0760
Finland	3.353%			0.9833	1.0460		
Italy	2.998%			0.9898	1.0440		
Japan	1.121%			0.9855	1.0270		
Netherlands	1.342%	4.810%		0.9740	0.9957	1.0510	
UK	3.396%	6.075%		0.9838	1.0090	1.0470	
USA	0.816%	5.854%		0.9704	0.9952	1.0560	
All sample	4.111%			0.988	1.047		

Dependent variable = PEC	Split point(s)			constants			
	$\hat{s}_1$	$\hat{s}_2$	$\hat{s}_3$	$\hat{c}_1$	$\hat{c}_2$	$\hat{c}_3$	$\hat{c}_4$
Australia	3.612%	11.797%		1.0210	0.9824	0.9067	
Denmark	1.906%	5.317%		1.0330	0.9991	0.9415	
Finland	3.684%	3.894%		1.0210	1.1640	0.9766	
Italy	3.558%			0.9829	0.9436		
Japan	0.386%	1.083%		1.0020	1.0380	0.9941	
Netherlands	1.017%	5.071%		1.0540	1.0210	0.9692	
UK	6.075%			0.9977	0.9593		
USA	5.179%	5.305%		1.0190	1.1900	0.9739	
All sample	3.867%			1.0140	0.9691		