The role of Information & Communication Technology in Europe: evidence at industry-level

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Introduction

The acceleration of US economy in the last decay of twentieth century has been thoroughly documented and widely discussed. A main part of the literature has recognized in the investment in Information and Communication Technology (ICT from now on) one of the main sources of this great performance of US economy, even if there is still no consensus on the magnitude of the impact of ICT on growth.

In the same period Europe doesn't face a comparing increase in productivity, experiencing instead a decline in aggregate output growth compared to the previous decay. Even if there is a broad consensus on this fact, very few studies have been done to understand both how European economic has changed at industry level and what have determined this change.

Different scenarios are plausible and many kind of analysis may be helpful in this. From a time-perspective it appears that the 90s have been driven the result of the declining of output growth in Europe; a cross-country analysis could be helpful to understand if the European aggregate result depends on a very bad performance of few countries or a relative bad performance of all countries; finally a sector analysis inside each country could be used to detect if there have been interesting trends in similar industries.

An extensive descriptive analysis - and an extensive database that could cover both the time dimension and the country and sector cross-section dimension- is needed to reconstruct the history of the European productivity decline.

In this work I will use variables taken by two different dataset compiled by the *Groningen Growth and Development Centre*. These datasets have been constructed trying to reduce the measurement errors and with particular care in the harmonization of the price index, thus obtaining comparable data for a range of sectors in different countries over the period 1979-2001. To deal with an industry analysis I follow the sector sub-classification proposed by Von Ark and Piatkowski (2004) and I consider six groups of sectors according to their use of ICT and to their manufacture or service vocation. All the analysis is conducted considering as a focal point the use of ICT and its impact on growth. This last point is analyzed using a growth accounting methodology developed by Jorgenson, Gollop and Fraumeni (1987) that sheds light on the different impact of ICT and non-ICT capital on U.S. and European growth.

What emerges is that Europe growth has been different over countries, with some countries growing at higher rate than U.S. one. More important, this growth has been different over sectors: in particular ICT sectors, the ones that produce ICT or that use heavily this kind of capital, grow much more than non-ICT ones. Still this trend has been more or less the same for all countries, without creating a new specialization pattern in Europe. Data show that the increase in ICT sectors output goes hand in hand with an increase in volatility, thus confirming the Imbs (2003) hypothesis about the negative correlation among growth and volatility at disaggregated level. Finally it emerges that for almost four European countries the contribution of ICT capital (computing equipment, software and communication equipment) to output growth has been smaller once we compare it with the U.S. one. Non-ICT capital (non-residential building and structure, transport equipment, other non-ICT equipment), instead, accounts for European growth more than for U.S. one.

The first part suggests that ICT adoption has an important role in driving different growth rates both between Europe and U.S. and inside European countries. The second part deals with the ICT adoption that could be considered part of the technology adoption process. There may be many reasons why ICT adoption has actually been different across countries and across sectors. Some recent papers, Caselli and Colemann II (2001) and Comin and Hobijn (2003) deal with the adoption of technology using aggregate data at country level. The first paper considers, in particular, the adoption of computers (using as a proxy the value of computers' imports), while the second one analyzes the adoption of a broad variety of technologies. Both the papers use a growth-kind regression with their measure of technology adoption as dependent variable. Both works find that human capital is the main important regressor in their specifications.

Other works, at micro level, emphasize the importance of human capital considering, this time, the schooling of the workforce. Bosworth (1996) and Faria, Barbosa (2004) find that, for different samples, the skills of the workers have a significant and positive impact in the likelihood of adopting advanced production technologies.

From a theoretical perspective, the relation among human capital and technology adoption has been firstly proposed by Nelson and Phelps (1996). They argue that for educated people is better to discriminate among promising and unpromising ideas an this leads them to make less mistake once they decide to adopt a new technology. Departing from this idea some papers have been written trying to explore this interesting relation. In particular Iyigun and Owen (1999) show the importance of adaptive skill of workforce in the use of new technology. It's broadly recognized that ICT is a General Purpose Technology (GPT), like electricity in the first part of this century and steam engine during the Industrial Revolution. These technologies have some features in common;one of these is that they need complementarity inventions to be used efficiently. Thus the adaptability of labour force, that is its capacity to learn fast and efficiently how to use a new technology, is a central part of this mechanism.

Following the last intuition and the robust literature findings I will support evidence on the importance of human capital in adoption of ICT at industry level. Using the IGAD panel dataset I will conduct some regressions of ICT capital on a measure of the schooling of the workforce. Using a panel dataset will be helpful to solve some econometric problems, like the control of unobserved heterogeneity. Moreover I will deal with other econometric problems, like potential endogeneity of the regressor and the omission of important variables.

Finally a robustness check of the empirical part is done, trying, from one hand to eliminate the possible business cycle effect on the data, and, from another hand to test the basic relation considering a number of control variables.

The rest of the paper is organized as follow.
In section 1 I present the two dataset used; section 2 deals with a broad analysis of output growth in European countries and US, trying to shed light on the role of ICT in different country performances; section 3 deals with the ICT adoption process pointing at the relation among technology and skills of the workers. After presenting the related literature I turn to describe the empirical specification and the different methodologies I use to solve some econometric problems; finally a brief robustness check of the results is presented; section 4 concludes and suggests possible extensions.

1. Data

In this paper I will use variables taken from two different databases constructed and updated from the *Groningen Growth and Development Centre* (GGDC) on the base of different sources.

The first database, the Industry Labour Productivity Database (ILPD), contains, among other variables, the value added at constant price of 15 European countries and of US in a range of 56 sectors and 22 years[1].
The dataset is constructed departing from the OECD STructural ANalysis (STAN) database, which in turn is largerly based on recent national accounts of individual OECD member state. The STAN data is then complemented using information from industry survey and (historical) national accounts of individual countries to provide a complete and up-to-date data set for the period 1979-2001.
The output I consider in the first part of my descriptive analysis is the gross value added measured at producer prices or at basic prices, depending on the valuation used in the national accounts. I will consider this variable at the constant 1995 prices[2].

The sectors considered have then been sub-classified, following Von Ark and Piatkowski (2004), in different ones according to their use of ICT (Information and Communication Technology). In particular we can distinguish ICT-producing industries, industries that makes intensive use of ICT and industries that use ICT less intensively[3]. The first group includes producers of IT hardware, communication equipment, telecommunications and computer services (including software), and has been distinguished on the base of an OECD classification. The second and the third groups are distinguished in terms of their intensity of use of ICT. ICT intensity is measured by the share of ICT capital in total capital services in the US: the top part of

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[1] Details on country, sectors and years coverage are reported in the appendix.
[2] Everything is expressed in Euro. In some cases (Denmark, Sweden, UK and US) the database does not report the Euro conversion. In these cases I convert the data using the 1998 yearly conversion rate obtained on the website http://www.uic.it, "Ufficio Italiano dei Cambi".
[3] In my dataset the ict_index control for these different sub-sectors. The sub-classification is reported in the data appendix.

industries, according to this measure, are classified as ICT using ones and the bottom half as non-ICT ones.
A problem with this classification is that it is constructed under the hypothesis that the distribution of ICT capital in industries is equal for all countries to that of US. A sensitivity check of this taxonomy index should be done to improve the robustness of the data analysis results[4].

The series of this dataset are adjusted for the deflation of ICT goods. Since the quality of computers has been growing in the last years, their price has been declining continuously. Thus traditional methods of sampling and quality adjustment could lead to an underestimation in the rate of the output price declining. Since now only few countries as U.S., Canada and France measure computers and semiconductor prices with an adequate and harmonized system. Other countries measurement system, instead, underestimate the productivity growth of the ICT producing industries. In this dataset a harmonized procedure, based on the application of sector specific U.S. deflators, is used for EU-15 countries, thus avoiding both the comparability problem and the downward bias.

In addition to this, my analysis also contains data taken from another database, The Industry Growth Accounting Database (IGAD), also constructed by GGDC. The IGAD contains data on output, labour quality, labour, ICT and non-ICT investment, TFP, ICT share and labour share for US, France, Germany, The Netherlands and UK. The sectors considered are 26 and the year coverage goes from 1979 and 2001, even if many observations in the extreme years are incomplete.

"Output" is measured as the growth rate of the value added at constant price; "Labour" is the growth rate in total hours worked, while "Labour quality" is the growth in skill-adjusted labour input minus the growth in total hours worked; "ICT capital and "Non-ICT capital" are the growth rate in ICT and non-ICT capital service; "TFP" is the growth rate in total factor productivity, and the ICT share and labour share are respectively the share of ICT and of labour compensation in value added.

This data allow the researcher to use the growth-accounting methodology proposed by Jorgenson (1995), which is aimed to decompose the output growth[5] into contribution from factor inputs and productivity growth.
This framework has been extensively applied in studies on the ICT contribution to growth, such as Oliner and Sichel (2000), Jorgenson and Stiroh (2000) among others.
In this growth accounting system, inputs are assumed to earn their marginal products, thus the compensation share of an input is equal to the output elasticity of that input.
The output of each industry can be decomposed in the following way (omitting the industry subscript):

$$\Delta \ln Y_t = \bar{v}_t^L \Delta \ln L_t + \bar{v}_t^K \Delta \ln K_t + \Delta \ln TFP_t$$

[4] See van Ark, Inkaalar and McGuckin (2003) for a more detailed description of this industry taxonomy methodology.
[5] In this database the TFP measure is based on value added instead of gross output, since to account for the role of intermediate inputs, we need input/output tables that are not yet available for all countries.

where the LHS is the growth of real gross value added, $\Delta \ln L_t$ is the growth of labour input and $\Delta \ln K_t$ is growth of capital input. The coefficients, $\bar{v}_t^L$ and $\bar{v}_t^K$, are respectively the average share of labour and capital compensation over the two periods, and, since constant return to scale are assumed, they sum up to one.

Input growth rates are given by growth in each labour type (1,…, h) and in each capital type (1,…, j) weighted by their two period average share in total nominal input compensation. In particular labour has been divided into a number of skills categories that varies from three in Germany to seven in Netherlands and that is based on the schooling of the workforce. The division of workers by age and gender[6] is, instead, precluded from the data. Capital input, instead, is divided in computing equipment, software and communication equipment, non-residential building and structure, transport equipment and other non-ICT equipment: the first three are ICT capital and the others are non-ICT capital. Also here hedonic deflators based on US ones are applied to ICT capital to avoid the downward bias deriving from the quality-adjustment.

2. European and U.S. output growth in the last two decays.

2.1 output growth analysis

A well-known fact of the last decays is that European and US growth rates have been very different. This first paragraph will provide a descriptive analysis to point out the magnitude and the characteristics of the different growth rate not only between US and Europe, but also inside different European countries and inside different sectors.

Graph 1 compares European and US growth rate in the last two decays: Europe grows less than US and, this tendency, becomes worst in the last decay in which it scores a low 2.14 % compared to the slightly higher 2.37 % of the 80s. U.S. growth, instead, ranges from 2.80% of the first decay to an average of 3.29% in the last one.

Within Europe there is some variation among countries how reported in table 1 and, considering U.S. as the numeraire, in graph 2. We can thing to divide European countries in 4 groups:

- Three fast growing countries: Ireland, Portugal and Finland[7]. Ireland is undoubtedly the most growing country with a 4% in the first decay of the

[6] These variables have been considered by Jorgenson in his pioneering work on this growth accounting methodology.

[7] Ireland great performance is confirmed in the output level over population analysis, while Portugal and Finland one isn't, that is the last two countries experienced high growth rate but small output level.

analysis and a much stronger 8,33% grow rate in the last decay; Portugal performed very well in the ‘80s, but just slightly faster than the average in the 90s; Finland performed well even if in the years from 1990 to 1995 it experiences a fall in the growth rate of –0,56[8];

- Slightly faster than average growth countries: Austria, Netherlands, Spain. While the first two keep a robust high growth rate in both decays, Spain shows a decline in the last decay;
- Countries growing at the average: Germany, Sweden and UK. Unfortunately in the ‘90s both Germany and Sweden experienced a decline in growth rate, that has been lower than the European average;
- Finally less than the average growth countries: Belgium, Denmark, France, Greece, Italy. In this last group it worth notice that Denmark and Greece performed badly in the 80s but show a catch-up in the 90s (growing at the average), while the other three get bad results in the last decay.

Many observers have pointed at the ICT capital to explain the US high performance of the second half of 90s.

Oliner and Sichel (2000) use a neoclassical growth accounting methodology to show that computers, in the first half of ‘90s, contribute modestly to U.S. growth since ICT capital still represents a small fraction of the total industry capital stock. In an update work, however, they find that ICT capital role has been very important in the second half of ‘90s, accounting for 44% of the total output growth.

Is ICT also playing a role in different European countries’ performance?

Some works have been done to estimate the impact of ICT in European countries. Hernando and Nuñez (2004) applies the Jorgenson growth accounting methodology to Spanish industries from 1992 to 2000; Jorgenson (2004), instead, compares the ICT impact over output growth and over labour productivity for the G7[9] countries, finding that a great surge in investment in information technology and equipment after 1995 characterizes all seven countries. ICT capital accounts for a large portion of the resurgence of U.S. economic growth, but contributes substantially to output growth in the other economies as well.

To study properly this impact one needs comparable country data, that treat in a homogeneous way the measurement problems in this kind of dataset. The IGAD, for example, allows me to conduct a comparable analysis in four European countries and to compare it with U.S. results obtained from the same source.

However, another way to study the importance of the impact of ICT over growth is to consider an industry level analysis. The need of sector analysis has been emphasized by many economists, since it allows the researcher to disentangle among different growth-patterns. A country could show a high growth rate if all its sectors are growing fast or if few sectors are driving the entire growth. Hansen, for example,

Also for US growth rate are generally low with respect to some European countries, but output level is the highest one.

[8] Finland suffered a great loss of export markets in the beginning of the ‘90s.

[9] France, Germany, Italy, Japan , United Kingdom, Canada and U.S.

used this analysis to test the mushrooms-growth (driven by few sectors) against the yeasty-growth (driven by a uniform growth of all sectors) hypothesis. He introduced these two hypothesis in addressing the question about the importance of some inventions in enhancing the industrial productivity.

The problem with disaggregate analysis is, obviously, the lacking of data that sometimes are just collected for one country (US) or for few years.

The ILPD provide me the kind of data I need. First, consider the sub-sector classification exposed in the previous paragraph. The 56 sectors of the ILPD can be classified in 6 groups: ICT-producing manufacture sectors, ICT-producing service sectors, ICT-using manufacture sectors, ICT-using service sectors, non-ICT manufacture, non-ICT service and other non-ICT sectors. The first four will be consider ICT sectors since they are the ones that either produce or heavily use ICT in their production, the others will be considered non-ICT sectors[10].

Table 3 shows the average growth rate in ICT and non-ICT for all countries in the database and for different periods.

A comparison of EU-15 and US show that, except for the second half of '80s, US growth has been higher than EU-15 one both in the ICT and in non-ICT sectors.

Once again there is high heterogeneity among European countries. Interestingly two of the best-performing countries, Ireland and Portugal, show the highest growth rate in ICT-sector in the last decay; while three of the worst-performing countries, Belgium, France and Italy, have the lowest growth rate in ICT-sector in the last five years of the sample. ICT and non-ICT sector have generally increased in an asymmetric way, but the new sector has increased, in many cases, more than the traditional one. Looking, however, at the value added at constant price divided by population[11], I find that even if the ICT sectors are growing more, the non-ICT once are still the biggest sectors in Europe since their level output is almost double than the ICT one. This finding may suggest that a shift from traditional to new sectors is happening in Europe and that this change has different proportion in different countries.

Looking back at table 3 another important evidence is suggested by the time-series analysis. Both sub-sectors show low growth in the period 90-95. Europe on average and U.S. experienced a lower growth rate than the previous half decay. However in the second half of the decay ICT sectors manage to recoup the bad performance, while non-ICT sectors do not. Once again, looking at European overall performance and U.S. one we find that the ICT sectors more than double their growth rate, while the non-ICT ones grow from 1.37% to 1.80% in Europe and from 1.46% to 2.20% in U.S.

European decline of last decay, according to some researchers, relies upon a poor performance of the traditional non -ICT sectors more than upon the fact that European countries did not use heavily ICT capital. However it worth notice that almost ten countries in the old continent show a less-performing ICT sector when

[10] See the appendix for a clearer classification
[11] These statistics are not reported

compared to the US one in the last five years, thus supporting the idea that European slowdown may also have its origin in an under-exploiting of the new technology.

A further step may be done to see if the surge of ICT sector has driven a specialization pattern in Europe.

Specialization is defined as the extent to which a given country specializes its activities in a small number of industries or sectors. Thus the production structure of a country is “highly specialized” if a small number of industries accounts for a large share of its production.

To account for specialization I’ve constructed the concentration ratio, CRn, that is the share of the largest n sectors (with n equals to 5 and to 10) in the all economy[12]. Graphs 3 and 4 and table 6 shows the results. These may be summarized as follow:

- Ireland is the country with the greatest positive change in the concentration ratio between the two decays;
- Finland and UK, by converse, show a little decrease in specialization;
- In most of the other cases the magnitude of the change is marginal.

This analysis confirms results of other works[13] and indicates that the evidence does not suggest a trend toward specialization. The only notably difference is the Ireland case: this seems to be the only country in Europe that has experienced a rapid growth rate in the last years, expecially in the ICT sector and that has experienced an increase in specialization also due to some capital-intensive sectors as office machinery, chemicals, electronic valves and tube.

2.2 Variability analysis

Ramey and Ramey (1995) found that the growth rate is inversely proportional to the volatility. This empirical result was found in a cross-country analysis with aggregate values. Many theories in the last years predict this result. However both theories and empirical works don’t account for a sectoral analysis. Only Imbs (2003), to my knowledge, test this relation at industry-level and finds that even if from an aggregate point of view growth and volatility covariate negatively, the relation get inversed once one consider different sectors.

Table 4 reports the mean and the standard deviation of the growth rate for EU-15 and U.S., in different time periods.

Average and standard deviation follow the same pattern in EU-15 and in U.S., even if they have different magnitude. Their relation is not clear since they seem to be negatively correlated from 1985 to 1995 and positively correlated after 1995.

[12] All the sectors, and not only manufactures ones, have been included.
[13] In particular the finding confirms that of the OECD “The Competitiveness of European Industry: 1999 Report”

Once we consider ICT versus non-ICT industries we see that the first have always a higher variability, and a higher mean, than the second ones. Moreover the magnitude in the new sectors appears very high, being in five over eight observations almost the double of the average growth rate. The traditional sectors, instead, have lower growth rate associated with lower and more stable standard deviations. At first sight, this result seems to be in accordance with Imbs one: the most growing sectors are the most volatile ones.

From a country perspective the higher volatility of the last half decay has been driven by countries such Austria and Ireland, among the most growing ones.

Finally to assess further the results I consider an ANOVA analysis reported in table 5. This show that slightly more than the 90 percent of the variation can be explained byn country and industry variation. Moreover, as suggested by previous standard deviation tables, the sector effect is much more pronounced than the country one.

Conclusions of this analysis are listed below:

- The volatility in the growth rate has risen in the second half of the 90s
- The acceleration in volatility has been greater in countries where also growth has accelerated more (Ireland, Austria): this means that only some sectors have been active in rising the average growth rate and that their growth rate have been extremely high;
- The volatility has been much higher in the ICT sector than in the non-ICT one, suggesting that changes in the first sector have driven the total economy volatility;
- This difference in the volatility of non-ICT sector and ICT one is common in all European countries;
- A comparison among U.S. and Europe shows that U.S. has grown more than Europe in all periods and in both sub-sectors; the standard deviation in the ICT sector has always been smaller in Europe (except for the last period);
- The recent high volatility is mostly explained by sector variations than by country ones: if the second hypothesis would have been confirmed by the dataset we should have concluded that country specific environment, economic policy and macroeconomic development in single countries where the main dimensions to analyze to understand the recent years economic performance; instead we conclude that also this analysis point at the ICT revolution and at its impact on different sectors as one of the main factor at work in the European industrial system.

2.3 ICT capital deepening and non-ICT capital deepening

Table 7 reports the contribution of ICT and non-ICT capital deepening to the output growth for EU-4 and U.S. in different periods, using IGAD, while table 8 considers U.S. as the numeraire.

The values have been obtained with the growth accounting methodology a la' Jorgenson in which the contribution from the two kinds of capital is calculated weighting the growth rate of each input with its average income share.

What emerges in the analysis is that U.S. output growth relies more heavily on ICT deepening than European ones. Except from the second half of '80s, the ICT deepening in Europe has always had a lower impact on output growth, ranging from 3.8% to 8.3%.

In the last years, however, the country-table shows that a new pattern emerges: it seems that Germany, UK and Netherlands exploited more the ICT capital reaching very high levels. A notably exception is the France where, even if the ICT capital contribution is more than three times that of the previous half decade, it still remains too low compared with the other countries.

When we turn to analyze the contribution of non-ICT capital the things reverse. The contribution of this capital to European growth is very high for almost all observations. Nevertheless, we should notice that since ICT capital still represent a small fraction of the total capital stock, its share in total cost is rather small compared to the share of other fixed capital. So, relative to its share, the contribution of ICT capital has been considerable, expecially in the last five years for Europe and in the last ten years for U.S.

2.4 Does ICT deepening has a role in the different output growth?

The question in this first part was about the existence of a positive role of ICT capital in explaining the difference growth in European and U.S. output and among European countries.
I briefly summarize the evidence found:

- US experiences a great output growth in the last decade while Europe doesn't;
- The contribution to US output growth coming from ICT capital deepening has been greater than in Europe; conversely non-ICT capital has been more important in Europe than in US. In the last part of '90s, however, also Europe seems to rely more on ICT capital;
- Output growth has been higher in ICT sectors both in Europe and in US even if US scores higher values;
- Mixing the country and the sector analysis an interesting fact emerges: the countries that grew more, like Ireland and Portugal, are the same in which ICT sectors grew more.

We can conclude that US and European growth in the last years have been driven, at some extent, by the adoption of ICT. In the last five years Europe seems to begin a catching up process, driven by some countries such us Ireland, Portugal, Finland and Austria. These countries have grown a lot, mostly in the ICT sector. So in Europe the ICT contributed less than in US to the last years growth, but the changes of the last years can also been interpreted as a delay of European adoption of these new technologies, thus leaving open the option that European countries may still gain from this source exploiting all its potentialities.

Ireland great performance may be attributed to a sort of "lock-in" effect: once Ireland begun its convergence towards other European countries, it bet more in ICT deciding to specialize in these new sectors. It won its bet, since now Ireland is not only the first ICT-producer European country, but it is also the most growing European country.

The fact that the industry-variability is more pronounced than the country-one may reflects the fact that European growth differences depend more on specific-industry dynamics than on macroeconomic patterns at country-level.

3. The technology adoption.

3.1 Empirical and theoretical literature.

In the first part of the paper we saw how difference in productivity changes among European countries and US are connected with the ICT sector.
We now turn to ask what can explain the difference in adoption of ICT in different industries and countries.
Some empirical studies have been done trying to explain the determinants of technology adoption at the macro level.

Caselli and Colemann II (2000) (CC) conduct a case study of the diffusion of computers in a panel of countries. They measure the adoption of computers using the value of their import as a proxy. Their measure is justified by two reasons: first, since ICT is a capital-embedded technology, the physical diffusion of computers is actually a measure of its adoption, second since most countries don't have an ICT producing sector, the import of computers is the actual installed capacity. Running a growth-kind regression using the import of computers as dependent variable, the authors find a strong role for human capital and trade. They interpret the importance of human capital in computer adoption as a confirming evidence of the skill-biased component of ICT.

Comin and Hobijn (2003) (CH) document a general cross-country technology adoption using 25 technologies in a cross-country time-series analysis. Also in their regressions, that again consider many potential explanators of the dependent variable, one of the most important variable in explaining technology adoption is the human capital. This important role is robust even when the regressions are run cutting for time-dimension or for different kind of technology, even if education seems matter less for not skill-intensive technology like textiles, steel and shipping.

Lee (2000) points out the human skill capacity as a key factor for ICT adoption in developing countries since without a minimum level of know-how this technology is neither applicable nor productive. Using data for ICT indicators over the period 1995-1998 he finds that human capital, in particular the secondary education, and income explain almost the 78% of the dependent variable.

A different analysis is made by Cummins and Violante (2002) who estimate how the improvement of the average productivity of capital depends on the technological gap between the best and average technology and on "adaptable" labour defined with measures like the share of graduate college and of young people in labour force. They use US data for major US industry in a large period going from 1948 to 2000. They actually find a positive and significant correlation between the dependent variable and the adaptable labour.

Aside from this macro evidence one would ask if, considering a sector or firm analysis the same pattern would arise. Actually the evidence on the impact of labour skill on technology adoption at micro-level is relatively scarce due to the lack of disaggregated data.

A Portuguese plant-level manufacturing industry dataset is analyzed by Faria and Barbosa (2004). They find that the share of skilled employees has a significant positive impact on the likelihood of adopting advanced production technologies. A similar pattern is found from Bosworth (1996) who shows that qualifications and skills of workers have a significant and positive impact in a model of technology adoption.

With regard to the theories that explore the relationship between human capital and technology adoption, we have to distinguish among "skill-in-adoption" and "skill-in-use" theories: the first ones points at the importance of the skilled of flexible labour in the initial phase of adoption of any new technology, while the second emphasize the complementarity relation between human capital and skill-biased technology only. The first "skill-in-adoption" theory is proposed from Nelson and Phelps (1996). In their influent paper they emphasize for the first time the link between education and technology adoption. Departing from evidence from US agriculture they state that farmers with a relatively high level of education have tended to adopt productive innovations earlier than other farmers. Their hypothesis is based on the idea that for educated people is better to discriminate between promising and unpromising ideas and so is less likely to make mistakes in the adoption of new technologies. Their hypothesis states the following: "The rate at which the latest, theoretical technology is realized in improved technological practice depends upon educational attainment and upon the gap between the theoretical level of technology and the level of technology in practice".

Krueger and Kumar (2003) build a growth model in which households can choose between skill-specific "vocational" education that is cheaper to obtain and "general" education that, even if more costly, enables workers to operate new technologies incorporated into production. Their theory suggest that vocational education, more diffused in Europe, works well, in terms of growth rate and welfare effect, in a more static environment. However in the Information Era of the last two decays in which new technologies are invented at a faster pace, this kind of education could be in part responsible of the low performance of European economics.

A similar intuition is in the model built by Iyigun and Owen (1999) in which the interaction between the development of new technologies and human capital accumulation is studied considering the importance of adaptive skills. These skills determined how new technologies are effectively utilized in production since they help the workforce to innovate and improve them. This variable can explain why countries with similar development stage may be different in the adoption of new technology. Also the "human capital" literature gives us some intuitions that allow for this interpretation of the facts. Schultz (1975) for example finds that human capital is more valuable in periods of change and explains this finding with the argument that education encourages adaptability, and this is more valuable in periods in which technology changes at a faster rate. Juhn, Murphy and Brooks find a similar result: they show that the unobservable component of skills has been more rewarded during 1963-1989, a period in which many new technologies have been used in the production.

Finally Jovanovic (2004) builds an AK model to describe how technology adoption from firms may generate asymmetric business cycle. In his model any technology has specific skills that are needed to maximize the productivity of the technology itself. The quantity of skills, however, is known only after a firm commits itself to the adoption of a technology. This random element of the model determines how the new technology affects the productivity. This model is consistent with the fact that the same technology may have different productivity in different countries or sectors.

Departing from these theories and from the robust empirical pattern that have been described I want to analyze the relation between ICT adoption and labour-skill. From a theoretic point of view I'm interested in the causal relation that goes from skill to adoption.

It's broadly recognized that ICT is a General Purpose Technology (GPT). These kind of technologies, such as electricity and steam engine, have in common some features. One of the most important is that their enhancing effect on productivity is connected to the numbers of complementary inventions that are created time after time. The simplest way of getting new complementary inventions is through the utilization of these technologies. This points out the importance of the workers in this process. If the workers are able to learn as fast as possible the way a technology works, they could improve it and maximize its potentialities.

My empirical analysis differs from the previous ones in many ways.

First, differently from CC and CH I study this relation at an industry level, since the importance of technological adoption is in its impact on industrial productivity. Macro evidence use the aggregate human capital and ICT adoption, thus these works don't help in understanding the adoption process at the firm level. Moreover differently from the other microeconomics studies, I use more countries and deal with different econometric specifications.

Second, I use a new dataset that contains information both on ICT investment and on labour schooling for 5 countries, 26 sectors and 20 years: this three-dimensional dataset allows me to explore the relation cutting the data in different ways to search for periods, sectors or countries in which the correlation among ICT investment and labour-skill is stronger or more significant.

Third, my strategy is different from the others. My regressions are not growth-kind ones, since I'm not interesting in finding which variable is more likely to explain technology adoption, I would like, instead, to explore a specific relation, and use, in a second moment some control variables to check if omitted variables are driving the results.

3.2 Basic regressions: methodology and results.

The aim of this paragraph is to explore how labour skill growth influences the growth in ICT capital investment by industry. Since ICT is a capital-embedded technology, the scope of my regressions is beyond the simple exploration of the relation between labour-skill and ICT investment, but can also measure how skill-labour (or human capital) influences the adoption of a (new) technology.
The basic regressions to test this hypothesis are

$$ictk_{ijt} = \beta * labskill_{ijt} + \alpha_i + \alpha_j + \alpha_{ij} + \varepsilon_{ijt} \tag{1}$$

$$ictk_{ijt} = \beta * labskill_{ijt} + \gamma * labskill_{ijt-1} + \alpha_i + \alpha_j + \alpha_{ij} + \varepsilon_{ijt} \tag{2}$$

where
$ictk_{ijt}$ is the exponential growth rate of the investment in ICT capital;
$labskill_{ijt}$ is the exponential growth rate in the schooling of workers[14];
"i" is the country-index, "j" is the industry index and "t" the time one;
α_i, α_j, α_{ij} are respectively unobserved country-specific, sector-specific and country-sector specific effects and finally ε_{ijt} is the error term.

Technology adoption is measured as investment in ICT while adaptability of labour skill is measured as labour-schooling. Measuring technology adoption with ICT investment is straightforward since ICT may be considered the last, even if broad general, technology. Measuring labour-adaptability is, instead, a much more difficult task. Adaptability, in this work, is considered as that particular quality of labour force that allows it to use more profitably a new technology adopted by the firm. So adaptability could be determined by some observed and unobserved characteristics. Among the observed characteristics one could consider the *schooling* since people

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[14] Labskill is a weighted average of the growth rates of different types of labour. Different types of labour are measured by different schooling while the assigned weights are the share of each type in labour compensation. This assumes that each type of worker gets paid his marginal product.

with more years of schooling are on average more flexible or are simply more up-dated; the *kind of schooling* may also have a role since we expect vocational schooling to be less adaptable than a general one; another important variable may be the *age* of the workers since people that use a kind of technology or simply a production method for many years are less willing to learn a new technology, while for young people this may be easier[15]. Among the unobserved workers' characteristics the most important is the *ability* of a worker to learn how to use a new technology, also the *effort* a worker use to learn could explain part of the process, but it is not measurable.

In this work the adaptability variable will be proxied by the schooling of labour-force. Even if this measure is not the best or the complete way to account for the "adaptability", it is a first attempt to analyze this relation at an industry level. Future work will aim to measure "adaptability" in a more complete way.

If the intuitions exposed in the last paragraph are correct we should expect a positive and significant value of both the coefficients. In particular g should be significant since the causality relation we would like to capture is the one that goes from the skill-adaptability to the technology-adoption.

The panel data I will use for the estimations is a three-index panel data. In general panel data offers several advantages over cross-sectional estimation.
First, a panel estimation uses much more information than a cross-sectional one, since it is possible to check over time or in different time sub-periods the relation in which the researcher is interested in. In my case, moreover, the three-index panel data allow me to obtain country-specific or sector-specific estimations, thus controlling if the tested hypothesis is stronger in different sub-samples. Second, it is possible to control for unobserved heterogeneity and to obtain consistent estimators. Third, it is possible to check for endogeneity of one or more regressors.

I will treat the possible problems of my basic regressions and the way I deal with it in the following lines.
To estimate consistently these regressions using the standard OLS we need to assume the following conditions:

$$\begin{aligned} &\text{cov}(labskill_{ijt}, e_{ijt}) = 0 \\ &\text{cov}(labskill_{ijt-1}, e_{ijt}) = 0 \end{aligned} \tag{3}$$

and

$$\begin{aligned} &\text{cov}(labskill_{ijt}, a_i) = \text{cov}(labskill_{ijt}, a_j) = \text{cov}(labskill_{ijt}, a_{ij}) = 0 \\ &\text{cov}(labskill_{ijt-1,} a_i) = \text{cov}(labskill_{ijt-1,} a_j) = \text{cov}(labskill_{ijt-1,} a_{ij}) = 0 \end{aligned} \tag{4}$$

Assumption (4) is nor standard and probably is neither correct. It states that the growth rate of the schooling of the labor-force specific to a country and to a sector

[15] There is a part of the literature pointing at the "flexibility of labour market" as an important variable connected with the innovation at industry-level. From this perspective another crucial variable may be *turnover* simply because if a firm can easily fire and employ new labourers it could adjust "exogenously" its labour-force to be adaptable to the new technology.

is independent from any effect that may concern the country or the sector. Actually it's possible to think to many potential violations of this strong hypothesis: a country could have a greater supply of skill labor than another and this could be in part the cause of the strong skill-labor observed in the industry; there could be incentives to skill-labor adoption deriving from government policies at a country-level; moreover there could be strategies at industry-level responsible for the greater presence of skilled labor. To test if assumption (4) is correct I run these regressions both using fixed effect (that using a transformation of the regression to eliminate these unobserved effects) and random effect and check the hypothesis with a Hausman test.

Once controlled for unobserved heterogeneity another important problem that may arise is the endogeneity one: it could be, for example, that changes in ICT capital drives a contemporaneous changes in labour skill. This hypothesis is plausible since an inverse process may be in act: it may happen that a sector with high investment in ICT capital increases the number of skilled workers since these are more able to use this kind of capital[16] [17]. To control for these endogeneity problems, I run an IV regression in which labskill is instrumented with its past values. The underlying assumptions in using this procedure are that past values of labskill are not correlated with the present error term ("weak exogeneity" of the explanatory variable), being, instead, highly correlated with the present labskill value. The second assumption seems reliable since a sector with high number of skill-workers is more probable to have high number of them after few years.

The last step is to control for possible omitted variables. The first variable I will control for is the ICT capital in previous year. This could be an important determinant for the investment in ICT, since it could be part of the same investment decision. With this variable the regressions become dynamic regressions and other econometric techniques should be used to get consistency. Consider the new model and the standard transformation in first difference to get rid of the unobservable terms:

$$ictk_{ijt} = l * ictk_{ijt-1} + g * labskill_{ijt-1} + a_i + a_j + a_{ij} + e_{ijt}$$

$$ictk_{ijt} - ictk_{ijt-1} = l * (ictk_{ijt-1} - ictk_{ijt-2}) + g * (labskill_{ijt-1} - labskill_{ijt-2}) + (e_{ijt} - e_{ijt-1})$$

In the last line, by construction, we have correlation between the first regressor and the error term, thus the usual techniques don't find a consistent estimator.
To solve this problem I use the standard GMM Arellano-Bond. This methodology let me have consistent estimator eliminating not only the correlation problem described before, but also the plausible endogeneity of the regressors.

[16] This hypothesis is the "complementarity" one.
[17] It may also happen that the skill of workers of the previous period (labskill(t-1)) is driven by ICT capital today: this may happen if the investment in ICT capital and in skill-labor are part of the same strategy, and the second precedes the first just to avoid labour market rigidities. I will also report regressions in which this hypothesis is taken into account.

Under the assumption that the error term is not serially correlated and that the explanatory variable *labskill* is weakly exogenous (being uncorrelated with the future realization of error term), the GMM dynamic panel estimator is based on this conditions:

$$E\left[ictk_{i,t-s}\left(e_{i,t}-e_{i,t-1}\right)\right]=0$$
$$E\left[labskill_{i,t-s}\left(e_{i,t}-e_{i,t-1}\right)\right]=0$$

where s>2 and t=3,…,T.

The Sargan test and the second autocorrelation test are reported in the tables. The first is a test of over-identification restriction where the null hypothesis is that the instruments are not correlated with the error term, thus to have good instruments we need not to reject the null and this needs the p-value of the test being greater than the usual 0.05; the second test is run under the null that the errors in the first-difference regression exhibit no second-order serial correlation, and also in this case we need not to reject the null, so a good regression will show a p-value higher than 0.05.

The results are reported in table 9 at the end of the paper: here all the basic specifications are used in different regressions. Columns 1 to 4 report the results of fixed and random-effect panel regressions and the result of the Hausman test. The Hausman test suggests that there is no correlation among the regressor and the unobserved effects, thus allowing for a consistent use of the random effect specification. The correlation among ICT capital growth and labour skill growth is positive and significant, even if it becomes not significant once the labour skill growth of the previous year is included in the regression. The fifth column reports the result of the instrumental variable regression where *labskill* is instrumented with lag values (second and third year lag values are considered). Also in this regression we find a positive and significant correlation among the variable and this correlation is smaller than the previous ones. Dynamic regressions improve consistently the previous ones, since the lagged value of ICT capital is high and strongly significant. These regressions satisfy both the Sargan and the second-order autocorrelation tests. Also in these regressions the lagged value of skill labour maintains its explanatory power. Finally the log of value added in the previous year is not significant.

If we divide the sample along time-dimension and cross-dimension we obtain the results shown in table 10 and 11. In these regressions we actually use few observations and this may be a problem for some results, but still we have an indication of the importance of labour skill for the adoption of ICT capital. In particular the coefficient is positive and significant in the second decay and in U.S., even if, once introduced the lagged dependent variable, the Arellano-Bond specification doesn't pass the Sargan and the second autocorrelation test. Still in the IV- FE specifications the coefficient is positive, being of 0.34 in the second decay and 0.44 in U.S. sub-sample. Finally table 11 reports the regressions run in sub-sectors. The small number of observations prevent me from using Arellano-Bond, so these specifications are not dynamic. The correlation under analysis is much stronger in the

ICT sectors than in non-ICT ones, being of 0.46 in the first sub-sample and 0.27 in the second one. Moreover also the contemporaneous correlation is significantly positive in sectors where the ICT capital is more used. An interesting, even if statistically weak, result is the correlation among labour skill and ICT capital in the non-ICT manufacture sectors. Here the contemporaneous correlation turns out to be negative, even if the T-statistic is less than 2. This partial result would deserve a deeper analysis since it could be interpreted as a substitutive-effect among technology and skill in this sector.

3.3 Robustness check.

The robustness analysis consists of two steps: firstly I control for the business cycle effect and secondly I consider a set of control variables. In order to find results less sensitive to business cycles fluctuations, the basic regressions are run again considering the five-years averages of both the dependent and the independent variables. Table 12 reports the results of FE regressions that confirm the previous findings with an increased value of β and γ [18].

The set of control variable I could use to deal with the robustness check can contain time-specific, country-specific, sector-specific variables or variables that change in two dimensions. Here I will consider two different variables that may be important in the regressions. The first variable is labour market rigidity that is measured by the share of labour force whose wages are set by centralized collective bargaining. This index has been constructed by researchers at the Fraser Institute (Jim Gwartney, Robert Lawson, Dexter Samida, 2001), mainly using data from the Global Competitive Report.

Labour market rigidities are supposed to have a role in this history, since, they have both an effect on the labour force and, perhaps, on the technology adoption.

Finally a last regression is run adding to the previous variable the log of the value added at constant price of the beginning of the period, to check if the starting point has been important to explain the results.

All these regressions are run considering a IV specification and using random effect instead of fixed effect.

The results are reported in table 13 and show that the labour skill is significant and high in every specification ranging from 0.24 to 0.32. Labour market rigidities, as expected, are negatively correlated with the ICT capital. Finally the log of the value added at the initial period doesn't seem to explain the dependent variable, and neither to have effect on the other regressors used.

[18] In these regressions I can control only for unobserved heterogeneity since the dataset has too few years to run more precise estimations.

4. Conclusions.

This paper first examines the output growth in different European countries and compares it with U.S. one. An industry-analysis puts in evidence the role of ICT capital in the different performance found. In the second part an econometric analysis is done to find the relation between the skills of the workers, measured with their schooling, and the ICT capital. After controlling for unobserved heterogeneity, endogeneity and potential problems associated with the lagged dependent variable, the relation found is positive and significant. A partial robustness check also supports the finding. The paper may be improved in different direction: first a theory that explains how workers' skill may drive the ICT adoption process may be relevant to give a theoretical support to the findings; second, we need to measure the skills in different and more precise way, since the schooling may not be the only relevant thing to account for this; third, we need to improve the robustness check using different variables that vary according to the different dimension of the basic dataset: in particular a variable that accounts for trade needs to be consider.

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TABLE A.1 : ILPD coverage

Period covered:1980-2000

	Countries ict_sector	index iict_sector	Sector	ISIC rev 3	
1	Austria	1	Agriculture	01	7
2	Belgium	2	Forestry	02	7
3	Denmark	3	Fishing	05	7
4	Finland	4	Mining and quarrying	10-14	7
5	EU15	5	Food, drink & tobacco	15-16	5
6	France	6	Textiles	17	5
7	Germany	7	Clothing	18	3
8	Greece	8	Leather and footwear	19	5
9	Ireland	9	Wood & products of wood and cork	20	5
10	Italy	10	Pulp, paper & paper products	21	5
11	Netherlands	11	Printing & publishing	22	3
12	Portugal	12	Mineral oil refining, coke & nuclear fuel	23	5
13	Spain	13	Chemicals	24	5
14	Sweden	14	Rubber & plastics	25	5
15	United Kingdom	15	Non-metallic mineral products	26	5
16	U.S.	16	Basic metals	27	5
		17	Fabricated metal products	28	5
		18	Mechanical engineering	29	3
		19	Office machinery	30	1
		20	Insulated wire	313	1
		21	Other electrical machinery and apparatus	31-313	3
		22	Electronic valves and tubes	321	1
		23	Telecommunication equipment	322	1
		24	Radio and television receivers	323	1
		25	Scientific instruments	331	1
		26	Other instruments	33-331	3
		27	Motor vehicles	34	5
		28	Building and repairing of ships and boats	351	3
		29	Aircraft and spacecraft	353	3
		30	Railroad equipment and transport equipment nec	352+359	3

31	Furniture, miscellaneous manufacturing; recycling	36-37	3	1
32	Electricity, gas and water supply	40-41	7	0
33	Construction	45	7	0
34	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel	50	6	0
35	Wholesale trade and commission trade, except of motor vehicles and motorcycles	51	4	1
36	Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods	52	4	1
37	Hotels & catering	55	6	0
38	Inland transport	60	6	0
39	Water transport	61	6	0
40	Air transport	62	6	0
41	Supporting and auxiliary transport activities; activities of travel agencies	63	6	0
42	Communications	64	2	1
43	Financial intermediation, except insurance and pension funding	65	4	1
44	Insurance and pension funding, except compulsory social security	66	4	1
45	Activities auxiliary to financial intermediation	67	4	1
46	Real estate activities	70	6	0
47	Renting of machinery and equipment	71	4	1
48	Computer and related activities	72	2	1
49	Research and development	73	4	1
50	Legal, technical and advertising	741-3	4	1
51	Other business activities, nec	749	6	0
52	Public administration and defence; compulsory social security	75	6	0
53	Education	80	6	0
54	Health and social work	85	6	0
55	Other community, social and personal services	90-93	6	0
56	Private households with employed persons	95	6	0
57	Extra-territorial organizations and bodies	99	7	0

Note: ict_sector: 1=ICT producing manufacture; 2=ICT producer service; 3=ICT user manufacture; 4=ICT user service; 5=non-ICT manufacturer; 6=non-ICT service; 7=other non-ICT;

iict_sector: 1 if the sector is ICT (ict_sector=1 or 2 or 3 or 4); 0 otherwise.

TABLE A.2: IGAD coverage

Period covered:1980-2000

	Countries	index	Sector	ISIC rev 3	ict_sector	iict_sector
1	France	11	Agriculture, Forestry and Fishing	01-05	7	0
2	Germany	12	Mining and Quarrying	10-14	7	0
3	UK	13	Food, Drink & Tobacco	15-16	5	0
4	Netherlands	14	Textiles, Leather, Footwear & Clothing	17-19	5	0
5	US	15	Wood & Products of Wood and Cork	20	5	0
		16	Pulp, Paper & Paper Products; Printing & Publishing	21-22	6	0
		17	Mineral Oil Refining, Coke & Nuclear Fuel	23	5	0
		18	Chemicals	24	5	0
		19	Rubber & Plastics	25	5	0
		20	Non-Metallic Mineral Products	26	5	0
		21	Basic Metals & Fabricated Metal Products	27-28	5	0
		22	Mechanical Engineering	29	3	1
		23	Electrical and Electronic Equipment; Instruments	30-33	1	1
		24	Transport Equipment	34-35	3	1
		25	Furniture, Miscellaneous Manufacturing; recycling	36-37	3	1
		26	Electricity, Gas and Water Supply	40-41	7	0
		27	Construction	45	7	0
		28	Repairs and wholesale trade	50-51	6	0
		29	Retail trade	52	4	1
		30	Hotels & Catering	55	6	0
		31	Transport	60-63	6	0
		32	Communications	64	2	1
		33	Financial Intermediation	65-67	4	1
		34	Real Estate Activities and Business Services	70-74	4	1
		35	Other Services	90-95	6	0
		36	Non-Market Services	75-85	6	0

Note: ict_sector: 1=ICT producing manufacture; 2=ICT producer service; 3=ICT user manufacture; 4=ICT user service; 5=non-ICT manufacturer; 6=non-ICT service; 7=other non-ICT;

iict_sector: 1 if the sector is ICT (ict_sector=1 or 2 or 3 or 4); 0 otherwise.

TABLE A.3

Dataset used in this work

Variable	Description
vak	value added (in millions of Euro) at constant prices of 1995
out**	exponential growth rate of vak
pop	total population per year in each country
vakpop**	value added (in millions of Euro) at constant 1995 price over population
ex_rate*	exchange rate for Denmark, Finland, UK, US
ictk	exponential growth in ICT capital (computers, communication equipment and software)
nictk	exponential growth in Non-ICT capital (non-IT equipment, non-residential structures and transport equipment)
labskill**	exponential growth in skill-adjusted labour
ictsh	share of ICT capital in total capital compensation

Source: GGDC; * Ufficio Italiano dei Cambi; **my calculus on GGDC variables

TABLE 1: Output growth

country	1980-2000	1980-1990	1990-2000
Austria	2.65	2.62	2.69
Belgium	2.10	2.28	1.91
Denmark	1.88	1.66	2.12
Finland	2.78	3.40	2.11
France	2.07	2.43	1.67
Germany*	2.29	2.40	2.16
Greece	2.00	1.70	2.34
Ireland	6.15	4.00	8.33
Italy	1.99	2.35	1.60
Netherlands	2.62	2.52	2.73
Portugal	2.79	3.18	2.38
Spain	2.60	2.87	2.31
Sweden	2.28	2.53	2.01
United Kingdom	2.38	2.18	2.61
eu15	2.26	2.37	2.14
U.S.	3.03	2.80	3.29

note: data from ILPD dataset, data on Luxembourg are not included, but they are considered in the eu15

* data on Unified Germany

TABLE 2 :Output Growth (U.S.=100)

country	1980-2000	1980-1990	1990-2000
Austria	87	93	82
Belgium	69	81	58
Denmark	62	59	64
Finland	92	121	64
France	68	87	51
Germany*	75	86	66
Greece	66	61	71
Ireland	200	142	254
Italy	66	84	49
Netherlands	86	90	83
Portugal	92	113	73
Spain	86	102	70
Sweden	75	90	61
United Kingdom	79	78	79
eu15	75	85	65
U.S.	100	100	100

note: data from ILPD dataset, data on Luxembourg are not included, but they are considered in the eu15

* data on Unified Germany

TABLE 3: output growth by ICT and non-ICT sectors

country	non-ICT sectors				ICT sectors			
	80-85	85-90	90-95	95-00	80-85	85-90	90-95	95-00
Austria	1.74	2.28	3.41	3.17	5.57	6.23	3.50	9.18
Belgium	1.72	2.75	0.61	1.91	3.86	6.40	3.21	4.00
Denmark	1.71	-0.04	0.75	3.21	6.21	5.36	2.83	5.84
Finland	2.64	2.87	0.29	3.80	9.83	5.82	1.62	5.58
France	-0.42	1.32	0.40	2.32	6.06	4.12	2.49	5.13
Germany*	0.62	2.54	0.97	1.31	5.08	5.85	0.84	7.16
Greece	1.45	1.47	1.60	2.74	4.65	3.78	3.70	10.15
Ireland	2.16	2.51	3.68	4.81	8.93	9.41	7.95	12.60
Italy	1.77	2.33	1.46	0.39	5.62	5.19	3.44	4.03
Netherlands	1.88	2.69	1.64	2.22	3.94	7.38	3.89	6.85
Portugal	0.94	5.41	0.30	3.69	4.97	4.73	8.27	10.52
Spain	1.23	3.34	1.57	2.88	3.51	7.91	2.83	6.72
Sweden	1.86	2.82	0.13	2.23	5.83	3.12	2.60	7.30
United Kingdom	0.24	2.71	1.33	1.00	4.42	6.44	3.38	5.71
eu15	0.65	2.26	1.37	1.80	4.95	5.65	2.40	6.48
U.S.	2.67	2.24	1.46	2.20	5.97	5.06	3.04	7.49

note: data from ILPD dataset, data on Luxembourg are not included, but they are considered in the eu15

* data on Unified Germany

TABLE 4: Average and standard deviation in output growth rate

		average	s.d.	average	s.d.
country		EU-15		US	
years					
	80-85	2,80	5,83	4,32	7,99
	85-90	3,96	4,03	3,65	4,61
	90-95	1,88	5,76	2,25	7,24
	95-00	4,14	10,36	4,85	10,2
ICT-sector					
	80-85	4,9	7,9	5,97	10,9
	85-90	5,6	4,8	5,06	5,8
	90-95	2,3	8,5	3,04	10
	95-00	6,4	15,2	7,49	14,6
non-ICT sector					
	80-85	0.65	2,26	2,6	4,2
	85-90	2,25	2,47	2,23	2,9
	90-95	1,36	1,84	1,46	3,9
	95-00	1,80	2,11	2,2	3,7

note: my calculations on ILPD dataset

Table 5 : Analysis of variance of industry growth (1980-2000)

Source	**Partial SS**	**df**	**F**	
Model	493.448	71	3.359	**
i_country	2.143	15	69	**
i_sector	490.305	56	4.441	**
Residual	43.152	20.904		
Total	535.601			
N	20.976			
R^2	0.92			

note: my calculations on ILPD dataset

TABLE 6: Concentration Ratio

	Concentration ratio (n=5)		Concentration ratio (n=10)	
	1979-1990	1990-2001	1979-1990	1990-2001
Austria	0.3392	0.3469	0.5639	0.5746
Belgium	0.3910	0.3669	0.5998	0.5738
Denmark	0.4236	0.4066	0.6337	0.6090
eu15	0.3549	0.3350	0.5565	0.5525
Finland	0.3711	0.3358	0.5762	0.5426
France	0.3671	0.3638	0.5635	0.5605
Germany	0.3556	0.3491	0.5610	0.5496
Greece	0.4639	0.4390	0.6849	0.6759
Ireland	0.3567	0.4025	0.5661	0.7286
Italy	0.3360	0.3138	0.5458	0.5327
Netherlands	0.3855	0.3618	0.5770	0.5507
Portugal	0.3498	0.3548	0.5888	0.5708
Spain	0.3395	0.3429	0.5879	0.5710
Sweden	0.4261	0.3903	0.6122	0.5759
UK	0.3498	0.3041	0.5362	0.5179
US	0.4075	0.3970	0.6247	0.5918

note: my calculations on ILPD dataset

Table 7: ICT and non-ICT contribution to output growth

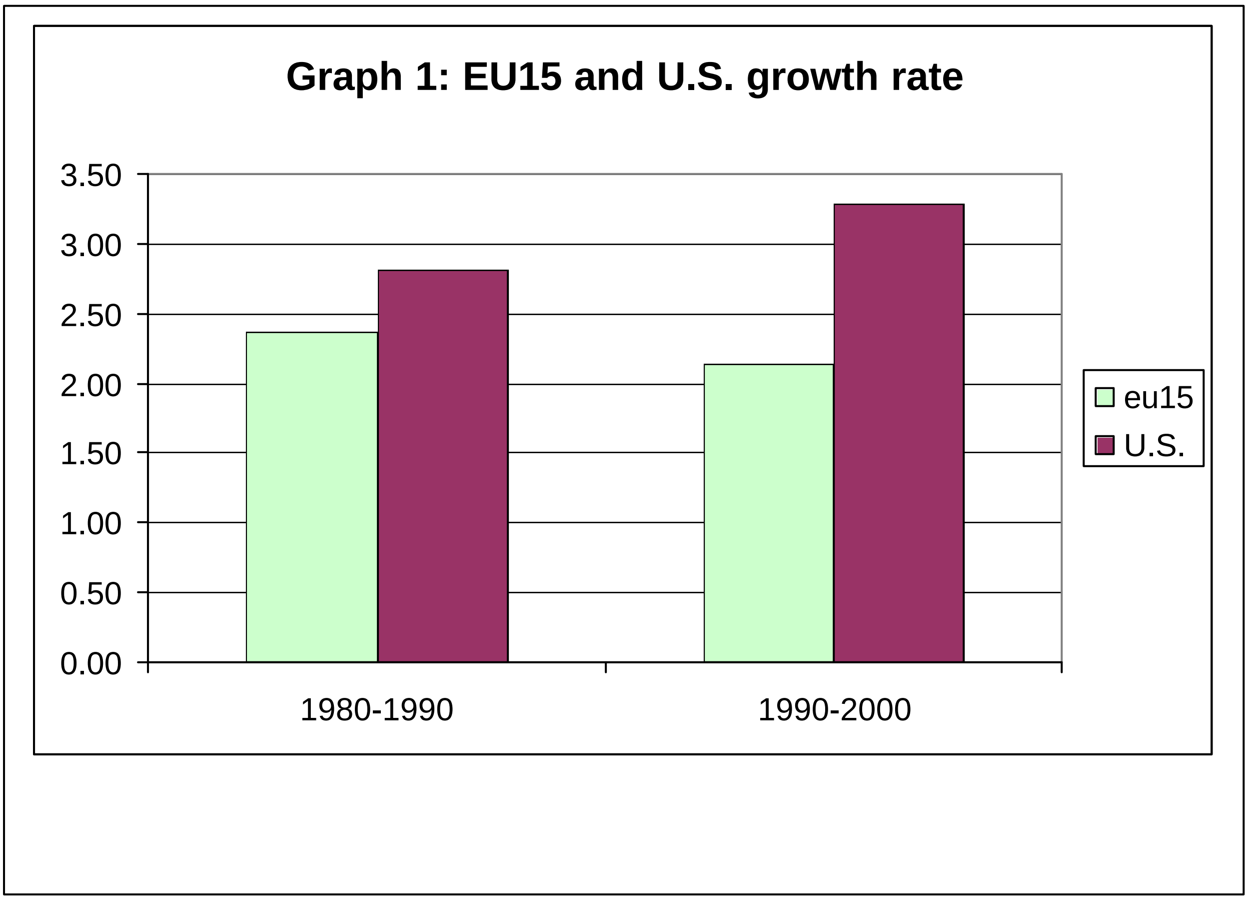
variable	years	US	EU-4
ICT- capital percentage contribution to output growth	80-85	7.7	5.1
	85-90	5.5	6.3
	90-95	7.9	3.8
	95-01	11.1	8.3
non-ICT capital percentage contribution to output growth	80-85	5.8	7.9
	85-90	5.2	15.9
	90-95	9.9	9.6
	95-01	11.8	11.0

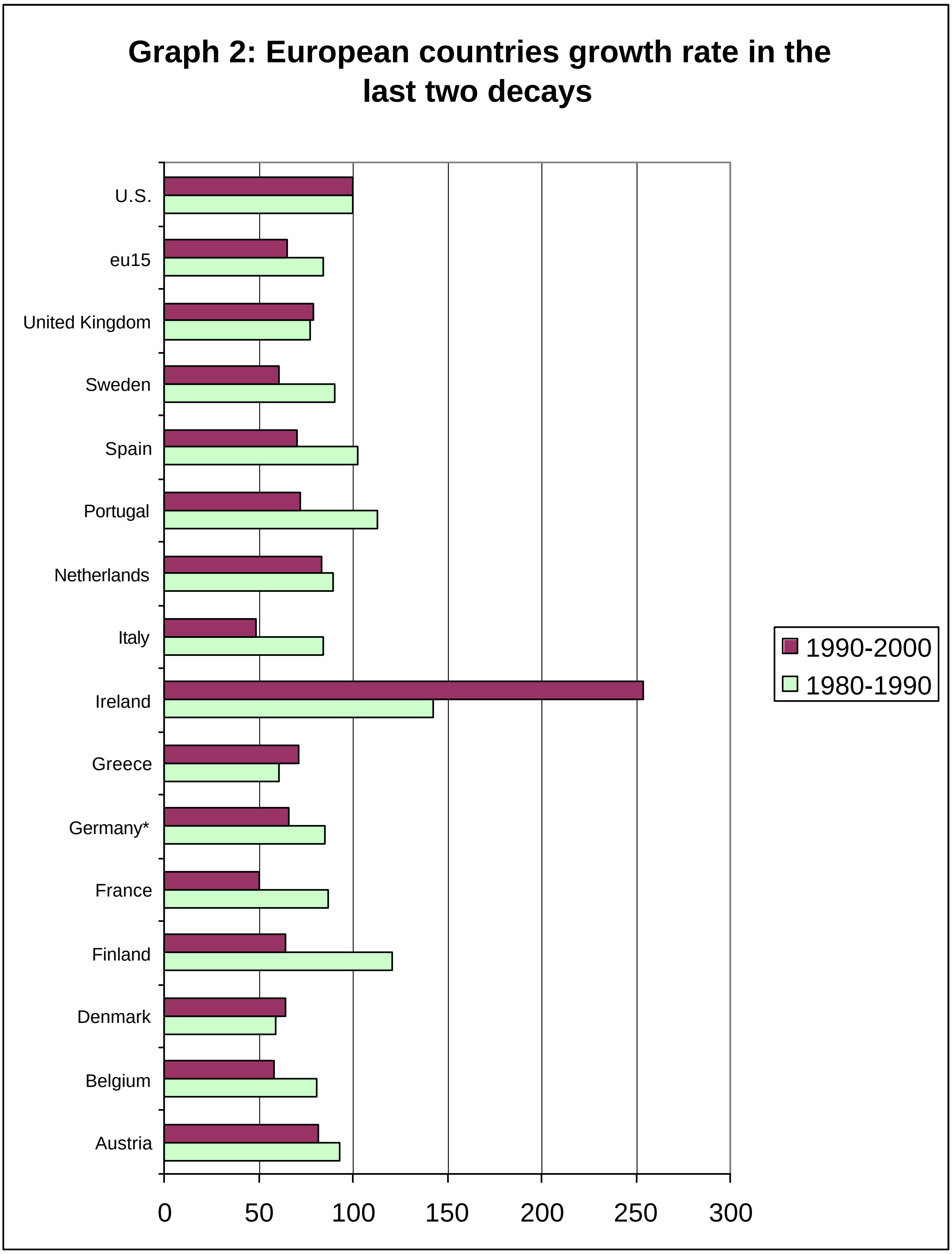
note: my calculations on IGAD dataset

Table 8: ICT and non-ICT contribution to output growth (U.S.=100)

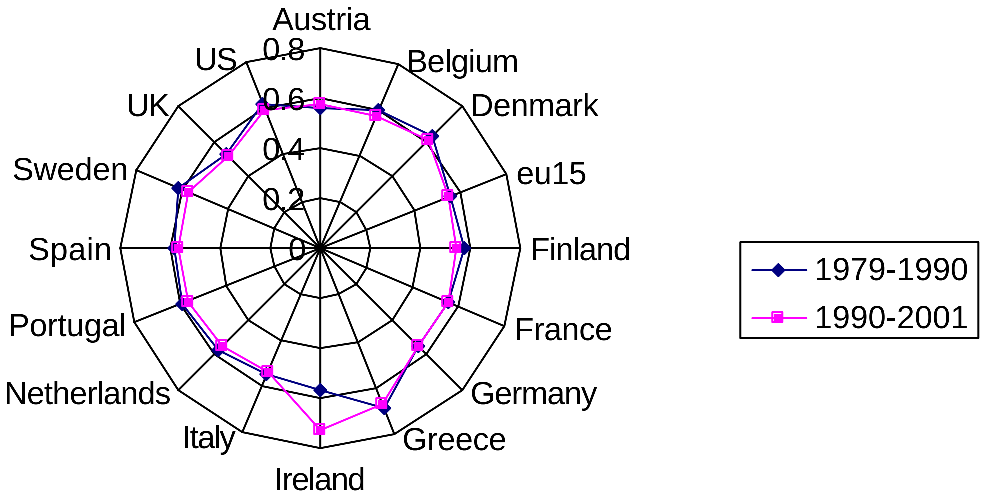
	years	country				
		France	Germany	UK	Netherlands	US
ICT- capital percentage contribution to output growth	80-85	43.7	85.0	86.2	49.0	100.0
	85-90	71.1	175.6	107.3	101.8	100.0
	90-95	10.1	55.7	73.4	54.4	100.0
	95-01	32.2	96.7	85.3	86.8	100.0
non-ICT capital percentage contribution to output growth	80-85	138.1	186.8	145.3	82.2	100.0
	85-90	327.9	286.3	305.8	300.0	100.0
	90-95	52.5	139.4	33.3	160.6	100.0
	95-01	34.3	94.1	124.2	121.2	100.0

note: my calculations on IGAD dataset


Graph 1: EU15 and U.S. growth rate
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
1980-1990
1990-2000
eu15
U.S.


Graph 2: European countries growth rate in the last two decays
U.S.
eu15
United Kingdom
Sweden
Spain
Portugal
Netherlands
Italy
Ireland
Greece
Germany*
France
Finland
Denmark
Belgium
Austria
0
50
100
150
200
250
300
1990-2000
1980-1990

Graph 3: Specialization measured as concentration ratio of the largest 10 industries



Graph 4: Specialization measured as concentration ratio of the largest 5 industries

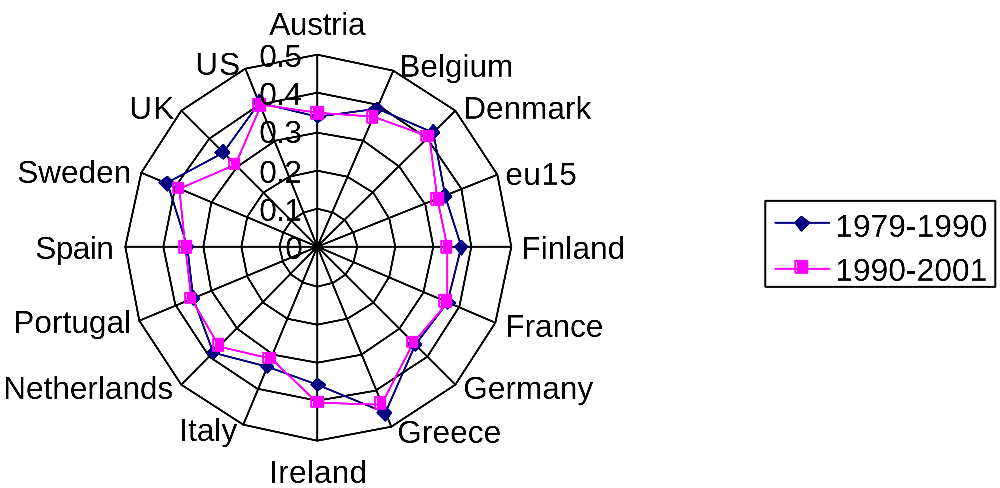


Table 9: basic panel regressions

dependent variable	ICT capital								
	fe	fe	re	re	iv-fe*	fe	re	AB**	AB**
labour skill	.22	0.1	0.25	0.11	0.081	0.14	0.16		
	(3.28)	(1.49)	(3.82)	(1.64)	(0.97)	(2.42)	(3.07)		
labour skill (t-1)		**0.36**		**0.37**	**0.24**	**0.17**	**0.16**	**0.27**	**0.27**
		(5.40)		(5.60)	(2.81)	(3.07)	(3.06)	(2.88)	(2.90)
ict capital (t-1)						0.52	0.6	0.51	0.5
						(31.21)	(37.9)	(15.60)	(15.60)
value added at constant proce (t-1)									-5.63
									(-1.47)
Number of observations	2417	2417	2417	2417	1505	2417	2417	1208	1208
R-squared within	0.0045	0.016	0.0045	0.016	0.007	0.29	0.29		
R-squared between	0.22	0.21	0.2	0.21	0.06	0.93	0.94		
Hausman test (p-value)^	0.1	0.78							
Sargan test[o] (p-value)								0.15	0.17
Second autocorrelation test[a]								0.18	0.15

T-stat in parenthesis
* labour skill is instrumented with labour skill (t-2) and labour skill (t-3)
** Arellano-Bond: ict capital (t-1) is instrumented with ict capital (t-3) and ict capital (t-4)
^ the null hypothesis is that the covariance between the regressor and the unobserved effect is zero
[o] the null hypothesis is that the instruments used are nor correlated with the residuals
[a] the null hypothesis is that the errors in the first-difference regression exhibit no second-order serial correlation.

Table 10: panel regressions in sub-samples

sub-sample	1979-1990		1991-2001		US		EU-4	
	iv-fe*	AB**	iv-fe*	AB**	iv-fe*	AB**	iv-fe*	AB**
labour skill	-0.05		0.31		0.09		0.08	
	(-0.37)		(3.41)		(0.82)		(0.82)	
labour skill (t-1)	0.09	0.26	0.34	0.8	0.44	0.54	0.14	0.15
	(0.68)	(1.39)	(3.51)	(17.5)	(3.76)	(7.65)	(1.30)	(1.22)
ict capital (t-1)		0.43		0.26		0.7		0.49
		(8.33)		(3.91)		(20.85)		(13.07)
Number of observations	732	556	773	652	324	266	1181	942
R-squared within	0.0008		0.04		0.05		0.003	
R-squared between	0.15		0.15		0.35		0.04	
Sargan test[o] (p-value)		0.64		0		0.0009		0.97
Second order autocorrelation test[a]		0.53		0		0		0.36

T-stat in parenthesis
* labour skill is instrumented with labour skill (t-2) and labour skill (t-3)
** Arellano-Bond: ict capital (t-1) is instrumented with ict capital (t-3) and ict capital (t-4)
[o] the null hypothesis is that the instruments used are nor correlated with the residuals
[a] the null hypothesis is that the errors in the first-difference regression exhibit no second-order serial correlation.

Table 11: panel regressions in ICT sub-sectors: IV-FE regressions

dependent variable	ICT capital					
	1	2	3	4	5	6
labour skill	0.65	0.35	-0.18	0.2	0.48	-0.012
	(3.36)	(2.05)	(-1.63)	(0.98)	(3.72)	(-0.11)
labour skill (t-1)	0.5	0.42	0.34	0.15	0.46	0.27
	(2.48)	(2.30)	(3.18)	(0.74)	(3.37)	(2.46)
Number of observations	153	238	469	271	391	1114
R-squared within	0.14	0.05	0.02	0.008	0.09	0.005
R-squared between	1	0.19	0.29	0.68	0.01	0.17

T-stat in parenthesis
* labour skill is instrumented with labour skill (t-2) and labour skill (t-3)
1: ICT-producing sectors
2: ICT-using sectors
3: non-ICT manufacturing sectors
4: non-ICT service
5: ICT sectors
6: non-ICT sectors

five years of dependent and indipendent variables

dependent variable	five years-averge ICTK	
five years-average labskill	0.625	0.017
	(8.12)	(0.14)
lagged five-years average labskill		0.68
		(5.97)
Number of observations	520	520
R-squared within	0.026	0.041
R-squared between	0.2	0.21

T-stat in parenthesis

Table 13 : panel regressions IV-FE^

dependent variable	ICT capital		
	basic regression	1	2
labour skill (t-1)	0.32	0.25	0.24
	(3.99)	(2.91)	(2.91)
labour market rigidity[o]		-2.06	-2.06
		(-4.08)	(-4)
value added at constant prices, 1979 (logs)			0.46
			(.08)
Number of observations	1505	1505	1505
R-squared within	0.007	0.01	0.07
R-squared between	0.07	0.02	0.26

^ labour skill (t-1) is instrumented with labour skill (t-2) and labour skill (t-3)
[o] share of labour force whose wages are set by centralized collective bargaining (Global Competitiveness Report)
[a] share of trade in GDP (%), WDI 2003