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The Long-Run Impact of ICT

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Abstract

Using some new techniques of panel cointegration analysis, this paper describes the long-run impact of digital capital on the aggregate performance of the US and EU-15 member countries.
ICT is found to significantly impact on output levels without substantial cross-country variation when one adopts the dynamic extension of panel OLS (PDOLS). In this case, however, the long-run elasticity of factor inputs does not differ from the one estimated in the short-run.
The time-series version of seemingly unrelated regression (DSUR) provides more plausible findings, showing a significant cross-countries heterogeneity. The effect of ICT on growth appears relevant - and higher than emerging from short-differences - for most economies but not for the EU largest countries.

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The Long-Run Impact of ICT*

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1 Introduction

In a recent paper Jorgenson and Vu (2005) have shown that capital input accumulation has been the primary source of the world's output growth between the end of the twentieth century and the beginning of the current one. Since 1995 the acceleration in the growth rate of output and labour productivity can be traced for a large fraction to the advances in Information and Communication Technology (ICT).
The impressive improvement in the price-performance ratio of microelectronic components has fuelled the rise in technical efficiency of ICT producing industries and the rapid adoption of computers, software and communication equipment by firms and households, as a consequence of price decline.
The growth impact of ICT has been particularly sizeable in the US as well as in some other countries of OECD area (Finland, Korea and Australia). Also, it has been substantial even in such developing economies as China and India. Instead, aside from few episodes, Europe seems to have lost momentum; for this reason, recently, the EU institutions have renewed with great emphasis their medium-term initiative towards the construction of a common information-based economic space (*i2010*; see EC (2005)).

Thus far the relevance of ICT for national performance has been detected mainly through growth accounts, decomposing output growth into the income share-weighted rise of various factor inputs. On the other hand, econometric literature has focussed principally on short-run effects of high-tech equipment, sometimes comparing countries on the basis of industry data. After a decade from the advent of the often-called information age and, not secondarily, a quarter of century from the first wave of investments in office machinery, it seems useful to investigate the growth effects of ICT from a

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long-run perspective, through a panel cointegration analysis. Given the nature of general purpose technology, the productive impact of digital capital is likely to fully materialize only in a long-term horizon, especially at the most aggregate level of analysis. Accordingly, by applying the usual methods of estimation on short-differences, there is the risk that a part of its contribution remains neglected.

This paper aims at gauging the impact of high-tech equipment on GDP levels for the US and the EU-15 countries over the period 1980-2004. It employs two newly available procedures which represent the dynamic extension of panel ordinary least squares and seemingly unrelated regression (PDOLS and DSUR). However, the latter will be shown to be more suited for our international comparison on ICT, as able to account more powerfully for cross-country dependence, yielding non-trivial differences in results.

The remainder is organized as follows. Section 2 surveys the empirical literature on the role of ICT capital in aggregate performance. Section 3 presents the analytical framework at the basis of the work; it describes the properties of PDOLS and DSUR but, at the same time, discusses the disadvantages related to their application to our data. A short statistical analysis is reported in section 4 where output growth is decomposed into factor inputs' contributions.

Section 5 lays out the econometric findings. Initially, it analyses the trend stationary properties of series (par. 5.1); then, it quantifies the long-run impact of ICT by estimating an aggregation production function (par. 5.2).

Results do vary sizeably in relation to the technique utilised. ICT is found to indistinctly affect output within PDOLS regression, after controlling for country-specific heterogeneity. In this case, however, long-run elasticity does not differ from the one estimated in the short-run.

By employing DSUR there is confirmation that ICT matters for growth, but not uniformly within Europe. In line with the sound of growth accounts studies and previous econometric literature, it is documented that the largest EU economies (France, Germany Italy and UK) have not benefited significantly from digital capital.

Moreover, there emerges a wide discrepancy between the long-run results and the ones obtained on short differences by static SUR, stressing the importance of adopting panel cointegration techniques to study the growth effects of ICT. Finally, section 6 concludes.

2 ICT and economic growth

The impact of ICT investment on economic performance has been scrutinized from more than one perspective. There is a large international evidence that computer use exerts a positive effect on firms' productivity. Dedrick *et al.* (2003) and Pilat (2004) survey this large body of studies concluding that, to be profitable, IT equipment requires complementary investments in communication equipment and software, together with some other collaborating inputs such as human capital and organizational factors. ICT capital acts as enabler of further innovations in many business activities, with a clear advantage for companies undertaking R&D projects.

Yet, as pointed out by Pilat (2004), the benefits gained at the firm-level may be not appearing in aggregate statistics as the poor performance of less productive businesses may obscure the growth of the most innovative ones. This aspect is more accentuate in presence of strong market rigidities that prevent successful firms from emerging, reducing the incentives to high-tech investment. According to Bassanini and Scarpetta (2002), such institutional factors make Europe a scarcely dynamic economic space, in part explaining why ICT has contributed to economic growth to a smaller extent with respect to the US[1].

The prominence of information technology for the US aggregate economy was initially stressed by Jorgenson and Stiroh (2000) and Oliner and Sichel (2000). At the beginning, however, it was believed that US productivity gains were confined within IT production sectors (Gordon (2000))[2]. Now, instead, there is a large consensus on the pervasiveness of growth effects of ICT. The formidable fall in semiconductors' price has fuelled both TFP growth of ICT-producing sectors and high-tech capital deepening in the rest of the economy, accounting for the full one-percent acceleration in labour productivity occurred after 1995 (Jorgenson *et al.* (2003))[3].

Either a lower ICT specialization or a smaller usage of innovative equipment are considered the main determinants of the slower growth experienced by Europe (Timmer *et al.* (2003)).

Nevertheless, a low degree of high-tech specialisation is not necessarily bad for growth as stressed by the performance of Australia, Canada and Mexico

[1] See also Daveri (2004).

[2] Investigating the localization of productivity acceleration within the US, Daveri and Mascotto (2002) find that states where labour productivity grew at a faster rate present an IT specialisation above the national mean. For the EU-15 member states, the evidence provided by O'Mahony and van Ark (2003) goes towards the same direction.

[3] Cette *et al.* (2005) postulate that if the decline in relative prices did persist, the potential output growth in the US could be enhanced by over two percent points per year.

(Pilat and Wolfl (2004)). In terms of welfare, then, relevant benefits from technical advances in ICT production also accrue to using countries, as a consequence of price decline (Bayoumi and Haacker (2002)).

Searching for the industry sources of US resurgence, Stiroh (2002b) and Nordhaus (2005) observe that it originated entirely from those sectors that produce and intensively use digital capital. Relative to the US, O'Mahony and van Ark (2003) point out that the EU is severely lagging in some ICT using service sectors like finance, wholesale and detail trade, where new asset types facilitated radical business re-organisations in the last decade (McGuckin *et al.* (2004)).

The econometric evidence on the nexus between high-tech capital deepening and industry labour productivity growth is mixed. According to Stiroh (2002a), US manufacturing sectors have not taken a particular advantage from high-tech assets, apart from ICT producing firms. On the other hand, O'Mahony and Vecchi (2005) find a positive effect for all US market industries, but not for the UK. For the latter country, however, a favorable indication comes from Oulton and Srinivasan (2005).

At the highest level of aggregation, the scarcity of econometric studies is attributable to the limited availability of comparable statistics. Moreover, evidence does vary depending on the nature of the data employed, timeframe, country coverage and estimation technique.

Relying upon a private source (until 1993), Dewan and Kraemer (2000) find a significant contribution to output from ICT only for developed countries. Park and Shin (2004) 'update' that kind of study to a more recent period (1992-2000), employing the World Development Indicators by the World Bank. A positive effect can be identified either for richer or less industrialised nations, proportionally to the relative level of IT capital. In addition, there emerges an indirect effect of ICT on productivity growth.

A less orthodox attempt of assessing the existence of ICT knowledge spillovers is carried out by Dutta and Otsuka (2004), using patents application data for a small group of nations. Given that the flow of new knowledge (applications) is strongly and positively correlated to the stock of patents applied by high-tech industries, ICT patents are used as a proxy of knowledge within an output production function framework. Nevertheless, in contrast to the prescriptions of new growth theories, GDP is not affected by knowledge input, perhaps due to the short time span considered in this study[4].

Similar in the spirit is the work by Becchetti and Adriani (2005) who regard

[4] Likewise, Alginger and Falk (2005) observe that the technological specialisation, measured by the share of high-tech exports and EPO ICT patent application, does not add much information to R&D intensity as a source of growth for OECD countries.

ICT as enabler of knowledge diffusion in a growth regression *à la* Mankiw-Romer-Weil. In this respect, the uptake of new technologies emerges as a crucial additional factor to explaining income differentials across countries.

Fuss and Waverman (2005) evaluate instead whether ICT engender networking effects, building a system of simultaneous equations where TFP is supposed to depend on the penetration rate (and digitalisation) of telecom infrastructures. The underlying idea is that advanced communication equipment puts in connection the stock of computers, fuelling the social value of ICT capital over private return. Disentangling TFP into various sources (scale economies, time trend and spillovers), Fuss and Waverman (2005) document that ICT externality was the main contributor of productivity in the late 1990s for most OECD countries. Following this line of discussion, it is reasonable to believe that productivity spillover might be even higher than estimated in this paper as it does not consider the benefits stemming from the connection with IT capital of trading partner countries.
To a broad extent, this is the goal pursued by Lee and Guo (2004). They explicit foreign high-tech investment as a determinant of national TFP growth, reporting a robust evidence in favour of spillovers going from richer to less developed countries. According to Gholami *et al.* (2005), the relation between ICT and international trade is double-sense. On one hand, digital capital boosts foreign direct investment from more industrialized economies since it facilitates the access to information on new markets and co-ordination with headquarters. On the other hand, the inflow of FDI also favours the dissemination of new technologies in less developed countries.

3 Analytic framework

After 1995 there has been a valuable research effort to assess the fraction of output growth traceable to the deployment of digital capital. Aside from few exceptions, econometric studies have adopted techniques more suited for the short-run, being based on first-differenced variables. This has advantage of working with stationary series and using traditional inference to test the robustness of results. As known, however, it happens at the cost of losing some useful information when there exists a long-run stationary relation between dependent variable and regressors (cointegration).

Real investment in high-tech equipment has accelerated enormously in the last decade, growing annually at double-digit rates. Although, it should not be forgotten that the installed capacity was no-negligible already in the first half of the 1990s. At least partially, current earnings may originate from the past (Gordon (2004)). Given the nature of general purpose technolo-

gies, ICT needs a long time to yield returns since its introduction is usually accompanied by business re-organizations, complementary investment and, more generally, adjustment costs. This is the main explanation put forward by Brynjolfsson and Hitt (2003) and Oulton and Srinivasan (2005) to justify why high-tech capital exhibits a larger coefficient when estimated on long differences in comparison to annual growth rates.
Moreover, it is likely that both direct effects and productivity spillovers of ICT become more apparent in the long-run at an economy-wide level, in light of those compensation effects working between firms and/or industries. In this connection, looking at a long-term horizon, O'Mahony and Vecchi (2005) find a significantly positive impact of ICT on output growth, which is also compatible with the presence of spillovers, being well above the income share.

This paper seeks to measure the long-run elasticity of digital capital across a moderate panel of countries, by estimating an output production function through two new techniques of cointegration analysis. The former is the dynamic version of panel OLS estimator (PDOLS; Mark and Sul (2003)). Recently, it has been used by Bottazzi and Peri (2006) to study the impact on national stock of knowledge (patents) of R&D expenditure and the patenting ability of trading partner countries. The latter estimator has been proposed by Mark *et al.* (2005) and Moon and Perron (2005), consisting in the time series extension of seemingly unrelated regression (DSUR).

Assuming a log-linear Cobb-Douglas production function, GDP (Y) can be expressed as dependent on hours worked (H), traditional capital and ICT assets (K_N and K_{ICT})[5]:

$$y_{it} = \underline{\alpha}_i' \underline{d}_{it} + \underline{\beta}_i' \underline{x}_{i,t} + u_{it}$$

$$\ln Y_{it} = \alpha_{0i} + \alpha_{1i} t + \beta_{1i} \ln H_{it} + \beta_{2i} \ln K_{N,it} + \beta_{3i} \ln K_{ICT,it} + u_{it}; \qquad (1)$$

i=1,...,N denotes the cross-sectional units (N=16), t=1,...,T time dimension (T=25) whilst $\underline{d}_{it}$ is the vector of deterministic components. This includes an individual intercept, a time trend and, also, common time dummies when running PDOLS.
It is evident that equilibrium error u_{it} is affected by the endogeneity with own-equation regressors and cross-dependence with the disturbances of other

[5]The hypothesis that a Cobb-Douglas specification is valid for the entire sample may be debatable. For the US, Antràs (2004) reports evidence against this assumption while, for instance, it seems to hold for the Finnish case only on a very long time horizon (Jalava *et al.* (2005)). However, for a large panel of countries, Kumbhakar and Wang (2005) obtain with a Cobb-Douglas factor inputs' elasticities very close to the ones resulting from a translog specification, once controlled for heterogeneity (fixed effects).

equations. If first-differenced variables are stationary, they can be modelled as correlated random walks ($\Delta x_{it} = e_{it}$) and the long-run covariance matrix of equations' system error (u_{it}, e_{it}) can be represented as follows:

$$\Omega = \begin{pmatrix} \Omega_{u'u} & \Omega_{u'e} \\ \Omega_{e'u} & \Omega_{e'e} \end{pmatrix}.$$

The covariance matrix of u_{it} shows the degree of correlation among equations ($\Omega_{u'u}$); non-null values of off-diagonal parameters determine the inefficiency of least squares estimator, imposing the adoption of seemingly unrelated regression. $\Omega_{e'e}$ regulates instead the cross-equation dependence of regressors, explaining why some efficiency gain can be obtained by a system estimator relative to the ones based on single equations. Finally, $\Omega_{e'u}$ models the endogeneity between error term and regressors that, within each equation, is source of bias for static estimation techniques.

In order to purge the equilibrium errors u_{it} from the effect of reverse causality, Mark *et al.* (2005) suggest of including into equation (1) p lags and leads of first-differenced regressors of own-equation (Δx_{it}). The insertion of the ones of other panel units (Δx_{jt}) is designed to remove cross-section dependence.

Operatively, PDOLS and DSUR can be obtained through a feasible two stages procedure. As a first step, any individual dependent variable (y_{it}) and each element of regressors' matrix ($\hat{\mathbf{x}}_{it}$) are regressed on the vector of p lags and leads (v_{it}). Then, after stacking residuals (denoted by a hat) of auxiliary regressions into a system, the cointegration vector can be computed by means either of the estimator of least squares or seemingly unrelated regression[6] :

$$\underline{\hat{\beta}}_{pdols} = [\sum_{t=p+1}^{T-p} \hat{\mathbf{x}}_t \hat{\mathbf{x}}_t^{'}]^{-1} [\sum_{t=p+1}^{T-p} \hat{\mathbf{x}}_t \underline{\hat{y}}_t]$$

$$\underline{\hat{\beta}}_{dsur} = [\sum_{t=p+1}^{T-p} \hat{\mathbf{x}}_t \Omega_{u'u}^{-1} \hat{\mathbf{x}}_t^{'}]^{-1} [\sum_{t=p+1}^{T-p} \hat{\mathbf{x}}_t \Omega_{u'u}^{-1} \underline{\hat{y}}_t].$$

$\underline{\hat{\beta}}_{dsur}$ is thus shaped as computed under the assumption of cross-sectional homogeneity of cointegrating vector ($\beta_1 = ... = \beta_N$; *restricted* DSUR) which seems plausible when only few annual observations are available (Mark and Sul (2003); p. 4). Accordingly, individual heterogeneity is confined to short-run dynamics.

[6]The effect of truncation is not discussed for sake of brevity. $\hat{\mathbf{x}}_t = (\underline{x}_{1,t}, ..., \underline{x}_{N,t})$ is a k x N matrix.

In addition, the Wald test aimed at assessing the similarity among single-equation cointegration vectors cannot be used when time dimension is limited (less than 300) as leads to reject the null hypothesis of homogeneity, being systematically oversized.

The family of PDOLS and DSUR estimators represents a valid alternative to error correction models (ECM) where short- and long-run parameters are estimated jointly. The latter framework has been adopted by Guellec and van Pottelsberghe (2004) to study the impact of R&D expenditure on TFP - estimated through three-stage least squares and static SUR- for a panel of countries similar to ours.

To account for heterogeneity in a ECM setting, Pesaran *et al.* (1999) propose a maximum likelihood approach that imposes common long-run parameters while allowing a different (short-run) dynamics among the panel units (pooled mean group; PMG). The logic underlying such a procedure is close to one employed in this paper but, computationally, requires a larger amount of cross-sectional observations. PMG estimator has been employed by O'Mahony and Vecchi (2005) and, also, by McMahon *et al.* (2005) to assess the effect of ICT on global investment cycle. Nevertheless, given the short size of panel, the latter work utilises a modified version of PMG based on SUR.

Numerous alternative procedures of panel cointegration analysis have been developed recently. For instance, Larsson *et al.* (2001) extend to multiple equations the Johansen's method of rank cointegration. Instead, Pedroni (2000) suggests a version of fully modified OLS estimator (FM-OLS) corrected for long-run endogeneity. This body of literature is accurately surveyed by Breitung and Pesaran (2005).

4 Data characteristics and some descriptive results

Our study employs the GGDC Total Economy Growth Accounting database that has been developed at the University of Groningen (Netherlands) by Bart van Ark and his scholars[7]. It includes all the European Union member states before the enlargement (EU-15) and refers to the period 1980-2004. As a measure of output it considers GDP net of rentals paid for residential buildings in order to avoid any distortion related to large cross-country differences

[7]http://www.ggdc.net/dseries/growth-accounting.html, release June 2005. See van Ark *et al.* (2002) and Timmer *et al.* (2003) for details and the underlying growth accounting methodology.

in their measurement. Hours worked (in million thousands) are adopted as a proxy of labour input and, as a result, the contribution of labour quality is embedded into the residual (TFP).
Capital is disentangled into three kinds of ICT asset (computer and office machinery, communication equipment and software) and three non-ICT related types (non-IT equipment, transport equipment and non-residential buildings). For high-tech investment, a qualitative adjustment based on the US hedonic deflators is made to guarantee a homogeneous treatment of technical characteristics, especially for computers (price harmonisation).

All monetary variables have been converted from national currencies into US constant dollars of 2002 but are not transformed into a PPP base, given the lack of relative prices for ICT.
A vigorous debate has developed around the validity of purchasing power parity hypothesis, that is whether exchange rates compensate disparities in relative prices over a long-term horizon (see Sarno and Taylor (2002)). Evidence does vary according to sample coverage and data frequency; the usage of monthly price indexes may lead to refute such an assumption, as demonstrated, among others, by Moon and Perron (2005) adopting DSUR. Using highly frequency series Coakley *et al.* (2005) have shown that the parity hypothesis cannot be accepted when built on consumption price index while the opposite happens if based on producer price indexes.
Annual data instead usually provide favourable evidence (Pedroni (2004)). This is also confirmed for the group of EU-15 member countries by trend stationary of PPP index (OECD (2005))[8]. Therefore, as common in cross-country regressions focused on the long-run, the bias provoked by the missing conversion of monetary series into international dollars should be minimal[9].

As for descriptive analysis, **Table 1** reports the decomposition of output growth into factor inputs' contribution. If one considers Europe and United States as a whole (section A), it is possible to notice that the share-weighted growth of ICT capital has been as high as the one of traditional assets over the period 1980-2004. In average, it amounts to 0.6%-points per year, reflecting an annual average growth of 14% and an income share of 0.04. ICT accounts for one seventh of all capital services.
Looking at various time intervals, it is striking the acceleration in TFP growth occurred after 2001. In the last years, labour contribution zeroed while the value of ICT capital services more then halved with respect to 1995-2001.

[8]Trend stationary is displayed in Table A.1 of Appendix. Panel unit roots tests utilised are described in section 5.1.

[9]It should be reminded that the log-levels specification employed in this work includes a time trend whilst short-run variations are eliminated by the first step of regression.

Taking into account the EU-15 and US distinctly (section B), it becomes evident that productivity exploded only in the US between 2001 and 2004, while it showed an inexorable downward trend in Europe since the mid-1990s. In the latter period the EU-15 has not been able to technologically catch up the US; the growth contribution of high-tech equipment decreased to 0.2% per year from 0.6 of 1995-2001 and, in practice, the delay remained almost unchanged.

For the aim of the work it is particularly useful to focus on country-specific data. **Table 2** shows the wide heterogeneity within Europe in the contribution of ICT which ranges from 0.22 percentage points of Greece to 0.70-0.74 of Belgium and Luxembourg. The aggregate contribution of ICT hides a substantially different dynamics in high-tech expenditure (office machinery, communication equipment and software). A large fraction of the EU lag can be ascribed to the small contribution of computers and software, especially in the major continental economies. Figures comparable to the US are exhibited only by Belgium and Luxembourg for computers, Scandinavian countries for software and, finally, Finland and Italy for communication equipment.

With regard to the other sources of growth, TFP arises as the main driver of output for most countries except for Austria, Greece, Italy, Luxembourg and Spain. It is remarkable the reduction in the growth contribution of labour quantity (hours worked); relevant values are shown only from those countries that liberalised more intensively the labour market during the 1990s (Ireland, Luxembourg, Netherlands and Spain). Likely, as illustrated by Jorgenson and Vu (2005), human capital has been another key factor for development but this does not appear in our data as incorporated into Solow's residual.

Finally, it should be pointed out that traditional capital accounted for a sizeable part of GDP growth either in most catching-up countries or such advanced economies as France and Italy. In the latter group, it has been the driver of economic growth, showing a contribution largely superior to high-tech capital, contrarily to what happens for Germany.

5 Econometric results

5.1 Panel unit roots and cointegration analysis

This section is devoted to demonstrate that the macro-economies series employed in the estimation are trend stationary and there exists a relation of cointegration among them.

As a first step, we need to show that log-levels variables are not stationary

but they do if considered in first differences. To check the integration degree of series we employ the t-bar statistics developed by Im, Pesaran and Shin (2003) (in so forth IPS) that consists in an average of ADF tests carried out on each country equation.
IPS test assumes a null hypothesis of non-stationary ($\beta_i = 0$ for all i). It diverges to a negative infinite under the alternative one, allowing for heterogeneity in short-run dynamics ($\beta_i < 0$ for some i). Contemporaneous interdependence is removed by subtracting out the cross-sectional mean (time demeaning), that is equivalent to working with common time dummies:

$$\Delta y_{it} = \underline{\alpha}_i^{'}\underline{d}_{it} + \beta_i y_{it-1} + \sum_{p=1}^{T} \gamma_{ip} \Delta y_{it-p} + u_{it}.$$

Im *et al.* (2003) have demonstrated that t-bar is more powerful than the previous generation of unit roots tests, based on the alternative hypothesis of homogeneity ($\beta_i < 0$ for all units), as the one proposed by Levin and Lin (1993) (hereinafter LL).

Table 3 reports both kinds of tests where the optimal number of ADF lags is chosen by a step-wise procedure minimizing the Akaike information criterion. Along with country-specific intercepts, a time trend is included in log-levels specification but not with annual growth rates. The acceptance of the null hypothesis in the first regression (levels) and, contemporaneously, the rejection in the second one (growth rates) mean that our series are trend stationary.
Unequivocally, this is the conclusion indicated by inference based on IPS test. Moreover, the log-levels specification makes apparent the relatively large power of such a test that, in contrast to LL, points to non-stationary of both capital series. This outcome signals the presence of a considerable degree of cross-sectional heterogeneity for these two variables.
According to Pesaran (2005), IPS test is not fully affordable with high levels of cross-sectional dependence, as only partly removed by time demeaning. In this case, the coefficient of lagged level is downward biased and the null hypothesis of non-stationary is over-rejected by t-bar[10]. However, as the

[10]In alternative, Pesaran (2005) proposes a test consisting in a average of t-ratio statistics carried out on Dickey-Fuller regressions ($CIPS = (1/n)\sum_i CADF_i$) which are augmented either with the lagged level or the growth rate of cross-sectional mean of the dependent variable ($\overline{y}_{t-1}$ and $\Delta\overline{y}_{t-p}$). When residuals are serially correlated the equation can be expressed as follows:

$$\Delta y_{it} = \underline{\alpha}_i^{'}\underline{d}_{it} + \beta_i y_{it-1} + \phi_i \overline{y}_{t-1} + \sum_{p=0}^{T} \gamma_p \Delta \overline{y}_{t-p} + \sum_{p=1}^{T} \gamma_{ip} \Delta y_{it-p} + u_{it}.$$

values of test statistics for log-levels in **Table 3** show, this does not hold for our case and IPS test works reasonably well.

Next we have to verify whether macro-economic series are cointegrated, that is there exists a long-run production function. In so doing, we rely upon the ADF-type statistics proposed by Pedroni (1999) and (2004); they belong to a set of seven tests built on the residuals of least squares regression of the potentially cointegrated relation (eq. 1). All these tests are shown to be robust to double-sense causality. They can be distinguished into two types (panel and group mean tests), both sharing the null hypothesis of no cointegration but diverging for the alternative one. Being computed on pooled annual data, panel tests assume a common cointegrating vector while the group mean tests, which consist in between-averages of the individual statistics, admit heterogeneity in parameters.

As analogous to the augmented Dickey-Fuller approach, panel ADF statistics can be regarded as the closest to the unit roots test proposed by Levin and Lin (1993), whilst the group mean ADF statistics to the test devised by Im *et al.* (2003). The latter should be preferred, especially in short panels, otherwise the null hypothesis of no cointegration might be accepted even though valid for few units.

Nevertheless, as **Table 3** illustrates, this possibility is excluded for our analysis; the null hypothesis is always rejected when the output production function is specified with time trend (along with time dummies). This indicates the existence of a cointegration relation among output and factor inputs[11].

5.2 Estimation of direct effect of ICT on GDP

Panel dynamic ordinary least squares estimation (PDOLS)

The estimation of long-run output production function is carried out initially by panel DOLS[12]. The first section of **Table 4** considers the EU-15 countries and the US as a whole (columns I-IV). The second part instead leaves out

Along with IPS test, this statistics has been employed to check the trend stationary of PPP index for the EU-15 member countries displayed in Table A.1 of Appendix.

[11]Both statistics are one sided tests which are distributed as normal standard, diverging to a negative infinite under the alternative hypothesis (cointegration). Panel statistics are not weighted for the long-run variance as outperforming the weighted tests in small sample. See Pedroni (2004), note 4.

[12]Panel cointegration estimation is carried out with Gauss codes made available by Donggyu Sul. Both in PDOLS and DSUR, the maximum value for the step-down procedure selecting the optimal number of lags (and leads) of first-differenced regressors is fixed to one; standard errors are corrected with pre-weighting method (see Mark *et al.* (2005); p. 802).

Finland and Sweden as, how it will be discussed later, they are source of a severe noise for the estimation (col. V-VI).

For sake of completeness, columns I-II also display the estimates obtained without trend, even though in the following attention will be paid only to trend stationary case, based on the inclusion of this deterministic component. It should be noticed from the first two columns that the elasticity of factor inputs are slightly different from the income shares reported in section 3. Labour and traditional capital are estimated a somewhat smaller (about a fifth) contrarily to ICT whose coefficient is three times higher[13]. In line with a large international evidence, there is proof of slightly decreasing returns (around 0.90).

The inclusion of time trend reduces remarkably the size of coefficients. Since macro-economic series grow uniformly over time, a large fraction of their variance can be explained deterministically, lowering R-squared (col. III-IV).

Note that traditional assets are no longer significant. Instead, the coefficient of hours worked passes from 0.52 to 0.32 whilst ICT capital from 0.14 to 0.09 when not controlling for the effect of contemporaneous shocks. Introducing time dummies reduces only the output elasticity to labour, given the more pronounced cyclical nature of this factor input.

The insignificance of low-tech capital might be interpreted in two alternative ways. Once controlled for time trend, its dynamics may be characterised by a low variance so to be uninformative for explaining output levels.

On the other hand, it may depend on some noise in data. Indeed, looking at de-trended values, it is possible to see a clear break for Finland and Sweden around 1991-92[14]. As discussed by Daveri and Silva (2004), Finland started a transition from a semi-planned to an open-market economy in those years, dismissing a large part of its inefficient over-installed capacity (capital shedding). A similar story seems to hold for Sweden as well; Lindbeck (2000) argues that the severe recession of the early 1990s forced Swedish firms to a more intensive utilisation of capital. This effect overlapped to a deceleration in real investment started in the mid-80s, leading to a downsized process of capital accumulation.

As a consequence, we have re-estimated the output production function excluding such countries (col. V). Expectedly, traditional capital becomes sig-

[13]Table 1 shows the annual average of pooled income shares (0.69 for labour, 0.26 for traditional capital and 0.04 for ICT equipment). Being time invariant, these values coincide with the cross-sectional average of time-series means.

[14]Unified Germany does not present any relevant change in series, as macro-economic aggregates have been estimated backwardly from post-unification levels by using the annual growth rates of West Germany (see Timmer *et al.* (2003)).

nificant at a 1% level, showing a coefficient of nearly 0.19. Moreover, in comparison to column IV, there is a fall in the elasticity of labour and ICT capital. It should be also emphasized that restricting the focus on the European member states does not modify results at all.

At this point it seems useful to compare the long-run elasticity of factor inputs with the short-run values which can be estimated by applying usual techniques to first-differenced (stationary) variables.

Table 5 shows the results for the full sample (US and EU-15) either over the whole timeframe or for the post-1992 period, thus to avoid any possible distortion due to the break in Swedish and Finnish series. Similarly to PDOLS, the model is also re-estimated over 1980-2004 dropping out these countries (col. VI-IX). In order to guarantee some minimal heterogeneity among panel units, all specifications include country-specific intercepts, allowing for time dummies but not time trend.

Despite the well-known problems of reverse causality (endogeneity), panel static OLS regression yields coefficients not dissimilar from such instrumental variables procedures as IV-2SLS and the one-step difference GMM estimator (Arellano and Bond (1991))[15]; a consistent finding is obtained by Rincon and Vecchi (2004) in a firm-level analysis on ICT. Diff-GMM relies upon valid instruments as illustrated by the p-value of Hansen test and seems appropriate for our model in light of Arellano-Bond tests on serial correlation of residuals. Although, by removing fixed-effects, it loses some useful information in coefficients' estimation in comparison with IV-2SLS.

For the whole period and full sample (col. I-III), there is confirmation of the irrelevance of low-tech capital for GDP growth, in line with previous outcomes. On the other hand, the coefficient of hours worked is larger than in the long-run while ICT shows a smaller elasticity; at the best, the latter is estimated a tenth of percentage point lower than in the PDOLS regression (0.085 with IV-2SLS against 0.094).

Restricting the analysis to the most recent years (1992-2004) improves the estimation of traditional capital only by running IV-2SLS. By contrast, labour contribution lessens, probably because of the decline in hours worked per

[15] All short-run regressions utilise standard errors robust to heteroskedasticity. To reduce as much as possible the asynchrony of business cycle, IV-2SLS employs as instruments four-year lagged variables for the estimation over 1980-2004 and two-year lags for 1992-2004. Alternative procedures have provided findings qualitatively inferior the ones reported in Table 5. To limit the larger variability of small economies' observations, we run a weighted least squares regression but results do nearly coincide with OLS; instead, admitting AR(1) errors reduces of about a fifth the size of least squares coefficients. Finally, given the scarce persistency of first differenced variables, sys-GMM performed more poorly than diff-GMM (Blundell and Bond (1998)). All results cited hereinafter but that are not reported in the main text are available on request from the author.

employed occurred in Europe in the last fifteen years (McGuckin and van Ark (2005)).
More interesting outcomes emerge when Finland and Sweden are maintained out from the first-differences regression (col. VI-IX). Adopting IV-2SLS low-tech capital is significant at a 10% level and, most importantly, factor inputs' elasticities become close to the long-run ones reported in the last two columns of **Table 4**.
Therefore, no relevant gain seems to come from the usage of cointegration techniques in the estimation of output production; this finding leaves open some doubt on the validity of PDOLS estimator for our type of analysis and, accordingly, now we turn to estimate dynamic SUR.

Dynamic seemingly unrelated estimation (DSUR)

Thus far cross-countries correlation has been shaped through common time dummies but PDOLS findings display only small variation when they are introduced in the estimation.
Modelling cross-sectional dependence in this way may be too restrictive and relevant efficiency gains can be obtained by means of seemingly unrelated regression. The dynamic SUR estimator devised by Mark *et al.* (2005) computes one cointegrating vector for each single equation, verifying whether they can be considered statistically identical within the system through a Wald test. Unfortunately, this test is systematically oversized when the time dimension is no sufficiently long and, given T, this problem rises with the size of panel.
Furthermore, to implement DSUR there is need to calculate a larger amount of parameters with respect to panel DOLS. As a result, with relatively short time series available, one has to divide the cross-sectional units into various sub-groups[16], even though it lowers the estimates' precision in comparison with a full system regression.
Therefore, output production function is estimated by means of DSUR over different groups under the hypothesis of a homogeneous cointegration vector for each of them. Breaking sample has nevertheless the disadvantage of producing results that may differ among groups because of their composition, rather than the underlying production technology. As a consequence, the robustness of such differences is checked by a version of Chow test robust to heteroskedasticity (Wald test).
We assume a positive relation between scale and production technology and

[16]Mark *et al.* (2005) stress that cross-sectional units should be at least a twelfth of the time dimension to make unrestricted DSUR feasible and with all desirable properties.

divide the sample into three groups: big, medium and small countries[17]. This classification is robust to various alternatives and, as it will be evident later, leaves unchanged the final results of analysis. Preliminarily, we attempted to cluster countries on the basis of their interdependence - measured by the import share on GDP - but it did not provide convincing findings.

Table 6 presents either DSUR or PDOLS results to facilitate the comparison between these estimators and see how the estimation improves when cross-sectional dependence is more powerfully controlled for[18].

First of all, it should be noticed that the parameters of sub-regressions are always statistically different, as shown by the values of Wald test. The unique exception is given by the inclusion of the US in DSUR estimation where there emerges a similarity between large and small countries ($\chi^2(3) = 0.06$). This contrasts with the idea that, if some link exists between technology and scale of production, a larger similarity should be expected between large and medium-sized economies or, alternatively, between the ones localised in the middle and in the right tail of the distribution. However, we can anticipate, this anomaly will disappear when Finland and Sweden are excluded from the analysis.

PDOLS results present some remarkable points. First, labour elasticity is higher in the largest countries by a three times factor relative to the other states (around 0.62-0.67 against 0.21-0.25). Second, low-tech capital is uninformative for explaining output levels only for the first group of countries while, not surprisingly, it enters with a wrong sign for the medium-sized ones as including Sweden. Note that the same happens in DSUR for the smallest members of the EU due to the presence of Finland. Last but not least, digital capital exhibits a positive and significant coefficient only for the group of small countries (0.094) that is made up by some notorious ICT-intensive users like Denmark, Finland, Ireland and Luxembourg[19].

[17] Big countries: US, Germany, France, UK and Italy. Intermediate countries: Spain, Netherlands, Belgium, Sweden and Austria. Small countries: Greece, Portugal, Denmark, Finland, Ireland and Luxembourg.

[18] In a single-equation regression, PDOLS and DSUR coincide with the estimator of dynamic ordinary least squares of Saikkonen (1999); these results are presented in Table A.2 of Appendix. Given the wide discrepancy in estimates, the similarity of coefficients between one-equation and system regressions is always refused; for simplicity, the corresponding values of Wald test are not reported in Table 6 and 7.

[19] To check the robustness of this finding to sample composition, we have re-estimated the model separately for ICT-intensively users on the one hand and less technological advanced countries on the other (Greece and Portugal). The null hypothesis of homogeneity in the cointegration vector cannot be rejected, meaning that the similarity in the contribution of labour and traditional capital is stronger than heterogeneity appearing in the deployment of Information Technology.

As apparent from the right section of the table, relevant efficiency gains stem from using dynamic seemingly unrelated regression in place of PDOLS. Also, coefficients show some change. The growth effect of hours worked is now slightly smaller for the entire group of big countries (col. V), but it rises when the US are left out (col. VI). A comparable coefficient is presented by the smallest economies but not by medium-sized ones, which instead exhibit a rather downsized elasticity.
Traditional capital is significant at a 10% level considering together all the largest economies, showing a coefficient of 0.074. Restricting the focus on the EU states the coefficient jumps up to nearly 0.19 and reaches the highest level of significance. Again, the disappointing performance of the other two groups can be widely attributed to Sweden and Finland.
It is surely in the estimation of ICT impact that DSUR outperforms panel dynamic OLS. Digital capital emerges now as a driver of growth for most countries except for the EU big states. Its coefficient ranges from 0.054 for the intermediate group to 0.171 of smaller economies whilst, evidently, the value reported in column V (0.124) reflects the inclusion of the US[20].
This result is consistent with growth accounts evidence. In Europe the major continental economies have not been able to exploit the growth potential of high-tech equipment because of more general problems of competitiveness. Despite relatively higher investment rates in technologically advanced capital, also the performance of the United Kingdom is downsized if compared to the US, confirming the findings reported by Basu *et al.* (2004) and O'Mahony and Vecchi (2005).
The large improvement in estimating the long-run impact of ICT suggests that cross-country correlation may be stronger for this factor input than for labour and traditional assets. It is likely to mirror the technique adopted to deflate national investment, relying upon US hedonic prices (Schreyer (2002)). This aspect makes DSUR the optimal procedure to assess the growth effects of ICT across countries.

As in the foregoing analysis, now we turn to assess how the inclusion of Sweden and Finland affects the results. There is an important distinction between PDOLS and DSUR; the former estimation does no longer exhibit significant differences among various groups and, thus, all countries can be pooled. Note, however, that this specification has been already estimated and presented above in **Table 4** (col. V-VI).
One the other hand, by running DSUR significant divergencies persist be-

[20]It is interesting to underline that factor inputs' elasticity are aligned to income shares only for France, Germany, Italy and UK.

tween the major EU countries and the rest of the sample[21]. Therefore, we have re-run dynamic seemingly unrelated regression joining together small and medium-sized countries. Outcomes are summarized in the left section of **Table 7** which, for comparative aims, reports once again the values relative to the top economies.

A rather clear picture emerges now on the role played by various factor inputs in the European development over the last quarter of century.

The largest economies exhibit a growth pattern dominated by labour input. Instead, the deployment of low-tech capital has been substantially homogeneous among countries whilst the ICT contribution does vary remarkably (0.041 vs 0.117). Indirectly, **Table 7** provides confirmation of the US leadership in terms of high-tech capital utilisation, given that the coefficient reported in the first column exceeds the one of EU countries.

Finally, to compare long- and short-run elasticities we have also estimated static version of seemingly unrelated regression (Zellner (1962)) on first-differenced variables. Albeit the well-known problems of endogeneity between regressors and disturbances, one can observe that the coefficients of dynamic regression are always larger[22], further witnessing the importance of using DSUR for this kind of study.

Sensitivity analysis of parameters

One of the main outcomes of the preceding analysis is that the size of ICT elasticity is always above the income share when significant. Several arguments have been advanced in productivity literature to explain a similar result, all pointing to the inadequacy of neoclassic assumptions at the basis of income shares' calculation (perfect competition and full exhaustion of output).

Our evidence excludes increasing returns and, also, error measurements given the usage of hedonic deflators for high-tech expenditure. Furthermore, it is difficult to believe that the market of ICT assets behaves less competitively than the one of traditional equipment. Thus, only two explanations remain valid for our findings (see Stiroh (2002a)).

On one hand, the size of ICT coefficient might reflect the presence of external effects caused by networking or productivity spillovers that push up the social value of digital capital over private return.

On the other hand, it might be upward biased because of the omission of

[21] Intermediate regressions are reported in Table A.3 of Appendix.

[22] It makes exception labour contribution in the smallest economies. As above discussed, the strong cyclical nature of hours worked makes this factor input extremely sensitive to double-sense causality.

labour quality in output production function. Increasing levels of firms' spending in IT have been accompanied over time by complementary investments in human capital which, by nature, tend to further enhance the returns of IT equipment. The mutual self-enforcing effect between these factors is stressed by Brynjolfsson and Hitt (2003) who underline the difficulty of disentangling the two components in absence of accurate data. Sometimes, however, ICT elasticity shows small variation between using quality-adjusted or raw labour data (O'Mahony and Vecchi (2005)).

In the following we check the sensitivity of ICT coefficient on a group of countries (France, Germany, Netherlands, UK and US) for which labour quality series are available from a consistent source, even though for a shorter time span (1980-2000)[23].

Table 8 reports DSUR results. For comparative aims, the first two columns also present findings relative to 1980-2004 based on hours worked. The coefficient of ICT changes remarkably depending on the inclusion of the US; it amounts to 0.092 for the EU-4 countries, rising to 0.140 when the US are comprised. In light of the results of the previous section, the significance of digital capital for the EU countries is clearly attributable to the good performance of the Netherlands.

The second part of **Table 8** highlights the scarce covariation between ICT and human capital as the contribution of former factor remains stable albeit the quality adjustment of labour. By contrast, there is a fall in the coefficient of traditional assets and, as expected, an increase in labour elasticity[24].

Although this finding cannot be generalized as reflecting the subgroup composition, it leads to believe that the upward bias of ICT coefficient may be small for the overall sample as well (EU-15 and US). Indirectly, this supports our previous results.

6 Concluding remarks

Despite a global convergence in the uptake of digital technologies occurred after 1995, this work has shown that non-negligible differences persist within

[23]GGDC Industry Growth Accounting database. The growth rate of labour quality is calculated at an industry level and then aggregated for the overall economy. The relative level of labour quality among countries has been fixed to the values reported by Jorgenson and Vu (2005) using 1995 as benchmark year. Finally, a synthetic measure of labour input has been computed multiplying hours worked by the index of human capital.

[24]When the focus is restricted on the EU-4 countries, the coefficient of ICT does modify marginally. A long-difference regression for the period 1989-95 and 1995-2003 carried out on all EU-15 countries (less Luxembourg) and US, exploiting labour quality data built by Jorgenson and Vu (2005), qualitatively support the previous evidence.

Europe in the growth effects of ICT.
In line with the large body of growth accounts literature, the leading countries of the EU are found to sensibly lag behind the US in terms of productive impact of new asset types. On the other hand, there is a core of small dynamic economies in Europe whose growth pattern has been positively influenced by the deployment of Information Technology.
The disappointing technological performance of the major continental states is usually ascribed to the structural weakness of their economies, become apparent in the last decade. A low specialization on innovative productions and a rigid regulation of internal markets are the roots of the fall of competitiveness. These factors have lessened the incentives to high-tech investment, depressing the global returns of ICT; it is known that digital capital makes firms more flexible but, at the same time, needs a dynamic environment to yield efficiency gains.
In this connection, the renewed commitment of the EU institutions for creating a common digital platform (i-2010) and sustaining ICT usage goes towards the right direction. Yet, these interventions are unlikely to stimulate productivity until stronger policies for competition and innovation are not pursued by national institutions.
Another remarkable feature of the paper can be identified in the usage of panel cointegration techniques to estimate the sources of growth. At an economy-wide level of analysis, this is indispensable to assess the contribution of ICT whose nature of general purpose technology confines relevant productivity gains to the long-run. In this respect, dynamic seemingly unrelated regression arises as the most suited procedure of estimation, allowing to identify the wide discrepancies existing within Europe and between the EU and US.

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Table 1: **Overall growth contribution of ICT capital in Europe and the US** (1980-2004)

annual average growth rates (% points)

Table 1.A — **OVERALL SAMPLE**

	GDP growth	*contributions:* TFP	Hours worked	Non-ICT capital	ICT capital
1980-2004	2.7	0.9	0.5	0.6	0.6
1980-85	2.5	0.9	0.3	0.6	0.8
1985-90	3.3	0.9	1.1	0.8	0.5
1990-95	2.0	0.9	0.1	0.6	0.4
1995-2001	3.1	0.8	0.8	0.6	0.8
2001-04	2.2	1.4	0.0	0.4	0.3

Decomposition of factor inputs contributions (1980-2004)

	Hours worked	Non-ICT capital	ICT capital
Contribution:	0.51	0.61	0.62
Income share	0.69	0.26	0.04
Growth rate	0.74	2.33	14.0

Table 1.B

	EUROPEAN UNION-15 GDP growth	*contributions:* TFP	Hours worked	Non-ICT capital	ICT capital	**UNITED STATES** GDP	*contributions:* TFP	Hours worked	Non-ICT capital	ICT capital
1980-2004	2.1	1.0	0.1	0.7	0.4	3.2	0.9	0.9	0.6	0.8
1980-85	1.5	1.2	-0.7	0.6	0.4	3.2	0.6	1.1	0.6	1.0
1985-90	3.2	1.1	0.8	0.9	0.5	3.3	0.6	1.4	0.6	0.6
1990-95	1.6	1.2	-0.6	0.7	0.3	2.5	0.5	0.9	0.4	0.6
1995-2001	2.5	0.7	0.6	0.6	0.6	3.6	0.9	1.0	0.6	1.0
2001-04	1.4	0.5	0.1	0.5	0.2	3.0	2.3	-0.1	0.4	0.5

Source: Own elaboration on data from Timmer et. al (2003), updated June 2005. Contributions are share-weighted growth rates.

Table 2: **Sources of national GDP growth** (1980-2004)
annual average growth rates (% points)

	GDP	TFP	Hours worked	Non-ICT capital	ICT capital
Austria	2.09	0.73	0.14	0.79	0.43
Belgium	1.94	0.99	-0.05	0.31	0.70
Denmark	1.92	0.81	-0.18	0.64	0.66
Finland	2.35	1.82	-0.28	0.34	0.48
France	1.98	0.95	-0.21	0.95	0.29
Germany	1.75	1.39	-0.43	0.37	0.42
Greece	1.91	0.49	0.58	0.62	0.22
Ireland	5.33	3.01	0.62	1.38	0.32
Italy	1.71	0.42	0.15	0.76	0.38
Luxembourg	4.69	1.27	1.41	1.26	0.74
Netherlands	2.22	0.73	0.58	0.47	0.45
Portugal	2.49	1.14	0.27	0.76	0.33
Spain	2.81	0.84	0.67	0.97	0.33
Sweden	2.19	0.96	0.14	0.49	0.60
United Kingdom	2.57	1.29	0.14	0.61	0.52
EU-15	2.12	0.96	0.06	0.66	0.44
United States	3.16	0.89	0.93	0.55	0.78

Source: Own elaboration on data from Timmer et. al (2003), updated June 2005. Contributions are share-weighted growth rates.

Table 3: **Panel unit roots and cointegration analysis**

	UNIT ROOTS			
	Levels (incl. time dummies and trend)			
	GDP	Hours worked	Non-ICT capital	ICT capital
Levin-Lin (1993)	-0.33	-0.11	-1.57	-3.09**
IPS (2003)	-1.06	-0.79	-1.20	-1.45
	First differences (incl. time dummies)			
Levin-Lin (1993)	-2.45**	-5.45**	-1.46	-2.18**
IPS (2003)	-4.29**	-7.20**	-3.98**	-5.66**
	PANEL COINTEGRATION			
	Levels (incl. time dummies and trend)			
	Panel ADF		Group ADF	
Pedroni (1999)	-2.20**		-2.47**	

Notes: All statistics are distributed as standard normal, diverging to an infinite negative under the alternative hypothesis; a step down procedure is employed to select ADF lags for each equation. Variables are cross-sectionally de-meaned; time trend is admitted only in log-levels specifications.
Unit roots tests assume the null hypothesis of non-stationary; under the alternative hypothesis, Levin and Lin's test admits a common coefficient for the lagged dependent variable while IPS a non-homogenous one for at least a positive fraction of individuals.
Pedroni's tests assume the null hypothesis of no cointegration; the alternative hypothesis is of a homogeneous cointegration vector for panel ADF t-statistics and of heterogeneity for group ADF t-statistics; tests are not weighted for the long-run variance.
** significant at a 5% level.

Table 4: **Long-run estimation of aggregate production function** (1980-2004), *levels*

	PDOLS					
	US and EU-15 (full sample)				**US and EU-13**[a]	**EU-13**[a]
	I	II	III	IV	V	VI
Hours worked	0.522***	0.505***	0.321***	0.293***	0.261***	0.262***
	(0.079)	(0.079)	(0.031)	(0.05)	(0.032)	(0.033)
Non-ICT capital	0.235**	0.236***	0.021	0.028	0.188***	0.184***
	(0.096)	(0.087)	(0.043)	(0.043)	(0.058)	(0.058)
ICT capital	0.138***	0.138***	0.092***	0.094***	0.084***	0.085***
	(0.018)	(0.016)	(0.010)	(0.011)	(0.011)	(0.011)
Intercept	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Time dummies	*no*	*yes*	*no*	*yes*	*yes*	*yes*
Trend	*no*	*no*	*yes*	*yes*	*yes*	*yes*
Obs. (N*T)	400	400	400	400	350	350
Adj. R-squared	0.93	0.92	0.55	0.53	0.70	0.69

Notes: GDP is the dependent variable; all variables are in log-levels. Standard errors are parametrically corrected with pre-weighting method. The maximum lag in the step-down procedure selecting the number of leads (and lags) is fixed to 1.

[a] EU-13 excludes Finland and Sweden.

*, **, *** significant at 10, 5 and 1% levels.

Table 5: **Short-run estimation of aggregate production function**, *first differences*

	US and EU-15					US and EU-13[a]		EU-13[a]	
	1980-2004			1992-2004		1980-2004		1980-2004	
	OLS	**IV-2SLS** (4 lags)	**diff-GMM**	**IV-2SLS** (2 lags)	**diff-GMM**	**IV-2SLS** (4 lags)	**diff-GMM**	**IV-2SLS** (4 lags)	**diff-GMM**
	I	II	III	IV	V	VI	VII	VIII	IX
Hours worked	0.331***	0.378***	0.327***	0.148***	0.201***	0.268***	0.231***	0.260***	0.196***
	(0.066)	(0.073)	(0.087)	(0.055)	(0.051)	(0.063)	(0.066)	(0.066)	(0.060)
Non-ICT capital	0.116	0.073	0.108	0.285**	0.256	0.194*	0.205*	0.202*	0.215
	(0.087)	(0.090)	(0.097)	(0.127)	(0.158)	(0.112)	(0.114)	(0.114)	(0.121)
ICT capital	0.078***	0.085***	0.076***	0.082**	0.068**	0.087***	0.079***	0.084**	0.075***
	(0.030)	(0.031)	(0.018)	(0.033)	(0.032)	(0.033)	(0.018)	(0.034)	(0.019)
Obs. (N*T)	400	320	368	160	176	160	322	160	299
Adj. R-squared	0.62	0.65	0.61	0.83	0.68	0.67	0.65	0.67	0.63
F-test of no significant fixed effects (P-value)	3.15 (0.01)	4.72 (0.00)		6.59 (0.00)		5.48 (0.00)		5.30 (0.00)	
Hansen test p-value			1.00		1.00		1.00		1.00
AR(1) p-value	0.00	0.00	0.02	0.03	0.01	0.00	0.03	0.01	0.04
AR(2) p-value	0.18	0.17	0.33	0.54	0.27	0.41	0.46	0.30	0.67

Notes: GDP is the dependent variable; all variables are in first differences (annual growth rates). Standard errors robust to heteroskedasticity are in brackets. Time dummies and country-specific intercepts are included but not reported.
F-test checks the null hypothesis of insignificant fixed effects. The P-value of Hansen test for instruments' over-identification and Arellano-Bond tests of no serial correlation in residuals is reported on the bottom.
[a] EU-13 excludes Finland and Sweden.
*, **, *** significant at 10, 5 and 1% levels.

Table 6: **Long-run estimation of production function by groups: a comparison between PDOLS and DSUR** (1980-2004)

	PDOLS				DSUR			
	Big Countries	EU Big Countries	Medium Countries	Small Countries	Big Countries	EU Big Countries	Medium Countries	Small Countries
	I	II	III	IV	V	VI	VII	VIII
Hours worked	0.624***	0.670***	0.249***	0.209***	0.518***	0.710***	0.165***	0.653***
	(0.137)	(0.149)	(0.045)	(0.113)	(0.041)	(0.060)	(0.012)	(0.012)
Non-ICT capital	0.150	0.072	-0.280***	0.047***	0.074*	0.186***	0.028	-0.076***
	(0.107)	(0.109)	(0.093)	(0.045)	(0.042)	(0.054)	(0.033)	(0.029)
ICT capital	0.030	-0.007	0.008	0.094***	0.124***	0.041	0.054***	0.171***
	(0.053)	(0.059)	(0.033)	(0.017)	(0.014)	(0.029)	(0.006)	(0.007)
Obs. (N*T)	125	100	125	150	125	100	125	150
Adj. R-squared	0.88	0.82	0.24	0.46	0.81	0.95	0.33	0.76
Wald test of parameters' homogeneity among groups								
	PDOLS				**DSUR**			
	Big	EU Big	Medium	Small	Big	EU Big	Medium	Small
Big	0				0			
EU big		0				0		
Medium	30.1***	17.5***	0		8.43**	28.2***	0	
Small	17.4***	10.0**	10.0**	0	0.06	13.3**	15.3***	0

Notes: GDP is the dependent variable. All estimates include country-specific intercepts (fixed effects) and time trend; PDOLS also considers time dummies. Standard errors are parametrically corrected with pre-weighting method. The maximum lag in the step-down procedure selecting the number of leads (and lags) is fixed to 1. The Wald test checks the null hypothesis of no significant difference in cointegration vector among groups.
Big Countries: US, Germany, France, UK and Italy; *Intermediate Countries*: Spain, Netherlands, Belgium, Sweden and Austria; *Small Countries*: Greece, Portugal, Denmark, Finland, Ireland and Luxembourg.
*, **, *** significant at 10, 5 and 1% levels.

Table 7: **Long-run vs short-run estimation: a comparison between DSUR and SUR** (1980-2004)

	Long-run estimation (*levels*)			Short-run estimation (*first differences*)		
	DSUR			SUR		
	Big Countries	EU Big Countries	Small & Medium Countries[a]	Big Countries	EU Big Countries	Small & Medium Countries[a]
	I	II	III	IV	V	VI
Hours worked	0.518***	0.710***	0.121***	0.354***	0.229***	0.214***
	(0.041)	(0.060)	(0.001)	(0.096)	(0.111)	(0.054)
Non-ICT capital	0.074*	0.186***	0.193***	0.046	-0.046	0.206**
	(0.042)	(0.054)	(0.002)	(0.213)	(0.256)	(0.093)
ICT capital	0.124***	0.041	0.117***	0.038	0.003	0.082***
	(0.014)	(0.029)	(0.001)	(0.060)	(0.066)	(0.022)
Obs. (N*T)	125	100	225	120	96	216
Adj.R -squared	0.81	0.95	0.63	0.60	0.59	0.67
F-test of no significant fixed effects (P-value)				2.24 (0.07)	1.62 (0.19)	8.37 (0.00)

Notes: GDP is the dependent variable. All estimates include country-specific intercepts (fixed effects); time trend is comprised in log-levels specification but not in first differences; the reverse holds for time dummies. In DSUR, standard errors are parametrically corrected with pre-weighting method. The maximum lag in the step-down procedure selecting the number of leads (and lags) is fixed to 1.

[a] excludes Finland and Sweden.

*, **, *** significant at 10, 5 and 1% levels.

Table 8: **Parameters' sensitivity to the inclusion of labour quality**, EU-4 vs US (DSUR)

	1980-2004		1980-2000	
	EU-4 and US *(hours worked)*	**EU-4** *(hours worked)*	**EU-4 and US** *(hours worked)*	**EU-4 and US** *(quality-adjusted labour)*
	I	II	III	IV
Labour	0.308***	0.532***	0.020	0.121***
	(0.035)	(0.033)	(0.022)	(0.008)
Non-ICT capital	0.111***	0.086	0.311***	0.233***
	(0.040)	(0.059)	(0.038)	(0.030)
ICT capital	0.140***	0.092***	0.186***	0.183***
	(0.011)	(0.019)	(0.009)	(0.003)
Obs. (N*T)	125	100	105	105
Adj. R-squared	0.70	0.80	0.72	0.76

Notes: GDP is the dependent variable. All estimates include country-specific intercepts (fixed effects) and time trend. Standard errors (in brackets) are parametrically corrected with pre-weighting method. The maximum lag in the step-down procedure selecting the number of leads (and lags) is fixed to 1.
EU-4: France, Germany, Netherlands and UK.
*, **, *** significant at 10, 5 and 1% levels.

APPENDIX

Table A.1: **Unit roots tests for PPP index of EU-15 countries** (1970-2002), annual values

	IPS (Im, Pesaran and Shin, 2003)		CIPS (Pesaran, 2005)	
	test statistics	cv 5%	test statistics	cv 5%
Levels (with trend)	-1.50	-2.85	-2.14	-2.76
First differences	-3.49**	-1.85	-2.36**	-2.25

Source: OECD (2005); United States are the numeraire country.
Time trend is included in log-levels specification but not in first-differences; values are not standardised. IPS test utilises cross-sectionally de-meaned data.
** significant at a 5% level.

Table A.2: **Dynamic OLS estimation for single equation**, (1980-2004) (Saikkonen, 1991)

	Hours worked		**Non-ICT capital**		**ICT capital**	
	Coef.	*SE*	*Coef.*	*SE*	*Coef.*	*SE*
Austria	-0.269	0.328	1.224**	0.561	-0.039	0.057
Belgium	-1.167***	0.237	-0.919***	0.156	-0.140***	0.026
Denmark	-0.607***	0.099	-0.123	0.103	-0.176***	0.025
Finland	0.024	0.473	-0.856***	0.217	0.680***	0.160
France	-0.849***	0.272	0.243***	0.055	-0.287***	0.075
Germany	-0.250	0.362	1.010***	0.052	0.073***	0.030
Greece	-0.647***	0.162	0.721***	0.128	0.060	0.055
Ireland	1.221***	0.153	-0.111	0.200	0.021	0.016
Italy	-0.727***	0.062	0.904***	0.127	0.067***	0.021
Luxembourg	-1.275***	0.307	2.020***	0.351	0.638***	0.090
Netherlands	0.627***	0.022	2.154***	0.094	0.166***	0.012
Portugal	1.154***	0.131	0.128***	0.038	-0.160***	0.037
Spain	0.391***	0.023	0.420***	0.064	0.192***	0.018
Sweden	1.906***	0.377	-0.547***	0.042	-0.094	0.076
United Kingdom	1.219***	0.083	0.382***	0.077	-0.014	0.015
United States	-0.378***	0.062	2.529***	0.186	0.005	0.017

Notes: GDP is dependent variable; all variables are expressed in cross-sectionally demeaned log-levels. All equations include country-specific intercepts (fixed effects) and time trend. Standard errors in brackets are parametrically corrected with pre-weighting method. The maximum lag in the step-down procedure selecting the number of leads (and lags) is fixed to 1.

*, **, *** significant at 10, 5 and 1% levels.

Table A.3.1: **PDOLS and DSUR estimation by groups excluding Finland and Sweden** (1980-2004)

	PDOLS				DSUR			
	Big Countries	EU Big Countries	Medium Countries[a]	Small Countries[b]	Big Countries	EU Big Countries	Medium Countries[a]	Small Countries[b]
	I	*II*	*III*	*IV*	*V*	*VI*	*VII*	*VIII*
Hours worked	0.624***	0.670***	0.217***	0.080	0.518***	0.710***	0.199***	0.147***
	(0.137)	(0.149)	(0.036)	(0.100)	(0.041)	(0.060)	(0.016)	(0.069)
Non-ICT capital	0.150	0.072	0.426***	0.242***	0.074*	0.186***	0.068	0.169***
	(0.107)	(0.109)	(0.131)	(0.070)	(0.042)	(0.054)	(0.053)	(0.053)
ICT capital	0.030	-0.007	0.063***	0.094***	0.124***	0.041	0.078***	0.180***
	(0.053)	(0.059)	(0.029)	(0.016)	(0.014)	(0.029)	(0.010)	(0.015)
Obs. (N*T)	125	100	100	125	125	100	100	125
Adj. R-squared	0.88	0.82	0.88	0.61	0.81	0.95	0.46	0.64

Wald test of parameters' homogeneity among groups

	PDOLS				DSUR			
	Big	EU Big	Medium[a]	Small[b]	Big	EU Big	Medium[a]	Small[b]
Big	0				0			
EU big		0				0		
Medium[a]	0.04	0.99	0		5.34	21.5***	0	
Small[b]	10.8**	5.22	15.9***	0	2.81	22.4***	2.21	0

Notes: GDP is dependent variable; all variables are expressed in log-levels. All estimates include country-specific intercepts (fixed effects) and time trend; PDOLS also considers time dummies. Standard errors in brackets are parametrically corrected with pre-weighting method. The maximum lag in the step-down procedure selecting the number of leads (and lags) is fixed to 1. The Wald test checks the null hypothesis of no significant difference in cointegration vector among groups.

[a] excludes Sweden; [b] excludes Finland.

*, **, *** significant at 10, 5 and 1% levels.

Table A.3.2: **PDOLS and DSUR estimation by groups excluding Finland and Sweden** (1980-2004)

	PDOLS			DSUR		
	Big & Medium Countries [a]	EU Big & Medium[a] Countries	Small Countries[b]	Big Countries	EU Big Countries	Small & Medium Countries[a,b]
	I	II	III	IV	V	VI
Hours worked	0.277***	0.276	0.080	0.518***	0.710***	0.121***
	(0.041)	(0.044)	(0.100)	(0.041)	(0.060)	(0.001)
Non-ICT capital	0.149	0.107	0.242***	0.074*	0.186***	0.193***
	(0.095)	(0.101)	(0.070)	(0.042)	(0.054)	(0.002)
ICT capital	0.052*	0.044	0.094***	0.124***	0.041	0.117***
	(0.029)	(0.031)	(0.016)	(0.014)	(0.029)	(0.001)
Obs. (N*T)	225	200	125	125	100	225
Adj. R-squared	0.64	0.58	0.60	0.81	0.95	0.63

Wald test of parameters' homogeneity among groups

	PDOLS				DSUR		
	Big & Medium[a]	EU Big & Medium[a]	Small[b]		Big	EU Big	Medium & Small [a,b]
Big & Medium[a]	0			Big	0		
EU Big & Medium [a]		0		EU Big		0	
Small[b]	0.09	0.15	0	Medium & Small [a,b]	6.16	38.6***	0

Notes: GDP is dependent variable; all variables are expressed in log-levels. All estimates include country-specific intercepts (fixed effects) and time trend; PDOLS also considers time dummies. Standard errors in brackets are parametrically corrected with pre-weighting method. The maximum lag in the step-down procedure selecting the number of leads (and lags) is fixed to 1. The Wald test checks the null hypothesis of no significant difference in cointegration vector among groups.
[a] excludes Sweden; [b] excludes Finland.
*, **, *** significant at 10, 5 and 1% levels.