The Productivity Challenge
What to expect from better-quality labour and capital inputs?

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Abstract

The aim of this paper is to develop and implement an analytical framework assessing whether better-quality inputs, via a rise of TFP, could compensate an ageing-induced slowing of economic growth. Here "better-quality" means more educated and older/more experienced workforces; and also better-quality capital proxied by its ICT content. Economic theory predicts that these trends should raise TFP. To assess these predictions, we use EU-KLEMS data, with information on the age/education mix of the workforce, as well as the importance on ICT in total capital, for 34 industries within 16 OECD countries, between 1970 and 2005. We generalise the Hellerstein-Neumark labour-quality index method to simulateneously capture workers' age/experience or education contribution to TFP growth, alonside that of ICT. The conclusion of the paper is that the quality of inputs matters for TFP. We find robust microeconometric evidence that better-educated and older/more experienced workers are more productive than their less-educated and younger/less-experienced peers. Also, ICT capital turns out to be more productive than other forms of capital. And when used in a growth accounting exercise covering the 1995-2005 period, these estimates suggest that up to 40% of the recorded TFP growth could be ascribed to the rising quality of inputs.

Keywords: TFP growth, Ageing, Input quality, ICT
JEL Codes: J11, J24, D24, O30

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1. Introduction

Most statistical offices across the OECD countries project that the fraction of the population aged 60 or older will increase over the coming decades. In the US for instance, the administration projects that share of the United States population aged 60 or older will increase by 21% between 2010 and 2020, and by 39% between 2010 and 2050 (Maestas, Mullen & Powell 2014). And that phenomenon is not specific to the OCDE. In China for instance the percentage of people aged 65 years and over will be rising from 5.5% in 1990 to a predicted 13.3% in 2025 and 23% by 2050. Such a dramatic shift in the age structure of populations – itself the effect of the historical rise in longevity and decline in fertility – has led Morrow & Roeger (1999) and many others (e.g. Gruber & Wise, 2004) to predict a sharp rise of the dependency ratio (Figure 1).

The point is that global demographic trends have the potential to affect living standards of most advanced economies. Voluntarily, or due to mandatory retirement rules, people reduce labour supply when they get older, and finance consumption with assets and transfers from Social Security. Thus, as the proportion of older persons in the population increases, producers (i.e., workers) become less important in proportion of the total number of consumers. And this means that economies risk growing more slowly or even shrink. [1] In other words, an ageing-induced contraction in the overall size of the labour force can reduce the growth rate of an economy.[2]

Economists have examined how such a trend could be combatted. One response consists of lifting the overall employment rate, essentially by postponing the moment of retirement (i.e. broadening the definition of the working age) and reducing underemployment in that working-age population. The point we make in this paper is that a shrinking pool of working-age individuals can also be compensated, in terms of its negative effect on growth, by a higher labour productivity.[3] In other words, demographic ageing – and the perspective of shrinking

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[1] In $Y/P = Y/L*L/P$ where Y is total output, P is total population, L is labour force, population ageing means that L/P¨goes down; potentially causing a reduction of output per head (Y/P).

[2] Macroeconomists estimate that the average annual per capita growth in Belgium may not exceed 0.5% per year until at least 2040 (Heylen et al., 2016), and it may stay below 1% until almost 2060. Demographic ageing[2] is by far the most influential cause of low growth. A strongly rising dependency ratio due to the retirement of the baby boom generation, increasing longevity and (to a lesser extent) a temporary fall in the population at working age, implies that the output of fewer workers must be shared with more inactive people. Arithmetically this could drag down annual per capita growth by about 1%-point between 2010 and 2040

[3] In $Y/P = Y/L*L/P$ population ageing (L/P↘) can be compensated by higher labour productivity (Y/L↗). Cutler et al. (1990) even posit that L/P↘ could boost labour productivity gains, arguing that "scarcity is the mother of invention". This scarcity view assumes that in a situation of relatively slow population growth, there is an acceleration, on a per capita basis, in human capital accumulation. In their cross-national analysis of 29 non-OPEC countries for the period 1960-1985, Cutler et al estimate that a decline in the annual labour force growth

labour forces – should lead economists to focus more on the determinants of labour productivity: capital intensity, economies of scale and (total factor) productivity (TFP) growth.[4] What we propose to examine in this paper is the impact on TFP growth of better-quality inputs.

Economists since at least Griliches (1957) have argued that TFP could reflect the quality of inputs. Here, better-quality labour refers to the propensity of workers to be more experienced and better educated (Vandenberghe & Lebedinski, 2014). The latter is the consequence the constant rise of educational attainment over the past decade. Also, better-quality labour can mean that workers have more professional experience. And this is a trend that one can legitimately expect in a context of ageing workforces.[5] Ever since Arrow (1962), experience, or learning by doing/on the job, has occupied a central place within human capital economics. Arrow conceptualized learning by doing within the actual activity of production, with cumulative gross investment as the catalyst for experience. Nearly two decades later, the role of experience in shaping and driving productivity growth was central in Lucas' explanations of increasing returns to human capital (Lucas, 1988). Indeed, as Lucas stresses, "on-the-job-training or learning-by-doing appear to be at least as important as schooling in the formation of human capital". This said, a rise of average labour-market experience almost invariably entails that of the age of the workforce. And many economists would argue that experience-related TFP gains can be (totally or partially) offset by age-related productivity losses. There is evidence that earnings in many advanced industrialised countries tend to peak for workers at some point in their 50s and then decline, possibly due to net productivity losses (Skirbekk, 2004, 2008).

But there is more than the quality of labour. One should not ignore the changing nature of capital. More traditional and material forms of capital can vary in quality in ways not captured by standard measures. We focus here on one type of capital – information and communication technology (ICT). It is viewed by many as a promising source of productivity gains[6], and is the

rate of 1 percentage point is associated with about a 0.5 percentage point increase in (labour) productivity growth.

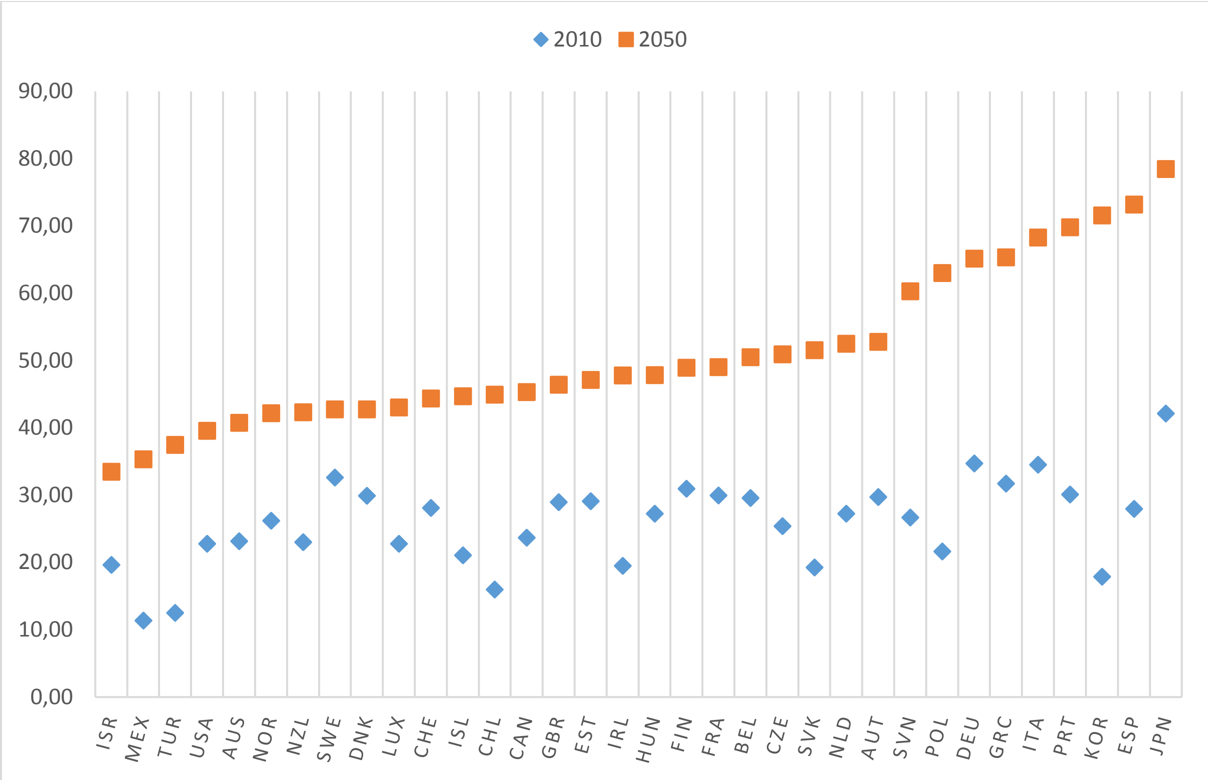
4 Total Factor Productivity (TFP) is the portion of output (value-added) not explained by the amount of inputs used in production. As such, its level depends on how efficiently and intensely inputs are utilized in production, but also on the quality of these inputs.

5 That is induced by demographic/population ageing but should not be confounded with it.

6 The magnitude of productivity gains potentially generated by ICT/digitalisation (big data, internet-of-things…) remains debated among economists. Could it be that robots, computers, e-platforms are about to generate a rise of labour productivity of a magnitude recorded in the wake of the two previous industrial revolutions (IR) that is, IR1 (steam, railroads) from 1750 to 1830 and IR2 (electricity, internal combustion engine, running water, indoor toilets, communications, entertainment, chemicals, petroleum) from 1870 to 1900? Brynjolfsson & Mc Afee (2014), strongly believe that we are about the embark in IR3. The key idea is

subject of intense study (Syverson, 2011). The way we explore this assumption here this is by exploiting evidence on the rise of spending on ICT. That trend has been observed across most OECD countries over the past decades, and many economists think it will persist or even expand (Brynjolfsson & Mc Afee, 2014).

Figure 1 – Old dependency ratio[7] : observed 2010 level vs predicted 2050 level



Source: OECD, 2015, our calculus

In this paper, we base our analysis on the estimation of production functions expanded by the specification of an input-quality index à-la Hellerstein & Neumark (1995) (HN henceforth). The key idea of HN is to estimate a Cobb-Douglas production function with and heterogeneous labour input, where different types of workers (e.g. men/women, young/old, educated/less educated) diverge in terms of marginal product. Most of the works using the HN framework focus on productivity differences across types of labour, and how these relate to wage

that rapid growth in computation and artificial intelligence will cross some threshold after which productivity will accelerate sharply, as an ever-accelerating pace of improvements cascade through the economy.

7 Old Dependency Ratio = $P^{65+}/\ P^{20\text{-}64}$. Note, more generally, that $Y/P=Y/L*L/P$ can be rewritten as $Y/P=Y/L*1/(1+D)$ where D is the total dependency ratio (i.e. old + young).

differences. [8] We show in this paper that HN is perfectly suitable to assess the determinants of TFP, singularly the role of the quality of labour inputs.

Following Ilmakunnas & M, Tatsuyoshi (2013), we also show that the HN idea can be used to decompose capital, and assess the contribution of its different constituent parts. Our HN production function integrates a capital-quality index, where ICT and non-ICT capital potentially diverge in terms of marginal product.

Finally, we take steps to correctly measure TFP and avoid possible endogeneity/simultaneity concerns. The idea is to control for time-varying unobserved (demand) shocks that may affect simultaneously output and trends in the use of labour and capital inputs. To control for this source of bias we follow here the strategy of Levinsohn & Petrin (2003) (LP henceforth), and the one suggested more recently by Ackerberg, Caves & Fraser (2006) (ACF hereafter). All these methods consist of using observed intermediate input decisions (i.e. purchases of raw materials, services, electricity) to "control" for unobserved short-term productivity shocks.

The data used in this paper are industryXcountry-level panel data from the EU-KLEMS project.[9] The latter represents a unique collective effort to provide comparable data, capable of delivering fundamental policy insights into the dynamics of productivity (and related issues) at the industry level in Europe, the US and Japan, over recent decades (1970 to 2005).

The main result of the paper is that the quality of inputs matters for TFP. We find robust microeconometric evidence that better-educated and older (presumabley more experienced) workers have a higher marginal productivity than their less educated/younger peers. Also, ICT turns out to be more productive than other, more traditional, forms of capital. And using the estimates in a growth accounting exercise for the 1995-2005 period, we conclude that up to 40% of the TFP growth recorded during that period could be ascribed to better-quality inputs.

The rest of this paper is organised as follows. Section 2 prensents the HN methodology, its relationship to TFP and its extention to capital decomposition. Section 3 presents the EU-KLEMS data. Our econometric results are presented in Section 4. The last section concludes.

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8 With the aim of assessing the employability of different categories individuals, by comparing (labour) productivity to wage profiles (e.g. Vandenberghe, 2011, 2013; Cataldi, Kampelmann & Rycx, 2011).

9 http://www.euklems.net/

2. Methodology

2.1. Basic Hellerstein-Neumark model

Consider a quality-of-labour-augmented Cobb-Douglas technology specified for (echoing the panel structure of the data used) entity *i* in year *t*:

[1.] $Y_{it}=A_{it}\,K_{it}^{\alpha}\,(QL_{it})^{\beta}$

where Y_{it} is productivity, K_{it} capital, and QL_{it} a quality-of-labour-aggregate à-la-HN, assuming perfect substitutability between labour types L_{it}^{j}

[2.] $QL_{it}=\mu_1 L_{it}^{1}+\ldots+\mu_n L_{it}^{n}=\sum \mu^{j} L_{it}^{j}$

with

$j=1\ldots n$ labour types (e.g. age/education categories)

μ_j reflecting contribution of type j labour to productivity of entity i

To simplify notation, we choose a reference category $j=r$ and divide/multiply all labour terms by $\mu_r L_{it}$. The quality-of-labour-aggregate becomes

[3.] $QL_{it}=\mu_r\,L_{it}\left(S_{it}^{r}+\sum_{j\neq r}\lambda_j\,S_{it}^{j}\right)$

with $S_{it}^{j}=L_{it}^{j}/L_{it}$; $j=1\ldots n$ the share of labour of type j; $\lambda_j\equiv\mu_j/\mu_r$; $j=1\ldots n; j\neq r$ reflecting the (relative) contribution to productivity of type j labour**.**

Exploiting the fact labour shares add up to 1, we can further rewrite the aggregate as

[4.] $QL_{it}=\mu_r\,L_{it}\left(\left[1-\sum_{j\neq r}S_{it}^{j}\right]+\sum_{j\neq r}\lambda_j\,S_{it}^{j}\right)=\mu_r\,L_{it}\left(1+\sum_{j\neq r}(\lambda^{j}-1)\,S_{it}^{j}\right)$

Injecting [4] into [1] and taking the logs lead to

[5.] $lnY_{it}=lnA_{it}+\beta ln\mu_r+\alpha ln(K_{it})+\beta ln(L_{it})+\beta ln\left(1+\sum_{j\neq r}(\lambda_j-1)\,S_{it}^{j}\right)$

HN further exploit the fact that when x is small $ln(1+x)\approx x$. Thus, assuming the λ*'s* oscillate around 1 and/or that labour shares are small, they propose fully linearizing [5]. The HN version of the labour-quality adjusted production function becomes

[6.] $y_{it}=B_{it}+\underbrace{\alpha k_{it}+\beta l_{it}}_{observable\ inputs}+\sum_{j\neq r}\eta_j\,S_{it}^{j}$

with $B_{it}= lnA_{it}+ \beta ln\mu_r; y_{it}=lnY_{it}; k_{it}=lnK_{it}, l_{it}=lnL_{it}, j=1 \ldots n; j\neq r; S_{it}^j=L_{it}^j/L_{it}$;
$\sum_j S_{it}^j=1;\eta^j=\beta(\lambda^j-1); \lambda_j \equiv \mu_j/\mu_r$;

In [6] k_{it}, l_{it} are the usual inputs of a Cobb-Douglas production function. An the part of output y_{it} that is not accounted for by these two variables and their coefficients[10] amounts to (log of) TFP — often called the Solow residual.

$$[7.]\ y_{it}= \underbrace{\alpha k_{it} + \beta l_{it}}_{Total\ capital\ \&\ labour} +lnTFP_{it}$$

where $lnTFP_{it} = B_{it} + \sum_{j\neq r}\eta^j S_{it}^j$

In other words, TFP is directly driven by $\sum_{j\neq r}\eta^j S_{it}^j$ meaning that the HN framework – in particular, the econometric estimation of the η^j – can be used to assess the contribution of different types of labour to TFP; or how changes over time in the mix of labour types impact on TFP growth.

2.2. Accounting for the quality of capital

The data we exploit in this paper (see Section 3) contain information about the amount of capital spending dedicated to ICT. Greater use of ICT is seen by many economists as a potential source of FTP growth enhancement. We will explore this assumption (see Section 4). The point at this stage is to realize that our model can allow for time-varying shares of different types of capital: e.g. ICT vs non ICT.

$$[8.]\ y_{it}= \tilde{B}_{it}+ \underbrace{\alpha k_{it} + \beta l_{it}}_{Total\ capital\ \&\ labour} + \sum_{j\neq r} \eta_j S_{it}^j+ \eta_{ICT} S_{it}^{ICT}$$

with $S_{it}^{ICT}=ICT_{it}/K_{it}$ the share of ICT capital and $\eta^{ICT}=\alpha(\lambda_{ICT} -1);\ \tilde{B}_{it} = lnA_{it}+ \beta ln\mu_r+ \alpha ln\mu_{NICT}$

Note first, that expressions [7], [8] being log linear, the estimated η*'s* capture the impact (in percentage points) on FTP of a unit (i.e. 100%) rise of the share of type j workers (or ICT capital).

Second, if all η*'s*=0 (meaning, if $\beta\neq 0$, that all λ's are equal to 1) then the production function boils down to the standard log-linearized Cobb-Douglas, where labour/capital quality does not matter for TFP. Conversely, if the η's are statistically different from zero (λ's different than 1) then the conclusion is that different quality of labour/capital inputs (e.g. changing levels of

[10] The term $\alpha k_{it} + \beta l_{it}$ *captures* the contribution of capital deepening and (dis)economies of scale. Ignoring the latter (*i.e.* assuming $\alpha + \beta=1$) we have $1+\alpha(k_{it}-l_{it}) = 1+ ln(K_{it}/L_{it})$

educational attainment, degrees of experience workers, or ICT content of capital) matters for TFP. By the same token, any change over time of the labour/capital quality mix will affect TFP *growth*.

Third. As shown by HN in their seminal paper, *QL* [3] can be defined to assume that workers differ along several dimensions (age, education, gender, marital status). An industry's worforce can then be fully described in each of the possible combinations of these sociodemographic characteristics. But either due to data constraints (as in our case) or due to the dimensionality of the problem, it is necessary/convenient to impose two restrictions on the form of *QL*. First: equal relative marginal productivities: i.e. one restricts the relative marginal product of two types of workers (ex: with different educational attainment) within one demographic group (eg. older workers) to be equal to the relative marginal products of those some two types within and other demographic group (e.g. prime-age workers). Second: equiproportionality. This consists of restricting the proportion of workers in an industry defined by a demographic trait (e.g. being old) to be constrant across all other groups (e.g. identical across educational groups). This considerably reduces the number of parameters. Moreover, the production remains fully loglinear. In the case of two dimensions defining a total number of types $j=1...N$ with $N=N_1*N_2;$ $\sum_j S_{it}^j=1$

[9.] $QL_{it}= \mu_r L_{it} \left(1+\sum_{j\neq r}(\lambda_j-1) S_{it}^j\right)$

simplifies to

[10.] $QL_{it}= \mu_{r_{1,2}} L_{it} \left[1+\sum_{j1\neq r_1}(\lambda_{j_1}-1) S_{it}^{j_1}\right] \left[1+\sum_{j\neq r_2}(\lambda_{j_2}-1) S_{it}^{j_2}\right]$

$j_1=1....N_1;\ j_2=1...N_2\ ;\ \sum_{j1} S_{it}^{j_1}=1;\ \sum_{j2} S_{it}^{j_2}=1$

leading to

[11.] $y_{it}= \tilde{B}_{it}+ \alpha k_{it} + \beta l_{it} +\sum_{j1\neq r_1}\eta_{j_2} S_{it}^{j_1} +\sum_{j1\neq r_2}\eta_{j_1} S_{it}^{j_2}+ \eta_{ICT} S_{it}^{ICT}$

Finally, is worth keeping in mind that an estimation of λ_j – that can be retrieved from estimated η and α,β – is equal to the (relative) *marginal* productivity of labour/capital type, and to its marginal contribution to TFP. For example, at the margin, the impact of the share of type *r* workers on total output writes

[12.] $\frac{\partial Y_{it}}{\partial S_{it}^{r}}=A_{it} K_i^{\alpha} L_i^{\beta} \beta(QL_{it})^{\beta-1}\mu_r$

and, almost equivalently, its impact on TFP

[13.] $\frac{\partial TFP_{it}}{\partial s_{it}{}^{r}}= A_{it}\, \beta (QL_{it})^{\beta\text{-}1}\, \mu_r$

For type *j* we have

[14.] $\frac{\partial TFP_{it}}{\partial s_{it}{}^{j}}= A_{it}\, \beta (QL_{it})^{\beta\text{-}1}\, \mu_j$

And, relative to type *r* worker,

[15.] $\frac{\partial TFP_{it}}{\partial s_{it}{}^{j}} / \frac{\partial TFP_{it}}{\partial s_{it}{}^{r}} = \mu_j/\mu_r = \lambda_j$

2.3. Econometric identification

In this paper, achieving a good estimation of parameters α, β and η_j, η_{ICT} is crucial to be able to *i)* isolate TFP from capital intensity and scale issues *ii)* assess the contribution of diverse labour and capital inputs to TFP. Considering that $A_{it}=A_0 e^{\omega it}$, and that $\omega_{it}= \theta_i + v_t + \pi_{it} + \varepsilon_{it}$, we get the econometric version of model [11] to write

[16.] $y_{it}= \tilde{B}_{it}+ \alpha k_{it} + \beta l_{it} +\sum_{j\neq r} \eta_j\, S_{it}{}^{j}+ \eta_{ICT}\, S_{it}{}^{ICT} + v_t + \theta_i+ \pi_{it} + \varepsilon_{it}$

The residual consists of time (v_t) and industryXcountry fixed effects (θ_i) which are easily dealt with using first-difference methods or dummy variables. For simplicity of exposition, we drop them hereafter, and adopt the writing conventions that all variables hereafter correspond to *within* industryXcountry deviations; themselves centred on the international yearly average deviations.

The ε_{it}'s represent productivity shocks that are not observable (or predictable) by industries before making their input decisions (S_{it}'s) at time *t*. In contrast, the π_{it}*'s* are shocks observed/anticipated by decision-makers when choosing their inputs. Intuitively, π_{it} might represent expected defect rates in a manufacturing process, or cold spells affecting some industries (but not observed by the econometrician). We refer to π_{it} as "productivity shocks" of industryXcountry *i* in period *t*. The classic endogeneity problem when estimating [16] is that an industry's optimal choice of inputs k_{it}, $S_{it}{}^{ICT}$, l_{it}, $S_{it}{}^{j}$ could be correlated with the observed or predictable productivity shock $\pi_{it.}$ This may render OLS estimates biased and inconsistent.

Fixed effect models may help. But that amounts to assuming that $\pi_{it.} = \pi_{i}$. and is subsumed into θ_i. One alternative is to use instrumental variable estimation (IV). That requires variables that are correlated with input choices and uncorrelated with $\pi_{it.}$ But that approach has not worked well in practice (see Ackerberg et al. (2007) for more discussion of the limitations of FE and IV).

Here, we rather follow the LP and ACF more structural approach to identification of production functions. ACF generalize the framework developed by LP. Like ACF, we assume that industries' (observable) demand for intermediate inputs (int_{it}) – such as electricity, fuel, or materials − is a function of the time-varying unobserved term π_{it} as well as capital (and its components i.e. the share of ICT) and labour (and its components captured by the labour shares). By contrast, LP assume that the demand of intermediate goods is not influenced by labour inputs. But ACF consider this unrealistic. If $l_{it,}\, S_{it}^{j}$ are chosen before int_{it}, a profit-maximizing (or cost-minimizing) optimal choice of int_{it} will generally directly depend on $l_{it,} S_{it}^{j}$. The ACF specification thus becomes

$$[17.]\ int_{it} = f_t(\pi_{it}, k_{it}, S_{it}^{ICT}, \underbrace{l_{it}, S_{it}^{j}}_{ACF\ addition})$$

Both LP and ACF further assume that this function f_t is monotonic in π_{it} and its other determinants, meaning that it can be inverted to deliver an expression of π_{it} function of int_{it}, k_{it}, S_{it}^{ICT} and also – with ACF – $l_{it,} S_{it}^{j}$, leading to

$$[18.]\ y_{it} = \tilde{B} + \alpha\, k_{it} + \beta l_{it} + \sum_{j\neq r} \eta_j\, S_{it}^{j} + \eta_{ICT}\, S_{it}^{ICT} + f_t^{-1}(int_{it}, k_{it}, S_{it}^{ICT}, l_{it,} S_{it}^{j}) + \varepsilon_{it}$$

The LP-ACF algorithm consists of two stages. For simplicity of exposure we focus on the ACF version that generalizes LP's.

In stage one, ACF regress productivity on a composite term Φ_t that comprises a constant plus a 3^{rd} order polynomial expansion in int_{it}, k_{it}, S_{it}^{ICT},$l_{it,} S_{it}^{j\neq r}$. This leads to

$$[19.]\ y_{it} = \Phi_t(int_{it}, k_{it}, S_{it}^{ICT}, l_{it,} S_{it}^{j\neq r}) + \varepsilon_{it}$$

Note that Φ_t encompasses $\pi_{it} = f_t^{-1}(.)$ displayed in [18] and that α, $ß$ and η_j, η_{ICT} are clearly not identified yet.[11] The point made by ACF is that this first-stage regression delivers an estimate of the composite term Φ_{it}^{hat}; i.e total output net of the purely random term ε_{it}

[11] With LP, coefficients $ß$, η^{j} (i.e. labour input coefficients) are identified at stage 1.

At stage two, key is the idea that one can generate implied values for π_{it} using first-stage estimates Φ_{it}^{hat} and candidate[12] values for the coefficients α, $ß$, η_j, η_{ICT}:

[20.] $\pi_{it}= \Phi_{it}^{hat} - \ddot{\alpha}k_{it} - \ddot{\beta}l_{it} - \sum_{j\neq r}\ddot{\eta}_j S_{it}^{j} - \ddot{\eta}_{ICT}S_{it}^{ICT}$

ACF assume further that the evolution of π_{it} follows a first-order Markov process

[21.] $\pi_{it}= E[\pi_{it} \mid \pi_{it-1}] - \xi_{it}$

That assumption simply amounts to saying that the realization of π_{it} depends on some function $g(.)$ of $t-1$ realisation and a partially known innovation term ξ_{it}.

[22.] $\pi_{it}= g(\pi_{it-1}) +\xi_{it}$

Regressing non-parametrically (implied) π_{it} on (implied) π_{it-1}, π_{it-2}, delivers residuals corresponding to the (implied) ξ_{it} ; that can form a sample analogue to the orthogonality – or moment[13] – conditions identifying α, $ß$ and η_j, η_{ICT}.

Following ACF, we assume that capital (and also its components) in period t were determined during period $t-1$ (or earlier). The economics behind this is that it may take a full period for new capital to be ordered and put to use. Since k_{it}, S_{it}^{ICT} are decided upon $t-1$, $t-2$…, they are assumed uncorrelated to ξ_{it}:

[23.] $E[\xi_{it} \mid k_{it}]=0$; $E[\xi_{it} \mid S_{it}^{ICT}]=0$

Labour inputs observed in t are probably also chosen sometime before, although after capital – say in $t-b$, with $0<b<1$. Therefore, l_{it}, S_{it}^{j} are correlated with at least part of the productivity innovation ξ_{it}. On the other hand, assuming *lagged* labour inputs were chosen at time $t-b-1$ (or earlier), l_{it-1}, S_{it-1}^{j} l_{it-2}, S_{it-2}^{j} … should be uncorrelated with ξ_{it}. This gives us the third (vector) of moment conditions needed for identification via GMM:

[24.] $E[\xi_{it} \mid l_{it-1}, l_{it-2} \cdots]=0$

[25.] $E[\xi_{it} \mid S_{it-1}^{j}, S_{it-2}^{j} \cdots]=0$

[12] OLS estimates, for example.
[13] That can thus be used in a GMM analysis.

3. Data

All the results presented in this paper come from the analysis of the March 2008 release of the EU-KLEMS Growth and Productivity Accounts.[14] This database includes measures of output and inputs at the industry level (i.e. NACE 1-digit, #34). The input measures include various categories of capital (ICT vs non-ICT) and labour (i.e. breakdown by age and educational attainment), but also energy, material and service inputs, that we use to implement the LP and ACF methods mentioned above. These measures are available for 16 countries, mainly EU member states (Austria, Belgium, Czech Republic, Spain, Finland, Germany, Hungary, Italy, the Netherlands, Slovenia and the UK), plus Canada, Australia, South Korea, Japan and the US. They cover country-specific periods ranging from 1970 to 2005. Because of missing information on labour characteristics or ICT the period reported in column 1 of Table 1 is much shorter for most of the countries (Table 1, column 1).

The key variables of the EU-KLEMS data used for the analysis are described in Table 1 and Figure 1. Our dependant variable is the real gross value added (i.e. deflated by the 1995 industryXcountry specific price index). All the results reported in this paper are based on the log-linear HN model [11] and stem from *within* countryXindustry variation over time. Columns 2,3 & 4 of Table 1 describe productivity (gross value added), capital[15] and labour (total hours). The following columns describe the labour and capital mixes at the heart of the HN decomposition. The columns in the middle present the 3 age categories (young [15-29], prime age [30-49] and old [50+]) and the 3 educational types [low, middle and highly-educated[16]]. The last column is about the share of ICT in total capital compensation i.e. our proxy for the quality of capital. Note that in EU-KLEMS, ICT includes computing equipment, communications equipment, and software.

Focusing on the evolutions of the labour/capital mix (Figure 2), the stylised evidence is that of a sharp rise of the share of work accomplished by highly educated (ISCED6+) and

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14 The data series are publicly available on http://www.euklems.net/euk08i.shtml#top

15 In EU-KLEMS, capital service input has been measured in a standard way, using harmonised depreciation rates and common rules to deal with a variety of practical problems, such as weighting and rental rates. Importantly, capital input is measured as capital services, rather than stocks.

16 Respectively ISCED<3, b:ISCED3-5, c: ISCED6+; where ISCED<3, b:ISCED3-5, c: ISCED6+; where ISCED stands for ISCED: International Standard Classification of Education: level 0 – Early childhood education; level 1 – Primary education; level 2 – Lower secondary education; level 3 – Upper secondary education; level 4 – Post-secondary non-tertiary education; level 5 – Short-cycle tertiary education; level 6 – Bachelor’s or equivalent level; level 7 – Master’s or equivalent level; level 8 – Doctoral or equivalent.

old/experienced workers (50+). In most countries, the share of ICT is also on the rise, but less markedly.

Table 1: Descriptive statistics. Country mean[$]

Country (first, last observation)	Value added[gross][£]	Capital[£]	Labour[hours]	Labour, capital mix (shares) Young (15-29)	Prime age (30-49)	Old (50+)	Low edu[a]	Medium edu[b]	High edu[c]	Spending on ICT[d]
AUS82_05	6.93	5.84	7.90	0.33	0.49	0.18	0.52	0.36	0.13	0.12
AUT80_05	5.75	4.64	7.05	0.30	0.52	0.17	0.28	0.65	0.08	0.09
BEL80_05	6.00	4.94	6.94	0.27	0.55	0.18	0.47	0.42	0.10	0.13
CAN70_04	5.35	4.14	6.64	0.46	0.44	0.10	0.11	0.78	0.11	0.11
CZE95_05	8.03	7.10	7.42	0.25	0.51	0.23	0.09	0.80	0.11	0.10
ESP80_05	6.79	5.77	8.37	0.28	0.50	0.22	0.65	0.22	0.13	0.10
FIN70_05	5.10	3.82	6.58	0.31	0.51	0.18	0.43	0.36	0.22	0.10
GER91_05	8.33	7.08	9.31	0.22	0.57	0.22	0.29	0.63	0.08	0.13
HUN95_05	9.49	8.53	7.22	0.27	0.55	0.18	0.17	0.68	0.14	0.12
ITA70_05	7.38	6.10	8.69	0.28	0.62	0.10	0.04	0.90	0.06	0.09
JPN73_05	13.59	12.63	9.90	0.29	0.48	0.23	0.23	0.59	0.18	0.08
KOR77_05	13.31	12.04	8.79	0.38	0.51	0.11	0.26	0.46	0.28	0.07
NLD79_05	6.38	5.15	7.55	0.31	0.52	0.17	0.11	0.81	0.08	0.12
SVN95_05	3.11	1.77	5.63	0.24	0.60	0.16	0.20	0.65	0.15	0.18
UK70_05	7.08	5.76	9.07	0.35	0.46	0.19	0.33	0.59	0.09	0.13
USA70_05	9.51	8.40	10.63	0.41	0.46	0.13	0.16	0.61	0.23	0.11
N	13,237									

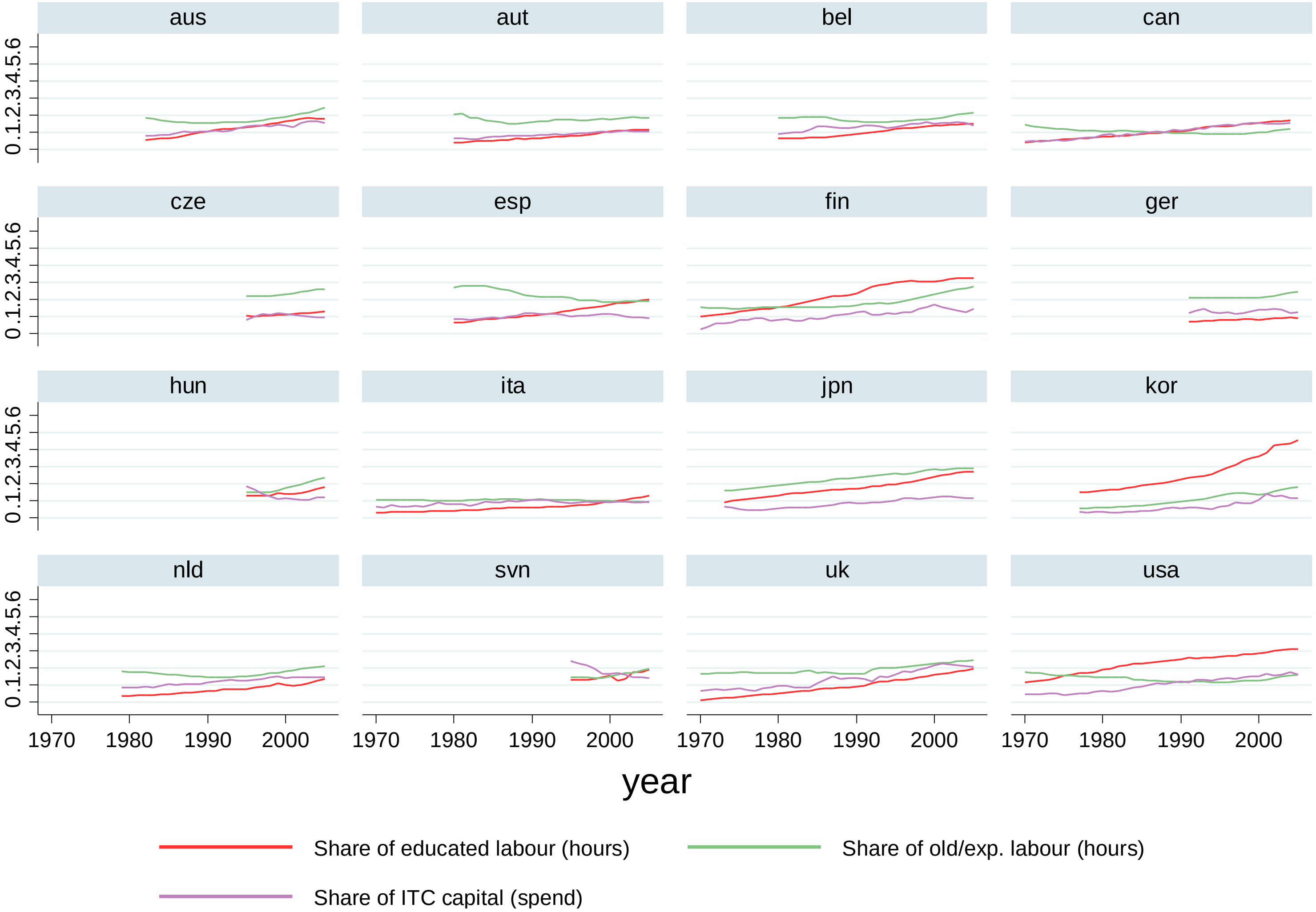
Source:EU-KLEMS 2008.

$ Intracountry weights= industryXcountry number of hours worked

£ Log of (*x*), where *x* in 1995 millions of local currency.

a : ISCED<3, b:ISCED3-5, c: ISCED6+, d: ICT capital compensation (share in total capital compensation)

Figure 2 - Descriptive statistics. Share[$] of hours worked by (highly) educated[a] workers and old/experienced workers and share of ICT in total capital spending



Source : EU-KLEMS 2008.
$ Intracountry weights= Sector/country number of hours worked ; a: ISCED6+

4. Econometric results

4.1. Microeconometric estimates

All the results presented hereafter (Table 2) are obtained from the estimation the following econometric version of the HN log-linearized model [11].

[26.] $y_{it}= \tilde{B}_{it}+ \alpha k_{it} + \beta l_{it} +\eta_{Pa}\, S_{it}^{Pa} +\eta_{Old}\, S_{it}^{Old} + \eta_{Medu}\, S_{it}^{Medu}+\eta_{Hedu}\, S_{it}^{Hedu} + \eta_{ICT}\, S_{it}^{ICT}$

$+ v_t + \theta_i+ \pi_{it} + \delta_{it}$

The basic entity *i* consists of one of the 34 industries within one of the 16 countries documented in EU-KLEMS (i=1….N=34*16). This means that we systematically pool all the countries. But we account for country/industry fixed effects (θ_i), and also year fixed effects (v_t) to control for output/TFP growth common period-specific shocks.

The key results are reported in Table 2. They have been obtained using first differences [applied to 5-year intervals (t=1970, 1975…, 2005) data[17]] to account for fixed effects θ_i. While OLS assumes that π_{it} is nil on average and uncorrelated to the other inputs, both LP and ACF allow for this term to cause endogeneity.

The results essentially convey the idea that better-quality inputs are good for TFP (growth[18]). First we find strong evidence that rising share of older (and presumably more experienced) workers is positively correlated with TFP. Second, a larger share of highly educated workers (ISCED6+) is also strongly positively correlated with TFP growth. Note that there is no statistically evidence that workers with a medium educational attainment (i.e. ISCED3,4,5 for most countries) are more productive than low-educated workers forming the reference category. Finally, Table 2 contains evidence that ICT is good for TFP.

The lower part of Table 2 reports estimates the relative marginal productivities that may be inferred from the estimated α,β and η*'s*. First education. We find that the implied marginal productivity for the medium educated workers is not statistically different than that of the reference group (i.e. low-educated workers). By contrast, highly-educated workers appear much more productive: between 87 and 130%. Turning to age, compare to younger workers aged 15-29, those aged 30-39 appear about 50% more productive. What is more, older workers

17 As a robustness check, we replicated the analysis using 3-year intervals. Results are very like those reported in Table 2.

18 Our variables consist of first-differenced logs, i.e. approx. growth rates.

aged 50 or more appear between 140 and 220% more productive.[19] Finally, ICT appears between 30 and 50% more productive than more traditional forms of capital. From a more econometric point of view, note that LP and ACF deliver results that are qualitatively equivalent to OLS (used in combination with IndustryXCountry and year fixed effects). This suggests an absence of serious endogeneity bias in the EU-KLEMS time series.

Table 2 – Output (gross value added) as function of age, education and ICT use. OLS, LP and ACF estimated. HN log-linear specification. Point estimates (standard errors) based on 5-year intervals

	OLS	LP	ACF
α [Capital]	0.267***	0.264***	0.140***
	0.000	0.000	0.000
β [Labour]	0.682***	0.374***	0.573***
	0.000	0.000	0.000
η_{Medu} *[Share medium-educated]* [a]	0.126*	-0.0777	-0.0559
	(0.096)	(0.099)	(0.101)
η_{Hedu} *[Share highly-educated]* [a]	0.595***	0.661***	0.751***
	(0.157)	(0.162)	(0.166)
η_{Pa} *[Share prime age 30-49]* [a]	0.369***	0.198	0.288*
	(0.106)	(0.109)	(0.112)
η_{Old} *[Share old 50+]* [a]	0.992***	0.828***	0.975***
	(0.145)	(0.150)	(0.153)
η_{ICT} *[Share ICT]* [b]	0.102*	0.133**	0.0422
	(0.042)	(0.043)	(0.044)
Controls	IndustryXcountry, 5-year interval		
Nobs	2,453	2,453	2,453
Implied relative marginal productivities			
Ref. (low-educ, young (15-29), non-ICT capital)	1	1	1
λ_{Medu} *[medium educated]*	1.185	0.792	0.903
Prob λ_{Medu} =1	0.188	0.432	0.581
λ_{Hedu} *[highly educated]*	1.872***	2.766***	2.309***
Prob λ_{Hedu} =1	0.000	0.000	0.000
λ_{Pa} *[30-49]*	1.541***	1.529*	1.502**
Prob λ_{Pa} =1	0.000	0.070	0.010
λ_{Old} *[50+]*	2.453***	3.215***	2.700***
Prob λ_{Old} =1	0.000	0.000	0.000
λ_{ICT} *[ICT]*	1.385*	1.505**	1.302
Prob λ_{ICT} =1	0.014	0.002	0.337

Standard errors in parentheses
Source: EU-KLEMS 2008. All results stem from within industry(#34)Xcountry(#16) variations
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[a] $\eta_j \equiv \beta(\lambda_j - 1)$; [b] $\eta_{ICT} \equiv \alpha(\lambda_{ICT} - 1)$

4.2. Quantifying the impact of better-quality inputs on TFP growth

One of the objectives of this empirical paper is to quantify the aggregate impact of better-quality inputs on TFP. To do this, we use the OLS[20] estimated $\hat{\alpha}, \hat{\beta}, \hat{\eta}$ (the parameters of [26] displayed

19 The worker sample underpinning EU-KLEMS might not be representative of the entire population of older individuals aged 50 and more. This means that there is a risk of a *selection bias*, due to early ejection from the workforce of less productive/motivated older workers. To the extent that this selection bias is an issue, we could view our estimated coefficients for older workers' productivity as upper boundaries.

20 LP, ACF deliver coefficients that are very similar to those obtained using OLS. They deliver similation/growth accounting results that are qualitatively very similar to those exposed hereafter.

in Table 2) alongside observed values of the labour shares S_t^j or ICT shares S_t^{ICT} and compute the (log of) TFP as

[27.] $\widehat{lnTFP}_{it} = y_{it} - \hat{\alpha} k_{it} - \hat{\beta} l_{it}$

and, the part that can be ascribed to its mix of labour and capital types

[28.] $\hat{\psi}_{it} = \sum_{j \neq r} \hat{\eta}^j S_{it}^j + \hat{\eta}_{ICT} S_{it}^{ICT}$

More importantly [27] and [28] can be used to explore baseline vs counterfactual scenarii. Typically, considering a period (e.g. 1995-2005), one can estimate how the (log of) TFP would have evolved had the educational/age/ICT mix remained partially or totally unchanged (i.e. with some or all the shares 'blocked' at their reference (e.g. 1995) level)

[29.] $lnTF\widehat{P^{counterf}}_{it} = \widehat{lnTFP}_{it} - \hat{\psi}_{it}(\hat{\eta}, S_{it}^j, S_{it}^{ICT}) + \hat{\psi}_{it}(\hat{\eta}, S_{iref}^j, S_{iref}^{ICT})$

First, we compute [27] the baseline and [29] the counterfactual scenarii (distinguishing case 1: no educational change, case 2: no educational and age mix changes, case 3: no education, age and ICT mix changes).

Second, we aggregate these estimates at the level of each countryXyear using the total number of hours worked in each industry as weights.

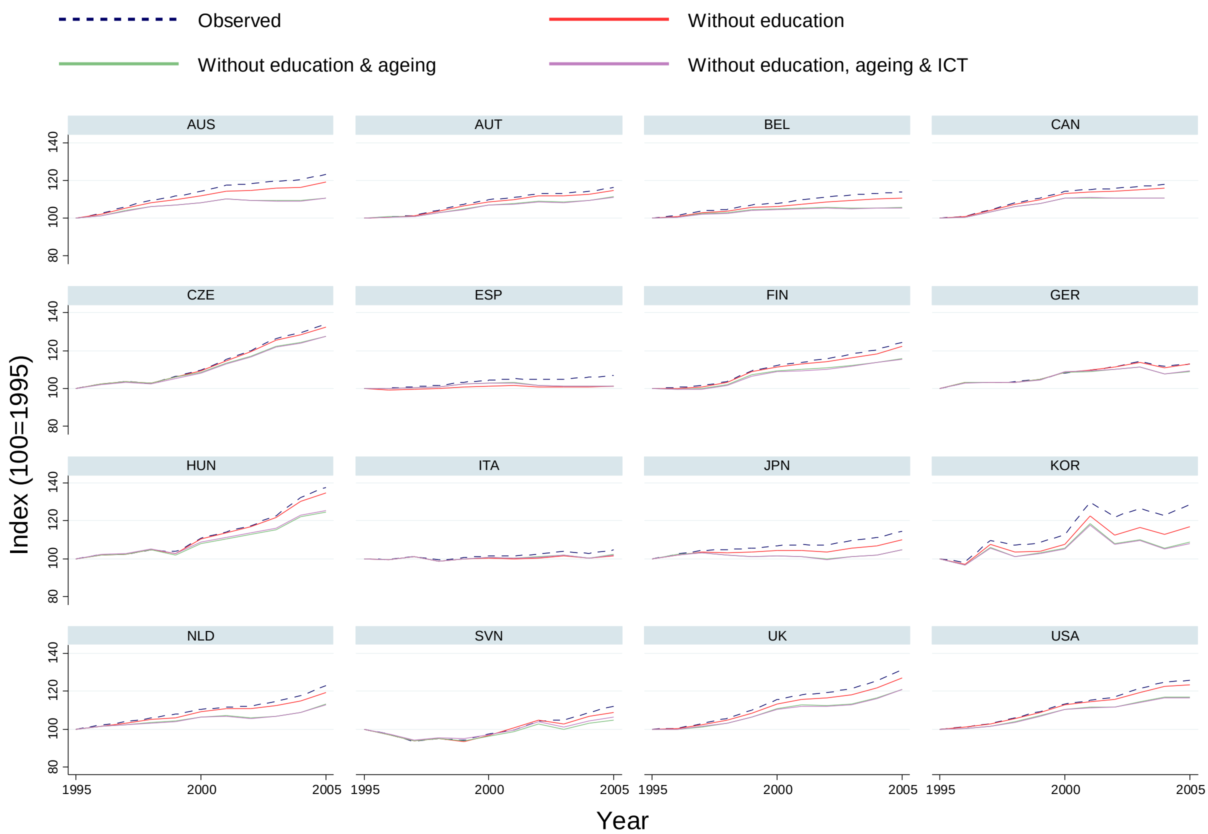
Third, we compute three growth-rate indices covering the period 1995-2005 (100=1995). The first one (Table 3, col. [a]) corresponds to the baseline (i.e observed) TFP growth. The second one to TFP growth minus the contribution of larger shares of better-educated workers [b]. It informs about what would have happened to TFP growth in the absence of changes in the educational composition of the workforce. The third index [c] is equal to observed TFP growth minus the contribution of both education and ageing (i.e. larger (smaller) shares of older (younger) workers). The last index [d] is equal to observed TFP growth minus the contribution of education, ageing and changing share of ICT.

Figure 3 plots these three indices. In Figure 4, we single the USA out. Table 3 reports the end-of-period (i.e. 2005) value of the three indices plotted on Figures 3.

The results that emerge from Figures 3,4 and Table 3 (last column) suggest that, on average, 40% of the TFP growth recorded during the 1995-2005 period could be ascribed to an improvement of the quality of inputs. But this is an average. For some countries (CZE), results show a limited contribution (<20%) of changes in the age, education and ITC mixes. For other countries (KOR), these exceed 70%. In all, it is the rise of experience (proxied here by the share of older workers) that turns out to be the biggest contributor ([b]-[c]), followed by that of the rising educational attainment of the workforce ([a]-[b]). Finally, the dissemination of ICT seems to have had a negligible impact on TFP growth ([c]-[d]).

Note finally that our simulations confirm the presence of cross-country heterogeneity, often in line with well-known stylised facts. South Korea (KOR) for instance displays a solid TFP growth performance whereas Italy (ITA) lags behind. Also Figure 3, shows that in South Korea's educational attainment rose dramatically over the recent decades; in line with what is commonly said about the country's rapid transformation.

Figure 3 - Sensitivity of cumulative TFP growth over the 1995-2005 period (100=1995) to changes in the education/age composition of the workforce and share of ICT in total capital



Source: EU-KLEMS 2008, our calculus

Figure 4 – USA, sensitivity of cumulative TFP growth over the 1995-2005 period (100=1995) to changes in the education/age composition of the workforce and share of ICT in total capital

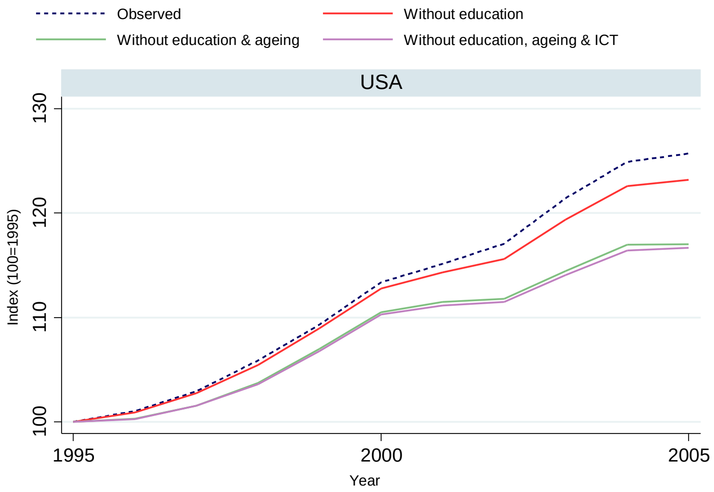


Table 3 - Sensitivity of cumulative TFP growth over the 1995-2005 period (100=1995) to changes in the education/age composition of the workforce and share of ICT in total capital

Country	Observed TFP [a]	TFP without edu. change [b]	[a]-[b]	TFP without edu & age changes [c]	[b]-[c]	TFP without edu. age & ICT changes [d]	[c]-[d]	[e]=[a]-[d]	[e]/([a]-100)%
AUS	123.16	119.06	4.09	111.19	7.87	110.94	0.26	12.22	52.77%
AUT	116.18	114.61	1.57	111.56	3.05	111.34	0.22	4.84	29.91%
BEL	113.77	110.81	2.96	106.04	4.77	105.93	0.12	7.84	56.96%
CAN	117.93	115.89	2.04	111.10	4.78	111.06	0.04	6.87	38.29%
CZE	133.92	132.44	1.47	127.95	4.49	127.92	0.03	5.99	17.68%
ESP	106.80	101.18	5.62	101.28	-0.10	101.37	-0.09	5.43	79.86%
FIN	124.34	122.39	1.96	116.37	6.02	115.95	0.42	8.39	34.46%
GER	112.97	112.84	0.13	109.11	3.73	109.59	-0.48	3.38	26.07%
HUN	137.68	134.73	2.95	125.06	9.67	125.86	-0.80	11.82	31.36%
ITA	104.65	101.53	3.12	102.08	-0.55	101.99	0.09	2.66	57.14%
JPN	114.68	109.89	4.79	104.95	4.94	104.90	0.05	9.78	66.62%
KOR	128.66	116.60	12.06	108.98	7.62	108.52	0.46	20.15	70.29%
NLD	122.89	119.39	3.49	113.39	6.01	113.05	0.34	9.84	42.99%
SVN	112.17	108.81	3.36	104.94	3.86	106.46	-1.52	5.71	46.91%
UK	131.32	127.11	4.20	121.39	5.72	121.20	0.19	10.11	32.29%
USA	125.70	123.10	2.60	117.28	5.82	116.94	0.34	8.75	34.06%
Average[a]	***120.42***	***116.90***	***3.53***	***112.04***	***4.86***	***112.06***	***-0.02***	***8.36***	***40.94%***

Source: EU-KLEMS 2008, our calculus

a: arithmetic

Conclusion

Demographic changes in most advanced economies are synonymous with population ageing. Thus, working-age pools of individuals tend to level off or even shrink, implying that GDP growth can no longer be driven by a rise in the size of labour forces. This should lead economists and policymakers to focus on the other main source of growth: labour productivity gains. This paper contributes to this stream of research by looking at the role of better-quality inputs in explaining total factor productivity (TFP) growth.

Using industry-level panel data covering the US, Europe and the most advanced economies of Asia (Japan and South Korea), we try to quantify the causal impact of larger share of better-educated, but also older/more experienced workforces on TFP growth. The fact that workforces become better educated is the direct consequence of a continuous rise in participation to formal education observed over the past decades in most advanced economies. And the rise of labour-market experience is a direct by-product of ageing: when populations growth older, the share of prime-age and older workers — with more on-the-job experience — tend to rise concomitantly. In this paper, we also explore the role of better-quality capital, by looking at the impact on TFP of rising shares of information and communication technology (ICT) in total capital spending.

Our results derive primarily from the estimation of production functions specified as Cobb-Douglas expanded to include input-quality indexes à-la Hellerstein & Neumark (1995). This is a way to account for the heterogeneity of labour (i.e. educated/less educated; young/prime age/old workers…). We show that this method can be use to reflect that of capital inputs (e.g. ICT/non-ICT capital). Another novelty of the paper is to show the HN approach amounts to establishing input heterogeneity as a direct component of the TFP/Solow residual.

The results of the paper are essentially sixfold.

First, our microeconometric results show that highly-educated workers (ISCED6+) contribute positively to TFP growth. This is not the case of medium-educated workers (ISCED3-5). Such a results points at the key role of innovation-driven productivity growth in advanced economies (Aghion et al., 2006). The idea is that only the most advanced forms of education (typically tertiary/university degrees) contribute to the technological-, product- or managerial changes underpinning productivity growth. This perspective emphasizes the importance of increasing access and participation to tertiary education.

Second, older/more experienced workers also contribute positively to TFP growth. Many economists stress the risk of age-related productivity losses (Skirbekk, 2004, 2008; Vandenberghe, 2011; Vandenberghe et al. 2013). We find no evidence of this here. Quite the contrary.

Third, we also find a positive – but intrinsically smaller – effect on TFP of rising ICT shares in total capital.

Fourth, turning to our 1995-2005 simulations[21], based on the above microeconometric results, we find that up to 40% of the TFP growth recorded over that period could be ascribed to an improvement of the quality of inputs. Although not entirely comparable due data differences, our results contrast with those of Fox & Smeets (2011): their (rather detailed) measures of the quality of labour explain only 15 to 18% of TFP dispersion across Danish firms.[22]

Fifth. Our data hint at a lot of cross-country heterogeneity as to the magnitude of input quality changes. But all told, it is the rise of experience (proxied by the share of older workers) that turns out to be the biggest contributor to TFP growth, followed by that of the rising educational attainment of the workforce. And it is ICT that seems to have had the smallest combined[23] impact. The latter result could be interpreted of another illustration of the Solow computer paradox.[24]

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[21] In a nutshell, our simulations are driven by two things: the magnitude of the estimated coefficients and that of the changes in the input share. They thus reflect thus the combined effect of the two dimensions.

[22] Labour market history, such as experience and firm and industry tenure, as well as general human capital measures such as schooling and gender

[23] A relatively small marginal productivity premium for ICT, combined to not-so-large rises of the share of ICT into total capital.

[24] In reference to Robert Solow's 1987 quip: "You can see the computer age everywhere but in the productivity statistics".

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