On the Measurement of Technological Progress Across Countries

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Abstract. We construct 14 alternative measures of technological progress for 19 OECD countries over the period 1970–2000, distinguishing between measures of productivity gains actually obtained in a given country (TFP growth, Malmquist index) and technological progress at the world technology frontier (potential TFP growth, the "frontier shift" index). We then compare these measures according to a range of characteristics, shedding light on some of their relative weaknesses and strengths. We find that these characteristics are sensitive to the precision of estimates of the world technology frontier, and then we demonstrate that this precision can be increased substantially by allowing for imperfect substitutability between unskilled and skilled labor and using US state-level data apart from cross-country data for estimating the world technology frontier. Because none of the 14 measures dominates all others on all dimensions, we conclude that the choice of appropriate measurement method should be suited to the question addressed in each particular study.

Keywords and Phrases: technological progress, world technology frontier, country-level data, US state-level data, production function, DEA

JEL Classification Numbers: E23, O11, O14, O33, O47

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1 Introduction

Since the seminal work of Solow (1957) technological progress has been casually identified with growth of *residual productivity*, an umbrella term containing everything that could not be traced back to the accumulation of factors of production, included in the aggregate production function. It is however uncertain – and competing methodologies provide conflicting clues on that – what exactly this production function should be. The objective of the current article is to investigate this matter more closely. Rather than trying to provide direct empirical evidence on the actual shape of the production function, we shall remain agnostic about it and instead carry out an indirect study focusing on the properties of 14 alternative specifications of technological progress (i.e., growth of residual productivity). In particular, we will investigate the following measures: two versions of total factor productivity (TFP) growth, four versions of *potential* TFP growth, four measures of shifts in the world technology frontier (WTF), and four Malmquist indices. By contrasting the standard TFP growth-based approach with approaches based on deterministic frontier models,[1] we will show in which respects the predictions for technological progress are robust to changes of the production function specification, and in which respects they are not.[2]

The contribution of the current article to the literature is to provide a synthetic, numerical assessment of the relative advantages and disadvantages of a number of approaches to the measurement of technological progress across countries. To this end, we will compute (i) the fraction of growth in GDP per worker explained by the technological progress (residual) component in each of the 14 specifications, and (ii) the explained fraction of its cross-sectional and intertemporal variance. We will also calculate the correlations of these residual measures with productivity growth as well as ex post prediction errors when productivity growth is predicted as the factor-only component. The focus of the study will be with 19 high-income OECD countries in the period 1970–2000.

The novelty of the current study is twofold. First, we are probably the first to bring together several alternative methods of measurement of technological progress across countries, including both parametric and non-parametric ones, with the objective of comparing their properties. Second, 10 of our 14 measures of technological progress are based on estimates of the world technology frontier computed with an auxiliary use of US state-level data, an approach which is likely to improve the precision of these estimates markedly, and which has not been analyzed in the literature yet.

[1]See, among others, Färe et al. (1994), Kumar and Russell (2002), Henderson and Russell (2005), Jerzmanowski (2007), Badunenko, Henderson and Zelenyuk (2008), and Growiec (2009).

[2]By doing so, we omit the strand of literature which deals with CES production functions (e.g., Duffy and Papageorgiou, 2000; Antràs, 2004). Clearly, relaxing the Cobb–Douglas production does not imply the need for an immediate jump into the "extreme" non-parametric case where no explicit functional form of the production function is assumed. The class of CES production functions is perhaps the most natural extension of the Cobb–Douglas baseline. Hence, incorporating (appropriately calibrated) CES functions into the comparison is left for further research.

From our results, a clear picture emerges that there are actually two entirely different and complementary groups of measures of technological progress: productivity gains actually obtained in a given country (TFP growth, Malmquist index), and technological progress at the world technology frontier (potential TFP growth, the "frontier shift" index). The differences between these two groups of measures are visible in almost all analyzed characteristics. To emphasize them further, we also carry out a confirmatory factor analysis and justify the validity of two composite measures obtained when the variables are considered as dimensions in respective summary scales.

In the end, the bottom line of the study is that the researcher's choice of method of measuring technological progress across countries should always be selected in accordance with the analyzed question. There is no unique best choice; all "goodness of fit" measures vary significantly with changes in methodology, and different methods are best in explaining average productivity growth rates, and different methods excel in capturing their variance. The only two general rules are that in principle, (i) the precision of frontier estimates matters a lot for the predictions on technological progress, especially if progress at the world technology frontier is considered, and that (ii) the results of our non-parametric analysis indicate marked departures from the Cobb–Douglas benchmark and from perfect substitution between skilled and unskilled labor.

The article is structured as follows. In Section 2, we specify the 14 alternative measures of technological progress. In Section 3, we describe our dataset. In Section 4, we provide our main results regarding the quality and usefulness of each particular measure of technological progress. Section 5 provides evidence why it is important to distinguish between measures of technological progress at the frontier and in each given country. Section 6 concludes.

2 Measurement of technological progress

2.1 Information sets

In the current study, we consider 14 alternative specifications of technological progress. This multiplicity can be logically grouped into four categories of specifications according to the information set used for computing the rate of technological progress, or – alternatively – into four categories differing in methodology. These two complementary dimensions naturally lead to a 4×4 matrix with the four alternative information sets used for inferring about the shape of the WTF in columns and the four methodologies of construction of the production function in rows. Hence, in columns of this matrix we put information sets $\mathcal{I}_i,\ i = 1, 2, 3, 4$:

- $\mathcal{I}_1$: data on OECD countries and US states, including GDP per worker and the stock of physical capital per worker;
- $\mathcal{I}_2$: data on OECD countries only, including GDP per worker as well as physical

and human capital per worker;

- $\mathcal{I}_3$: data on OECD countries and US states, including GDP per worker as well as physical and human capital per worker;
- $\mathcal{I}_4$: data on OECD countries and US states, including GDP per worker, physical capital and the stocks of unskilled and skilled labor per worker.

Having defined the information sets as above, we immediately note the following nesting relationships: $\mathcal{I}_1 \subset \mathcal{I}_3 \subset \mathcal{I}_4$ and $\mathcal{I}_2 \subset \mathcal{I}_3 \subset \mathcal{I}_4$.

The obvious advantage of using $\mathcal{I}_3$ over $\mathcal{I}_1$ is that human capital is widely agreed in the literature to be one of the important factors driving short-to-medium run productivity growth and convergence, and thus omitting it overstates the role of residual productivity growth.

The advantage of using $\mathcal{I}_3$ over $\mathcal{I}_2$ comes from the fact that the US are a country with substantial internal heterogeneity in productivity, which always spans the world technology frontier (WTF hereafter) when considered as a single data point (cf. Henderson and Russell, 2005). Hence, we expect that the WTF will be estimated with less precision when internal heterogeneity of the US is disregarded than in the case when the particular US states are included in the dataset as well.[3]

In the case of $\mathcal{I}_4$ we assume that the stocks of unskilled and skilled labor are a decomposition of human capital per worker h such that $h = L^U + L^S$. L^U captures human capital per worker in the sub-population with less than secondary education, whereas L^S captures human capital per worker in the sub-population with secondary or higher education. Allowing unskilled and skilled labor to be imperfectly substitutable in the aggregate production function follows from, among others, Caselli and Coleman (2006) and empirical evidence in Pandey (2008), thus explaining the advantage of using $\mathcal{I}_4$ over $\mathcal{I}_3$.

One possible *disadvantage* of using larger information sets instead of smaller ones is, on the other hand, that all our macroeconomic variables are measured (constructed) with inevitable error, and some of these errors may cancel out in the aggregate case but (unwillingly) drive some of our results in the disaggregate case.

2.2 Methods of measurement

If the four information sets are arranged in consecutive columns of the 4×4 matrix, then in its rows we put the following four alternative methods for computing technological progress, sorted according to increasing methodological sophistication:

1. <u>TFP growth rate</u> from a Cobb–Douglas production function, computed using either only physical capital and labor as inputs (in the first column of the matrix),

[3]See Growiec (2009) for a discussion on the appropriateness of sub-national disaggregation of the US and consequences of the idea to disaggregate other countries, or US states themselves.

or both physical and human capital (other three columns). This measure captures growth of the Solow residual:

$$\frac{A_t - A_{t-1}}{A_{t-1}} = \frac{y_t}{y_{t-1}} \left(\frac{k_{t-1}}{k_t}\right)^{\alpha} - 1$$

or

$$\frac{A_t - A_{t-1}}{A_{t-1}} = \frac{y_t}{y_{t-1}} \left(\frac{k_{t-1}}{k_t}\right)^{\alpha} \left(\frac{h_{t-1}}{h_t}\right)^{1-\alpha} - 1$$

respectively, where α takes the "consensus" value of 1/3 (Kydland and Prescott, 1982), k denotes physical capital per worker, h denotes human capital per worker, y denotes output per worker, and the stock of labor drops out due to constant returns to scale.

2. Potential TFP growth rate from a Cobb–Douglas production function, computed using either only physical capital and labor as inputs (in the first column of the matrix), or both physical and human capital (other three columns). This measure captures growth of the "potential" Solow residual:

$$\frac{A_t - A_{t-1}}{A_{t-1}} = \frac{y_t^*(x_t)}{y_{t-1}^*(x_{t-1})} \left(\frac{k_{t-1}}{k_t}\right)^{\alpha} - 1$$

or

$$\frac{A_t - A_{t-1}}{A_{t-1}} = \frac{y_t^*(x_t)}{y_{t-1}^*(x_{t-1})} \left(\frac{k_{t-1}}{k_t}\right)^{\alpha} \left(\frac{h_{t-1}}{h_t}\right)^{1-\alpha} - 1$$

respectively, where $\alpha = 1/3$ and y^* is the maximum output per worker attainable given inputs. This number is evaluated from the world technology frontier, computed using data from the particular information set $\mathcal{I}_n, n = 1, 2, 3, 4$, according to the non-parametric Data Envelopment Analysis (DEA) algorithm (cf. Fried, Knox Lovell, and Schmidt, 1993). By x we denote the country-specific vector of inputs: $x_t = k_t$ for the information set $\mathcal{I}_1$, $x_t = (k_t, h_t)$ for $\mathcal{I}_i, i = 2, 3$, and $x_t = (k_t, L_t^U, L_t^S)$ for $\mathcal{I}_4$.

3. Rate of technological progress at the world technology frontier (WTF), computed from a production function constructed with the non-parametric DEA algorithm, using the information set $\mathcal{I}_n, n = 1, 2, 3, 4$. The formula for the relevant growth rate is

$$\frac{A_t - A_{t-1}}{A_{t-1}} = \sqrt{\frac{y_t^*(x_t)}{y_{t-1}^*(x_t)} \frac{y_t^*(x_{t-1})}{y_{t-1}^*(x_{t-1})}} - 1.$$

This measure isolates the effects of technological progress at the WTF from the effects of factor accumulation and movements along the WTF.[4]

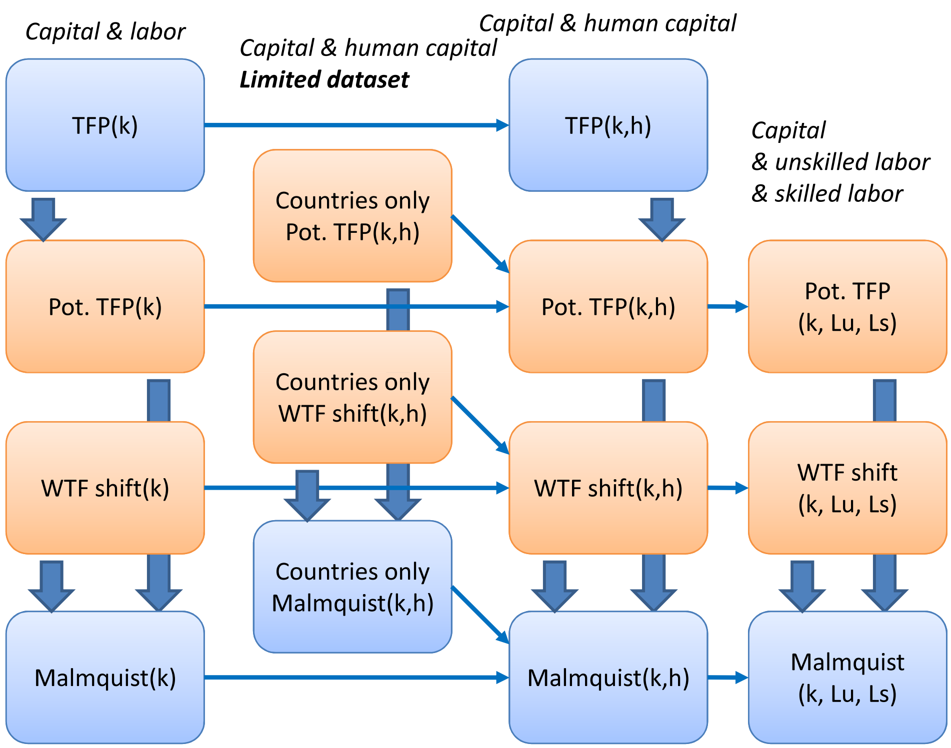
[4] Here and in the next formula, the square root appears for the index to be Fisher-ideal (see e.g., Henderson and Russell, 2005, for a discussion).

4. The Malmquist productivity index, computed from a production function constructed with the non-parametric DEA algorithm, using the information from set $\mathcal{I}_n, n = 1, 2, 3, 4$. The formula for the relevant growth rate is

$$\frac{A_t - A_{t-1}}{A_{t-1}} = \frac{E_t}{E_{t-1}} \sqrt{\frac{y_t^*(x_t)}{y_{t-1}^*(x_t)} \frac{y_t^*(x_{t-1})}{y_{t-1}^*(x_{t-1})}} - 1,$$

where E_t measures technical efficiency, i.e. the percentage of maximum attainable output which is actually produced by the given country: $y_t = E_t \cdot y_t^*$. Since the Malmquist index is a product of the efficiency ratio and the WTF shift factor, it both isolates the effects of technological progress at the WTF from effects of factor accumulation and movements along the WTF, and captures technological progress actually observed in a given country.

Figure 1: Diagram of nested specifications.



Notes: small arrows $A \rightarrow B$ indicate that the set of information used in A is a subset of the one used in B. Thick arrows $A \Rightarrow B$ indicate that A is less sophisticated methodologically than B. Blue boxes indicate measures of technological progress in a given country. Red boxes indicate measures of technological progress at the frontier.

The following two facts are also worth noting. First, measurement of TFP growth across countries does not change whether we include US states in the dataset as well or not. Second, there is (unfortunately) no clear consensus in the literature on the elasticity of substitution between skilled and unskilled labor which could then be inserted as a "human capital" aggregate into a Cobb-Douglas production function with physical and human capital (cf. Caselli and Coleman, 2006). In earlier literature where human capital was treated as homogenous factor, this elasticity was assumed to be infinite. We replicate this assumption here to conform with that literature, and hence our measure of TFP growth boils down to the same number in the cases of all three information sets $\mathcal{I}_2, \mathcal{I}_3, \mathcal{I}_4$, resulting in two empty slots in our 4×4 matrix.

A diagram of relationships among all specifications and information sets is presented in Figure 1. To distinguish between measures of technological progress along the WTF and measures of progress actually observed in each given country, we have indicated this discrepancy in the diagram by coloring the boxes representing the first group of approaches in red, and the other group – in blue.

2.3 Data Envelopment Analysis

As is visible in the preceding discussion, in three of the four methodologies for computing technological progress across countries we view the technological developments in each country as relative to some estimate of the world technology frontier. Knowing the maximum attainable (frontier) productivity given factor inputs in country i at time t, $y_t^*(x_{it})$, is thus crucial for obtaining these measures of technological progress.

To obtain the estimates of productivity at the WTF, i.e., the best-practice production function, we use the nonparametric DEA algorithm, introduced to macroeonomics by Färe et al. (1994) and followed by, among others, Kumar and Russell (2002), Henderson and Russell (2005), Jerzmanowski (2007), Badunenko, Henderson and Zelenyuk (2008), and Growiec (2009). The principal idea behind DEA is to envelop all data points in the "smallest" convex cone and to infer the production function as a fragment of the boundary of this cone for which output is maximized given inputs, i.e. as a convex hull of production techniques (input–output configurations) used in the current data. For each country i and period t, the DEA method provides a decomposition of output y_{it}:

$$y_{it} = E_{it} y_t^*(x_{it}), \tag{1}$$

into a product of the maximum attainable output given inputs $y_t^*(x_{it})$ and the (output-oriented Debreu–Farell) efficiency index $E_{it} \in (0, 1]$. The efficiency index E_{it} measures the "vertical" distance of country i to the technology frontier at time t.

Since each dataset contains a finite number of data points, one for each territorial unit and each year, by construction the DEA–based production function will be piecewise linear and its vertices will be the actually observed *efficient* input–output configurations. A detailed description of the DEA procedure is available e.g. in Fried, Knox Lovell and Schmidt (1993).

3 Data

The dataset used in the study covers 19 highly developed OECD countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and United States, as well as 40 US states.[5] The sample covers the period 1970–2000, in 5-year intervals. Even though the frequency of the data is low, due to the limited availability of human capital data, it is nevertheless sufficient the purposes of the current study which focuses on medium-to-long run phenomena. All the data we are using are set in *per worker* terms.

International data on GDP and GDP per worker are taken from the Penn World Table 6.2 (Heston, Summers, and Aten, 2006), and US state-level GDP and GDP per worker – from the Bureau of Economic Analysis, Regional Accounts. The unit of measurement is the PPP converted US dollar under constant prices as of year 2000. US state-level data have been adjusted to guarantee internal coherence with the aggregate US data from the Penn World Tables.

The physical capital series have been constructed using the perpetual inventory method described, among others, by Caselli (2005) and OECD (2009). We have taken country-level investment shares as well as government shares from the Penn World Tables 6.2. The procedure for constructing state-level physical capital data for our study is more complicated due to missing data. Description of the imputation process can be found in the appendix.[6]

Country-level human capital data have been taken from de la Fuente and Doménech (2006), and US state-level human capital data – from the National Priorities Database. US state-level data have been imputed when data were missing, using the indirect evidence from Turner, Tamura, Mulholland, and Baier (2007).Unskilled labor L^U and skilled labor L^S are measured in "no-schooling equivalents", indicating that each worker's labor input is weighted by her educational attainment. This requires us to split the overall level of human capital per worker into stocks of "human capital within unskilled labor" and "within skilled labor".

In sum: from the raw educational attainment data we have constructed the stock of human capital per worker using the Mincerian exponential formula with a concave

[5]We dropped Germany due to the presence of the unification shock in the data, Luxembourg because of its extraordinarily high productivity primarily due to specialization and the activity of multinational firms, and the following US states: AK, CO, DC, DE, LA, NV, NH, NM, UT, WV, WY, due to reasons such as high oil extraction rents, specialization, special tax status, etc. The precise reasons for these omissions are discussed in the appendix.

[6]Two alternative methods for computing TFP growth have recently been proposed by Burda and Severgnini (2008). These methods do not require one to construct the physical capital series. We do not apply these methods here because capital stocks are necessary for computing the three measures of technological progress other than TFP growth as well, and because we want to maintain strict comparability between the methods throughout the whole study.

exponent following Hall and Jones (1999), Bils and Klenow (2000) and Caselli (2005):

$$L^U = e^{\phi(s)} \text{ for } s < 12, \qquad L^S = e^{\phi(s)} \text{ for } s \geq 12, \tag{2}$$

where s represents years of schooling, and $\phi(s)$ is a concave piecewise linear function (cf. Caselli, 2005):

$$\phi(s) = \begin{cases} 0.134s & s < 4, \\ 0.134 \cdot 4 + 0.101(s-4) & s \in [4, 8), \\ 0.134 \cdot 4 + 0.101 \cdot 8 + 0.068(s-8) & s \geq 8. \end{cases} \tag{3}$$

Furthermore, assuming that everyone who has not completed high school is counted as unskilled, and everyone who has completed it – as skilled, we decompose the overall scale of human capital per worker into its two components: $h = L^U + L^S$. Setting the cutoff point at high school level seems adequate for OECD economies are typically technologically advanced and highly capitalized.[7] For any further caveats carried forward by our dataset, please consult the appendix.

4 Main results

4.1 Technological progress across OECD countries, 1970-2000

Let us now pass to the presentation of our foremost set of results: technological progress rates across the 19 OECD countries in our sample, for the entire period 1970–2000, calculated according to each of the 14 specifications. These results are summarized in Table 1. Please note that the last row in that table contains unweighted cross-country averages, computed as annualized growth rates from the geometric averages of the respective 2000/1970 ratios of technology levels.

From Table 1 we observe that expanding the information set from $\mathcal{I}_1$ or $\mathcal{I}_2$ towards $\mathcal{I}_4$, as well as using more and more sophisticated measurement strategies, generally decreases the estimates of technological progress rates. This is because by allowing more degrees of freedom in the production function, we allow it to fit the observed patterns of factor accumulation and productivity growth better, and so there is less space left for residual productivity growth.

Even more importantly, already at this point we observe the importance to distinguish between measures of "genuine" technological progress at the WTF (in our case, potential TFP growth and the WTF shift factor), and measures of technological progress actually observed in each given country (TFP growth and the Malmquist index). The first discrepancy is that for the former group of measures, technological progress is by construction constrained to non-negative rates. Since our methodology

[7]It might be set too high if developing economies were to be considered as well, though (cf. Caselli and Coleman, 2006).

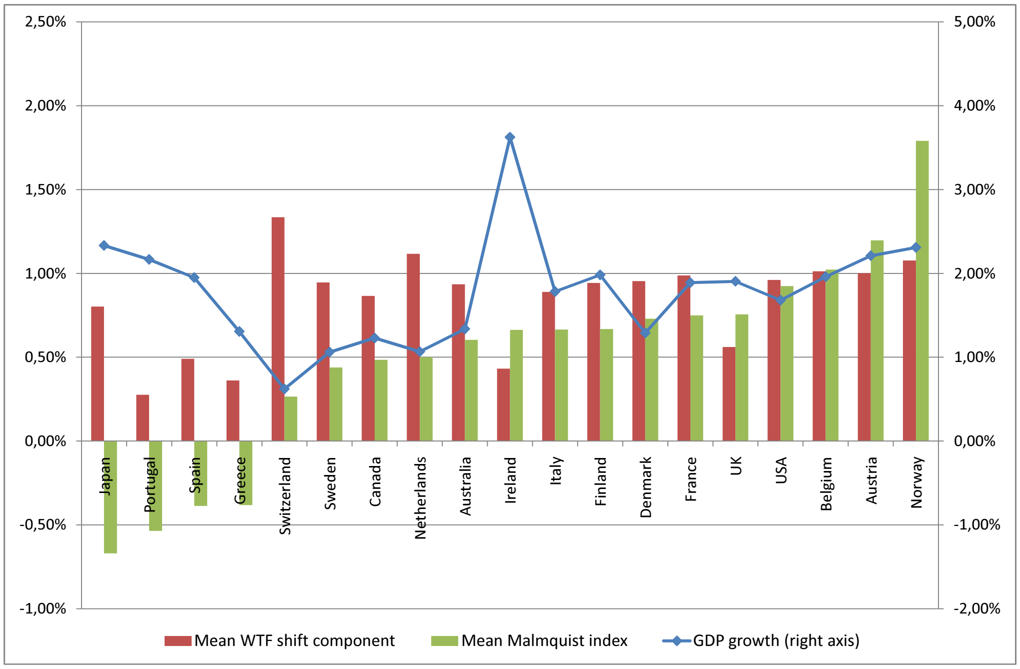
includes the assumption that all input-output configurations, once used, remain available forever, technological regress *at the frontier* is impossible. For the latter group of measures, in contrast, technological progress can easily be negative: if only productivity growth is outpaced by the rate of factor accumulation, then this difference will be reflected in a fall in technical efficiency, and the residual measure of technological progress will become negative. We in fact observe exactly this kind of dynamics in our data in Japan, Portugal, Spain, and Greece in the case where both physical and human capital per worker are included in the production function. The second discrepancy is that technological progress at the WTF is positively correlated to the initial capital stock (cf. Kumar and Russell, 2002; Jerzmanowski, 2007) and negatively correlated with the rates of subsequent productivity growth, whereas technological progress in a given country, due to taking account of efficiency changes as well, is more dispersed across countries and correlates positively with overall productivity growth and the initial stock of human capital. All these regularities are visible in Figure 2.[8]

One should note, however, that the results presented in Table 1 and Figure 2 are averaged over the entire period 1970–2000. Even though this already gives some information about the properties of each particular measure of technological progress, allows for first comparisons, and gives a clue that certain measures may be more useful for some purposes and less useful for others, it does not produce enough data for a reliable analysis of the relative weaknesses and strengths of each measure. This can only be done with the use of panel data, able to account both for the spatial and the temporal dimension of the dataset. A table of all 14 measures of technological progress in all 5-year subperiods (1970–75, 1975–80, 1980–85, 1985–90, 1990–95, 1995–2000) is too long to be presented here in full, but it is that table which underlies all further analyses.[9]

[8] In the lower panel of Figure 2, the stock of physical capital per worker (right axis) is expressed in US dollars in 2000 prices. The units of human capital per worker (right axis as well) are not directly interpretable but are comparable across countries and time.

[9] The table is available from the author upon request.

Figure 2: Means over Malmquist indices (technological progress in each country) and over WTF shift measures (technological progress at the WTF), and their relation to overall productivity growth and inital physical and human capital stocks.



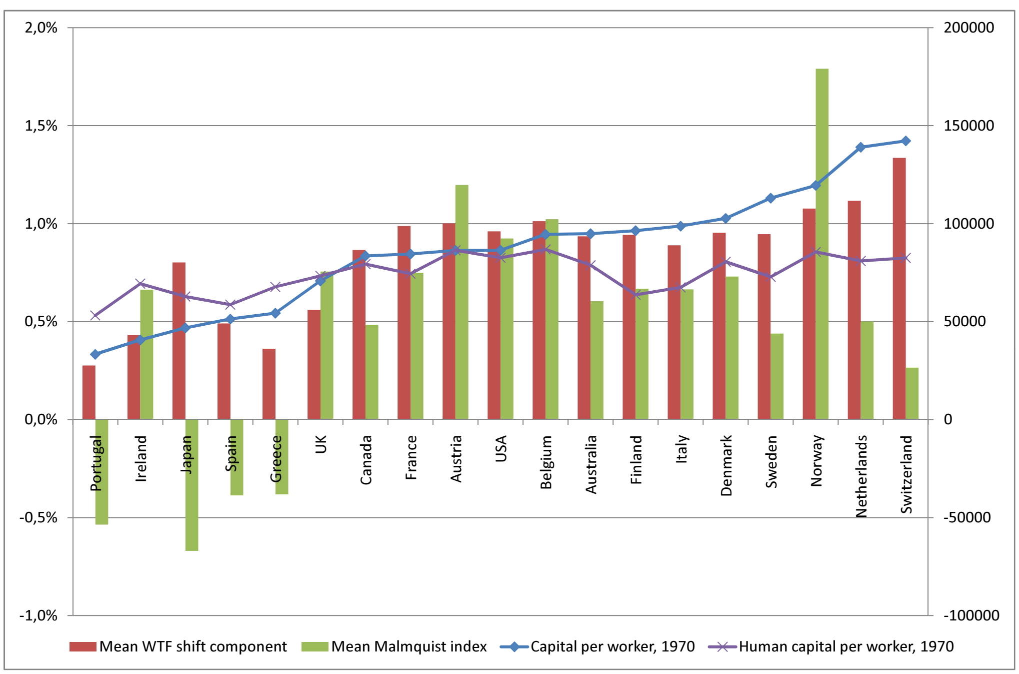


Table 1: Average annual rates of technological progress in 19 OECD countries in 1970–2000, according to 14 alternative measures.

	GDP growth	(1) TFP(k)	(2) Pot(k)	(3) WTF(k)	(4) Malm(k)	(5) Pot(C.)	(6) WTF(C.)	(7) Malm(C.)	(8) TFP(k,h)	(9) Pot(k,h)	(10) WTF(k,h)	(11) Malm(k,h)	(12) Pot(Ls,Lu)	(13) WTF(Ls,Lu)	(14) Malm(Ls,Lu)
Australia	1,34%	0,81%	1,03%	0,95%	0,73%	0,79%	0,98%	0,59%	0,39%	0,62%	0,95%	0,72%	0,87%	0,86%	0,38%
Austria	2,21%	1,31%	1,22%	1,14%	1,22%	0,37%	0,80%	1,33%	0,89%	0,81%	1,14%	1,22%	0,80%	0,93%	1,02%
Belgium	1,96%	1,15%	1,25%	1,19%	1,10%	0,33%	0,92%	1,25%	0,66%	0,76%	1,19%	1,10%	0,76%	0,74%	0,64%
Canada	1,23%	0,62%	0,96%	0,82%	0,48%	0,74%	0,76%	0,29%	0,27%	0,61%	0,82%	0,48%	0,65%	1,05%	0,68%
Denmark	1,29%	0,75%	1,11%	1,07%	0,72%	0,73%	0,94%	0,84%	0,62%	0,89%	1,02%	0,76%	0,80%	0,78%	0,60%
Finland	1,98%	1,33%	1,13%	1,07%	1,28%	1,35%	1,08%	0,25%	0,52%	0,57%	0,95%	0,89%	0,95%	0,67%	0,25%
France	1,89%	1,04%	1,15%	1,05%	0,94%	0,73%	0,97%	0,77%	0,53%	0,69%	1,08%	0,92%	1,02%	0,85%	0,36%
Greece	1,31%	0,64%	1,20%	0,33%	-0,22%	0,64%	0,39%	-0,38%	-0,13%	0,52%	0,36%	-0,29%	0,88%	0,36%	-0,64%
Ireland	3,62%	2,42%	2,23%	0,41%	0,60%	1,81%	0,57%	0,68%	1,92%	1,72%	0,41%	0,61%	1,49%	0,34%	0,77%
Italy	1,78%	1,22%	1,09%	1,04%	1,17%	1,14%	1,07%	0,40%	0,47%	0,49%	0,95%	0,92%	0,79%	0,50%	0,18%
Japan	2,33%	0,75%	2,21%	0,86%	-0,58%	1,09%	0,73%	-0,44%	-0,08%	1,36%	0,85%	-0,59%	1,78%	0,78%	-1,07%
Netherlands	1,07%	0,78%	1,32%	1,36%	0,82%	0,61%	1,09%	0,72%	0,25%	0,81%	1,33%	0,76%	1,25%	0,69%	-0,30%
Norway	2,31%	1,67%	1,25%	1,35%	1,78%	0,67%	1,10%	2,10%	1,67%	0,91%	1,17%	1,94%	1,01%	0,69%	1,35%
Portugal	2,17%	0,93%	2,72%	0,34%	-1,41%	0,77%	0,42%	0,23%	0,57%	1,68%	0,19%	-0,89%	0,80%	0,15%	-0,07%
Spain	1,95%	0,90%	1,62%	0,49%	-0,22%	1,10%	0,65%	-0,45%	-0,01%	1,00%	0,56%	-0,44%	0,69%	0,26%	-0,43%
Sweden	1,06%	0,70%	1,06%	1,07%	0,70%	0,98%	0,92%	0,29%	0,36%	0,73%	0,98%	0,61%	1,02%	0,82%	0,16%
Switzerland	0,62%	0,18%	1,40%	1,50%	0,27%	0,48%	1,09%	0,38%	-0,22%	1,00%	1,47%	0,24%	0,89%	1,28%	0,16%
UK	1,91%	1,29%	0,85%	0,49%	0,93%	0,93%	0,66%	0,64%	0,90%	0,55%	0,52%	0,88%	0,89%	0,56%	0,58%
USA	1,68%	1,00%	1,05%	0,94%	0,89%	0,79%	0,80%	0,80%	0,79%	0,84%	0,94%	0,89%	0,82%	1,15%	1,11%
mean*	**1,77%**	**1,03%**	**1,36%**	**0,92%**	**0,59%**	**0,84%**	**0,84%**	**0,54%**	**0,54%**	**0,87%**	**0,89%**	**0,56%**	**0,96%**	**0,71%**	**0,30%**

Notes: * Mean = unweighted geometric average of 2000/1970 ratios, transformed into annualized growth rates.

Here and in further tables: "TFP" denotes TFP growth. "Pot" denotes potential TFP growth. "WTF" denotes the rate of WTF shift. "Malm" denotes the Malmquist index.

4.2 Accounting for productivity growth

We shall now turn to the analysis of most important properties of the alternative methods of measurement of technological progress. The first of those properties is the ability to explain productivity growth, summarized in Table 2 and Figure 3. The numbers in Table 2 are unweighted averages over countries (in the cross-sectional case), or over countries and time periods (in the panel case), of percentages of productivity (GDP per worker) growth attributed to factor accumulation and technological progress in each of the specifications. The larger is the share of factors in this decomposition, the better is the fit of the underlying production function to the data, and the smaller is the residual "measure of our ignorance".

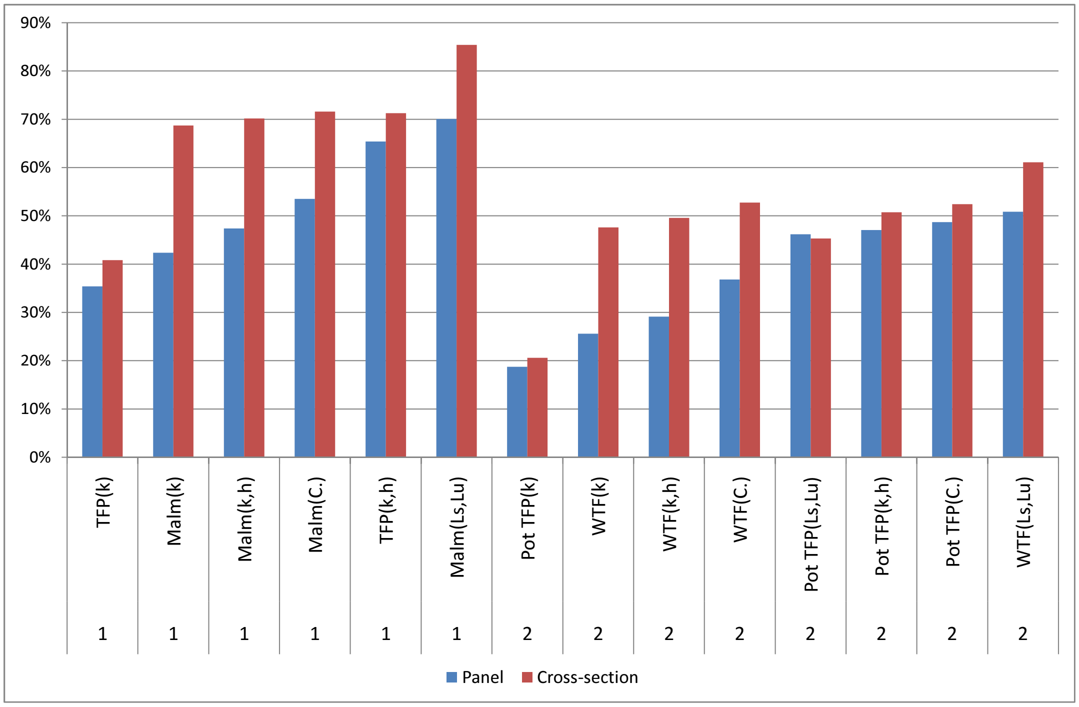
Table 2: Percentage of productivity growth attributed to factor accumulation and technological progress in each of the specifications.

		Panel		Cross-section	
		Factors	Technology	Factors	Technology
(1)	TFP(k)	35,40%	64,60%	40,84%	59,16%
(2)	Pot(k)	18,75%	81,26%	20,60%	79,40%
(3)	WTF(k)	25,58%	74,42%	47,61%	52,39%
(4)	Malm(k)	42,35%	57,65%	68,70%	31,30%
(5)	Pot(C.)	48,69%	51,31%	52,41%	47,59%
(6)	WTF(C.)	36,80%	63,20%	52,74%	47,27%
(7)	Malm(C.)	53,51%	46,49%	71,58%	28,42%
(8)	TFP(k,h)	65,38%	34,62%	71,27%	28,73%
(9)	Pot(k,h)	47,07%	52,93%	50,76%	49,25%
(10)	WTF(k,h)	29,13%	70,87%	49,59%	50,41%
(11)	Malm(k,h)	47,40%	52,60%	70,17%	29,83%
(12)	Pot(Ls,Lu)	46,17%	53,83%	45,32%	54,68%
(13)	WTF(Ls,Lu)	50,86%	49,14%	61,09%	38,91%
(14)	Malm(Ls,Lu)	70,04%	29,96%	85,40%	14,60%

Not surprisingly, we observe that if technological progress includes changes in technical efficiency (distance to the frontier), as it does in the case of TFP growth and the Malmquist index, then the factor-only model does a better job in explaining productivity growth than residual technological progress. The opposite is true for WTF shift and potential TFP growth, where it is technological progress which explains a significantly larger fraction. The reason for this discrepancy lies with the treatment of technical efficiency changes. In the first two cases, it is part of the technological progress measure. In the latter two, it remains within the factor-only model.

We also see that generally all factor-only models do a better job in capturing productivity growth when the dataset is a cross-section rather than when it is a panel. One reason for that might be that over the long run, productivity rises primarily due

Figure 3: Percentage of productivity growth attributed to factor accumulation in each of the specifications.



Note: "1" labels measures of technological progress in a given country.
"2" labels measures of technological progress at the WTF.

to factor accumulation and some frontier productivity growth, whereas in shorter time periods there is more room for efficiency changes. Finally, we also see that both in the panel and in the cross-section, the largest fraction of productivity growth is explained by factors if technological progress is estimated as the Malmquist index under the full information set $\mathcal{I}_4$.

4.3 Accounting for the variance of productivity growth, correlation with productivity growth, and forecast accuracy

Table 3 and Figure 4 summarize a few more characteristics of each of the measures of technological progress, such as the variance of productivity growth accounted by the factor-only model, correlations with productivity growth, and forecast accuracy. Obviously, each of these characteristics captures a different aspect of the productivity growth decomposition into "factors" and "technology", and thus – even though each statistic might be understood as some measure of "goodness of fit" – they cannot be used directly for picking winners and losers, or for judging which measure of technological progress is generally the "most appropriate" one. It clearly depends on the desired application. We do see several regularities, though.

Table 3: Selected characteristics of the 14 measures of technological progress.

		Levels P	Levels C	Corr. P	Corr. C	Variance	Var+Cov	MAE	RMSE
(1)	TFP(k)	35,40%	40,84%	0,964	0,901	7,58%	11,42%	0,288	0,033
(2)	Pot(k)	18,75%	20,60%	0,065	0,554	131,02%	95,95%	0,301	0,029
(3)	WTF(k)	25,58%	47,61%	-0,072	-0,410	146,82%	103,80%	0,271	0,026
(4)	Malm(k)	42,35%	68,70%	0,790	0,041	46,78%	19,28%	0,302	0,034
(5)	Pot(C.)	48,69%	52,41%	0,422	0,649	91,29%	72,35%	0,220	0,020
(6)	WTF(C.)	36,80%	52,74%	0,332	-0,365	99,08%	78,38%	0,249	0,024
(7)	Malm(C.)	53,51%	71,58%	0,808	0,186	39,37%	18,06%	0,295	0,031
(8)	TFP(k,h)	65,38%	71,27%	0,912	0,752	18,40%	12,03%	0,254	0,026
(9)	Pot(k,h)	47,07%	50,76%	0,040	0,641	137,49%	97,61%	0,221	0,018
(10)	WTF(k,h)	29,13%	49,59%	-0,043	-0,441	134,82%	101,81%	0,253	0,022
(11)	Malm(k,h)	47,40%	70,17%	0,784	0,077	52,14%	16,24%	0,308	0,035
(12)	Pot(Ls,Lu)	46,17%	45,32%	0,128	0,474	112,36%	93,88%	0,208	0,014
(13)	WTF(Ls,Lu)	50,86%	61,09%	0,140	-0,478	106,43%	93,23%	0,171	0,011
(14)	Malm(Ls,Lu)	70,04%	85,40%	0,879	0,235	25,17%	11,38%	0,264	0,027

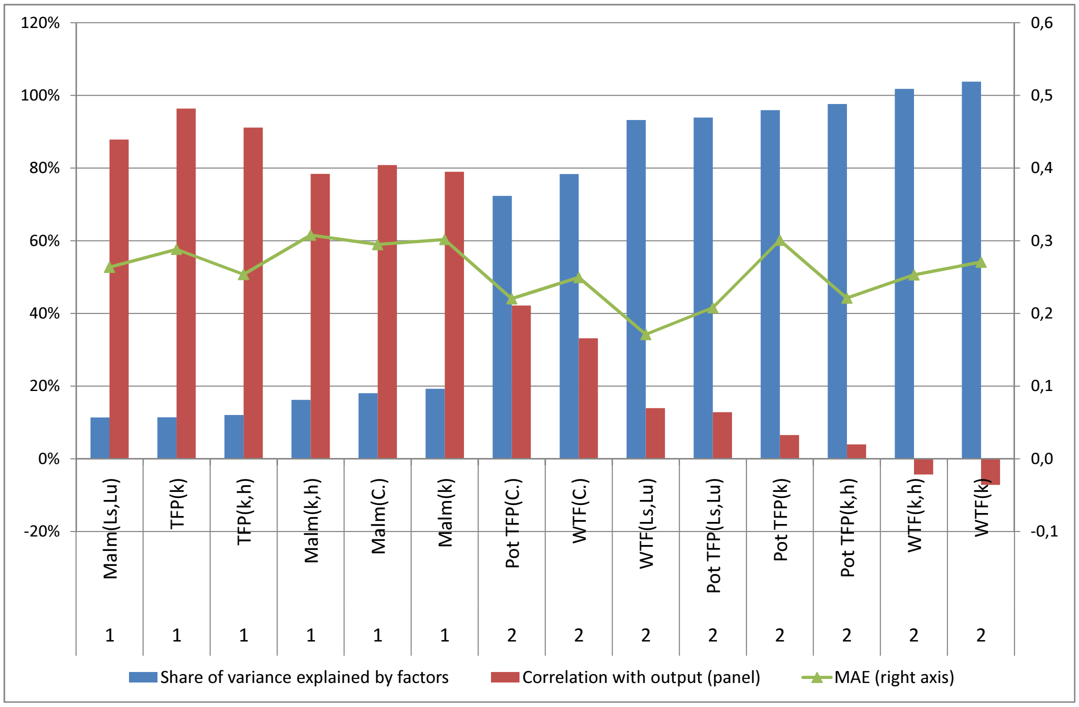
Legend:

- "Levels" – percentage of total productivity growth explained by factor accumulation. Index P denotes averages over a panel of 5-year intervals spanning 1970–2000, index C denotes the cross-sectional average.
- "Corr." – correlation of the technological progress measures with productivity growth. Index P denotes averages over a panel of 5-year intervals spanning 1970–2000, index C denotes the cross-sectional average.
- "Variance" denotes the percentage of variance of productivity growth rates explained by the factor-only model, assuming that productivity growth equals the technological progress factor times the factor accumulation factor.
- "Var+cov" is the Caselli (2005) measure of success – the ratio of variance of the factor-only model plus one covariance of the factor-only model and technological progress (numerator) over the variance of productivity growth rates (denominator). Both "variance" measures have been computed using a panel of 5-year intervals spanning 1970–2000.
- MAE and RMSE denote, respectively, the mean absolute error and the root of mean square error, obtained when productivity growth is predicted ex post as the growth rate of the factor-only model.

The regularities are the following:

1. TFP growth is very strongly correlated with productivity growth, both in the cross-section and in the panel, which suggests a possible problem of an inappropriate functional form, but also leaves a relatively large fraction of productivity growth to be explained by factor accumulation which is a desirable property.
2. The Malmquist index is, however, visibly less correlated with productivity growth than TFP growth, especially in the cross-section, and leaves an even larger fraction of productivity growth to be explained by factor accumulation.

Figure 4: Selected characteristics of the 14 measures of technological progress.



3. Potential TFP growth is very weakly correlated with productivity growth, especially in the temporal dimension. The factor-only model associated with this measure of technological progress does a bad job in explaining productivity's rate of growth, but a very good job in explaining its variance across countries and time. The fact that potential TFP growth accounts for a large fraction of differences in growth performances suggests that technological progress at the WTF is highly non-neutral and targets selected factor ratios only.

4. WTF shift is robustly negatively correlated with productivity growth in the cross section. This is probably because of the convergence process in the data and the fact that technological progress is observed mostly in the domain of high physical and human capital intensities (cf. Kumar and Russell, 2002; Jerzmanowski, 2007). Its factor-only model explains a very large part of variance of productivity growth across countries and time, corroborating the finding that technological progress at the WTF is highly non-neutral.

5. The most striking general finding from Figure 4 is that all measures of technological progress in each given country (TFP growth, the Malmquist index) are highly

correlated with productivity growth[10] but do a bad job in explaining its variance, whereas measures of technological progress at the WTF are weakly correlated with productivity growth and do a good job in explaining its variance.

6. Enlarging the information set by including further factors of production increases the percentage of productivity growth explained by factors and lowers the correlation of each given measure of technological progress with productivity growth. This regularity justifies the inclusion and the subsequent decomposition of human capital in the production function.

7. Increasing the precision of WTF estimates by adding auxiliary US state-level data to the dataset generally increases the percentage of variance explained by the factor-only model.

8. The factor-only model does the best job in predicting productivity growth (that is, MAE and RMSE are minimized) when technological progress is defined as WTF shift, taking into account the decomposition of human capital into unskilled and skilled labor. This last decomposition is particularly important for reducing the ex post prediction errors of the factor-only model.

9. The difference between *average* performances of measures of technological progress in each country and at the frontier in terms of forecast accuracy is statistically insignificant. This is probably due to the trade-off in accuracy of forecasting mean productivity growth which is better in the former case, and its deviations from the mean, which is better in the latter case.

4.4 Pairwise correlations

A further piece of information is conveyed in Table 4, containing pairwise (Pearson) correlation coefficients among the 14 measures of technological progress. The graphical layout of Table 4 emphasizes the fact that what matters most for the "character" of a measure is the methodology of its construction, not the information set upon which it is based. All TFP growth measures are strongly correlated with each other, and so are all potential TFP measures, all WTF shift indices, and all Malmquist indices, whereas the correlation across methodologies is much less pronounced and in several cases it is actually negative.

[10] It is true particularly in the temporal dimension; in the cross-section, this correlation falls down to 0,041–0,235 for Malmquist indices.

Table 4: Pairwise correlations among the 14 measures of technological progress.

CROSS-SECTIONAL DATA, 1970–2000

		(1) TFP(k)	(8) TFP(k,h)	(2) Pot(k)	(9) Pot(k,h)	(5) Pot(C.)	(12) Pot(Ls,Lu)	(3) WTF(k)	(10) WTF(k,h)	(6) WTF(C.)	(13) WTF(Ls,Lu)	(4) Malm(k)	(11) Malm(k,h)	(7) Malm(C.)	(14) Malm(Ls,Lu)
(1)	TFP(k)	1,00	0,91	0,24	0,38	0,62	0,30	-0,23	-0,28	-0,12	-0,41	0,40	0,42	0,43	0,48
(8)	TFP(k,h)	0,91	1,00	0,14	0,35	0,38	0,17	-0,06	-0,13	-0,02	-0,20	0,50	0,59	0,68	0,73
(2)	Pot(k)	0,24	0,14	1,00	0,93	0,34	0,47	-0,43	-0,48	-0,52	-0,50	-0,67	-0,59	-0,26	-0,35
(9)	Pot(k,h)	0,38	0,35	0,93	1,00	0,40	0,51	-0,34	-0,38	-0,45	-0,34	-0,53	-0,42	-0,09	-0,11
(5)	Pot(C.)	0,62	0,38	0,34	0,40	1,00	0,47	-0,45	-0,49	-0,20	-0,44	-0,08	-0,17	-0,33	-0,12
(12)	Pot(Ls,Lu)	0,30	0,17	0,47	0,51	0,47	1,00	-0,02	-0,03	-0,05	-0,09	-0,17	-0,17	-0,14	-0,33
(3)	WTF(k)	-0,23	-0,06	-0,43	-0,34	-0,45	-0,02	1,00	0,98	0,91	0,68	0,59	0,59	0,53	0,29
(10)	WTF(k,h)	-0,28	-0,13	-0,48	-0,38	-0,49	-0,03	0,98	1,00	0,88	0,73	0,56	0,55	0,48	0,26
(6)	WTF(C.)	-0,12	-0,02	-0,52	-0,45	-0,20	-0,05	0,91	0,88	1,00	0,53	0,69	0,63	0,45	0,26
(13)	WTF(Ls,Lu)	-0,41	-0,20	-0,50	-0,34	-0,44	-0,09	0,68	0,73	0,53	1,00	0,32	0,33	0,24	0,35
(4)	Malm(k)	0,40	0,50	-0,67	-0,53	-0,08	-0,17	0,59	0,56	0,69	0,32	1,00	0,97	0,76	0,71
(11)	Malm(k,h)	0,42	0,59	-0,59	-0,42	-0,17	-0,17	0,59	0,55	0,63	0,33	0,97	1,00	0,89	0,80
(7)	Malm(C.)	0,43	0,68	-0,26	-0,09	-0,33	-0,14	0,53	0,48	0,45	0,24	0,76	0,89	1,00	0,83
(14)	Malm(Ls,Lu)	0,48	0,73	-0,35	-0,11	-0,12	-0,33	0,29	0,26	0,26	0,35	0,71	0,80	0,83	1,00

PANEL DATA, 5-YEAR INTERVALS SPANNING 1970–2000

		(1) TFP(k)	(8) TFP(k,h)	(2) Pot(k)	(9) Pot(k,h)	(5) Pot(C.)	(12) Pot(Ls,Lu)	(3) WTF(k)	(10) WTF(k,h)	(6) WTF(C.)	(13) WTF(Ls,Lu)	(4) Malm(k)	(11) Malm(k,h)	(7) Malm(C.)	(14) Malm(Ls,Lu)
(1)	TFP(k)	1,00	0,96	0,00	0,00	0,44	0,17	-0,05	-0,03	0,36	0,13	0,88	0,86	0,86	0,90
(8)	TFP(k,h)	0,96	1,00	0,03	0,10	0,45	0,27	0,02	0,03	0,38	0,19	0,86	0,86	0,90	0,92
(2)	Pot(k)	0,00	0,03	1,00	0,82	0,15	0,36	0,65	0,59	0,14	0,34	-0,20	-0,15	0,01	0,01
(9)	Pot(k,h)	0,00	0,10	0,82	1,00	0,31	0,60	0,49	0,55	0,19	0,42	-0,19	-0,21	0,01	-0,01
(5)	Pot(C.)	0,44	0,45	0,15	0,31	1,00	0,55	-0,04	0,02	0,79	0,34	0,27	0,24	0,26	0,32
(12)	Pot(Ls,Lu)	0,17	0,27	0,36	0,60	0,55	1,00	0,25	0,37	0,51	0,63	0,09	0,08	0,22	0,06
(3)	WTF(k)	-0,05	0,02	0,65	0,49	-0,04	0,25	1,00	0,93	0,19	0,56	0,16	0,19	0,17	0,14
(10)	WTF(k,h)	-0,03	0,03	0,59	0,55	0,02	0,37	0,93	1,00	0,28	0,70	0,17	0,21	0,20	0,16
(6)	WTF(C.)	0,36	0,38	0,14	0,19	0,79	0,51	0,19	0,28	1,00	0,57	0,35	0,36	0,48	0,37
(13)	WTF(Ls,Lu)	0,13	0,19	0,34	0,42	0,34	0,63	0,56	0,70	0,57	1,00	0,24	0,28	0,33	0,32
(4)	Malm(k)	0,88	0,86	-0,20	-0,19	0,27	0,09	0,16	0,17	0,35	0,24	1,00	0,97	0,87	0,89
(11)	Malm(k,h)	0,86	0,86	-0,15	-0,21	0,24	0,08	0,19	0,21	0,36	0,28	0,97	1,00	0,91	0,92
(7)	Malm(C.)	0,86	0,90	0,01	0,01	0,26	0,22	0,17	0,20	0,48	0,33	0,87	0,91	1,00	0,91
(14)	Malm(Ls,Lu)	0,90	0,92	0,01	-0,01	0,32	0,06	0,14	0,16	0,37	0,32	0,89	0,92	0,91	1,00

Interestingly, these negative correlations generally appear in the cross-sectional dimension and then disappear in the panel: in cross-sectional data, potential TFP growth is negatively correlated with the measures of WTF shift and (even more strongly so) with Malmquist indices; in the panel, these correlations are close to zero and often positive. The largest cross-section vs. panel differential is around 1 in the cases of potential TFP growth vs. WTF shift under the same information set. The reason is that all measures of technological progress move in a more or less parallel fashion across time. Two possible explanations of this regularity are the following: (i) technological progress at the WTF gradually trickles down over time to more backward countries as well, counteracting the negative cross-sectional correlation between measures of technological progress in each country and progress at the WTF, and (ii) function misspecification errors are repeated over time giving rise to "country-specific effects", creating a positive time-series correlation able to offset the negative cross-sectional correlation in the panel. We suppose that both these effects can potentially be important.

4.5 Corollaries from the main results

The principal conclusion from the results presented above is that for different purposes, different measures of technological progress should be used. If the objective is to account for the average productivity growth rate across countries or time, then measures of technological progress within each country should be used, and in this case the most successful measure is the Malmquist index computed using the information set $\mathcal{I}_4$. If the objective is, on the other hand, to find the sources of *variation* of growth rates across countries and time, most promising are the measures of technological progress at the WTF: potential TFP growth and the rate of WTF shift. If one wants to minimize ex post prediction errors when predicting productivity growth with growth of the factor-only model, then WTF shift with the information set $\mathcal{I}_4$ should be the most appropriate choice. Generally, one always has to draw a firm line between measures of technological progress at the WTF and measures of technological progress observed in a given country, where the latter one includes shifts in technical efficiency as well. Both types of measures may be weakly, or even negatively correlated to each other, and yield diverging results.

Another conclusion stemming from the study is that the variances and correlations are significantly different in the temporal dimension than in the cross-sectional dimension. One reason is that there is a lot of variation in technical efficiency across countries, but this index changes relatively slowly in time. A different reason could be that there are "country-specific effects" due to production function misspecification active in the panel.

Yet another lesson here is that increasing the precision of WTF estimates helps in increasing all our "goodness of fit" measures. Obviously, this applies strongly to adding a human capital measure into the production function. Interestingly enough, however, this applies even more strongly to decomposing human capital into skilled and unskilled labor, and we also record visible increases in our "goodness of fit" measures when the dataset is enlarged by using auxiliary US state-level data on top of our OECD country-level data, even though these numbers are measured with admittable error. To see how large these improvements could be looks like a promising line of further research.

4.6 A comparison with van Biesebroeck (2007)

An insightful reader might notice that the current article has the same objective as the one carried out by van Biesebroeck (2007), that is to compare the relative strengths and weaknesses of several alternative measures of factor productivity and technological progress. There are a few decisive differences between these two papers, though. First, van Biesebroeck's paper focuses primarily on measuring productivity of individual firms, and ours – of countries. Second, his study is based on artificial data, and ours is based on real-world data. While his approach has the relative advantage of providing a clear-cut metric of "distance to reality" – because he knows exactly his data-generating process and we do not – it also has the disadvantage that the properties of that data-generating process might be actually distant from the properties of a process generating real-world data, if it exists at all. Indeed, van Biesebroeck's data are generated from a model economy endowed with a Cobb–Douglas production function, deformed by a number of stochastic shocks. If the world is not fundamentally Cobb–Douglas, however, his results will be biased in favor of methods where this functional form is explicitly assumed, such as his parametric stochastic frontier estimations.[11] Third, most of the methods for computing technological progress considered by van Biesebroeck (2007) require the researcher to estimate the parameters of the production function and/or use data on the labor share in GDP, which we intentionally set aside in our analysis. In result, our study might be based on wrong calibrations, but for sure it will not face the problems of endogeneity of production decisions and equilibrium pricing behavior. Fourth, van Biesebroeck assumes the technology frontier to be the same for all periods of time. While that might be a legitimate assumption in industrial (micro)economics with relatively short time spans, it is certainly not in macroeconomic productivity analysis. Therefore in the current study we allow the WTF to shift in time, and we actually identify three out of four technological progress measures with appropriate functions of these shifts.

[11] In particular, one of van Biesebroeck's conclusions is that parametric methods have a clear advantage over non-parametric ones when factors of production are measured with error. In his study, though, measurement error is assumed to be centered around a Cobb–Douglas production function, which likely drives this result.

5 Measuring technological progress at the frontier vs. measuring technological progress actually observed in each given country

If it indeed is the case that our measures of technological progress could be effectively clustered into two groups measuring different aspects of productivity growth as we claimed in the preceding sections, then this fact should show up in the results of factor analysis.[12] Naturally, since our measures are computed under nested specifications and information sets, one should not reduce the number of dimensions by extracting principal components; factor analysis may however be effectively used for confirming that the aforementioned dichotomy is indeed a valid phenomenon.

In this regard, we see in Table 5 that two first principal components indeed explain more than 71% of total variance of the fictitious summary scale of (logarithms of) all 14 measures of technological progress. Adding two more components brings about a further increase of this number to about 91% of total variance. Such high numbers are reassuring that measurement problems have a relatively minor impact on the validity of our results.

Table 5: 14 alternative measures of technological progress: factor analysis results.

	Eigenvalue	Cumulative %
Factor 1	6,20378	0,4431
Factor 2	3,75556	0,7114
Factor 3	1,73635	0,8354
Factor 4	1,01856	0,9082

Now, it is instructive to see which variables enter each of the factors: Table 6 shows that there are clear patterns among factor loadings. The first, most important factor should be straightforwardly interpreted as "technological progress in the given country": it contains all the variants of the Malmquist index and TFP growth, irrespective of the choice of information set.

Equally naturally, the second factor should be interpreted as "technological progress at the world technology frontier". This factor contains high loadings from all measures of potential TFP growth and WTF shift, the exception being the measures computed using country-level data only. We conjecture that this is due to the fact that with technological progress at the WTF, precision of its estimates matters more than with measures of progress actually observed in each given country. Since our sample is very small in the case of the country-only information set, we suppose that these measures could be contaminated with substantial error due to an imprecise WTF estimation.

[12] Since all our technological progress measures have a multiplicative nature (one should use the original ratios rather than the annualized growth rates), further analysis shall be carried out in logs instead of levels.

This last assertion is strengthened by inspection of the loadings of factor three, containing primarily potential TFP growth and WTF shift factors computed from country-only data (as well as a negative contribution from the WTF shift factor computed with physical capital-only data). Hence, we conclude that there must be significant gains in precision in the WTF estimation when appending US state-level data to the countries-only dataset, and that these gains are particularly vital for the computation of measures of technological progress *at the frontier*.

Table 6: Factor loadings (no rotation).

		Factor 1	Factor 2	Factor 3	Factor 4
(1)	TFP(k)	**0,875**	-0,351	0,062	0,276
(2)	Pot TFP(k)	0,158	**0,792**	-0,149	0,472
(3)	WTF(k)	0,329	**0,700**	**-0,556**	-0,127
(4)	Malm(k)	**0,877**	-0,366	-0,190	-0,116
(5)	Pot TFP(C.)	0,506	0,208	**0,752**	-0,009
(6)	WTF(C.)	0,611	0,275	**0,511**	-0,368
(7)	Malm(C.)	**0,919**	-0,220	-0,122	0,048
(8)	TFP(k,h)	**0,908**	-0,268	0,059	0,291
(9)	Pot TFP(k,h)	0,192	**0,822**	0,100	0,460
(10)	WTF(k,h)	0,379	**0,744**	-0,461	-0,221
(11)	Malm(k,h)	**0,886**	-0,346	-0,242	-0,128
(12)	Pot TFP(Ls,Lu)	0,404	**0,588**	0,462	-0,019
(13)	WTF(Ls,Lu)	0,533	**0,609**	0,022	-0,424
(14)	Malm(Ls,Lu)	**0,909**	-0,276	-0,160	0,101

Note: loadings exceeding 0,5 in absolute value indicated in bold.

In sum, the results of our confirmatory factor analysis support the conclusion that two types of technological progress should be clearly distinguished: in each country, and at the frontier. Corroborating this result even more, we also find that when one attempts to construct a summary scale of our alternative technological progress measures (again, in logs), then by stepwise deletion of dimensions, one is able to arrive at a scale with a standardized Cronbach's alpha coefficient of 0,9799 which cannot be improved any more by deleting items, and which contains all 6 variables capturing technological progress within each country: 2 measures of TFP growth and 4 Malmquist indices. Complementarily, the scale of 8 remaining variables also cannot be improved by deleting items, and its standardized Cronbach's alpha coefficient is equal to 0,8535.

Hence, both confirmatory exercises support the initial presumption that it is crucial to distuingish between the measures of technological progress at the frontier and in each particular country. The choice of the information set seems less important here, however, but with one important exception: for measures of technological progress at the frontier, it is very important to have as precise estimates of the WTF as possible. An auxiliary use of US state-level data is particularly helpful in this respect.

Finally, one should note that it is not methodologically sound to take the factors obtained in the above factor analysis nor the aforementioned summary scales as valid measures of technological progress. They should rather be considered artificial constructs used to support (or invalidate) our hypotheses. The reasons are that (i) the information sets are nested, so it should always be an improvement to use a larger dataset, provided that the addition is not dominated by measurement error, and that (ii) the measures of technological progress have been constructed using conflicting assumptions on the shape of the aggregate production function so that they cannot be reconciled with each other.

6 Conclusion

The current article has brought together fourteen approaches to the measurement of technological progress across countries, providing a synthetic, numerical assessment of their relative advantages and disadvantages. We have investigated what fraction of total growth in GDP per worker and its variance is captured by the technological progress (residual productivity growth) component in each of the specifications. We have also computed the correlations of these residual measures with productivity growth and calculated the mean ex post prediction errors (MAE, RMSE) when productivity growth is predicted as the factor-only component. Results of this investigation, combined with the results of our confirmatory factor analysis indicate that (i) it is crucial to distinguish between measures of technological progress actually observed in each given country (TFP growth, Malmquist index) from measures of technological progress at the world technology frontier (potential TFP growth, WTF shift), (ii) it is generally worthwhile to use more information for constructing the WTF, in particular to allow for imperfect substitutability between skilled and unskilled labor and to use US state-level data apart from OECD country-level data, and (iii) above all, there is no unique optimal method of measurement of technological progress, hence the method should always be selected in accordance with the analyzed question.

A Data appendix

The original dataset covers 21 highly developed OECD countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and the United States, as well as 50 US states plus the District of Columbia: AL, AK, AZ, AR, CA, CO, CT, DE, DC, FL, GA, HI, ID, IL, IN, IA, KS, KY, LA, ME, MD, MA, MI, MN, MS, MO, MT, NE, NV, NH, NJ, NM, NY, NC, ND, OH, OK, OR, PA, RI, SC, SD, TN, TX, UT, VT, VA, WA, WV, WI, WY.

We have however decided to drop Luxembourg and the DC from our analysis because of the strong indication that these entities' productivity might be significantly overestimated because of workers commuting from outside of the territory (such as Belgium and France for Luxembourg, or Virginia and Maryland for DC).[13] We have also removed Germany from our sample because of the unification shock present in the data.

Furthermore, since the DEA method is extremely sensitive to outliers, we have also decided to drop US states with largest long-term average mining shares in the gross state product. There is an indication that productivity of these states might be overestimated since their gross state product encompasses substantial resource rents which are not captured in the estimated production function. These states are Alaska, Colorado, Louisiana, Nevada, New Mexico, Utah, West Virginia, and Wyoming.[14] We also dropped Delaware and New Hampshire as small, specialized economies with comparatively unusual tax systems.[15]

The time span of our analysis is 1970–2000, and the estimations are run in 5-year intervals. The crucial bottleneck here is the availability of schooling variables which are only measured in 5-year intervals. Most other data were available in annual frequency and a longer period.

The data we are using are set in *per worker* terms. This means that we abstract from the issues of labor market participation which may result in additional *per capita* productivity differences, and of the variation in hours worked per worker which means that our analysis convolutes productivity differences with labor-leisure choice of the employees: ceteris paribus, an increase in hours worked per worker will be reflected

[13]Admittedly, this caveat applies to some other EU countries and US states as well. The larger is the country or state, however, and the more likely is commuting to be bi-directional, the less important this problem becomes for our aggregate results.

[14]The sparsely populated oil-producing Alaska is probably the most remarkable among these states. With its mining share in GDP peaking at 50% in 1981, the state turned out to span the WTF any time it entered the estimation procedure, subsequently lowering the efficiency factor in most other US states by as much as 10-30 percentage points.

[15]In particular, Delaware is known as a within-US "tax haven" and a major center of credit card issuers. When included in the sample, both Delaware and New Hampshire tended to span the technology frontier at almost all years 1970–2000. Also, the number of frontier observations increased markedly after these states had been dropped. We consider this fact to be an indication that they indeed were outliers in our sample.

by increases in “productivity” as we measure it even though technology as such is unchanged. It is however difficult to find reliable and comparable data on hours worked per capita both across OECD countries and US states which would date back at least until 1970.

For international data on GDP and GDP per worker, we use the Penn World Table 6.2 (Heston, Summers, and Aten, 2006), available for 1960-2003. For state-level GDP and GDP per worker, we use data from the Bureau of Economic Analysis, Regional Accounts, available for 1963-2007. The unit of measurement is the PPP converted US dollar under constant prices as of year 2000. Since, to our surprise, we have found discrepancies up to 15% (in extreme cases) in the total number of workers employed across the US in the two datasets, and since international data are given priority in the analysis, the BEA data on GDP per worker have been proportionally adjusted to guarantee internal coherence with the aggregate US data from the Penn World Tables.[16]

The physical capital series have been constructed using the perpetual inventory method described, among others, by Caselli (2005) and OECD (2009). We have taken country-level investment shares as well as government shares from the Penn World Tables 6.2. There are two polar standpoints as for the role of government in capital accumulation: one is that government spending is all consumption, and the other one is that it is all investment. We have taken an intermediate stance here, assuming that the government invests the same share of its GDP share as the private economy does. Under this assumption, the overall (private and public) investment share is $s/(1-g)$ where s is the private investment share and g is the government share. Furthermore, following Caselli (2005), we assumed an annual depreciation rate of 6%. For state-level government shares, we compiled a dataset from primary sources at the US Census Bureau. Since the period of available data is 1992-2006 only, we extrapolated government shares backward in time using state-level averages and the long-run trend from the overall US economy. Unfortunately, there are no data on state-level investment shares apart from those computed by Turner, Tamura and Mulholland (2008) which are however not publicly available. Knowing that this introduces substantial error but not being able to obtain better proxies, we have imputed that state-level private investment shares are equal to the US countrywide private investment share.

Country-level human capital data have been taken from de la Fuente and Doménech (2006) – D-D hereafter. The raw variables are shares of population aged 25 or above having completed primary, some secondary, secondary, some tertiary, tertiary, or post-graduate education. The considered dataset is of 5-year frequency only and it ends in 1995. Among all possible education attainment databases, the D-D dataset has been given priority due to our trust in its superior quality. The original D-D series has been extrapolated forward to the year 2000 using Cohen and Soto (2007) schooling data as a predictor for the trends. Neither Barro and Lee (2001) nor Cohen and Soto (2007) data could be used directly for this purpose because neither of them is (even roughly)

[16]As a side effect, this adjustment helps solve the problem of the discontinuity between 1996 and 1997 in BEA data on the gross state product, arising due to a change in measurement methodology.

in agreement with the D-D dataset – nor with each other – in the period where all datasets offer data points.

US state-level human capital data have been taken from the National Priorities Database. Here, the variables are shares of population aged 25 or above having completed less than high school, high school, some college, college, or having obtained the Associate, Bachelor, or Master degree (the last category covering above-Master education as well). These data are available for 1995-2006 only. We have extrapolated the observed trends in the educational *composition* of the populations backwards using US country-wide trends documented in D-D and state-level differences in the period when the data were available. The aggregate state-level *quantities* of human capital have been, on the other hand, taken from Turner, Tamura, Mulholland, and Baier (2007). At the international level, cumulative years of schooling at each level of education have been taken from D-D and supplemented with data from country-specific web resources wherever necessary. The US state-level education attainment data have also been adjusted to guarantee comparability with D-D data.[17]

From the raw educational attainment data we have constructed the human capital aggregates using the Mincerian exponential formula with a concave exponent following Hall and Jones (1999), Bils and Klenow (2000) and Caselli (2005):

$$L^U = e^{\phi(s)} \text{ for } s < 12, \qquad L^S = e^{\phi(s)} \text{ for } s \geq 12, \tag{4}$$

where s represents years of schooling, and $\phi(s)$ is a concave piecewise linear function:

$$\phi(s) = \begin{cases} 0.134s & s < 4, \\ 0.134 \cdot 4 + 0.101(s-4) & s \in [4,8), \\ 0.134 \cdot 4 + 0.101 \cdot 8 + 0.068(s-8) & s \geq 8. \end{cases} \tag{5}$$

The overall human capital index can be computed as the sum of unskilled and skilled labor: $H = L^U + L^S$. We have however allowed these two types of labor to be imperfectly substitutable, and enter the production function separately. The perfect substitution case where only total human capital matters is an interesting special case of our generalized formulation; the data do not support this assumption, however.

Special attention should be paid to the cutoff point of 12 years of schooling delineating unskilled and skilled labor. It is roughly equivalent to the requirement of having completed secondary education to be skilled: secondary education is usually completed after 12 years of schooling (13 in some countries). We have thus assumed that everyone who has not completed high school is counted as unskilled, and who has – as skilled. This cutoff point seems adequate for OECD economies in our sample –

[17] We have found a roughly steady surplus of 8 percentage points in the share of population with less than high school completed in the National Priorities Database as compared to D-D, compensated by a shortage of 5.3 pp. in high school graduates, and of 2.7 pp. in the "some college" category. We have thus added/subtracted these values from the US state-level figures to guarantee coherence at the aggregate US level, keeping in mind that this procedure could have introduced some additional error.

which are usually technologically advanced and highly capitalized – though it might be set too high if developed economies were to be considered as well (cf. Caselli and Coleman, 2006). Another measurement problem which may potentially appear but which we do not consider a major obstacle here given our sample choice, is that schooling quality at different grades may vary across countries and states. This pertains both to the split between skilled and unskilled population and the estimates of aggregate human capital. Controlling for this heterogeneity is left for further research.

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