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On the measurement of technological progress across countries

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Abstract

The article considers 22 alternative empirical measures of country-level "technological progress", computed for 19 highly developed OECD countries over the period 1970–2000 based on (i) the neoclassical growth accounting approach that adopts the Cobb-Douglas production function specification, (ii) a nonparametric approach where the world technology frontier (WTF) is constructed with Data Envelopment Analysis, and (iii) a "hybrid" approach that combines the two. Measures of TFP growth (capturing all output gains actually obtained in a given country that cannot be traced back to factor accumulation) are carefully distinguished from measures of technical change (capturing only technological progress shifting the WTF). Empirical properties of all 22 measures are compared according to a range of characteristics frequently discussed in the macroeconomic literature. The conclusion is that the choice of appropriate measurement methodology should be suited to the question addressed in each specific study, the simple growth accounting approach is generally insufficient, and particular attention should be paid to the empirical treatment of technical efficiency changes. The results are also sensitive to the precision of WTF estimation.

Keywords: technological progress, growth accounting, TFP growth, technical change, aggregate production function

JEL: E23, O11, O14, O33, O47

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1. Introduction

Ever since the seminal work of Solow (1957), "technological progress" has been casually identified in the macroeconomic literature 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, and what factors it should take as inputs. Seen from a slightly different angle: it remains unsettled, how one should decompose output growth into the contributions of "factors" and "technology". The objective of the current article is to investigate these matters more closely, indicating that valuable lessons can be learned by macroeconomists from the established productivity analysis literature.

To this end, we will study the empirical properties of 22 alternative specifications of "technological progress" (i.e., growth of residual productivity): ten versions of total factor productivity (TFP) growth, and twelve versions of technical change, capturing technological progress at the world technology frontier (WTF), or TFP growth net of technical efficiency changes. The focus of the study will be with 19 high-income OECD countries in the period 1970–2000. All compared measures will be computed with the use of data on inputs per worker (physical capital, human capital, etc.) and output (GDP) per worker only.

By contrasting the neoclassical growth accounting approach based on the Cobb-Douglas production function specification (for example, Solow 1957 or Timmer, Ypma, van Ark 2003) with nonparametric approaches based on deterministic frontier models (for example, Färe et al. 1994; Kumar, Russell 2002; Henderson, Russell 2005: Jerzmanowski 2007; Badunenko, Henderson, Zelenyuk 2008 or Growiec 2012), we will show which predictions regarding "technological progress" across countries are robust to changes in the production function specification, and which are not. Concurrently, we will also assess the robustness of our conclusions to changes in the composition of the underlying dataset. To achieve this latter goal, 15 of our 22 measures of technological progress will be based on WTF estimates computed with an auxiliary use of US state--level data (beside the OECD country-level data). As demonstrated in a related study (Growiec 2012), such augmentation of the dataset is likely to improve the precision of WTF estimates markedly. The current article confirms that it also has a significant impact on the implied measures of technological progress.

The key difference between neoclassical growth accounting and frontier approaches to the measurement of technological progress lies with the treatment of each country's technical inefficiency of factor use. The growth accounting approach assumes 100% efficiency for all countries in all years. Frontier approaches, on the other hand, relax this restriction by applying the concept of the WTF. The WTF is defined as maximum output which could potentially be produced given inputs, and viewed as a function of the inputs. In the current study, it will be constructed with Data Envelopment Analysis (DEA), one of the most popular methodologies of productivity analysis. Technical inefficiency will then be directly interpreted as distance to the frontier. Having our constructed WTF in hand, we will also consider a "hybrid" parametric–nonparametric approach, put forward in the literature on "appropriate technology vs. efficiency" decompositions (Basu, Weil 1998; Jerzmanowski 2007).

One should also be aware of another important dividing line among “technological progress” measures. Namely, from the established productivity analysis literature (e.g., Färe et al. 1994; Ray, Desli 1997; Maudos, Pastor, Serrano 2000; Coelli et al. 2005; Zofio 2007; O’Donnell 2009) it follows that there are two distinct groups of such measures: TFP growth measures, capturing productivity gains actually obtained in a given country (e.g., TFP growth as defined by Solow 1957; Malmquist index), and technical change measures, capturing technological progress at the World Technology Frontier (e.g., potential technical change (PTC) and technical change (TC) indexes defined in Zofio 2007). The difference between these two groups of measures lies with the treatment of technical efficiency changes, i.e., changes in the countries’ distance to the common WTF. TFP growth measures include this component, whereas technical change indexes leave it out, as demonstrated in the following output growth decomposition:

$$\textit{Output growth} = \underbrace{\textit{Efficiency change} \times \textit{Technical change}}_{\textit{TFP growth}} \times \textit{Factor accum.} \tag{1}$$

By assuming 100% technical efficiency of all countries in all years, neoclassical growth accounting implicitly identifies TFP growth with technical change. However, when technical inefficiency is allowed for, the difference between both measures becomes important. Our empirical analysis indicates that large discrepancies between the two groups of measures are visible in terms of almost all analyzed characteristics. Changes in countries’ distance to the WTF turn out to be both sizeable and highly variable, and thus their appropriate treatment is essential in the assessment of the pace of technological progress across countries.

Despite all the aforementioned differences, several unifying theoretical frameworks have been proposed in the productivity analysis literature, where the neoclassical growth accounting approach and the nonparametric frontier analysis can be taken as special instances. Such encompassing structures are useful for pinpointing the theoretical foundations of the alternative approaches to the measurement of technological progress. In particular, the framework developed by Raa and Shestalova (2011) applies to our case directly. Among the four alternative measurement methods considered in that article, neoclassical growth accounting and the DEA approach are the only two which do not require any additional data beyond the volumes of inputs and output, thus implicitly confirming our choice of compared measures (see also Raa, Mohnen 2002; Raa 2005).

Yet another methodological insight from the productivity analysis literature is that one ought to be very careful when interpreting our “technological progress” measures in statistical terms. Indeed, throughout the current article, and in line with the usual approach in macroeconomics, we shall think of the inputs and output as uncertain quantities, subject to a range of known caveats related to composition effects, cross-country differences in relative prices, differential depreciation rates, etc. As it will be explained later, there are also several approximations inherent in the construction of our dataset. Formally, both growth accounting and DEA assume that inputs and output are known with certainty, though. The deterministic character of these methods implies that the constructed measures of “technological progress” are formally certain, too (provided that the method captures the real-world production processes correctly). In consequence, they do not offer any information of the true uncertainty of these measures if inputs and output are in fact subject to error or if the true production function cannot be exactly recovered by the method, due to e.g. finiteness of the sample. One should keep this remark in mind when referring to issues such as WTF approximation precision, forecast accuracy, etc.

Stochastic frontier models, on the other hand (e.g., Koop, Osiewalski, Steel 1999; 2000; Kumbhakar, Lovell 2000; Bos et al. 2010) offer both an assessment of each country's technical inefficiency (distance to the WTF) – a concept which is at heart of the current analysis – and an explicit statistical treatment of the estimation error – a feat which our methodology does not offer. They also allow more sophisticated functional forms to be estimated than just Cobb-Douglas: perhaps the most popular one in this literature is the relatively flexible translog production function, allowing for systematic deviations from constant returns to scale and a constant elasticity of substitution. A comparison between deterministic nonparametric, and stochastic parametric frontier models should thus be considered as an important task for further research.

Given this background, the contribution of the current article to the literature is to:

– discuss formally the methodology behind several alternative empirical approaches to the measurement of "technological progress" across countries,

– provide a synthetic, numerical assessment of their empirical properties, based on an international panel dataset encompassing 19 highly developed OECD countries in the period 1970–2000.

To the latter end, we will compute (i) the fraction of growth in GDP per worker explained by the technological progress (residual) component in each of the 22 specifications, as well as (ii) the explained fraction of its cross-sectional and intertemporal variance. We will also calculate the correlations of these residual measures with labor productivity growth, and *ex post* prediction errors when labor productivity growth is predicted solely by the "factor-only component" (i.e., when residual technological progress is set to zero). Another exercise would be to compute pairwise correlation coefficients among our 22 measures of technological progress, to see if they convey essentially the same information, or conversely – if the definitional differences are empirically meaningful.

To our best knowledge, the current paper constitutes the first attempt to bring together several alternative methods of measurement of "technological progress" across countries, with the objective of comparing their empirical properties, considering both measures based on neoclassical growth accounting (which is still a standard approach in macroeconomics) and the ones based on nonparametric WTF estimates.

In the end, the lesson from the current study is that the researcher's choice of the method of measuring technological progress across countries should always be selected in accordance with the analyzed research question, and the treatment of technical efficiency changes should be particularly closely studied. It seems that there is no unique choice which would be empirically "best"; on the contrary, all considered "goodness of fit" measures vary significantly with changes in methodology: different methods are best in explaining average labor productivity growth rates, different methods excel in capturing their variance, etc.

We do not observe any alignment of this sort in the literature, though. Instead, alternative analytical methods are used for answering the same sets of questions, often leading to diverging results. For example, methodological differences between alternative decompositions of overall growth in output per worker into contributions of physical capital accumulation, accumulation of other production factors, and residual productivity growth, seem to merely reflect the backgrounds of their authors, either in neoclassical macroeconomics and/or national accounts (e.g., Jorgenson 1995; Timmer, Ypma, van Ark 2003) or in productivity analysis dealing with firm--level data (e.g., Färe et al. 1994; Kumar, Russell 2002).

In the current study we also find that the precision of WTF estimates matters a lot for the predicted rates of technological progress, especially if technical change measures are considered (as opposed to TFP growth measures). Furthermore, the results of our nonparametric analyses indicate marked departures from (i) full technical efficiency, (ii) the Cobb-Douglas production function specification, and (iii) perfect substitution between skilled and unskilled labor (see also Growiec et al. 2011; Growiec 2012).

As far as the methodology of the current article is concerned, it should be mentioned that even though each of our 22 measures of technological progress is based on a different definition and/or dataset, we in fact disregard several alternative methodologies which could potentially be used for our purposes as well. First of all, we omit the strand of literature which deals with CES production functions (e.g., Duffy, Papageorgiou 2000; Antràs 2004; Klump, McAdam, Willman 2007; Chirinko 2008; León-Ledesma, McAdam, Willman 2010). Clearly, relaxing the Cobb-Douglas production does not imply the need for an immediate jump into the "extreme" nonparametric DEA case where no explicit functional form of the production function is assumed. The class of CES production functions is another natural extension of the Cobb-Douglas baseline. Secondly, we also do not consider stochastic frontier models here (see e.g., Koop, Osiewalski, Steel 1999; 2000; Kumbhakar, Lovell 2000; Bos et al. 2010). As these models are most often based on the translog production function specification, they are somewhere in between the Cobb-Douglas and the nonparametric production function along the generality–parsimony spectrum. Most importantly, however, this approach allows for explicit econometric estimation of the parameters of the production function based on a fully specified stochastic model.

Yet another question which ought to be addressed in near future is, how large is the uncertainty in our nonparametric estimations of the WTF. This question could be addressed with the use of bootstrap techniques for nonparametric frontier models (see e.g. Simar, Wilson 2000; Kneip, Simar, Wilson 2008; Badunenko, Henderson, Russell 2009). The article is structured as follows. In Section 2, we specify the 22 alternative measures of technological progress. In Section 3, we describe our dataset. In Section 4, we provide our main results regarding the empirical properties of each particular measure of technological progress. Section 5 concludes.

2. Measurement of technological progress

2.1. The growth accounting approach

Even though in macroeconomics, the term "technological progress" is used in a broad range of contexts, the productivity analysis literature requires us to be more precise here. In the current paper, we will therefore always specify if we are talking about measures of TFP growth (which include technical efficiency changes), or technical change measures (which leave them out).

In this respect, the development and growth accounting literature (see e.g., Solow 1957; Caselli, 2005) habitually defines total factor productivity (TFP) on the basis of a Cobb-Douglas production function, computed using either only physical capital and labor, or physical and (homogenous) human capital as inputs. For country i in year t, TFP (sometimes referred to as the Solow residual) is then computed as:

$$A_{it} = \frac{y_{it}}{k_{it}^{\alpha}} \quad \text{or} \quad A_{it} = \frac{y_{it}}{k_{it}^{\alpha} h_{it}^{1-\alpha}} \tag{2}$$

where y_{it} is the country's GDP per worker, k_{it} is physical capital per worker, and h_{it} is human capital per worker. Furthermore, α is most often assumed to take the "consensus" value of 1/3.[1]

Consequently, TFP growth is captured by the gross growth rate of the Solow residual:

$$TFP_{\mathbf{x}}(i, t-1, t) = \frac{y_{it}}{y_{i,t-1}} \left(\frac{k_{i,t-1}}{k_{it}} \right)^{\alpha} \tag{3}$$

or

$$TFP_{\mathbf{x}}(i, t-1, t) = \frac{y_{it}}{y_{i,t-1}} \left(\frac{k_{i,t-1}}{k_{it}} \right)^{\alpha} \left(\frac{h_{i,t-1}}{h_{it}} \right)^{1-\alpha} \tag{4}$$

The subscript **x** refers to the specific choice of variables entering the input vector – in the current study, $\mathbf{x} = (k)$ or $\mathbf{x} = (k, h)$.

This approach requires the researcher to assume the Cobb-Douglas production function specification, constant returns to scale, and full efficiency of all production units (i.e., countries). Hence, efficiency change is trivially set to unity, and TFP growth is equal to technical change, and both of them are equal to output growth divided by factor accumulation. By the same token, the best practice technology is identified with the average practice technology here. Yet, if we allow for technical inefficiency in production and relax the restrictions on the functional form of the aggregate production function, then the data may reject these assumptions or at least indicate some departures from this benchmark. Admitting that multiple methods for generalizing the growth accounting approach exist in the literature (as discussed in the Introduction), we limit ourselves to the nonparametric DEA approach which provides clear-cut implications for the measurement of TFP growth and technical change across countries.

[1] This value is based on the seemingly robust observation that the capital's share of GDP – which is equal to α in a perfectly competitive economy – has been remarkably constant for decades in the US, oscillating around 1/3 (e.g., Kydland, Prescott 1982; Caselli 2005). For single-factor production functions (e.g., physical capital only or labor only), $\alpha = 1$ due to the requirement of constant returns to scale.

2.2. Data Envelopment Analysis

DEA-based measures of TFP growth, technical change, and technical efficiency change are constructed on the basis of production possibility sets S^t of feasible input–output configurations, for $t = 1,\dots,T$. (in our study: 1970, 1975, 1980, 1985, 1990, 1995, 2000):

$$S^t = \{(\mathbf{x}_t, y_t): \mathbf{x}_t \text{ can produce } y_t\} \tag{5}$$

where $\mathbf{x}_t$ is the vector of inputs (which will be defined for each measure separately), y_i is the output (country's GDP per worker), and S^t satisfies Färe and Primont (1995) axioms for all t.

Based on this specification of the world's technology at each given year t, we can define the Shephard's output distance function (cf. Zofio 2007), capturing the country's distance to the frontier, as:

$$D_O^t(\mathbf{x}_t, y_t) = \inf_\theta \{\theta > 0 : (\mathbf{x}_t, y_t/\theta) \in S^t\} \tag{6}$$

which is linearly homogenous of degree +1 in yt and nonincreasing in $\mathbf{x}_t$. If $D_O^t(\mathbf{x}_t, y_t) = 1$ then the given country is technically efficient; otherwise it is inefficient.

The world technology frontier (WTF) is a fragment of the boundary of the production possibility set, for which output is maximized given inputs:

$$WTF^t = \{(\mathbf{x}_t, y_t) : D_O^t(\mathbf{x}_t, y_t) = 1\} \tag{7}$$

Hence, if a country i is technically efficient then it spans (i.e., belongs to) WTF^t.

It is critical to note that with the passage of time, each country will observe three different types of shifts: factor accumulation, shifts of the WTF (i.e., technical change), and changing distance to the frontier (i.e., efficiency change). The exact measurement of each of those shifts is conditional on the definition of the production technology, or the construction of S^t. Thus the computed pace of "technological progress" must also be conditional on these assumptions.

To compute output attainable at the WTF, i.e., to identify the best-practice production function, we use the nonparametric DEA algorithm, introduced to the context of cross-country productivity growth analyses 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 (2012). The principal idea behind DEA is to envelop all data points in the "smallest" convex set and to infer the production function as a fragment of the boundary of this set 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, DEA provides a decomposition of output y_{it}:

$$y_{it} = y_t^*(\mathbf{x}_{it}) \cdot D_O^t(\mathbf{x}_{it}, y_{it}) \tag{8}$$

i.e., into a product of the maximum attainable output given inputs $y_t^*(\mathbf{x}_{it})$ and the Shephard output distance function $D_O^t(\mathbf{x}^t, y^t) \in (0, 1]$, measuring the "vertical" distance of country i to the technology frontier at time t.

In the current analysis, we assume that technologies that were once available, remain available forever, and hence we do not allow for technical regress. This requires us to carry out a sequential WTF construction procedure where for each year t, WTF^t is spanned by observations from all years $\tau = 1,\ldots,t$ (cf. Henderson, Russell 2005).

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. Given our assumptions, the (output-oriented) deterministic DEA method is a linear programming technique allowing one find the Shephard output distance function $D_{jt} \equiv D_O^t(\mathbf{x}_{jt}, y_{jt})$, where $\mathbf{x}_{jt} = (x_{1,jt},\ldots,x_{n,jt})$, for each unit $j = 1, 2,\ldots, I$ in the sample, given $t \in \{1, 2,\ldots, T\}$ (Henderson, Russell 2005):

$$
\begin{aligned}
&\min_{\{D_{jt}, \lambda_{11},\ldots,\lambda_{It}\}} D_{jt} \\
&\text{s.t. } y_{jt}/D_{jt} \le \sum_{\tau=1}^{t}\sum_{i=1}^{I}\lambda_{i\tau} y_{i\tau} \\
&\sum_{\tau=1}^{t}\sum_{i=1}^{I}\lambda_{i\tau} x_{1,i\tau} \le x_{1,jt} \\
&\sum_{\tau=1}^{t}\sum_{i=1}^{I}\lambda_{i\tau} x_{2,i\tau} \le x_{2,jt} \\
&\qquad\vdots \\
&\sum_{\tau=1}^{t}\sum_{i=1}^{I}\lambda_{i\tau} x_{n,i\tau} \le x_{n,jt} \\
&D_{i\tau}, \lambda_{i\tau} \ge 0, \qquad i = 1, 2,\ldots, I,\ \tau = 1, 2,\ldots, t
\end{aligned}
\tag{9}
$$

It is additionally assumed that $\sum_{\tau=1}^{t}\sum_{i=1}^{I}\lambda_{i\tau} = 1$ in the VRS case (variable returns to scale). Under the CRS (constant returns to scale) assumption, no further restriction on parameter $\lambda_{i\tau}$ is necessary.[2]

Throughout the remaining text, and following Zofio (2007), the Shephard distance function taking into consideration as benchmark technology the DEA frontier with VRS will be denoted as $D_O^t(\mathbf{x}_{it}, y_{it})$, whereas the Shephard distance function from the DEA frontier with CRS – as $\breve{D}_O^t(\mathbf{x}_{it}, y_{it})$. Both functions coincide only if the true underlying technology is CRS. Consequently, $y_t^*(\mathbf{x}_{it})$ will denote the maximum attainable output given the DEA frontier with VRS, and $\breve{y}_t^*(\mathbf{x}_{it})$ – with CRS.

[2] The CRS case is sometimes referred to as the CCR model in the honor of its authors (Charnes, Cooper, Rhodes 1978). The VRS case is referred to as the BCC model (Banker, Charnes, Cooper 1984).

The choice of DEA as our WTF construction method was based primarily on the advantageous fact that it does not require any assumptions on the functional form of the aggregate production function (provided that it satisfies the free-disposal property and convexity). Indeed, the usual assumption of a Cobb-Douglas aggregate production function may lead to marked biases within growth accounting or levels accounting exercises leading to an overestimation of the role of total factor productivity (TFP) in explaining growth, as argued by Caselli (2005) and Jerzmanowski (2007), a feature which is avoided when the DEA approach is adopted.[3] Also, it does not require any additional data beside aggregate inputs and output.

One should also be aware of the limitations of the DEA approach. First, its deterministic character makes it silent on the estimation precision of the aggregate production function and of the predicted efficiency levels if inputs and outputs are subject to stochastic shocks. Second, the DEA provides a biased proxy of the actual technological frontier. In fact, even the most efficient units in the sample could possibly operate with some extra efficiency, since they are themselves aggregates of smaller economic units and must therefore have some internal heterogeneity. After taking account of that, the frontier would be shifted upwards; efficiency is nevertheless normalized to 100% for the most efficient units in the sample. Third, the DEA constructs the aggregate production function basing on the (relatively few) efficient data points. This makes it naturally sensitive to outliers and measurement error. We deal with this issue very carefully.

2.3. Malmquist indexes and their decompositions

Based on our DEA results, we are able to define a range of measures of TFP growth and technical change. The following classification of these measures is based on Zofio (2007); see also O'Donnell (2009). The measures of TFP growth are:

1. The CRS Malmquist productivity index, computed from a production function constructed with the non-parametric DEA algorithm with CRS:

$$
\begin{aligned}
M_{\mathbf{x}}^{CRS}(i,t-1,\,t) &= \sqrt{\frac{\breve{D}_O^t(\mathbf{x}_{it},y_{it})}{\breve{D}_O^t(\mathbf{x}_{i,t-1},y_{i,t-1})}\frac{\breve{D}_O^{t-1}(\mathbf{x}_{it},y_{it})}{\breve{D}_O^{t-1}(\mathbf{x}_{i,t-1},y_{i,t-1})}} = \\
&= \frac{\breve{D}_O^t(\mathbf{x}_{it},y_{it})}{\breve{D}_O^{t-1}(\mathbf{x}_{i,t-1},y_{i,t-1})}\sqrt{\frac{\breve{y}_t^*(\mathbf{x}_{it})}{\breve{y}_{t-1}^*(\mathbf{x}_{it})}\frac{\breve{y}_t^*(\mathbf{x}_{i,t-1})}{\breve{y}_{t-1}^*(\mathbf{x}_{i,t-1})}}
\end{aligned}
\tag{10}
$$

The CRS Malmquist index defined above is a geometric average – Fisher ideal index (see e.g., Henderson, Russell 2005 for a discussion) of CRS Malmquist indexes taking technology at time t and $t-1$ as the benchmark technology. It is also a product of the country's efficiency ratio at periods t and $t-1$, and the technical change ("WTF shift") factor. Intuitively, it captures technological progress actually observed in a given country, reflected both in the country's progress or regress with respect to the WTF, and the pace at which the WTF itself is shifted.

[3] As for the predicted shape of the production function, DEA can only offer its finite-sample, piecewise linear approximation. With sufficiently large data samples, however, certain parametric forms could be tested formally against this approximate DEA-based nonparametric benchmark, such as the Cobb-Douglas or translog (cf. Growiec et al. 2011).

As pointed out by several authors (e.g., O'Donnell 2009; Daskovska, Simar, Van Bellegem, 2010), the Malmquist index is not multiplicatively complete (circular), that is, in general $M_{\mathbf{x}}^{CRS}(i,t-2,t) \neq M_{\mathbf{x}}^{CRS}(i,t-2,t-1) \cdot M_{\mathbf{x}}^{CRS}(i,t-1,t)$.

2. The VRS Malmquist productivity index, computed from a production function constructed with the non-parametric DEA algorithm with VRS:

$$M_{\mathbf{x}}^{VRS}(i,t-1,t) = \sqrt{\frac{D_O^t(\mathbf{x}_{it}, y_{it})}{D_O^t(\mathbf{x}_{i,t-1}, y_{i,t-1})} \frac{D_O^{t-1}(\mathbf{x}_{it}, y_{it})}{D_O^{t-1}(\mathbf{x}_{i,t-1}, y_{i,t-1})}} = \frac{D_O^t(\mathbf{x}_{it}, y_{it})}{D_O^{t-1}(\mathbf{x}_{i,t-1}, y_{i,t-1})} \sqrt{\frac{y_t^*(\mathbf{x}_{it})}{y_{t-1}^*(\mathbf{x}_{it})} \frac{y_t^*(\mathbf{x}_{i,t-1})}{y_{t-1}^*(\mathbf{x}_{i,t-1})}} \quad (11)$$

Again, the VRS Malmquist index defined above is a geometric average (Fisher ideal index) of VRS Malmquist indexes taking technology at time t and $t-1$ as the benchmark technology. The difference is that this time we allow for variable returns to scale.

The VRS Malmquist index is not multiplicatively complete (circular) either, that is, in general $M_{\mathbf{x}}^{VRS}(i,t-2,t) \neq M_{\mathbf{x}}^{VRS}(i,t-2,t-1) \cdot M_{\mathbf{x}}^{VRS}(i,t-1,t)$.

The measures of technical change are the following:

1. Potential technical change PTC, capturing the rate of technical change at the WTF, constructed with the non-parametric DEA algorithm with CRS. It is defined as:

$$PTC_{\mathbf{x}}(i,t-1,t) = \sqrt{\frac{\breve{D}_O^{t-1}(\mathbf{x}_{it}, y_{it})}{\breve{D}_O^t(\mathbf{x}_{it}, y_{it})} \frac{\breve{D}_O^{t-1}(\mathbf{x}_{i,t-1}, y_{i,t-1})}{\breve{D}_O^t(\mathbf{x}_{i,t-1}, y_{i,t-1})}} = \sqrt{\frac{\breve{y}_t^*(\mathbf{x}_{it})}{\breve{y}_{t-1}^*(\mathbf{x}_{it})} \frac{\breve{y}_t^*(\mathbf{x}_{i,t-1})}{\breve{y}_{t-1}^*(\mathbf{x}_{i,t-1})}} \quad (12)$$

PTC, first proposed by Färe et al. (1994), isolates the effects of a shifting WTF (technical change at the WTF) from the effects of efficiency changes. As argued by Ray and Desli (1997), however, PTC is the exact measure of technical change at the WTF only if the data are in perfect alignment with the CRS restriction. Otherwise, it convolutes technical change with scale efficiency change.

It is also easily noticed that:

$$M_{\mathbf{x}}^{CRS}(i,t-1,t) = \frac{\breve{D}_O^t(\mathbf{x}_{it}, y_{it})}{\breve{D}_O^{t-1}(\mathbf{x}_{i,t-1}, y_{i,t-1})} \cdot PTC_{\mathbf{x}}(i,t-1,t) \equiv EC_{\mathbf{x}}(i,t-1,t) \cdot PTC_{\mathbf{x}}(i,t-1,t) \quad (13)$$

Hence, potential technical change is the CRS Malmquist index net of CRS technical efficiency changes.

2. Technical change TC, capturing the rate of technical change at the WTF, constructed with the non-parametric DEA algorithm with VRS. It is defined as:

$$TC_{\mathbf{x}}(i,t-1,t)=\sqrt{\frac{D_O^{t-1}(\mathbf{x}_{it},y_{it})}{D_O^{t}(\mathbf{x}_{it},y_{it})}\frac{D_O^{t-1}(\mathbf{x}_{i,t-1},y_{i,t-1})}{D_O^{t}(\mathbf{x}_{i,t-1},y_{i,t-1})}}=\sqrt{\frac{y_t^*(\mathbf{x}_{it})}{y_{t-1}^*(\mathbf{x}_{it})}\frac{y_t^*(\mathbf{x}_{i,t-1})}{y_{t-1}^*(\mathbf{x}_{i,t-1})}} \tag{14}$$

Just like PTC, the current measure TC isolates the effects of a shifting WTF (technical change at the WTF) from the effects of efficiency changes. As argued by Ray and Desli (1997), TC is the exact measure of technical change at the WTF in the general case of variable returns to scale.

It is also easily noticed that:

$$\begin{aligned}M_{\mathbf{x}}^{VRS}(i,t-1,t)&=\frac{D_O^{t}(\mathbf{x}_{it},y_{it})}{D_O^{t-1}(\mathbf{x}_{i,t-1},y_{i,t-1})}\cdot TC_{\mathbf{x}}(i,t-1,t)\equiv\\&\equiv TEC_{\mathbf{x}}(i,t-1,t)\cdot TC_{\mathbf{x}}(i,t-1,t)\end{aligned} \tag{15}$$

Hence, technical change is the VRS Malmquist index net of VRS technical efficiency changes.

To see how much "noise" is introduced into the analysis if CRS decompositions are used when the technology is truly VRS, the following decomposition is also useful (Zofio 2007):[4]

$$\begin{aligned}M_{\mathbf{x}}^{CRS}(i,t-1,t)&=M_{\mathbf{x}}^{VRS}(i,t-1,t)\cdot RTS_{\mathbf{x}}(i,t-1,t)=\\&=TEC_{\mathbf{x}}(i,t-1,t)\cdot TC_{\mathbf{x}}(i,t-1,t)\cdot RTS_{\mathbf{x}}(i,t-1,t)\end{aligned} \tag{16}$$

where:

$$RTS_{\mathbf{x}}(i,t-1,t)=\sqrt{\frac{\breve{D}_O^{t-1}(\mathbf{x}_{it},y_{it})D_O^{t-1}(\mathbf{x}_{i,t-1},y_{i,t-1})\breve{D}_O^{t}(\mathbf{x}_{it},y_{it})D_O^{t}(\mathbf{x}_{i,t-1},y_{i,t-1})}{D_O^{t-1}(\mathbf{x}_{it},y_{it})\breve{D}_O^{t-1}(\mathbf{x}_{i,t-1},y_{i,t-1})D_O^{t}(\mathbf{x}_{it},y_{it})\breve{D}_O^{t}(\mathbf{x}_{i,t-1},y_{i,t-1})}} \tag{17}$$

Hence, all differences between the CRS and VRS specifications can be lumped into the returns-to-scale component *RTS*. The interpretation of this component is the following (Zofio 2007): "if $RTS_{\mathbf{x}}(i,t-1,t)>1$ the firm [country] improves its performance on a scale basis with regard to the base period productivity benchmark by exploiting increasing returns to scale and getting closer to the MPSS [most productive scale size]. Contrarily, $RTS_{\mathbf{x}}(i,t-1,t)<1$ indicates that input change carries decreasing returns to scale and the firm [country] is moving away from optimal scale".

2.4. The "hybrid" approach

Alongside the simplest growth accounting approach and the more involved DEA-based measurement methods defined above, we shall also consider an intermediate, "hybrid" approach.

[4] Within the DEA framework, global returns to scale can also be directly tested, cf. Banker (1996) or Simar and Wilson (2002).

It goes along the lines of neoclassical growth accounting in defining TFP growth as the ratio of output and input growth, with the aggregate production function being defined as Cobb-Douglas with CRS. It also disentangles technical change along the WTF from changes in technical efficiency, however, by multiplying the TFP growth rate with the ratio of CRS DEA-based technical efficiency measures. Hence, conceptually, this hybrid TFP growth measure is a measure of technical change (technical change at the WTF):

$$\overline{TFP}_{\mathbf{x}}(i, t-1, t) = \frac{\breve{y}_t^*(\mathbf{x}_{it})}{\breve{y}_{t-1}^*(\mathbf{x}_{i,t-1})} \left(\frac{k_{i,t-1}}{k_{it}} \right)^{\alpha} \tag{18}$$

or

$$\overline{TFP}_{\mathbf{x}}(i, t-1, t) = \frac{\breve{y}_t^*(\mathbf{x}_{it})}{\breve{y}_{t-1}^*(\mathbf{x}_{i,t-1})} \left(\frac{k_{i,t-1}}{k_{it}} \right)^{\alpha} \left(\frac{h_{i,t-1}}{h_{it}} \right)^{1-\alpha} \tag{19}$$

where $\alpha = 1/3$ and y_t^* is the maximum output per worker attainable at time *t* given inputs.

This number is evaluated from the WTF, computed according to the nonparametric DEA algorithm with CRS. The CRS assumption is used here for coherence with the assumed Cobb-Douglas function which requires CRS as well. As opposed to TFP growth obtained via neoclassical growth accounting, the "hybrid" approach deals exclusively with the best practice technology, not the average practice technology.

Inserting the identity $y_{it} = D_O^t(\mathbf{x}_{it}, y_{it}) \cdot y_t^*(\mathbf{x}_{it})$ into the above definitions, we obtain the following decomposition of TFP growth, computed with the growth accounting approach:

$$TFP_{\mathbf{x}}(i, t-1, t) = EC_{\mathbf{x}}(i, t-1, t) \cdot \overline{TFP}_{\mathbf{x}}(i, t-1, t) \tag{20}$$

where $EC_{\mathbf{x}}(i, t-1, t)$ is the CRS technical efficiency change component defined in equation (13).

This leads to the following output growth decomposition:

$$\frac{y_{it}}{y_{i,t-1}} = EC_{\mathbf{x}}(i, t-1, t) \cdot \overline{TFP}_{\mathbf{x}}(i, t-1, t) \cdot \left(\frac{k_{it}}{k_{i,t-1}} \right)^{\alpha} \tag{21}$$

or

$$\frac{y_{it}}{y_{i,t-1}} = EC_{\mathbf{x}}(i, t-1, t) \cdot \overline{TFP}_{\mathbf{x}}(i, t-1, t) \cdot \left(\frac{k_{it}}{k_{i,t-1}} \right)^{\alpha} \left(\frac{h_{it}}{h_{i,t-1}} \right)^{1-\alpha} \tag{22}$$

known in the growth accounting literature as the "appropriate technology vs. efficiency" output growth decomposition (Basu, Weil 1998; Jerzmanowski 2007; Growiec 2012).

2.5. Information sets

As mentioned in the Introduction, the current paper considers 22 alternative empirical measurements of "technological progress" (i.e., TFP growth or technical change). Along one dimension, this multiplicity has been logically grouped above into six categories differing in methodology. Alternatively, however, they can also be classified into four categories according to the information set (or vector **x**) used for computing them. Intersecting these two dimensions naturally leads to a 4 × 6 matrix. In its rows we put the six alternative methods for computing "technological progress", described above, whereas in its columns we put information sets I_i, $i = 1, 2, 3, 4$:

I_1: data on OECD countries and US states, including GDP per worker and the stock of physical capital per worker ($\mathbf{x}_{it} = k_{it}$);

I_2: data on OECD countries only, including GDP per worker as well as physical and human capital per worker ($\mathbf{x}_{it} = (k_{it}, h_{it})$);

I_3: data on OECD countries and US states, including GDP per worker as well as physical and human capital per worker ($\mathbf{x}_{it} = (k_{it}, h_{it})$);

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 ($\mathbf{x}_{it} = (k_{it}, L^U_{it}, L^S_{it})$).

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

The obvious advantage of using I_3 over I_1 is that human capital is one of the important factors driving labor productivity growth and convergence, and thus omitting it overstates the role of physical capital accumulation (cf. Henderson, Russell 2005), and possibly also residual productivity growth.

The advantage of using I_3 over I_2 comes from the fact that the US are a country with substantial internal heterogeneity in inputs and output, which always spans the WTF when considered as a single data point (cf. Growiec 2012). 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.[5]

In the case of I_4 we assume that the stocks of unskilled and skilled labor are a decomposition of total human capital per worker h used in I_3 (such that $h = L^U + L^S$), but they enter the aggregate production function separately and thus are allowed to be imperfectly substitutable. 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); it explains the theoretical advantage of using I_4 over I_5.

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

[5] See Growiec (2012) for a discussion on the appropriateness of sub-national disaggregation of the US and consequences of the idea to further disaggregate other countries, or US states themselves.

Visually, the discussed 4×6 matrix is presented in Table 1. The notation "(C.)" denotes the countries-only dataset which does not include US state-level data.

Upon reading the table, the following facts are worth noting. First, the measurement of TFP growth across countries according to the Cobb-Douglas-based growth accounting procedure 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, 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 I_2, I_3, I_4, resulting in two empty slots in our 4×6 matrix.

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.[6] 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. This means that we assume constant returns to scale at level of the aggregate production function; the distinction between constant and variable returns to scale pertains to its intensive form only.

International data on GDP and GDP per worker are taken from the Penn World Table 6.2 (Heston, Summers, 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 multiplicatively 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.[7]

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

[6] We dropped Germany due to the presence of the unification shock in the data, Luxembourg because of its extraordinarily high output 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.

[7] 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 all other measures of technological progress, and because we want to maintain strict comparability between the methods throughout the whole study.

have been imputed when data were missing, using the indirect evidence from Turner et al. (2007). Unskilled labor L^U and skilled labor L^S are measured in "no-schooling equivalents": 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 human capital aggregates using the Mincerian exponential formula with a concave exponent following Hall and Jones (1999), and more directly, Caselli (2005):

$$L^U = \sum_{i \in S_U} \psi_i \, e^{\phi(s_i)} \qquad L^S = \sum_{i \in S_S} \psi_i \, e^{\phi(s_i)} \tag{23}$$

where S_U is the set of groups of people who completed less than 12 years of education (less than elementary, elementary, less than secondary), S_S is the set of groups of people who completed 12 years of education or more (secondary, less than college, college or more), ψ_i captures the share of i-th education group in total working-age population of the given country, s_i represents years of schooling in i-th education group (cf. de la Fuente, Doménech 2006), and $\phi(s)$ is a concave piecewise linear function (Psacharopoulos 1994; Hall, Jones 1999):

$$\phi(s) = \begin{cases} 0.134s & s < 4 \\ 0.134 \cdot 4 + 0.101(s-4) & s \in [4, 8) \\ 0.134 \cdot 4 + 0.101 \cdot 4 + 0.068(s-8) & s \geq 8 \end{cases} \tag{24}$$

Furthermore, assuming that everyone who has not completed high school is counted as unskilled, and everyone who has completed it – as skilled, we compute the overall scale of human capital per worker as a sum of 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.[8] 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

Keeping in mind all the methodological caveats, let us now pass to the presentation of our foremost set of empirical results: "technological progress" rates across the 19 OECD countries in our sample, for the entire period 1970–2000, calculated according to each of the 22 diverse specifications. These results are summarized in Tables 2–3. These rates have been computed as annualized growth rates, based on the 2000/1970 ratio of technology levels. The ultimate row in those tables contains cross-country averages, computed as root transformations of (unweighted) geometric averages of country-level 2000/1970 ratios (up to the first-order approximation, they are equal to simple arithmetic averages of growth rates).

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

From Tables 2–3 we observe that expanding the information set from I_1 or I_2 towards I_4, as well as using more and more general assumptions (i.e., relaxing the Cobb-Douglas restriction and then relaxing the CRS assumption), generally decreases 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 labor productivity growth better, and so there is less space left for residual productivity growth.

A curious reader might be interested why we have not recorded any technological progress in the PTC_k case. The reason is that this specification implies a linear single-factor production function, $y_s(k_{it}) = A_s k_{it}$ for any $i = 1,\ldots,I$ and $s,t = 1,\ldots,T$. In consequence, $PTC_k(i,t-1,t) = A_t/A_{t-1}$ for all $i = 1,\ldots,I$. In our data, however, the ratio y_{it}/k_{it} is maximized for Texas 1980, being as little as 0.08% higher than in Florida 1970. Hence, this particular measure implies that there has been hardly any technological progress since 1970 (and absolutely no progress since 1980).

Even more importantly, already at this point we observe the empirical relevance of the theoretical distinction between measures of technical change, interpreted as "genuine" technological progress at the WTF, and TFP growth measures, capturing technological progress actually observed in each given country. The first observed discrepancy is that for the former group of measures, "technological progress" is by construction constrained to non-negative rates. Since our methodology 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 labor productivity growth is outpaced by the rate of factor accumulation, then this difference will be reflected in a fall in technical efficiency, and residual technological progress will become negative. We in fact observe exactly this kind of dynamics in our data in Japan, Portugal, Spain, and Greece. The second empirical discrepancy is that technical change is positively correlated with initial physical and human capital stocks (correlation coefficients of 0.90 and 0.69, respectively; cf. Kumar and Russell 2002; Jerzmanowski 2007) and negatively correlated with the rates of subsequent growth in output per worker (-0.48), whereas TFP growth, due to taking account of efficiency changes as well, is much more dispersed across countries, and correlates positively both with overall labor productivity growth (0.15) and with the initial stocks of physical and human capital (0.52 and 0.73, respectively). All these regularities are visible in Figure 1.

Please note that the results presented in Tables 2–3 and Figure 1 have been averaged over the entire period 1970–2000. Even though this already gives some information about the empirical 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 22 measures of technological progress in all five-year subperiods (1970–1975, 1975–1980, 1980–1985, 1985–1990, 1990–1995, 1995–2000) is too long to be presented here in full, but it is that table which underlies all further analyses.[9] Hereafter, wherever we refer to cross-sectional results, we mean the results based on the set of 19 country-level measures being 1970–2000 averages. When we refer to panel results, on the other hand, we mean the results based on the set of $19 \times 6 = 114$ measures specific for each country and each five-year period.

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

4.2. Accounting for labor productivity growth

We shall now turn to the analysis of most important empirical properties of the alternative methods of measurement of technological progress across countries. The first of those properties is the ability of the "factor-only component" – capturing growth in output per worker less technological progress, computed in association with each of the considered measures, cf. Caselli (2005) – to explain growth in labor productivity, i.e. GDP per worker.

The results are summarized in Table 4 and Figure 2. The numbers in Table 4 are unweighted averages over countries (in the cross-sectional case), or over countries and time periods (in the panel case), of percentages of growth attributed to factor accumulation and residual 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 component. Please note that in the case of TFP growth measures, technical efficiency changes are included in "technological progress", whereas in the case of technical change measures, they are included in the "factor-only component".

We observe that for any given information set $I_1 - I_4$, if the "technological progress" measure includes changes in technical efficiency then the "factor-only component" does a better job in explaining labor productivity growth than residual technological progress. The opposite is true for technical change measures, where it is technological progress which explains a significantly larger fraction. The reason for this discrepancy lies with the treatment of technical efficiency change which therefore appears empirically very relevant (M_k^{CRS} and PTC_k are excluded from Figure 2 because they imply $PTC_k \approx 1$ and $M_k^{CRS} \approx EC_k$ and thus are not interesting from the point of view of the current comparison).

We also see that generally all factor-only components do a better job in capturing labor 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, output per worker rises primarily due to factor accumulation and some frontier productivity growth, whereas in shorter time periods there is more room for efficiency changes, partly because capital stocks cannot be instantaneously adjusted to the newly available technology. Finally, we also see that both in the panel and in the cross-section, the largest fraction of labor productivity growth is explained by factors if technological progress is computed as the CRS Malmquist index under the full information set I_4.

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

Table 5 and Figure 3 summarize a few more empirical characteristics of each of the measures of technological progress, such as the variance of growth in output per worker accounted by the factor-only component, correlations with labor productivity growth, and forecast accuracy if growth in output per worker is forecast solely with the factor-only component. Obviously, each of these characteristics captures a different decomposition, 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 in cross-country empirical applications. It clearly depends on the particular question asked and the assumptions made in each particular study, some of which will be discussed in the following paragraphs as well as in subsection 4.5.

We do see several regularities, though, complementing the knowledge we already have from the theoretical definition of each of our measures (M_k^{CRS} and PTC_k are excluded from Figure 3 because they imply $PTC_k \approx 1$ and $M_k^{CRS} \approx EC_k$ and thus are not interesting from the point of view of the current comparison). The regularities are the following:

1. The TFP growth measure derived from growth accounting is very strongly correlated with labor productivity growth, both in the cross-section and in the panel, which suggests a possible problem of an inappropriate functional form. This measure leaves a quite large fraction of labor productivity growth to be explained by factor accumulation, which is a generally desirable property, but is largely outperformed by several Malmquist indices in this respect.

2. Malmquist indexes are visibly less correlated with labor productivity growth, especially in the cross-section, and leave an even larger fraction of labor productivity growth to be explained by factor accumulation.

3. The hybrid parametric–non-parametric TFP growth measure is very weakly correlated with labor productivity growth, especially in the temporal dimension. The factor-only component associated with this measure of “technological progress” does a bad job in explaining rates of growth, but a very good job in explaining their variance across countries and time. The fact that hybrid 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. Standard growth accounting techniques, assuming a uniform technical change pattern, should therefore fall short in this respect.

4. Non-parametric technical change measures (PTC, TC) are robustly negatively correlated with labor 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, Russell 2002; Jerzmanowski 2007). Its factor-only component explains a very large part of variance of labour 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 3 is that all measures of TFP growth are highly correlated with labor productivity growth[10] but their factor-only components do a bad job in explaining its variance, whereas measures of technical change are weakly correlated with labor productivity growth (even negatively in the cross-section) and their factor-only components do a good job in explaining its variance.

6. Enlarging the information set by including further factors of production increases the percentage of labor productivity growth explained by factors and lowers the correlation of each given measure of technological progress with labor 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 (see Growiec 2012) generally improves the empirical properties of most considered

[10] It is true particularly in the temporal dimension; in the cross-section, this correlation falls down to 0.041–0.267 for Malmquist indices.

measures. In particular, it increases the percentage of variance explained by the factor-only component associated with a given measure of technical change; this regularity does not apply to TFP growth measures.

8. The factor-only component does the best job in predicting labor productivity growth (that is, MAE and RMSE are minimized) when "technological progress" is defined as PTC, taking into account the decomposition of human capital into unskilled and skilled labor.

9. Other things equal, PTC is superior to TC (as judged by the MAE and RMSE) in predicting labor productivity growth with the factor-only component. This suggests that in international data, returns to scale should be close to constant on average.

10. Average forecast accuracy of the factor-only component is better for measures of technical change than for measures of TFP growth. There is however a trade-off in accuracy of forecasting mean labor productivity growth which is better in the latter case, and its deviations from the mean, which is better in the former case.

4.4. Pairwise correlations

A further piece of information is conveyed in Tables 6–7, containing pairwise (Pearson) correlation coefficients among the 10 measures of TFP growth and the 12 measures of technical change, constructed for our dataset of OECD countries. The graphical layout of Tables 6–7 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. The parametric TFP growth measures are strongly correlated with each other, and so are all Malmquist indexes (irrespective of the CRS/VRS assumption), all hybrid TFP growth measures, and all PTC/TC measures (again, irrespective of the CRS/VRS assumption). The correlation across methodologies is much less pronounced and in several cases it is actually negative.

Still, on the basis of evidence discussed above, the auxiliary use of US state-level data seems helpful.

Interestingly, the negative correlations between hybrid TFP growth measures and non--parametric technical change indexes appear in the cross-sectional dimension but disappear in the panel. More generally, panel correlations are generally larger, with the exception of correlations between PTC and TC measures which are larger in the cross-section. The reason is that most measures of "technological progress" move in a more or less parallel fashion across time (but vary largely across countries). 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, and particular attention should be paid to the distinction between TFP growth and technical change because of the differential treatment of technical efficiency changes. If the objective is to account for the average labor productivity growth rate across countries or time, then TFP growth measures should be used, and in this case the most successful measure appears to be the CRS Malmquist index computed using the information set I_4.[11]

If the objective is, on the other hand, to find the sources of variation of labor productivity growth rates across countries and time, most promising are the measures of technical change, in particular the ones based on the information set I_4. If one wants to minimize *ex post* prediction errors when predicting labor productivity growth with growth of the factor-only component, then PTC computed with I_4 should be the most appropriate choice. Generally, one always has to draw a firm line between measures of technical change and measures of TFP growth, where the latter one includes shifts in technical efficiency as well. Both types of measures are distinct by definition, negatively correlated with 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 (cf. Growiec 2012), even though these numbers are measured with admittable error.

4.6. A comparison with van Biesebroeck (2007)

An insightful reader might notice that the current article has a similar 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 inputs and outputs of individual firms, and ours – of countries. Second, van Biesebroeck (2007) compares both deterministic and stochastic measures of factor productivity and technological progress, whereas the current study limits attention to deterministic approaches

[11] It may be surprising that the VRS Malmquist index is found somewhat inferior to the CRS variant in the considered dataset. Without implying, let us suggest that a possible reason behind this result might be a combination of approximately constant returns to scale at the cross-country level and substantial measurement error.

only. Third, 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.[12] Fourth, 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 factor prices, 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.

5. Conclusion

The current article has been the first one to bring together 22 approaches to the measurement of "technological progress" across countries, providing a synthetic, numerical assessment of their empirical properties on the basis of a few standard, easily interpretable statistics. The considered measures are based on the neoclassical growth accounting approach, nonparametric frontier analysis (DEA), and a "hybrid" parametric-nonparametric approach. The frontier approach enabled us to construct the world technology frontier (WTF) and subsequently control for changes in countries' technical inefficiency. Having discussed a range of definitional issues, we have investigated empirically what fraction of total growth in GDP per worker and its variance in the group of 19 OECD countries in 1970–2000 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 growth in output per worker and calculated the mean *ex post* prediction errors (MAE, RMSE) when future labor productivity growth is predicted as the implied factor-only component.

The results of this investigation indicate that (i) it is crucial to distinguish between measures of TFP growth, capturing technological progress actually observed in each given country, from measures of technical change proper, capturing technological progress at the WTF, (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 research question and special attention should be paid to the treatment of technical efficiency changes (shifts in the distance to the WTF).

[12] 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. It remains a caveat for our study, though, that deterministic methods used here such as DEA implicitly assume that the true data-generating process is adequately represented by the given method.

The current study can be extended in numerous ways, including the following ones. The first idea would be to compare the predictions regarding the cross-country measures of technological progress from deterministic nonparametric frontier models with their counterparts from stochastic parametric frontier models, preferably based on the translog production function specification (cf. Koop, Osiewalski, Steel 1999; 2000; Kumbhakar, Lovell 2000; Growiec et al. 2011) as well as with neoclassical growth accounting based on the CES aggregate production function specification with factor-augmenting technical change (cf. Duffy, Papageorgiou 2000; Klump, McAdam, Willman 2007; Chirinko 2008). Another question which could be addressed is, how large is the uncertainty in the non-parametric estimations of the WTF, underlying the measures of technological progress discussed above. This question could be addressed with the use of bootstrap techniques for non-parametric frontier models. Yet another idea would be to use different datasets to see if the results obtained here still go through.

References

Antràs P. (2004), Is the U.S. aggregate production function Cobb-Douglas? New estimates of the elasticity of substitution, *Contributions to Macroeconomics*, 4(1), 1–34.

Badunenko O., Henderson D.J., Russell R.R. (2009), *Bias-corrected production frontiers: application to productivity growth and convergence*, University of California Riverside, unpublished.

Badunenko O., Henderson D.J., Zelenyuk V. (2008), Technological change and transition: relative contributions to worldwide growth during the 1990's, *Oxford Bulletin of Economics and Statistics*, 70(4), 461–492.

Banker R.D. (1996), Hypothesis testing using Data Envelopment Analysis, *Journal of Productivity Analysis*, 7, 139–159.

Banker R.D., Charnes A., Cooper W.W. (1984), Some models for estimating technical and scale inefficiencies in Data Envelopment Analysis, *Management Science*, 30, 1078–1092.

Barro R.J., Lee J.-W. (2001), International data on educational attainment: updates and implications, *Oxford Economic Papers*, 53(3), 541–563.

Basu S., Weil D.N. (1998), Appropriate technology and growth, *Quarterly Journal of Economics*, 113(4), 1025–1054.

van Biesebroeck J. (2007), Robustness of productivity estimates, *Journal of Industrial Economics*, 55(3), 529–569.

Bos J.W.B., Economidou C., Koetter M., Kolari J.W. (2010), Do all countries grow alike?, *Journal of Development Economics*, 91, 113–127.

Burda M., Severgnini B. (2008), *Solow residuals without capital stocks*, SFB 649 Discussion Paper 2008-040, Humboldt University, Berlin.

Caselli F. (2005), Accounting for cross-country income differences, in: P. Aghion, S. Durlauf (eds.), *Handbook of economic growth*, Elsevier, Amsterdam.

Caselli F., Coleman W.J. (2006), The world technology frontier, *American Economic Review*, 96(3), 499–522.

Charnes A., Cooper W.W., Rhodes E. (1978), Measuring the efficiency of decision-making units, *European Journal of Operational Research*, 2, 429–444.

Chirinko R.S. (2008), σ: the long and short of it, *Journal of Macroeconomics*, 30(2), 671–686.

Coelli T.J., Rao D.S.P., O'Donnell C.J., Battese G.E. (2005), *An introduction to efficiency and productivity analysis*, Springer, New York.

Cohen D., Soto M. (2007), Growth and human capital: good data, good results, *Journal of Economic Growth*, 12(1), 51–76.

Daskovska A., Simar L., Van Bellegem S. (2010), Forecasting the Malmquist productivity index, *Journal of Productivity Analysis*, 33, 97–107.

Duffy J., Papageorgiou C. (2000), The specification of the aggregate production function: a cross--country empirical investigation, *Journal of Economic Growth*, 5, 83–116.

Färe R., Grosskopf S., Noriss M., Zhang Z. (1994), Productivity growth, technical progress, and efficiency change in industrialized countries, *American Economic Review*, 84(1), 66–83.

Färe R., Primont D. (1995), *Multi-output production and duality: theory and applications*, Kluwer, Dordrecht.

de la Fuente A., Doménech R. (2006), Human capital in growth regressions: How much difference does data quality make?, *Journal of the European Economic Association*, 4(1), 1–36.

Growiec J. (2012), The world technology frontier: What can we learn from the US states?, *Oxford Bulletin of Economics and Statistics*, 74(6), 777–807.

Growiec J., Pajor A., Pelle D., Prędki A. (2011), *The shape of aggregate production functions: evidence from estimates of the world technology frontier*, NBP Working Paper, 102, National Bank of Poland, Warsaw.

Hall R.E., Jones C.I. (1999), Why do some countries produce so much more output per worker than others?, *Quarterly Journal of Economics*, 114(1), 83–116.

Henderson D.J., Russell R.R. (2005), Human capital and convergence: a production-frontier approach, *International Economic Review*, 46(4), 1167–1205.

Heston A., Summers R., Aten B. (2006), *Penn World Table version 6.2*, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania.

Jerzmanowski M. (2007), Total factor productivity differences: appropriate technology vs. efficiency, *European Economic Review*, 51, 2080–2110.

Jorgenson D.W. (1995), *Productivity. Volume 2: International comparisons of economic growth*, MIT Press, Massachusetts.

Klump R., McAdam P., Willman A. (2007), Factor substitution and factor augmenting technical progress in the US: a normalized supply-side system approach, *Review of Economics and Statistics*, 89(1), 183–192.

Kneip A., Simar L., Wilson P.W. (2008), Asymptotics of DEA estimators in non-parametric frontier models, *Econometric Theory*, 24, 1663–1697.

Koop G., Osiewalski J., Steel M.F.J. (1999), The components of output growth: a stochastic frontier analysis, *Oxford Bulletin of Economics and Statistics*, 61(4), 455–487.

Koop G., Osiewalski J., Steel M.F.J. (2000), Measuring the sources of output growth in a panel of countries, *Journal of Business and Economic Statistics*, 18(3), 284–299.

Kumar S., Russell R.R. (2002), Technological change, technological catch-up, and capital deepening: relative contributions to growth and convergence, *American Economic Review*, 92(3), 527–548.

Kumbhakar S.C., Lovell C.A.K. (2000), *Stochastic frontier analysis*, Cambridge University Press, Cambridge.

Kydland F.E., Prescott E.C. (1982), Time to build and aggregate fluctuations, *Econometrica*, 50(6), 1345–1370.

León-Ledesma M., McAdam P., Willman A. (2010), Identifying the aggregate elasticity of substitution with biased technical change, *American Economic Review*, 100(4), 1330–1357.

Maudos J., Pastor J.M., Serrano L. (2000), Convergence in OECD countries: technical change, efficiency and productivity, *Applied Economics*, 32, 757–765.

O'Donnell C.J. (2009), An aggregate quantity-price framework for measuring and decomposing productivity and profitability change, CEPA Working Paper, WP072008, University of Queensland.

OECD (2009), *Measuring capital. OECD manual*, OECD, Paris.

Pandey M. (2008), Human capital aggregation and relative wages across countries, *Journal of Macroeconomics*, 30(4), 1587–1601.

Psacharopoulos G. (1994), Returns to investment in education: a global update, *World Development*, 22, 1325–1343.

Raa T. (2005), Debreu's coefficient of resource utilization, the Solow residual, and TFP: the connection by Leontief preferences, *Journal of Productivity Analysis*, 30, 191–199.

Raa T., Mohnen P. (2002), Neoclassical growth accounting and frontier analysis: a synthesis, *Journal of Productivity Analysis*, 18, 111–128.

Raa T., Shestalova V. (2011), The Solow residual, domar aggregation, and inefficiency: a synthesis of TFP measures, *Journal of Productivity Analysis*, 36, 71–77.

Ray S.C., Desli E. (1997), Productivity growth, technical progress, and efficiency change in industrialized countries: comment, *American Economic Review*, 87(5), 1033–1039.

Simar L., Wilson P.W. (2000), A general methodology for bootstrapping in non-parametric frontier models, *Journal of Applied Statistics*, 27(6), 779–802.

Simar L., Wilson P.W. (2002), Non-parametric tests of returns to scale, *European Journal of Operational Research*, 139, 115–132.

Solow R.M. (1957), Technical change and the aggregate production function, *Review of Economics and Statistics*, 39, 312–320.

Timmer M.P., Ypma G., van Ark B. (2003), *IT in the European Union: driving productivity divergence?*, Research Memorandum, GD-67, http://www.elibrary.lt/resursai/ES/memorandumai/gd67.pdf.

Turner C., Tamura R., Mulholland S.E. (2008), *How important are human capital, physical capital and total factor productivity for determining state economic growth in the United States: 1840–2000?*, Nicholls State University, unpublished.

Turner C., Tamura R., Mulholland S.E., Baier S. (2007), Income and education of the states of the United States: 1840–2000, *Journal of Economic Growth*, 12(2), 101–158.

Zofio J.L. (2007), Malmquist productivity index decompositions: a unifying framework, *Applied Economics*, 39, 2371–2387.

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Appendix

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.

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 data are of 5-year frequency. 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. Among other issues, 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. Hence, our analysis convolutes productivity differences with labor-leisure choice of the employees: *ceteris paribus*, an increase in hours worked per worker will be reflected 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* across both 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, 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

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[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.

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 postgraduate 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) 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 et al. (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]

[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.

[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 percentage points in high school graduates, and of 2.7 percentage points 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.

Special attention should be paid to the cutoff point of 12 years of schooling delineating unskilled and skilled labor (formula (23)). 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 – which are usually technologically advanced and highly capitalized. 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.

Moreover, using formula (24) for OECD countries is a simplification. Since these countries do not provide sufficient variation in data to yield a reliable estimate of returns to primary education, the 0.134 estimate follows from data on Sub-Saharan African countries; for analogous reasons, the 0.101 estimate follows from a worldwide dataset (cf. Hall, Jones 1999).

Table 1
Matrix of alternative specifications

			Information sets			
			I_1	I_2	I_3	I_4
	parametric	C-D	TFP_k		$TFP_{k,h}$	
TFP growth	nonparametric	Malmquist (CRS)	M_k^{CRS}	$M_{k,h}^{CRS}$ (C.)	$M_{k,h}^{CRS}$	$M_{k,L^U,\ L^S}^{CRS}$
	nonparametric	Malmquist (VRS)	M_k^{VRS}	$M_{k,h}^{VRS}$ (C.)	$M_{k,h}^{VRS}$	$M_{k,L^U,\ L^S}^{VRS}$
	hybrid	C-D + DEA	$\overline{TFP}_k$	$\overline{TFP}_{k,h}$(C.)	$\overline{TFP}_{k,h}$	$\overline{TFP}_{k,L^U,\ L^S}$
Tech change	nonparametric	PTC (CRS)	PTC_k	$PTC_{k,h}$(C.)	$PTC_{k,h}$	$PTC_{k,L^U,\ L^S}$
	nonparametric	TC (VRS)	TC_k	$TC_{k,h}$(C.)	$TC_{k,h}$	$TC_{k,L^U,\ L^S}$

Table 2
Average annual rates of "technological progress" in 19 OECD countries in 1970–2000, according to a range of TFP growth measures (in %)

	GDP ratio	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
		TFP_k	$TFP_{k,h}$	M_k^{CRS}	$M_{k,h}^{CRS}$ (C.)	$M_{k,h}^{CRS}$	M_{k,L^U,L^S}^{CRS}	M_k^{VRS}	$M_{k,h}^{VRS}$ (C.)	$M_{k,h}^{VRS}$	M_{k,L^U,L^S}^{VRS}
Australia	1.34	0.81	0.39	-0.24	0.35	0.37	0.14	0.73	0.59	0.72	0.38
Austria	2.21	1.31	0.89	-0.47	0.74	0.68	0.63	1.22	1.33	1.22	1.02
Belgium	1.96	1.15	0.66	-0.45	0.59	0.56	0.36	1.10	1.25	1.10	0.64
Canada	1.23	0.62	0.27	-0.57	0.12	0.09	0.68	0.48	0.29	0.48	0.68
Denmark	1.29	0.75	0.62	-0.31	0.76	0.69	0.56	0.72	0.84	0.76	0.60
Finland	1.98	1.33	0.52	0.05	0.63	0.57	-0.08	1.28	0.25	0.89	0.25
France	1.89	1.04	0.53	-0.63	0.56	0.53	0.12	0.94	0.77	0.92	0.36
Greece	1.31	0.64	-0.13	-0.67	-0.55	-0.53	-0.89	-0.22	-0.38	-0.29	-0.64
Ireland	3.62	2.42	1.92	0.05	0.71	0.60	0.57	0.60	0.68	0.61	0.77
Italy	1.78	1.22	0.47	0.10	0.50	0.48	-0.21	1.17	0.40	0.92	0.18
Japan	2.33	0.75	-0.08	-2.33	-0.60	-0.75	-0.65	-0.58	-0.44	-0.59	-1.07
Netherlands	1.07	0.78	0.25	0.21	0.25	0.25	-0.92	0.82	0.72	0.76	-0.30
Norway	2.31	1.67	1.67	0.42	2.11	1.92	1.44	1.78	2.10	1.94	1.35
Portugal	2.17	0.93	0.57	-1.49	-0.43	-0.59	-0.17	-1.41	0.23	-0.89	-0.07
Spain	1.95	0.90	-0.01	-1.17	-0.49	-0.47	-0.77	-0.22	-0.45	-0.44	-0.43
Sweden	1.06	0.70	0.36	-0.03	0.45	0.40	-0.02	0.70	0.29	0.61	0.16
Switzerland	0.62	0.18	-0.22	-0.71	0.01	-0.11	-0.12	0.27	0.38	0.24	0.16
UK	1.91	1.29	0.90	0.07	0.57	0.60	0.41	0.93	0.64	0.88	0.58
USA	1.68	1.00	0.79	-0.36	0.65	0.62	0.99	0.89	0.80	0.89	1.11
Mean	1.77	1.03	0.54	-0.45	0.36	0.31	0.11	0.59	0.54	0.56	0.30

Table 3
Average annual rates of "technological progress" in 19 OECD countries in 1970–2000, according to a range of technical change measures (in %)

	GDP ratio	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
		$\overline{TFP}_k$	$TFP_{k,h}$	$\overline{TFP}_{k,h}$	$\overline{TFP}_{k,L^U,L^S}$	PTC_k	$PTC_{k,h}$ (C.)	$PTC_{k,h}$	PTC_{k,L^U,L^S}	TC_k	$TC_{k,h}$ (C.)	$TC_{k,h}$	TC_{k,L^U,L^S}
Australia	1.34	1.05	0.87	0.55	0.68	0.00	0.82	0.53	0.43	0.95	0.98	0.95	0.86
Austria	2.21	1.79	0.80	0.75	0.67	0.00	0.64	0.54	0.40	1.14	0.80	1.14	0.93
Belgium	1.96	1.61	0.78	0.68	0.64	0.00	0.71	0.58	0.34	1.19	0.92	1.19	0.74
Canada	1.23	1.21	0.80	0.64	0.47	0.00	0.64	0.46	0.88	0.82	0.76	0.82	1.05
Denmark	1.29	1.07	0.77	0.60	0.48	0.00	0.91	0.66	0.42	1.07	0.94	1.02	0.78
Finland	1.98	1.28	0.88	0.64	1.01	0.00	0.99	0.69	0.41	1.07	1.08	0.95	0.67
France	1.89	1.68	0.73	0.65	0.85	0.00	0.76	0.65	0.44	1.05	0.97	1.08	0.85
Greece	1.31	1.32	0.64	0.55	0.99	0.00	0.22	0.16	0.22	0.33	0.39	0.36	0.36
Ireland	3.62	2.37	1.68	1.56	1.55	0.00	0.47	0.25	0.20	0.41	0.57	0.41	0.34
Italy	1.78	1.12	0.94	0.61	0.98	0.00	0.98	0.63	0.30	1.04	1.07	0.95	0.50
Japan	2.33	3.16	1.09	1.14	1.16	0.00	0.56	0.47	0.59	0.86	0.73	0.85	0.78
Netherlands	1.07	0.57	1.00	0.71	1.49	0.00	1.00	0.72	0.31	1.36	1.09	1.33	0.69
Norway	2.31	1.25	0.55	0.53	0.70	0.00	0.98	0.77	0.47	1.35	1.10	1.17	0.69
Portugal	2.17	2.46	1.50	1.47	0.87	0.00	0.49	0.30	0.13	0.34	0.42	0.19	0.15
Spain	1.95	2.10	1.07	0.79	0.96	0.00	0.58	0.32	0.19	0.49	0.65	0.56	0.26
Sweden	1.06	0.73	0.90	0.65	1.02	0.00	0.99	0.69	0.64	1.07	0.92	0.98	0.82
Switzerland	0.62	0.90	0.77	0.73	0.69	0.00	1.01	0.85	0.79	1.50	1.09	1.47	1.28
UK	1.91	1.22	0.93	0.66	0.87	0.00	0.60	0.36	0.38	0.49	0.66	0.52	0.56
USA	1.68	1.36	0.79	0.70	0.65	0.00	0.65	0.53	0.86	0.94	0.80	0.94	1.15
Mean	1.77	1.49	0.92	0.77	0.88	0.00	0.74	0.53	0.44	0.92	0.84	0.89	0.71

Table 4
Percentage of growth in output per worker 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)	$TFP_{k,h}$	65.38	34.62	71.27	28.73
(3)	M_k^{CRS}	106.70	-6.70	115.61	-15.61
(4)	$M_{k,h}^{VRS}$ (C.)	61.61	38.39	81.88	18.12
(5)	$M_{k,h}^{CRS}$	62.32	37.68	84.80	15.20
(6)	M_{k,L^U,L^S}^{CRS}	83.06	16.94	95.15	4.85
(7)	M_k^{VRS}	42.35	57.65	68.70	31.30
(8)	$M_{k,h}^{VRS}$ (C.)	53.51	46.49	71.58	28.42
(9)	$M_{k,h}^{VRS}$	47.40	52.60	70.17	29.83
(10)	M_{k,L^U,L^S}^{VRS}	70.04	29.96	85.40	14.60
(11)	$\overline{TFP}_{k,h}$ (C.)	28.07	71.93	13.66	86.34
(12)	$\overline{TFP}_{k,h}$ (C.)	41.50	58.50	47.59	52.41
(13)	$\overline{TFP}_{k,h}$	58.32	41.68	57.24	42.76
(14)	$\overline{TFP}_{k,L^U,L^S}$	52.00	48.00	50.13	49.87
(15)	PTC_k	100.00	0.00	100.00	0.00
(16)	$PTC_{k,h}$ (C.)	37.72	62.28	59.25	40.75
(17)	$PTC_{k,h}$	55.25	44.75	71.91	28.10
(18)	PTC_{k,L^U,L^S}	69.88	30.12	77.43	22.57
(19)	TC_k	25.58	74.42	47.61	52.39
(20)	$TC_{k,h}$ (C.)	36.80	63.20	52.74	47.27
(21)	$TC_{k,h}$	29.13	70.87	49.59	50.41
(22)	TC_{k,L^U,L^S}	50.86	49.14	61.09	38.91

Table 5
Selected characteristics of the 22 measures of technological progress

	Levels P (in %)	Levels C (in %)	Corr. P	Corr. C	Variance (in %)	Var + cov (in %)	MAE	RMSE	AIC	BIC
(1) TFP_k	35.40	40.84	0.964	0.901	7.58	11.42	0.0676	0.0074	-451.4	-438.6
(2) $TFP_{k,h}$	65.38	71.27	0.912	0.752	18.40	12.03	0.0580	0.0057	-460.6	-435.0
(3) M_k^{CRS}	106.70	115.61	0.673	0.012	68.21	34.27	0.0537	0.0051	-486.6	-473.8
(4) $M_{k,h}^{CRS}$ (C.)	61.61	81.88	0.834	0.234	33.90	17.21	0.0627	0.0061	-453.1	-427.6
(5) $M_{k,h}^{CRS}$	62.32	84.80	0.833	0.205	36.32	15.15	0.0626	0.0064	-448.7	-423.2
(6) M_{k,L^U,L^S}^{CRS}	83.06	95.15	0.863	0.267	30.20	8.59	0.0607	0.0059	-440.5	-402.2
(7) M_k^{VRS}	42.35	68.70	0.790	0.041	46.78	19.28	0.0722	0.0079	-444.3	-431.5
(8) $M_{k,h}^{VRS}$ (C.)	53.51	71.58	0.808	0.186	39.37	18.06	0.0674	0.0068	-443.0	-417.4
(9) $M_{k,h}^{VRS}$	47.40	70.17	0.784	0.077	52.14	16.24	0.0729	0.0081	-426.8	-401.2
(10) M_{k,L^U,L^S}^{VRS}	70.04	85.40	0.879	0.235	25.17	11.38	0.0605	0.0059	-441.7	-403.4
(11) $\overline{TFP}_k$	28.07	13.66	0.407	0.655	84.66	77.12	0.0630	0.0053	-481.9	-469.1
(12) $\overline{TFP}_{k,h}$ (C.)	41.50	47.59	0.399	0.657	94.15	74.11	0.0525	0.0049	-475.6	-450.1
(13) $\overline{TFP}_{k,h}$	58.32	57.24	0.148	0.706	108.05	92.91	0.0388	0.0024	-541.4	-515.9
(14) $\overline{TFP}_{k,L^U,L^S}$	52.00	50.13	0.070	0.453	114.56	97.11	0.0424	0.0027	-514.0	-475.7
(15) PTC_k	100.00	100.00	0.072	0.088	100.00	100.00	0.0000	0.0000	N/A	N/A
(16) $PTC_{k,h}$(C.)	37.72	59.25	0.322	-0.403	100.52	79.29	0.0535	0.0050	-473.1	-447.6
(17) $PTC_{k,h}$	55.25	71.91	0.080	-0.432	109.52	96.02	0.0387	0.0024	-543.3	-517.8
(18) PTC_{k,L^U,L^S}	69.88	77.43	0.156	-0.429	101.64	93.67	0.0264	0.0014	-577.0	-538.7
(19) TC_k	25.58	47.61	-0.072	-0.410	146.82	103.80	0.0638	0.0061	-470.0	-457.2
(20) $TC_{k,h}$(C.)	36.80	52.74	0.332	-0.365	99.08	78.38	0.0544	0.0051	-471.2	-445.6
(21) $TC_{k,h}$	29.13	49.59	-0.043	-0.441	134.82	101.81	0.0608	0.0053	-467.8	-442.2
(22) TC_{k,L^U,L^S}	50.86	61.09	0.140	-0.478	106.43	93.23	0.0424	0.0028	-511.9	-473.6

Notes:
"Levels" – percentage of total growth in output per worker 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 growth in output per worker. 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 labor productivity growth rates explained by the factor-only component, assuming that growth in output per worker 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 component plus one covariance of the factor-only component and technological progress (numerator) over the variance of labor 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 growth in output per worker is predicted *ex post* as the growth rate of the factor-only component.
AIC and BIC denote, respectively, the Akaike and the Bayesian (Schwarz) information criterion for the above forecast.

Table 6
Pairwise correlations among the 10 measures of TFP growth

Cross-sectional data, 1970–2000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	TFP_k	$TFP_{k,h}$	M_k^{CRS}	$M_{k,h}^{CRS}$ (C.)	$M_{k,h}^{CRS}$	M_{k,L^U,L^S}^{CRS}	M_k^{VRS}	$M_{k,h}^{VRS}$ (C.)	$M_{k,h}^{VRS}$	M_{k,L^U,L^S}^{VRS}
(1) TFP_k	1.00	0.91	0.44	0.53	0.52	0.44	0.40	0.43	0.42	0.48
(2) $TFP_{k,h}$	0.91	1.00	0.54	0.74	0.73	0.72	0.50	0.68	0.59	0.73
(3) M_k^{CRS}	0.44	0.54	1.00	0.72	0.76	0.43	0.81	0.58	0.78	0.56
(4) $M_{k,h}^{CRS}$ (C.)	0.53	0.74	0.72	1.00	1.00	0.81	0.85	0.91	0.93	0.82
(5) $M_{k,h}^{CRS}$	0.52	0.73	0.76	1.00	1.00	0.80	0.89	0.90	0.95	0.83
(6) M_{k,L^U,L^S}^{CRS}	0.44	0.72	0.43	0.81	0.80	1.00	0.61	0.79	0.72	0.95
(7) M_k^{VRS}	0.40	0.50	0.81	0.85	0.89	0.61	1.00	0.76	0.97	0.71
(8) $M_{k,h}^{VRS}$ (C.)	0.43	0.68	0.58	0.91	0.90	0.79	0.76	1.00	0.89	0.83
(9) $M_{k,h}^{VRS}$	0.42	0.59	0.78	0.93	0.95	0.72	0.97	0.89	1.00	0.80
(10) M_{k,L^U,L^S}^{VRS}	0.48	0.73	0.56	0.82	0.83	0.95	0.71	0.83	0.80	1.00

Panel data, 5-year intervals spanning 1970–2000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	TFP_k	$TFP_{k,h}$	M_k^{CRS}	$M_{k,h}^{CRS}$ (C.)	$M_{k,h}^{CRS}$	M_{k,L^U,L^S}^{CRS}	M_k^{VRS}	$M_{k,h}^{VRS}$ (C.)	$M_{k,h}^{VRS}$	M_{k,L^U,L^S}^{VRS}
(1) TFP_k	1.00	0.96	0.85	0.89	0.89	0.88	0.88	0.86	0.86	0.90
(2) $TFP_{k,h}$	0.96	1.00	0.84	0.94	0.95	0.94	0.86	0.90	0.86	0.92
(3) M_k^{CRS}	0.85	0.84	1.00	0.80	0.81	0.72	0.84	0.77	0.80	0.74
(4) $M_{k,h}^{CRS}$ (C.)	0.89	0.94	0.80	1.00	0.97	0.93	0.90	0.96	0.92	0.92
(5) $M_{k,h}^{CRS}$	0.89	0.95	0.81	0.97	1.00	0.94	0.91	0.93	0.93	0.92
(6) M_{k,L^U,L^S}^{CRS}	0.88	0.94	0.72	0.93	0.94	1.00	0.84	0.90	0.87	0.97
(7) M_k^{VRS}	0.88	0.86	0.84	0.90	0.91	0.84	1.00	0.87	0.97	0.89
(8) $M_{k,h}^{VRS}$ (C.)	0.86	0.90	0.77	0.96	0.93	0.90	0.87	1.00	0.91	0.91
(9) $M_{k,h}^{VRS}$	0.86	0.86	0.80	0.92	0.93	0.87	0.97	0.91	1.00	0.92
(10) M_{k,L^U,L^S}^{VRS}	0.90	0.92	0.74	0.92	0.92	0.97	0.89	0.91	0.92	1.00

Table 7

Pairwise correlations among the 12 measures of technical change

Cross-sectional data, 1970–2000

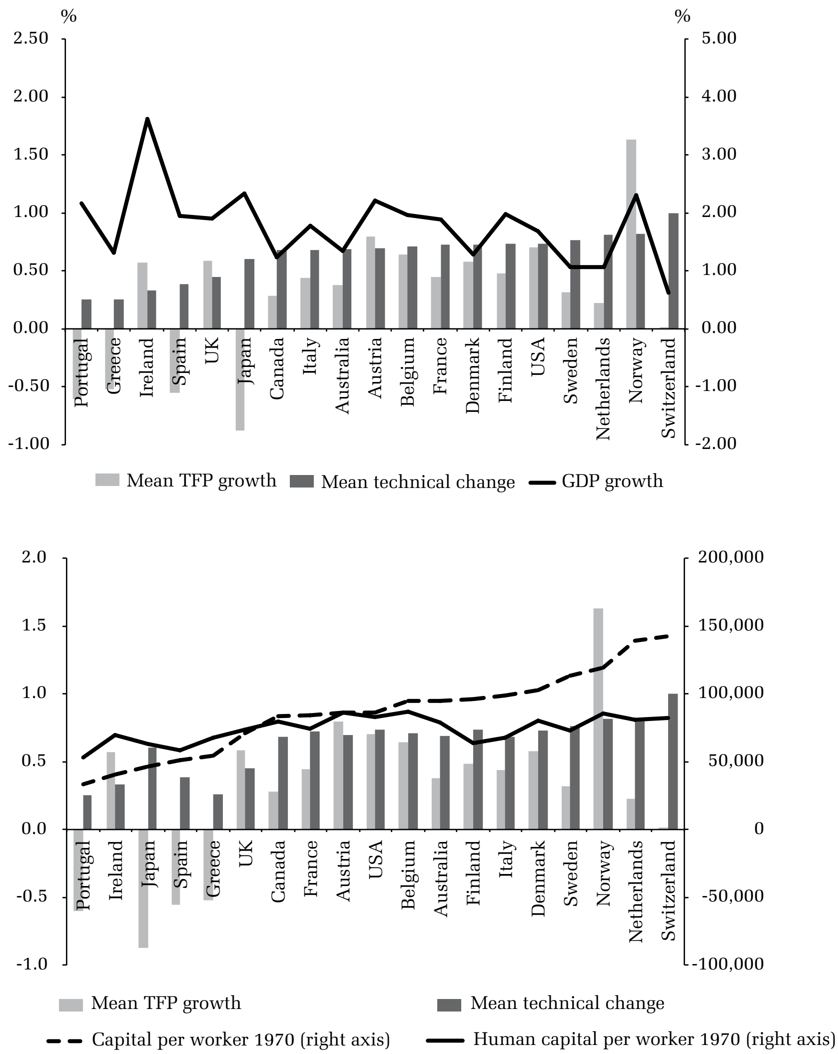
	(11) $\overline{TFP}_k$	(12) $\overline{TFP}_{k,h}$ (C.)	(13) $\overline{TFP}_{k,h}$	(14) $\overline{TFP}_{k,L^U,L^S}$	(15) PTC_k	(16) $PTC_{k,h}$ (C.)	(17) $PTC_{k,h}$	(18) PTC_{k,L^U,L^S}	(19) TC_k	(20) $TC_{k,h}$ (C.)	(21) $TC_{k,h}$	(22) TC_{k,L^U,L^S}
(11) $\overline{TFP}_k$	1.00	0.58	0.74	0.27	N/A	-0.59	-0.52	-0.25	-0.49	-0.56	-0.48	-0.37
(12) $\overline{TFP}_{k,h}$(C.)	0.58	1.00	0.93	0.62	N/A	-0.35	-0.50	-0.43	-0.55	-0.49	-0.58	-0.55
(13) $\overline{TFP}_{k,h}$	0.74	0.93	1.00	0.51	N/A	-0.46	-0.48	-0.32	-0.49	-0.55	-0.53	-0.44
(14) $\overline{TFP}_{k,L^U,L^S}$	0.27	0.62	0.51	1.00	N/A	-0.10	-0.23	-0.45	-0.23	-0.15	-0.24	-0.49
(15) PTC_k	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
(16) $PTC_{k,h}$(C.)	-0.59	-0.35	-0.46	-0.10	N/A	1.00	0.93	0.28	0.83	0.94	0.77	0.42
(17) $PTC_{k,h}$	-0.52	-0.50	-0.48	-0.23	N/A	0.93	1.00	0.43	0.95	0.94	0.91	0.62
(18) PTC_{k,L^U,L^S}	-0.25	-0.43	-0.32	-0.45	N/A	0.28	0.43	1.00	0.43	0.31	0.46	0.89
(19) TC_k	-0.49	-0.55	-0.49	-0.23	N/A	0.83	0.95	0.43	1.00	0.91	0.98	0.68
(20) $TC_{k,h}$(C.)	-0.56	-0.49	-0.55	-0.15	N/A	0.94	0.94	0.31	0.91	1.00	0.88	0.53
(21) $TC_{k,h}$	-0.48	-0.58	-0.53	-0.24	N/A	0.77	0.91	0.46	0.98	0.88	1.00	0.73
(22) TC_{k,L^U,L^S}	-0.37	-0.55	-0.44	-0.49	N/A	0.42	0.62	0.89	0.68	0.53	0.73	1.00

Panel data, 5-year intervals spanning 1970–2000

	(11) $\overline{TFP}_k$	(12) $\overline{TFP}_{k,h}$ (C.)	(13) $\overline{TFP}_{k,h}$	(14) $\overline{TFP}_{k,L^U,L^S}$	(15) PTC_k	(16) $PTC_{k,h}$ (C.)	(17) $PTC_{k,h}$	(18) PTC_{k,L^U,L^S}	(19) TC_k	(20) $TC_{k,h}$ (C.)	(21) $TC_{k,h}$	(22) TC_{k,L^U,L^S}
(11) $\overline{TFP}_k$	1.00	0.14	0.23	-0.13	N/A	0.07	0.09	0.11	-0.11	-0.01	-0.07	0.06
(12) $\overline{TFP}_{k,h}$(C.)	0.14	1.00	0.32	0.53	N/A	0.88	0.18	0.56	0.02	0.84	0.10	0.38
(13) $\overline{TFP}_{k,h}$	0.23	0.32	1.00	0.55	N/A	0.24	0.72	0.49	0.34	0.22	0.40	0.47
(14) $\overline{TFP}_{k,L^U,L^S}$	-0.13	0.53	0.55	1.00	N/A	0.46	0.27	0.60	0.02	0.48	0.08	0.33
(15) PTC_k	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
(16) $PTC_{k,h}$(C.)	0.07	0.88	0.24	0.46	N/A	1.00	0.35	0.68	0.21	0.94	0.28	0.52
(17) $PTC_{k,h}$	0.09	0.18	0.72	0.27	N/A	0.35	1.00	0.55	0.62	0.31	0.66	0.65
(18) PTC_{k,L^U,L^S}	0.11	0.56	0.49	0.60	N/A	0.68	0.55	1.00	0.24	0.67	0.33	0.77
(19) TC_k	-0.11	0.02	0.34	0.02	N/A	0.21	0.62	0.24	1.00	0.19	0.93	0.56
(20) $TC_{k,h}$(C.)	-0.01	0.84	0.22	0.48	N/A	0.94	0.31	0.67	0.19	1.00	0.28	0.57
(21) $TC_{k,h}$	-0.07	0.10	0.40	0.08	N/A	0.28	0.66	0.33	0.93	0.28	1.00	0.70
(22) TC_{k,L^U,L^S}	0.06	0.38	0.47	0.33	N/A	0.52	0.65	0.77	0.56	0.57	0.70	1.00

Figure 1

Means over TFP growth indexes and technical change measures, and their relation to growth in output per worker and initial physical and human capital stocks



Notes: in the lower panel, 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.

Figure 2
Percentage of growth in output per worker attributed to factor accumulation in each of the specifications of residual technological progress

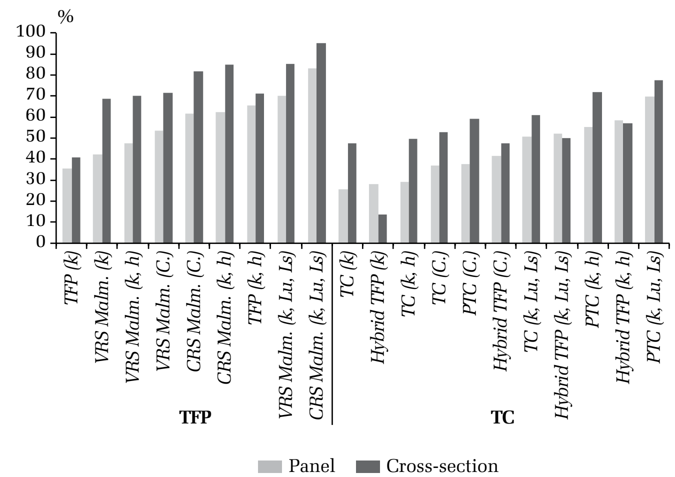


Figure 3
Selected characteristics of the 22 measures of technological progress