OXFORD BULLETIN OF ECONOMICS AND STATISTICS, 74, 6 (2012) 0305-9049
doi: 10.1111/j.1468-0084.2011.00686.x

The World Technology Frontier: What Can We Learn from the US States?*

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Abstract

We re-estimate the world technology frontier non-parametrically using a dataset covering OECD country-level data and US state-level data on GDP per worker and the stocks of physical capital, unskilled labour and skilled labour. The auxiliary use of US state-level data significantly reduces the upward bias in cross-country estimates of technical efficiency, and so does allowing for imperfect substitutability between skilled and unskilled labour. We then use our adjusted estimate of the world technology frontier in a series of decompositions of productivity differences and sources of economic growth in the OECD in 1970–2000, including also 'appropriate technology vs. efficiency' decompositions.

I. Introduction

Is it possible to use production factors more efficiently than in the US? Studies based on aggregate cross-country data provide, almost unanimously, the negative answer: since World War II, the US level of per-worker productivity has always been high enough to guarantee that the US was one of the countries spanning the world technology frontier (WTF).[1] Consequently, all post-war improvements in US productivity have been identified as either due to factor accumulation or technological progress at the frontier. We claim, however, that since the US is a huge country with substantial internal heterogeneity, we can learn more about the evolution of US productivity if we cease considering it as a single data point, as habitually done in earlier studies. US state-level data show that it *is* possible

*I am grateful to Aleksandra Iwulska and Łukasz Marć for their help with the data and to Mateusz Zawisza for performing the bootstraps. The article has benefitted considerably from the useful comments and suggestions of the Editor Jonathan Temple, as well as Maciej Bukowski, Andrzej Cieślik, Jacek Osiewalski, Małgorzata Pawłowska and Artur Prędki. Most of this research has been done at the Institute for Structural Research, Warsaw, Poland. The working paper version of this text was circulated under the title: 'Productivity Differences Across OECD Countries and US States, 1970–2000: The World Technology Frontier Revisited'. All errors are my responsibility.
JEL Classification numbers: E23, O11, O14, O33, O47.

[1]This is one of the conclusions of non-parametric studies by Kumar and Russell (2002), Henderson and Russell (2005), Jerzmanowski (2007) and Badunenko, Henderson and Zelenyuk (2008). In Caselli and Coleman (2006) as well as Badunenko, Henderson and Russell (2009), the US is found to fall behind the frontier, albeit very slightly.

to produce more efficiently than the US does on average. Even more interestingly,thanks to the generally high productivity across US states, disaggregating the single US data point into its constituent states should also lead to significant improvements in the precision of estimates of the entire WTF. Hence, this study will combine information from US states with country-level data to provide new estimates of the WTF.

The contribution of this study to the literature is threefold. First and foremost, as announced just above, we shall use US state-level data to revisit the economic debate on the shape of the WTF as well as on the sources of economic growth and cross-country productivity differences. The most important insight here is that appending the US sub-national dataset to the international one leads to a marked increase in the precision of non-parametric [data envelopment analysis (DEA)-based] WTF estimates, especially in the range of factor endowments observed across the US. Furthermore, thanks to a more accurate approximation of the WTF, the reliability of earlier growth and development accounting exercises can be substantially improved, too. These accomplishments are complementary to the ones obtained thanks to known DEA bootstrap techniques (Simar and Wilson, 1998, 2000; Kneip, Simar and Wilson, 2008): the advantage of our approach is that we add new valid data points to the dataset considered, carrying genuine additional information.

The second novelty of the current study with respect to the established literature is that we allow for imperfect substitutability between skilled and unskilled labour.[2] This leads to a further refinement of results presented in earlier studies. As far as we know, this decomposition has never been used before in non-parametric analyses of the kind adopted here.

The third contribution of the current study is to propose a novel decomposition of countries' productivity growth rates, indicating the extent to which the observed productivity changes represent shifts of the WTF, or movements along the WTF.

As far as the territorial coverage of the current study is concerned, we focus only on highly developed OECD countries located in Europe and North America (plus Australia and Japan), and set aside developing and transition economies as well as small open economies such as the Asian Tigers. This will reduce precision in the estimation of the WTF in the region of low capital and/or human capital endowments, where numerous developing countries are located. Such an approach does not compromise the precision of efficiency estimates in the range relevant to our study, though, under the rather innocuous assumption that non-OECD countries do not operate at the same factor ratios as OECD countries or, if they do, they are less efficient than at least one OECD country. In consequence, rather than attempting to identify the whole WTF, we aim at obtaining its best possible estimates in the range associated with factor ratios observed in the OECD countries (or US states). At the same time, this approach also makes our results less vulnerable to poor data quality (see the discussion about Sierra Leone spanning the WTF in Kumar and Russell, 2002).[3]

The time period considered is 1970–2000, and technologies from all earlier years are allowed to span the WTF in the given year alongside current ones (cf. Henderson and Russell, 2005). Indeed, it turns out that even some technologies used in 1970 remain effi-

[2]See Caselli and Coleman (2006) and Pandey (2008).

[3]We also use bootstrapping techniques to adjust for the inherent bias in efficiency estimates, thus somewhat neutralizing the impact of outlying observations (cf. Simar and Wilson, 1998, 2000; Kneip *et al.*, 2008; Badunenko *et al.*, 2009).

cient in 2000 despite substantial technological progress between these years, primarily because they strongly rely on unskilled labour which has been gradually disappearing in OECD countries over the period considered.

Accordingly, we also find that technological progress over these years has been strongly non-neutral, with the highest increases in frontier productivity observed in the range of technologies with high physical capital and skilled labour intensities. Our findings also imply that the non-parametrically constructed WTF departs systematically from the Cobb–Douglas functional specification.

The principal novelty of this study – that is, to use a decomposition of the US into its 50 constituent states in estimation of the WTF – has a number of interesting features. First, US states are large enough to be directly comparable to OECD countries in terms of population. The most populous state, California, has a population exceeding 35 million which is more than twice the size of the Netherlands, 16 million; the least populous state, Wyoming, has around 0.5 million inhabitants which makes it comparable with Luxembourg or Cyprus in terms of size. Second, a substantial number of US states are expected to span the WTF once US country-level data are disaggregated: if it is already the US as a whole – whose per-worker productivity is a weighted *average* of state-level productivities – which spans the cross-country estimate of the WTF, one can naturally expect the 'countries and US states' estimate of the WTF to be spanned by, inter alia, some above-average performing states. In effect, the WTF estimates based on country-level data only will be downward biased, and the estimates of countries' technical efficiency will be upward biased (i.e. towards unity). Third, the US state-level data are arguably of high quality and are relatively easy to obtain.

It must be noted that the state-wise decomposition procedure which we apply to the US here could also be carried forward to other OECD countries such as France, Germany, Japan or the UK, or to lower levels of aggregation, such as counties, townships, or even sectoral categories within the economy such as the Statistical Classification of Economic Activities in the European Community (NACE) sections, etc.[4] This procedure could even be extended to the level of individual people or firms. One crucial advantage of our approach is, however, that by sticking to macro-scale territorial entities, we remain within the standard 'productivity of nations' framework.

Another remark is that by going beyond the usual cross-country dataset, the current article provides the WTF literature with a complementary service to articles preoccupied with computing bias-corrected frontier estimates (cf. Simar and Wilson, 1998, 2000; Kneip *et al.*, 2008; Badunenko *et al.*, 2009; Enflo and Hjertstrand, 2009). The complementarity stems from the fact that instead of applying sophisticated bootstrapping techniques on country-level-only data to assess the magnitude of bias in those estimates, we use a more direct, data-driven method for correcting the bias. Both approaches identify diverse sources of potential bias. To prove this, we have compared the results of both approaches and then 'merged' them by computing bootstrap-based bias-corrected frontier estimates using the extended dataset constructed in the current study.

The remainder of the article is structured as follows. In section II we describe the methodology. In section III we present the sources and construction of our data. Section IV

[4]Enflo and Hjertstrand (2009) study the sources of regional productivity convergence among NUTS1-2 regions in Germany, France, Italy, Spain and Ireland.

presents our main estimate of the WTF and draws a few implications. In section V we use these results to decompose the differences in productivity across nations into differences in technical efficiency and the accumulated factors of production. An auxiliary derivation of factor-dependent total factor productivity (TFP) allows us to address the question of the 'appropriateness' of technology used by each country. Section VI is devoted to decomposing country-level 1970–2000 productivity growth into (i) changes in technical efficiency, (ii) technological progress shifting the WTF, and (iii) factor accumulation. Section VII discusses the robustness of our results. Section VIII concludes. A few corollaries and discussions are included in the Appendix.

II. Methodology

Data envelopment analysis

In this study, the WTF, or equivalently the best-practice production function, will be estimated non-parametrically, that is, constructed as a convex hull of production techniques (input–output configurations) used in the territorial units (countries/states) present in the data. To this end, we will use the deterministic data envelopment analysis (DEA) method introduced to the context of macroeconomics by Färe *et al.* (1994). We will thus follow the lines of Kumar and Russell (2002), Henderson and Russell (2005), Jerzmanowski (2007) and Badunenko *et al.* (2008). Also in line with these contributions, we shall use the output-oriented variant of the DEA and assume constant returns to scale.

The idea behind the use of (output-oriented, constant-returns-to-scale) DEA is to envelop all data points (consisting of a scalar-positive output y_j and a vector of n positive inputs, $\mathbf{x}_j$) in the smallest possible convex cone and to infer the production function as a fragment of the boundary of this cone for which output is maximized given inputs.[5] For each observation j, the DEA method then provides a decomposition of output y_j into a product of the maximum attainable output given inputs $y_j^* \equiv f(\mathbf{x}_j)$ and the Shephard distance function $E_j \in (0, 1]$, measuring (vertical) distance to the frontier:

$$y_j = E_j y_j^*. \tag{1}$$

For each unit $j = 1, 2, \dots, I$ in the sample, both the Shephard distance function E_j and the frontier output y_j^* are computed from the solution to a linear programming problem consisting in maximizing the Debreu–Farrell technical inefficiency index θ_j given a series of feasibility constraints (cf. Fried, Lovell and Schmidt, 1993):

$$\max_{\{\theta_j,\lambda_1,\dots,\lambda_I\}} \theta_j$$

$$\text{s.t. } \theta_j y_j \le \sum_{i=1}^{I} \lambda_i y_i,$$

$$\sum_{i=1}^{I} \lambda_i x_{1i} \le x_{1j},$$

[5]The vector of inputs $\mathbf{x}_j$ could in principle be of any length $n \in \mathbb{N}$, but if one distinguishes too many types of inputs then (i) the DEA could run into numerical problems due to the 'curse of dimensionality' (cf. Färe *et al.*, 1994), and (ii) the efficiency levels could be overestimated due to too small a sample size.

$$\sum_{i=1}^{I} \lambda_i x_{2i} \leq x_{2j},$$
$$\vdots \tag{2}$$
$$\sum_{i=1}^{I} \lambda_i x_{ni} \leq x_{nj},$$
$$\lambda_i \geq 0, \quad i=1,2,\ldots,I.$$

The output-oriented Shephard distance measure E_j (which we shall also refer to as the *technical efficiency score*) is computed as the reciprocal of the maximized Debreu–Farrell technical inefficiency index θ_j (i.e. $E_j = 1/\theta_j$). It is thus the inverse of the maximal proportional amount by which output y_j could be expanded while remaining technologically feasible, given input quantities and the available technology. For example, if y_j could be expanded maximally by 50%, then $y_j^* = 1.5y_j$, and so $E_j = 1/1.5 = 2/3$. A given observation j is said to span the frontier if and only if $E_j = 1$.

Since the data contain a finite number of observations, 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 (i.e. the ones with $E_j = 1$, non-dominated by any linear combination of other observed input–output configurations).

Advantages and limitations of the approach

The DEA is a deterministic, data-driven approach to deriving the production function from observed input–output pairs. Its unquestionable strength lies in the fact that it does not require any particular functional form of the aggregate production function (provided that it has constant returns to scale and satisfies the free-disposal property), and provides testable predictions on its shape instead.[6] Even though by construction, the predicted shape of the production function will be piecewise linear for any finite data sample, with reasonably large data samples, certain parametric forms could be tested formally against the DEA-based non-parametric benchmark, such as the constant elasticity of substitution (CES) or the Cobb–Douglas.

There are important limitations to the DEA approach as well. First, its deterministic character makes it silent on the precision of estimates of the aggregate production function and on the predicted efficiency levels if inputs and outputs are subject to stochastic variation.

Second, the DEA is a biased estimator of the actual technological frontier. Certainly, even the most efficient units in the sample could possibly operate with some extra efficiency: they are themselves aggregates of smaller economic units and must therefore have some internal heterogeneity. Taking account of that, the frontier could easily be shifted upwards; the Shephard distance measure is nevertheless normalized to 100% for the most efficient units in the sample. A bootstrap method due to Simar and Wilson (1998, 2000)

[6]For example, it has been argued that the usual assumption of a Cobb–Douglas production function may lead to marked biases within growth accounting or levels accounting exercises leading to overestimation of the role of TFP, cf. Caselli (2005) and Jerzmanowski (2007).

as well as Kneip *et al.* (2008) is helpful in this respect: it provides a way to adjust for the bias as well as to compute confidence intervals for the actual efficiency levels and the technological frontier.

Third, the DEA constructs the production function based on the efficient data points. This makes it naturally sensitive to outliers and measurement error. On the one hand, outliers characterized by obvious errors are easily spotted. Systematic mismeasurement associated with some units could be left unnoticed, however, if these units fall short of the frontier.

Implications for TFP

The non-parametric DEA approach taken here can be easily compared to somewhat more standard growth and development accounting exercises (e.g. Klenow and Rodriguez-Clare, 1997; Hall and Jones, 1999; Caselli, 2005) which rest upon the Cobb–Douglas production function assumption.

The reasoning is as follows. Generically, all functions $f(\mathbf{x}_i)$, where $\mathbf{x}_i \in \mathbb{R}^n$, could be rewritten as

$$f(\mathbf{x}_i) \equiv A(\mathbf{x}_i) \cdot x_{1i}^{\alpha_1} \cdot \ldots \cdot x_{ni}^{\alpha_n}, \quad \sum_{k=1}^{n} \alpha_k = 1, \tag{3}$$

where the residual term of the above identity, $A(\mathbf{x}_i)$, captures (factor-dependent) 'total factor productivity' based on the Cobb–Douglas specification (referred to as CDTFP hereafter). Let us then apply this reparametrization to our function $f(\mathbf{x}_i) = y_i^*$, constructed with DEA.

Since by construction, $f(\mathbf{x}_i)$ cannot be precisely Cobb–Douglas with constant returns to scale, $A(\mathbf{x}_i)$ will necessarily be a non-trivial function of inputs. Hence, even though equation (3) allows one to view any production function through the lens of the Cobb–Douglas specification, the factor-dependent character of CDTFP indicates that such a view will be incomplete unless $A(\mathbf{x}_i)$ is found to be approximately constant. As announced in the Introduction, this is *not* going to be the case in the current study.

Using the identities (1) and (3), we can decompose each country's output y_i into (i) its efficiency score (Shephard distance function) E_i, (ii) the CDTFP level specific to the country's configuration of inputs (the 'appropriate technology' factor, cf. Basu and Weil, 1998), and (iii) the Cobb–Douglas bundle of factor endowments:

$$y_i = E_i \cdot A(\mathbf{x}_i) \cdot x_{1i}^{\alpha_1} \cdot \ldots \cdot x_{ni}^{\alpha_n}. \tag{4}$$

This is the 'appropriate technology vs. efficiency' decomposition (cf. Jerzmanowski, 2007). If the actual production function were Cobb–Douglas, then from the above equation we would immediately obtain a TFP term identically equal to a constant $A > 0$, and 'appropriateness of technology' would have no role to play. However, in the current study the aggregate production function cannot be precisely Cobb–Douglas and hence the 'appropriate technology' factor $A(\mathbf{x}_i)$ will necessarily co-vary with factor endowments, thereby pointing at the potential CDTFP gains accruing from certain directed changes in the input mix. Results presented in the following sections will indicate that the empirically observed departures of the function $f(\mathbf{x}_i)$ from the Cobb–Douglas benchmark are actually quite large.

A large strand of contemporary macroeconomic literature aims at quantifying and understanding TFP differences, with TFP computed as the (Solow) residual from the Cobb–Douglas production function (cf. Caselli, 2005). As argued above, this approach might lead to results that are artefacts of this particular functional form. On the other hand, even articles relaxing the Cobb–Douglas assumption and dealing with different functional forms such as the CES instead (cf. Caselli and Coleman, 2006; León-Ledesma, McAdam and Willman, 2010a,b) might encounter function misspecification problems. The current contribution avoids this problem thanks to the flexibility of the DEA approach which does not require any parametric assumptions for the estimated production function.

When interpreting the 'appropriate technology vs. efficiency' decomposition, it must be remembered that the 'appropriate technology' (CDTFP) term $A(\mathbf{x}_i)$ may capture either the meaningful economic phenomenon of optimal technology choice given available inputs (cf. Basu and Weil, 1998; Jones, 2005; Growiec, 2008), or the systematic error associated with production function misspecification. Distinguishing empirically between these two options is not possible unless the dataset is extended beyond the information on input and output quantities. We leave this for further research.

Implications for the direction of technical change

The DEA approach can also help draw important implications for the direction of technical change (cf. León-Ledesma *et al.*, 2010a,b), once the best-practice production function is derived for (at least) two moments in time, allowing for intertemporal comparisons.

The procedure is the following. Having computed the 'appropriate technology' factor as the residual from the non-parametrically estimated frontier production function and its Cobb–Douglas counterpart for the current and the previous moment in time, $A_n(\mathbf{x}_n)$ and $A_s(\mathbf{x}_s)$, respectively, one analyses the ratio of the two as a function of inputs. This helps identify the factor mixes for which the technology frontier has been shifted most, and the regions for which it remained virtually unchanged.

III. Data

The WTF, spanned by some of the world's most developed regions, will be estimated here using a dataset including both OECD country-level data and US state-level data. Our original dataset covered 21 OECD countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, UK, US, as well as 50 US states plus the District of Columbia. The dataset which is actually used is reduced to 20 countries and 40 US states. The reasons for excluding a few territorial units from our study are the following.

First, we had to drop Luxembourg and the DC 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).[7] We have also removed Germany in the period before its unification from our sample.

Furthermore, since the DEA method is extremely sensitive to outliers, we have also decided to exclude the US states with the largest long-term average mining shares in state GDP.[8] There is an indication that productivity of these states might be overestimated since their GDP 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.[9] We have also dropped Delaware and New Hampshire because they are small, open, specialized economies with comparatively unusual tax systems.[10] It is important to drop these outlying observations because they carry information which is not included in the estimated production function and thus introduce 'noise' rather than 'signal'.

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

The frontier production function is constructed here with the DEA method taking physical capital K, unskilled labour L^{U}, and skilled labour L^{S} as inputs. We shall thus decompose the output (GDP) of each country i in each year t into the efficiency score (Shephard distance function) and the maximum attainable output given inputs:

$$y_{it} = E_{it} f(K_{it}, L_{it}^{\mathrm{U}}, L_{it}^{\mathrm{S}}). \tag{5}$$

Unskilled and skilled labour are measured in 'no-schooling equivalents', indicating that each worker's labour input is weighted by her educational attainment. Following Caselli and Coleman (2006), we have allowed unskilled and skilled labour to be imperfectly substitutable. This requires us to split the overall level of human capital per worker into 'human capital within unskilled labour' and 'within skilled labour'.[11]

The data we are using are set in *per worker* terms. This means that we abstract from the issues of labour market participation which may result in additional *per capita* productivity differences, and of the variation in hours worked per worker which means that our analysis convolutes productivity differences with labour-leisure choices of the employees:

[7]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.

[8]Needless to say, the sensitivity of the DEA method to outliers cannot justify arbitrary omissions of meaningful data. The primary objective in the current data preparation procedure is to keep as many units as possible in the sample, removing only those which are outliers for objectively explainable reasons, such as measurement error or the presence of certain 'accounting' facts in the data, unrelated to actual productivity. Clearly, removing too many US states would result in reducing the value added of this study as compared to the existing literature, as well as in lowering the precision of DEA-based frontier estimates.

[9]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.

[10]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.

[11]Empirical evidence of imperfect substitutability between unskilled and skilled labour is provided by Pandey (2008).

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 both across OECD countries and US states which would date back at least until 1970.[12]

For international data on GDP and GDP per worker, we use the Penn World Table 6.2 (Heston, Summens and Alen, 2006), available for 1960–2003. For state-level GDP and GDP per worker, we use data from the Bureau of Economic Analysis (BEA), Regional Accounts, available for 1963–2007. The unit of measurement is the Purchasing Power Parity (PPP) converted US dollar under constant prices as of year 2000. The BEA data on GDP per worker have been proportionally adjusted for the sake of internal coherence with the aggregate US data from Penn World Table 6.2.[13]

The physical capital series has been constructed using the perpetual inventory method described, among others, by Caselli (2005). We have taken country-level investment shares as well as government shares from Penn World Table 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.[14] Unfortunately, there are no data on state-level investment shares apart from those computed by Turner, Tamura and Mulholland (2008) which are however not publicly available. Knowing that this introduces substantial error but not being able to obtain better proxies, we have imputed that state-level private investment shares are equal to the US countrywide private investment share.

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

[12]For example, the well-known EU KLEMS dataset contains international data on hours worked, but it does not provide data on US states.

[13]As a side effect, our adjustment procedure helps solve the problem of the discontinuity between 1996 and 1997 in BEA data on state-level GDP, arising due to a change in measurement methodology.

[14]Approximate state-level goverment shares can also be constructed using BEA data on state-level subsidies and taxes on production and imports. Compared to the approach taken in the current study, this alternative idea has both advantages (e.g. longer time span of the BEA dataset) and disadvantages (e.g. only partial coverage of the government sector). We leave it for further research.

The 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 Masters degree (the last category covering above-Masters 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 for coherence with D-D data.

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

$$L^{\mathrm{U}} = \sum_{i \in S_U} \psi_i e^{\phi(s_i)}, \quad L^{\mathrm{S}} = \sum_{i \in S_S} \psi_i e^{\phi(s_i)}, \tag{6}$$

where S_U is the set of groups of people who completed less than 12 years of education (less than elementary, elementary and 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 ith education group in total working-age population of the given country, s_i represents years of schooling in ith education group (cf. de la Fuente and Doménech, 2006) and $\phi(s)$ is a concave piecewise linear function:

$$\phi(s) = \begin{cases} 0.134s & s < 4, \\ 0.134 \cdot 4 + 0.101(s-4) & s \in [4, 8), \\ 0.134 \cdot 4 + 0.101 \cdot 4 + 0.068(s-8) & s \geq 8. \end{cases} \tag{7}$$

Assuming perfect substitutability between unskilled labour L^{U} and skilled labour L^{S}, the overall human capital index is computed as $H = L^{\mathrm{U}} + L^{\mathrm{S}}$. We however allow these two types of labour to be imperfectly substitutable, and enter the production function separately. The perfect substitution case where only total human capital matters is an interesting special case of our generalized formulation; the data do not support this assumption, however.[15]

Special attention should be paid to the arbitrarily chosen cutoff point of 12 years of schooling, delineating unskilled from skilled labour in the current study. It is secondary education which 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 the remainder as skilled. This cutoff point seems adequate for OECD economies in our sample – which are usually technologically advanced and highly capitalized – though it might be set too high if developing economies were to be considered as well (cf. Caselli and Coleman, 2006). Another measurement problem which may potentially

[15]Temple (2001) discusses an interesting case where $H = L^{\mathrm{U}} + h \cdot L^{\mathrm{s}}$ with $h \geq 1$. Even though it is a naturally interpretable intermediate case between aggregating human capital according to $H = L^{\mathrm{u}} + L^{\mathrm{s}}$ and assuming that L^{u} and L^{s} enter the production function separately, we do not take it into account here because it retains the assumption of perfect substitutability between unskilled and skilled labour.

appear, but which we do not consider a major obstacle here given our sample choice, is that schooling quality at different grades varies across countries and states (as it can be seen in the results of international Programme for International Student Assessment (PISA) tests, cf. Hanushek and Woessmann, 2010). 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.

IV. The world technology frontier revisited

Let us now turn to our principal results. We shall first demonstrate the value added of using US state-level data in WTF estimation. Next we will show why it is also important to allow for imperfect substitutability between unskilled and skilled labour. Finally, we will provide some evidence for non-neutrality of technical change in the period 1970–2000 as well as departures of the WTF from the Cobb–Douglas functional specification.

The bias without US states

The auxiliary use of US state-level data increases the precision of WTF estimates in two ways: not only is estimation *error* reduced in this process, but the magnitude of the *bias* is also revealed. Accounting for the heterogeneity across US states uncovers that the US states are able to produce much more efficiently than the aggregate (averaged) data would suggest.

The results presented in Table 1 and visualized in Figure 1 indicate further that enlarging the dataset by adding US state-level data not only helps alleviate part of the bias inherent in DEA estimates, but is also clearly complementary to computing bootstrap-based bias-corrected efficiency estimates (cf. Badunenko *et al.*, 2009). Both of these methods provide sizeable downward corrections to the estimated Shephard distance measures; using *both methods simultaneously* lowers the estimates even further.

Figure 2 provides a convincing graphical illustration that WTF estimates are generally much lower if only country-level data are used in the estimation procedure. This figure views (factor-dependent) CDTFP as a function of the input ratio *K/H* (i.e. $\frac{K}{L^{U}+L^{S}}$), whether the WTF is constructed with or without US state-level data.[16] Applying the 'appropriate technology vs. efficiency' decomposition (4), CDTFP is computed as:[17]

$$A_t(K_{it}, L_{it}^{U}, L_{it}^{S}) = \frac{y_{it}}{E_{it}K_{it}^{\alpha}(L_{it}^{U}+L_{it}^{S})^{1-\alpha}}, \quad \alpha = \frac{1}{3}. \tag{8}$$

We see that thanks to the auxiliary use of US state-level data, WTF estimates are improved and their downward bias is reduced: many countries see their technical

[16] Please note that the WTF itself is a function of three variables, non-decreasing and concave in its whole domain. In Figure 2, and following Jerzmanowski (2007), only its projection on the *K/H* axis is presented. It should not be a surprise that Figure 2 is different from, for example, figures presented in Kumar and Russell (2002): the WTF must be a non-decreasing function of K, L^{u} and L^{s}, but it need not be a monotonic function of *K/H*.

[17] Perfect substitutability between skilled and unskilled labour is imposed in the denominator, because in the related literature, the Cobb–Douglas function is habitually specified with human capital as a homogeneous factor of production. Imperfect substitutability is still allowed in the computation of efficiency scores E_{it}, though. Hence, the assumption of imperfect substitutability between skilled and unskilled labour *does* have an impact on CDTFP.

TABLE 1

Efficiency levels (Shephard distance measures) in 2000 *estimated with and without the use of US state-level data, with and without the Simar and Wilson* (1998, 2000) *bootstrap*

	No US states				*With US states*			
	DEA	*Bootstrap*	*95% CI*		*DEA*	*Bootstrap*	*95% CI*	
Australia	0.7823	0.7340	0.7028	0.7768	0.7006	0.6838	0.6727	0.6960
Austria	0.8917	0.8641	0.8300	0.8880	0.7581	0.7304	0.7031	0.7546
Belgium	0.9416	0.9105	0.8833	0.9355	0.8529	0.8310	0.8087	0.8489
Canada	1.0000	0.7271	0.7251	0.9921	0.7045	0.6792	0.6599	0.7006
Denmark	0.8220	0.7858	0.7531	0.8168	0.7367	0.7158	0.6980	0.7329
Finland	0.7253	0.7025	0.6814	0.7207	0.6647	0.6503	0.6349	0.6624
France	0.8522	0.8214	0.7895	0.8468	0.7407	0.7183	0.6966	0.7374
Germany	0.7605	0.7012	0.6506	0.7570	0.6202	0.5934	0.5673	0.6184
Greece	0.6416	0.6205	0.5948	0.6394	0.5764	0.5645	0.5548	0.5733
Ireland	1.0000	0.9093	0.8827	0.9915	1.0000	0.9680	0.9559	0.9919
Italy	0.9002	0.8795	0.8587	0.8956	0.8439	0.8227	0.8030	0.8398
Japan	0.6785	0.6294	0.5996	0.6726	0.6336	0.5471	0.5283	0.5716
The Netherlands	0.8649	0.8351	0.8041	0.8593	0.7424	0.7182	0.6954	0.7380
Norway	1.0000	0.9301	0.8958	0.9928	0.9222	0.8890	0.8639	0.9190
Portugal	0.9789	0.9265	0.8801	0.9735	0.9360	0.8881	0.8486	0.9292
Spain	0.8222	0.7933	0.7738	0.8167	0.8125	0.8022	0.7909	0.8105
Sweden	0.7644	0.6869	0.6497	0.7583	0.6582	0.6362	0.6217	0.6531
Switzerland	0.8139	0.7664	0.7193	0.8083	0.6578	0.6199	0.5931	0.6543
UK	0.8610	0.8125	0.7793	0.8546	0.7710	0.7573	0.7472	0.7664
USA	1.0000	0.7251	0.7287	0.9908	0.8946	0.8535	0.8219	0.8859

Notes: DEA, data envelopment analysis; CI, confidence intervals. None of the 95% CI contains the respective DEA point efficiency estimate because of its upward bias.

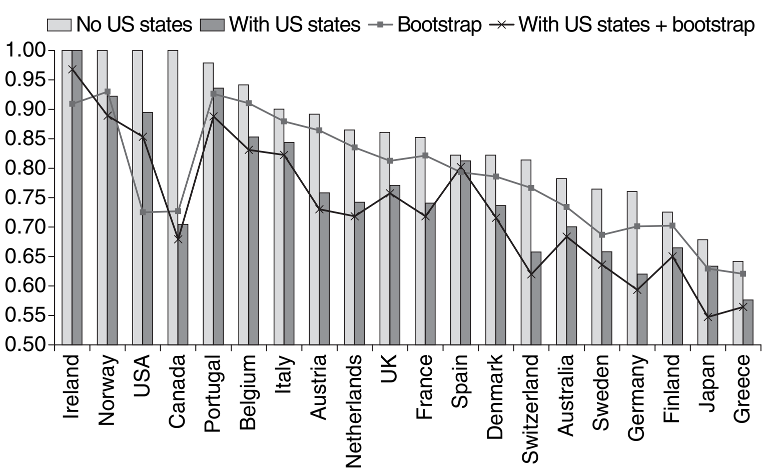

Figure 1. Efficiency levels (Shephard distance measures) in 2000: data-driven bias correction vs. bootstrap-based bias correction

efficiency (Shephard distance measures) lowered and their potential output increased because of this step. The average magnitude of the bias uncovered by our procedure is equal to 0.094, which stands on equal footing with the average magnitude of this bias,

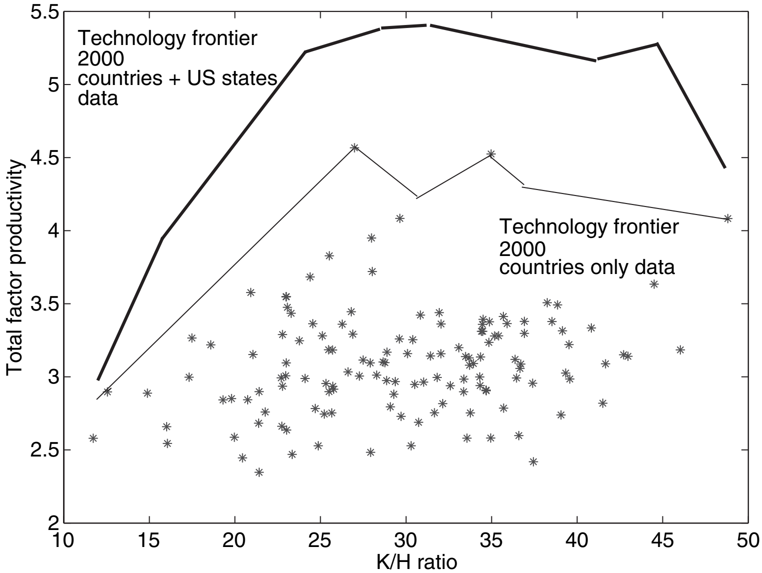

Figure 2. The world technology frontier in 2000: countries-only data vs. the dataset with both countries and US states

Notes: 'Total factor productivity' refers to CDTFP $A(K, L^{\mathrm{U}}, L^{\mathrm{S}})$ defined in equation (4). Asterisks denote technologies historically used in OECD countries in 1970–2000.

equal to 0.083, identified with the Simar and Wilson bootstrap procedure by Badunenko *et al.* (2009), or 0.067 which is the replica of their results computed for the current data sample. Most interestingly, if one appends the US state-level dataset to the cross-country one and then uses the bootstrap procedure too, then the total bias identified in such a procedure rises to 0.122. Both bias-correction mechanisms are thus complementary to one another.

The main corollary from this analysis is that the downward bias in WTF estimates from using country-level data only can be quite substantial, going up to 25% of estimated CDTFP, 30% of estimated technical efficiency and 32% of estimated bias-corrected technical efficiency, although the effect varies across countries, and may be small for some.

The differences among countries regarding the magnitude of bias in their efficiency estimates are indeed large. The maximum observed difference is 30 percentage points in the case of Canada, and the minimum is zero in the case of Ireland which is fully efficient in 2000 irrespective of whether US states are included in the sample or not. Apart from that, relatively poor countries such as Portugal, Spain or Greece record relatively small differences, up to 7 pp., whereas relatively rich (and highly capitalized) countries such as Germany or Austria see differences of 14 pp. or more. One potential explanation of this discrepancy is that the inclusion of US state-level data in our dataset might have increased the precision of WTF estimates to a much larger extent in some parts of the frontier than in other parts. In particular, upon inspection of the dataset, it should be expected that the increase should be most pronounced for high levels of physical capital and skilled labour.

The impact of our 'US-state data-driven' bias correction method on estimated technical efficiency scores is different from the bootstrap one. Bootstrap corrections tend to lower estimated efficiencies rather uniformly, with the exceptions of the US and Canada where visibly larger adjustments up to 27 pp. are obtained. Data-driven corrections proposed here affect the estimated efficiencies much more *un*evenly, with the smallest changes present in Ireland as well as countries with the least similarity in factor endowments to the leading US states: Spain, Portugal, Japan, Finland and Greece, and the largest change obtained for Canada. Bootstrap corrections imposed on US-state data-driven corrected estimates are again very even, with Japan being the only exception.

The bias from aggregating human capital

Let us now address the question, how much precision in WTF estimation is gained by allowing skilled and unskilled labour to be imperfectly substitutable. If the frontier estimated with aggregate human capital data approximately overlapped with the frontier estimated with skilled and unskilled labour separately, then there would be no substantial gain from making this distinction. On the other hand, the further away these two estimates are from each other, the stronger is the indication of limited substitutability between both types of labour, and the larger is the bias accruing from estimating the WTF with aggregate human capital data only.

TABLE 2

Estimated efficiency scores (Shephard distance measures) and CDTFP levels. Homogeneous vs. heterogeneous human capital. DEA results and bias-corrected estimates

	Technical efficiency				*CDTFP*			
	L^U, L^S	*Bootstrap*	H	*Bootstrap*	L^U, L^S	*Bootstrap*	H	*Bootstrap*
Australia	0.7006	0.6838	0.6858	0.6738	4.7991	4.9166	4.9020	4.9892
Austria	0.7581	0.7304	0.6890	0.6414	4.4581	4.6272	4.9048	5.2688
Belgium	0.8529	0.8310	0.7013	0.6504	3.9441	4.0479	4.7964	5.1721
Canada	0.7045	0.6792	0.6979	0.6873	4.8575	5.0388	4.9039	4.9794
Denmark	0.7367	0.7158	0.6684	0.6408	4.7406	4.8787	5.2251	5.4500
Finland	0.6647	0.6503	0.5723	0.5476	4.4468	4.5452	5.1653	5.3982
France	0.7407	0.7183	0.6802	0.6432	4.7347	4.8823	5.1563	5.4531
Germany	0.6202	0.5934	0.6202	0.5901	4.6729	4.8841	4.6729	4.9115
Greece	0.5764	0.5645	0.5621	0.5561	4.2429	4.3323	4.3510	4.3973
Ireland	1.0000	0.9680	0.9344	0.9238	4.5667	4.7176	4.8876	4.9433
Italy	0.8439	0.8227	0.6623	0.6448	3.9234	4.0247	4.9996	5.1350
Japan	0.5744	0.5471	0.5402	0.5023	4.9082	5.1534	5.2190	5.6125
The Netherlands	0.7424	0.7182	0.6968	0.6668	4.5480	4.7010	4.8453	5.0634
Norway	0.9222	0.8890	0.8069	0.7470	4.4271	4.5924	5.0600	5.4656
Portugal	0.9360	0.8881	0.7213	0.6459	3.6743	3.8726	4.7684	5.3246
Spain	0.8125	0.8022	0.6545	0.6433	4.0115	4.0633	4.9802	5.0669
Sweden	0.6582	0.6362	0.6332	0.6132	5.0094	5.1830	5.2073	5.3777
Switzerland	0.6578	0.6199	0.6207	0.5594	4.7740	5.0656	5.0597	5.6138
UK	0.7710	0.7573	0.7557	0.7459	4.8258	4.9129	4.9232	4.9882
USA	0.8946	0.8535	0.8868	0.8613	5.0570	5.3007	5.1016	5.2524

In Table 2 we have compared the estimates of technical efficiency obtained with the use of disaggregated unskilled and skilled labour variables to their counterparts computed under the assumption of a homogeneous human capital stock, with perfect substitutability ($H = L^{U} + L^{S}$). These results have also been corrected for a potential bias due to sampling error, using the Simar and Wilson (1998, 2000) bootstrap method.

The (L^{U}, L^{S}) efficiency estimates are, by construction, higher or equal than the simpler H-only estimates. Consequently, (L^{U}, L^{S}) CDTFP estimates must be lower or equal than their H-only counterparts, indicating that aggregating heterogeneous human capital into a homogeneous stock leads, by definition, to an overestimation of maximum potential productivity. The same inequality must hold, by definition, for original estimates and their bias-corrected counterparts.

We see that the difference between both approaches turns out to be very large in some countries, which emphasizes the economic importance of imperfect substitutability between skilled and unskilled labour. The same regularity is visible in bias-corrected estimates, too. Most importantly, however, the magnitude of this bias is very uneven across countries: for Germany, there is no difference between both DEA estimates (and essentially no difference between both bias-corrected estimates), whereas in the extreme cases of Italy and Portugal, the efficiency factor increases by 18–21 percentage points when human capital is disaggregated, and CDTFP decreases by 22–23%. This is because a relatively large fraction of the Italian and Portuguese workforce is unskilled (has completed less than high school) but the aggregate human capital measures are nevertheless arguably high there, because there are also reasonably large shares of university graduates – implying a heavily unbalanced workforce. Estimates of the Italian or Portuguese (as well as Spanish or Belgian) potential productivity which do not take into account the large dispersions in their human capital distributions are therefore likely to be particularly strongly upward biased.

Evidence for non-neutral technical change

CDTFP has been depicted as a function of the *K/H* ratio for the year 1970 and 2000 in Figure 3. These frontiers have been estimated with both country-level and US state-level data, covering either the year 1970 only, or the whole 1970–2000 period, respectively.

It is instructive to see how the WTF evolved during the 30 years between 1970 and 2000. On the one hand, technological progress has shifted the WTF in its (almost) whole domain; on the other hand, two additional results must be noted: (i) technical change has been strongest in the area where the *K/H* ratio is the largest; and (ii) continued physical capital accumulation extended the WTF into the range of larger *K/H* ratios, not observed in 1970. For lower *K/H* ratios, technical change was less pronounced, and for the lowest ones, recorded in Portugal and Spain in 1970, there has not been any technical change at all, at least in our data.

Finally, the finding that our empirically constructed measures of CDTFP are robustly factor-dependent (so that, in particular, the curves depicted in Figure 3 are not flat) implies that the true underlying WTF production function departs from the Cobb–Douglas benchmark.

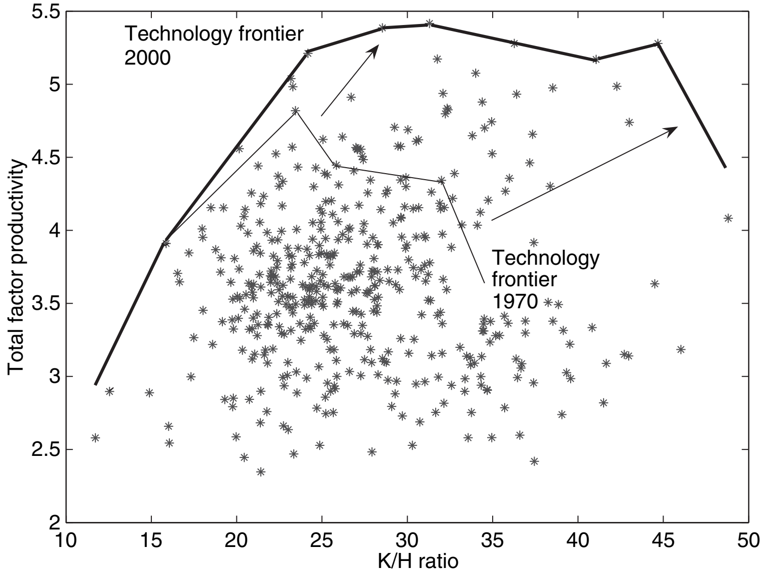

Figure 3. The direction of technical change, 1970–2000

Notes: 'Total factor productivity' refers to CDTFP $A(K, L^{\mathrm{U}}, L^{\mathrm{S}})$ defined in equation (4). Asterisks denote technologies that would be efficient in 2000 given factor combinations historically observed in OECD countries or US states in 1970–2000.

V. Decomposing the distance between OECD countries and the US

Development accounting

The non-parametric production frontier approach taken here is very useful for the purposes of development accounting: based on equation (1), the ratio of GDP per worker in any two countries (here, between each particular OECD country and the US in the year 2000) can be relatively straightforwardly decomposed into a product of (i) the efficiency ratio, and (ii) differences in potential output attributed to differences in the endowment of each separate factor of production.

The latter group of factors cannot be determined uniquely, though. The reason is that when we assess the impact on output of differences in one factor holding other factors constant, *we can hold them constant at different levels*: either at US levels, or country levels, or a mixture of the two. For two factors of production (say, physical capital K and human capital H), the situation is relatively simple. In such a case, the best idea would be to decompose the ratio of GDP per worker between country C and USA (denoted as U) according to the 'Fisher-ideal' decomposition (cf. Henderson and Russell, 2005):

$$\frac{y_C(K_C,H_C)}{y_U(K_U,H_U)} = \frac{E_C}{E_U} \cdot \frac{y^*(K_C,H_C)}{y^*(K_U,H_U)}$$

$$= \frac{E_C}{E_U} \cdot \underbrace{\sqrt{\frac{y^*(K_C,H_C)}{y^*(K_U,H_C)} \cdot \frac{y^*(K_C,H_U)}{y^*(K_U,H_U)}}}_{K\,\text{difference}} \cdot \underbrace{\sqrt{\frac{y^*(K_C,H_C)}{y^*(K_C,H_U)} \cdot \frac{y^*(K_U,H_C)}{y^*(K_U,H_U)}}}_{H\,\text{difference}}. \tag{9}$$

With three factors of production which we have in our analysis, the situation gets more complex: there is no single 'other factor' which should be fixed at a C or U level but there are two 'other factors' which may be fixed at $(C,C),(C,U),(U,C)$ or (U,U) levels. After a fair amount of algebra, the 'Fisher-ideal' decomposition for such a case is found to satisfy the following:

$$\begin{aligned}\frac{y_C(K_C,L_C^{\mathrm{U}},L_C^{\mathrm{S}})}{y_U(K_U,L_U^{\mathrm{U}},L_U^{\mathrm{S}})}&=\frac{E_C}{E_U}\cdot\frac{y^*(K_C,L_C^{\mathrm{U}},L_C^{\mathrm{S}})}{y^*(K_U,L_U^{\mathrm{U}},L_U^{\mathrm{S}})}\\&=\frac{E_C}{E_U}\cdot K\text{ diff}\cdot L^{\mathrm{U}}\text{ diff}\cdot L^{\mathrm{S}}\text{ diff}\end{aligned}\qquad(10)$$

where

$$K\text{ diff}=\sqrt[6]{\left(\frac{y^*(K_C,L_C^{\mathrm{U}},L_C^{\mathrm{S}})}{y^*(K_U,L_C^{\mathrm{U}},L_C^{\mathrm{S}})}\right)^2\frac{y^*(K_C,L_C^{\mathrm{U}},L_U^{\mathrm{S}})}{y^*(K_U,L_C^{\mathrm{U}},L_U^{\mathrm{S}})}\frac{y^*(K_C,L_U^{\mathrm{U}},L_C^{\mathrm{S}})}{y^*(K_U,L_U^{\mathrm{U}},L_C^{\mathrm{S}})}\left(\frac{y^*(K_C,L_U^{\mathrm{U}},L_U^{\mathrm{S}})}{y^*(K_U,L_U^{\mathrm{U}},L_U^{\mathrm{S}})}\right)^2},$$

$$L^{\mathrm{U}}\text{ diff}=\sqrt[6]{\left(\frac{y^*(K_C,L_C^{\mathrm{U}},L_C^{\mathrm{S}})}{y^*(K_C,L_U^{\mathrm{U}},L_C^{\mathrm{S}})}\right)^2\frac{y^*(K_C,L_C^{\mathrm{U}},L_U^{\mathrm{S}})}{y^*(K_C,L_U^{\mathrm{U}},L_U^{\mathrm{S}})}\frac{y^*(K_U,L_C^{\mathrm{U}},L_C^{\mathrm{S}})}{y^*(K_U,L_U^{\mathrm{U}},L_C^{\mathrm{S}})}\left(\frac{y^*(K_U,L_C^{\mathrm{U}},L_U^{\mathrm{S}})}{y^*(K_U,L_U^{\mathrm{U}},L_U^{\mathrm{S}})}\right)^2},$$

$$L^{\mathrm{S}}\text{ diff}=\sqrt[6]{\left(\frac{y^*(K_C,L_C^{\mathrm{U}},L_C^{\mathrm{S}})}{y^*(K_C,L_C^{\mathrm{U}},L_U^{\mathrm{S}})}\right)^2\frac{y^*(K_C,L_U^{\mathrm{U}},L_C^{\mathrm{S}})}{y^*(K_C,L_U^{\mathrm{U}},L_U^{\mathrm{S}})}\frac{y^*(K_U,L_C^{\mathrm{U}},L_C^{\mathrm{S}})}{y^*(K_U,L_C^{\mathrm{U}},L_U^{\mathrm{S}})}\left(\frac{y^*(K_U,L_U^{\mathrm{U}},L_C^{\mathrm{S}})}{y^*(K_U,L_U^{\mathrm{U}},L_U^{\mathrm{S}})}\right)^2}.$$

Please note that in each of the fractions indicated above, the numerator and denominator differ by a single variable only, being the variable whose contribution to the total GDP ratio we are about to measure.

The current development accounting exercise can be done for any given year in exactly the same way; to obtain maximum available precision, we have chosen to do this exercise for the year 2000. The results of our numerical computation of decomposition (10) are presented in Table 3. 'H diff' is the total impact of human capital differences, being the product of L^{U} diff and L^{S} diff.

Efficiency vs. 'appropriate technology'

Another advantage of the non-parametric frontier estimation method taken here is that it allows one to decompose the GDP ratio into the efficiency differential, the factor endowments differential, and the 'appropriate technology' ratio capturing the differences in maximum attainable production given factor endowments. Referring to equation (4) and adding the assumption of perfect substitutability between skilled and unskilled labour to attain comparability to the established literature, the 'efficiency vs. appropriate technology' decomposition can be written as:

$$\frac{y_C(K_C,L_C^{\mathrm{U}},L_C^{\mathrm{S}})}{y_U(K_U,L_U^{\mathrm{U}},L_U^{\mathrm{S}})}=\underbrace{\frac{E_C}{E_U}}_{\text{efficiency}}\cdot\underbrace{\frac{A(K_C,L_C^{\mathrm{U}},L_C^{\mathrm{S}})}{A(K_U,L_U^{\mathrm{U}},L_U^{\mathrm{S}})}}_{\text{appropriate tech.}}\cdot\underbrace{\frac{K_C^{\alpha}}{K_U^{\alpha}}}_{K\text{diff}}\cdot\underbrace{\frac{(L_C^{\mathrm{U}}+L_C^{\mathrm{S}})^{1-\alpha}}{(L_U^{\mathrm{U}}+L_U^{\mathrm{S}})^{1-\alpha}}}_{H\text{diff}},\qquad(11)$$

where $\alpha=1/3$.

TABLE 3

Decomposition of the distance between a given OECD country and the US in 2000

	GDP ratio	*Efficiency*	*K diff*	L^u *diff*	L^s *diff*	*H diff*
Australia	0.7544	0.7831	0.9789	1.0373	0.9489	0.9842
Austria	0.8712	0.8474	1.0766	1.0397	0.9185	0.9550
Belgium	0.8926	0.9534	1.0643	1.0903	0.8069	0.8797
Canada	0.7426	0.7875	0.9431	0.9958	1.0041	0.9999
Denmark	0.7521	0.8234	1.0172	1.0872	0.8259	0.8979
Finland	0.6737	0.7430	1.0269	1.1019	0.8014	0.8830
France	0.8242	0.8280	1.0510	1.0477	0.9040	0.9471
Germany	0.7605	0.6933	1.0812	1.0047	1.0097	1.0145
Greece	0.4781	0.6443	0.7487	1.2338	0.8033	0.9911
Ireland	0.8811	1.1178	0.8559	1.1948	0.7708	0.9210
Italy	0.7581	0.9433	1.0091	1.2124	0.6569	0.7964
Japan	0.6643	0.6421	1.0756	1.0346	0.9298	0.9619
The Netherlands	0.8451	0.8298	1.0553	1.0338	0.9335	0.9651
Norway	0.9528	1.0308	1.0679	1.0939	0.7912	0.8655
Portugal	0.5069	1.0456	0.8483	1.9419	0.2943	0.5714
Spain	0.6613	0.9082	0.9234	1.2555	0.6281	0.7885
Sweden	0.6939	0.7358	0.9942	1.0599	0.8950	0.9485
Switzerland	0.8096	0.7353	1.1074	1.0091	0.9853	0.9942
UK	0.7338	0.8618	0.8657	1.1020	0.8925	0.9836

Notes: For each country, the product of contributions of efficiency, physical capital K, unskilled labour L^u, and skilled labour L^S is equal to the GDP ratio. The product of L^u and L^s differentials is the total human capital differential ('H diff').

Please note the different definitions of the 'K diff' and 'H diff' terms in equations (10) and (11). In the former equation, they refer to the fraction of the cross-country productivity ratio attributable to differences in quantities of respective production inputs. In the latter one, they refer to the same fraction, albeit computed under the counterfactual assumption that the production function is Cobb–Douglas. This implies that in the typical case, factor contributions are better quantified in equation (10), whereas equation (11) can single out the 'appropriate technology' (CDTFP) terms only at the cost of compromising the precision of estimates of factor contributions. This cost is inherent in all 'appropriate technology vs. efficiency' decompositions which view the non-parametrically estimated WTF through the lens of the Cobb–Douglas production function structure.

The results of this exercise are presented in Table 4, from which we learn that the contributions attributed directly to factor endowments in the 'appropriate technology vs. efficiency' decomposition are much smaller than they were in the decomposition based on our non-parametric estimates (K diff and H diff are now markedly closer to unity), and a significant fraction of the productivity differential which was previously attributable to factor endowments is now shifted to the 'appropriate technology' (CDTFP) ratio. Indeed, for countries like Belgium or Italy, 'inappropriateness of technology' explains most of the productivity differential. There are also important counterexamples, however: Japan and Sweden could produce almost as much as the US given their factor endowments (their CDTFP is very close to the US one) but they do not because of markedly lower technical efficiency.

TABLE 4

Decomposition of the distance between a given OECD country and the US in 2000: efficiency vs. 'appropriate technology'

	GDP ratio	*Efficiency*	*Techn.*	*K diff*	*H diff*
Australia	0.7544	0.7831	0.9490	0.9857	1.0299
Austria	0.8712	0.8474	0.8816	1.0654	1.0947
Belgium	0.8926	0.9534	0.7799	1.0691	1.1229
Canada	0.7426	0.7875	0.9605	0.9665	1.0157
Denmark	0.7521	0.8234	0.9374	1.0148	0.9601
Finland	0.6737	0.7430	0.8793	1.0255	1.0055
France	0.8242	0.8280	0.9363	1.0411	1.0212
Germany	0.7605	0.6933	0.9241	1.0478	1.1328
Greece	0.4781	0.6443	0.8390	0.8520	1.0381
Ireland	0.8811	1.1178	0.9031	0.9022	0.9675
Italy	0.7581	0.9433	0.7758	1.0086	1.0270
Japan	0.6643	0.6421	0.9706	1.0612	1.0046
The Netherlands	0.8451	0.8298	0.8994	1.0417	1.0871
Norway	0.9528	1.0308	0.8754	1.0965	0.9628
Portugal	0.5069	1.0463	0.7266	0.8562	0.7788
Spain	0.6613	0.9082	0.7933	0.9366	0.9801
Sweden	0.6939	0.7358	0.9906	0.9957	0.9562
Switzerland	0.8096	0.7353	0.9440	1.1019	1.0584
UK	0.7338	0.8618	0.9543	0.9166	0.9736

Notes: For each country, the product of contributions of efficiency, appropriate technology, physical capital K and human capital H is equal to the GDP ratio.

VI. Decomposing GDP growth

Growth accounting

Analogously to the development accounting exercise described above, we will now conduct a growth accounting exercise aimed at decomposing the total 1970–2000 increase in GDP per worker into the impacts of (i) changes in efficiency relative to the WTF, (ii) technological progress at the WTF, and (iii) factor accumulation.

As compared to development accounting, there is one additional factor which ought to be disentangled here: technological progress at the frontier, which pushes the WTF forward so that potential productivity is increased. Formally, with three factors of production, $K, L^{\mathrm{U}}, L^{\mathrm{S}}$, the 'Fisher-ideal' (cf. Henderson and Russell, 2005) decomposition of the 2000/1970 productivity ratio is the following (denoting $s=1970, n=2000$):

$$\frac{y_n(K_n,L_n^{\mathrm{U}},L_n^{\mathrm{S}})}{y_s(K_s,L_s^{\mathrm{U}},L_s^{\mathrm{S}})}=\frac{E_n}{E_s}\cdot\frac{y_n^*(K_n,L_n^{\mathrm{U}},L_n^{\mathrm{S}})}{y_s^*(K_s,L_s^{\mathrm{U}},L_s^{\mathrm{S}})}$$
$$=\underbrace{\frac{E_n}{E_s}}_{\text{efficiency}}\cdot\underbrace{\sqrt{\frac{y_n^*(K_n,L_n^{\mathrm{U}},L_n^{\mathrm{S}})}{y_s^*(K_n,L_n^{\mathrm{U}},L_n^{\mathrm{S}})}\frac{y_n^*(K_s,L_s^{\mathrm{U}},L_s^{\mathrm{S}})}{y_s^*(K_s,L_s^{\mathrm{U}},L_s^{\mathrm{S}})}}}_{\text{techn. progress}}\cdot\underbrace{\sqrt{\frac{y_n^*(K_n,L_n^{\mathrm{U}},L_n^{\mathrm{S}})}{y_n^*(K_s,L_s^{\mathrm{U}},L_s^{\mathrm{S}})}\frac{y_s^*(K_n,L_n^{\mathrm{U}},L_n^{\mathrm{S}})}{y_s^*(K_s,L_s^{\mathrm{U}},L_s^{\mathrm{S}})}}}_{\text{factor accumulation}}. \quad (12)$$

The decomposition of GDP growth defined in equation (12) singles out the dynamic changes in efficiency, shifts in the technology frontier given factor endowments and factor accumulation holding the technological frontier fixed. Furthermore, each of the two factors making up the 'factor accumulation' part should be further decomposed following equation (10) so that the contribution of each particular factor's accumulation to productivity growth is properly accounted for.

The product of the 'efficiency change' and 'technological progress' factors is also known as the (output-oriented) Malmquist productivity index in the DEA literature (cf. Fried *et al.*, 1993). It measures, for each country and time period, the total change in productivity which resulted from anything but factor accumulation. In other words, the Malmquist productivity index captures the total productivity improvement under technologies *actually used* in the given country, whereas our 'technological progress' index measures the total productivity improvement under *frontier* technology, given the country's factor endowments.

Table 5 presents the results of the current growth accounting exercise for OECD countries. Once again, the WTF has been estimated here with the use of US state-level data as well, but the decompositions of state-level productivity growth are not presented. The numbers included in Table 5 (and in all further growth accounting exercises) are 2000/1970 ratios of respective variables, computed according to the definitions described in equation (12), and then transformed into average annual growth rates (in %) by applying the transform $x \mapsto (\sqrt[30]{x} - 1) \cdot 100\%$.

The remarkable growth experience of Ireland whose GDP per worker has almost tripled during the considered 30 years, turns out to be mostly due to rapid capital accumulation and the ability to draw from the pool of worldwide technological change. The same factors have also been crucial for Japan in the considered period, but the overall Japanese performance was somewhat less striking than the Irish one due to a simultaneous marked decline in technical efficiency.[18] An important group of countries encompasses Italy, the Netherlands, Finland and Spain which have all obtained remarkable gains in productivity due to improvements in the level of schooling. The positive impact of technological progress has been felt most strongly in Switzerland and the USA while it was least pronounced in Portugal and Spain which were initially too undercapitalized and undereducated to take full advantage of the incoming developments.

Shifts of the WTF vs. movements along the WTF

Using the auxiliary Cobb–Douglas production function structure inherent in all 'appropriate technology vs. efficiency' decompositions, the 2000/1970 productivity ratio can also be decomposed into contributions attributable to (i) efficiency changes (i.e. changes in the distance to the WTF), (ii) technological progress shifting the WTF, (iii) changes in factor-specific CDTFP given a certain WTF (i.e. movements along the frontier), and (iv) factor accumulation.

To our knowledge, this decomposition has not been considered in the literature yet. Its crux lies with the fact that CDTFP is dependent not only on factor endowments, but also on time, and that it may increase asymmetrically thanks to new technological developments. Formally, the 'Fisher-ideal' decomposition, taking full account of technological change,

[18]The Japanese technical efficiency in 1970 could have been sharply overestimated, however, due to data scarcity and a rather unusual (as compared to other units in the sample) factor mix observed in Japan in that year.

TABLE 5

Decomposition of average annual growth rates in the 1970–2000 period

	Growth (%)	*Efficiency (%)*	*Techn (%)*	*K diff (%)*	L^u *diff (%)*	L^S *diff (%)*	*H diff (%)*
Australia	1.34	−0.47	0.86	0.39	−0.21	0.78	0.56
Austria	2.21	0.09	0.93	0.63	−0.03	0.58	0.54
Belgium	1.96	−0.09	0.74	0.44	−0.03	0.90	0.86
Canada	1.23	−0.37	1.05	2.22	−3.56	2.00	−1.64
Denmark	1.29	−0.17	0.78	0.28	−0.08	0.48	0.40
Finland	1.98	−0.42	0.67	0.22	−0.69	2.21	1.51
France	1.89	−0.48	0.85	0.53	−0.87	1.87	0.98
Greece	1.31	−1.00	0.36	1.00	−0.17	1.13	0.95
Ireland	3.62	0.43	0.34	2.80	−0.96	1.01	0.04
Italy	1.78	−0.33	0.50	0.17	−0.22	1.65	1.43
Japan	2.33	−1.51	0.78	3.10	−2.25	2.31	0.00
The Netherlands	1.07	−0.99	0.69	0.08	−2.33	3.71	1.29
Norway	2.31	0.66	0.69	0.16	−0.52	1.32	0.79
Portugal	2.17	−0.22	0.15	1.82	−1.38	1.82	0.41
Spain	1.95	−0.69	0.26	0.84	−0.42	1.97	1.54
Sweden	1.06	−0.66	0.82	0.14	−2.08	2.90	0.77
Switzerland	0.62	−1.11	1.28	0.14	−0.13	0.45	0.32
UK	1.91	0.01	0.56	0.66	−0.40	1.06	0.65
USA	1.68	−0.04	1.15	1.45	−1.42	0.55	−0.88

Notes: For each country, the product of proportional contributions of efficiency change, technological progress at the world technology frontier, physical capital accumulation K, unskilled labour accumulation L^{u} and skilled labour accumulation L^{S} is equal to the total proportional GDP increase in 1970–2000. The proportional contribution of human capital H is the product of contributions of L^{u} and L^{S}. The values expressed here are annualized growth rates of these contributions.

is obtained from the following formula:

$$\frac{y_n(\mathbf{x}_n)}{y_s(\mathbf{x}_s)} = \underbrace{\frac{E_n}{E_s}}_{\text{efficiency}} \cdot \frac{A_n(\mathbf{x}_n)}{A_s(\mathbf{x}_s)} \cdot \underbrace{\frac{K_n^{\alpha}}{K_s^{\alpha}}}_{K\,\text{diff}} \cdot \underbrace{\frac{(L_n^U + L_n^S)^{1-\alpha}}{(L_s^U + L_s^S)^{1-\alpha}}}_{H\,\text{diff}},$$

$$\text{where } \frac{A_n(\mathbf{x}_n)}{A_s(\mathbf{x}_s)} = \underbrace{\sqrt{\frac{A_n(\mathbf{x}_n)}{A_s(\mathbf{x}_n)}\frac{A_n(\mathbf{x}_s)}{A_s(\mathbf{x}_s)}}}_{\text{WTF shift}} \cdot \underbrace{\sqrt{\frac{A_n(\mathbf{x}_n)}{A_n(\mathbf{x}_s)}\frac{A_s(\mathbf{x}_n)}{A_s(\mathbf{x}_s)}}}_{\text{movement along WTF}}, \tag{13}$$

where we denoted $\mathbf{x}_i = (K_i, L_i^{\mathrm{U}}, L_i^{\mathrm{S}})$, $i = n, s$ for simplicity.

The novelty in the decomposition summarized in equation (13) is that we are able to disentangle *three* characteristics of technological change here: efficiency, shifts of the WTF and movements along the WTF. In previous contributions such as Kumar and Russell (2002) or Jerzmanowski (2007), the last two factors were lumped together. We believe however that they should be separated, because they describe two conceptually different phenomena – of (presumably R&D-driven) technological change at the frontier and of getting access to better (already known) technologies applicable to the country's new factor mix.

The results of this decomposition, presented in the form of average annual growth rate contributions, are presented in Table 6. It is clear from this table that shifts of the WTF

TABLE 6

Decomposition of productivity growth in the 1970–2000 *period. Efficiency changes, shifts of the world technology frontier* (*WTF*) *and movements along the WTF*

	Growth (%)	*Efficiency (%)*	*WTF shift (%)*	*Along WTF (%)*	*K diff (%)*	*H diff (%)*
Australia	1.34	−0.23	0.95	−0.33	0.52	0.41
Austria	2.21	0.08	1.14	−0.32	0.89	0.41
Belgium	1.96	−0.10	1.19	−0.43	0.80	0.48
Canada	1.23	−0.34	0.82	−0.21	0.60	0.35
Denmark	1.29	−0.26	1.02	−0.14	0.53	0.13
Finland	1.98	−0.05	0.95	−0.37	0.64	0.81
France	1.89	−0.16	1.08	−0.39	0.84	0.51
Greece	1.31	−0.65	0.36	0.15	0.66	0.78
Ireland	3.62	0.20	0.41	1.31	1.18	0.49
Italy	1.78	−0.03	0.95	−0.45	0.56	0.75
Japan	2.33	−1.42	0.85	0.51	1.57	0.84
The Netherlands	1.07	−0.56	1.33	−0.51	0.28	0.53
Norway	2.31	0.75	1.17	−0.26	0.62	0.00
Portugal	2.17	−1.08	0.19	1.48	1.22	0.36
Spain	1.95	−0.99	0.56	0.43	1.04	0.91
Sweden	1.06	−0.37	0.98	−0.25	0.36	0.34
Switzerland	0.62	−1.21	1.47	−0.47	0.45	0.40
UK	1.91	0.35	0.52	0.02	0.61	0.38
USA	1.68	−0.05	0.94	−0.10	0.68	0.21

Notes: For each country, the product of proportional contributions of efficiency change, technological progress at the WTF, movement along the WTF, physical capital accumulation K and human capital accumulation H is equal to the total proportional GDP increase in 1970–2000. The values expressed here are annualized growth rates of these contributions.

due to technological progress have been the primary contribution to GDP growth in all considered OECD countries but Portugal (and to a lesser extent, Greece and Ireland). For a few interesting cases, movements along the frontier have constituted an important contribution as well: most notably, Ireland and Portugal, and to a lesser extent, Spain, Japan and Greece. Along-the-frontier movements are highly correlated with capital accumulation: both factors are strongest in the same group of countries, consisting of Japan, Portugal, Ireland and Spain.

One feature of these results is that the contributions of WTF shifts and movements along the WTF are strongly negatively correlated. Indeed, the raw *ex post* correlation between these two contributions (transformed into annualized growth rates) is −0.81. A negative interpretation of this fact could be that there is really just a single factor ‘technical change’ that matters, and decomposing it further adds very little new insight. In particular, this might be the case if the Cobb–Douglas specification severely misrepresents the true production function and the ‘appropriate technology vs. efficiency’ decomposition captures primarily this discrepancy, not the endogeneous technology choice within economies.

Nevertheless, we would rather advocate a positive interpretation instead, which seems very plausible empirically: since all the factor definitions put forward in equation (13) are interpretable in terms of the ‘appropriate technology vs. efficiency’ decomposition (4) – these factors indeed measure (i) shifts in the frontier CDTFP holding factor endowments constant, and (ii) changes in CDTFP due to factor accumulation, holding the WTF constant – arguably, we might have actually uncovered a more general real-world regularity here. In particular, it could be the case that, as suggested by the above-mentioned strong negative correlation between the 'WTF shift' and the 'movement along WTF' factors, CDTFP in a country can grow either due to the worldwide technical change increasing CDTFP at the frontier or due to movements along the frontier, but not due to both simultaneously. This interpretation is corroborated by the three following findings:

(i) The factor-dependent CDTFP level, characterizing the WTF, depends positively on the amount of available physical capital (confirming previous findings of Kumar and Russell, 2002; Henderson and Russell, 2005, etc.). Accumulating physical capital is therefore associated with moving along the WTF – from low values where frontier TFP is also low, to high values where frontier TFP is high. In our current sample, the *ex post* correlation between the capital accumulation factor and the 'movement along WTF' factor is $+0.74$.

(ii) Once the differences in technical efficiency are filtered away, there appears a clear *real convergence* pattern: countries which were relatively undercapitalized initially were accumulating capital faster (in percentage terms). This implies large technological benefits due to the movements along the WTF in these countries, but not in countries which were highly capitalized initially. As a result, the *ex post* correlation between the capital accumulation factor and the aggregate 'technical change factor' (WTF shift $\times$ movement along WTF) is $+0.71$.

(iii) Not only is CDTFP higher in the range of high capital levels, but it is also growing faster over time in that range. Therefore, countries which had an abundance of production factors in the beginning, were more able to reap the benefits of technological progress at the WTF than countries which lacked them (cf. Atkinson and Stiglitz, 1969; Basu and Weil, 1998; Kumar and Russell, 2002). On the other hand, due to the real convergence mechanism described above, these countries would accumulate capital slower (in percentage terms) than the catching-up countries, and thus gain less from capital deepening. The correlation between the capital accumulation factor and the 'WTF shift' factor is -0.51.

Summarizing, we view the strong negative correlation between the 'WTF shift' and 'movement along WTF' factors as an outcome of an interplay of real convergence, the fact that CDTFP is increasing in the country's capital endowment and that technological progress at the frontier is realized mostly for high capital levels.

Hence, one may conjecture that countries could actually grow thanks to *both* shifts of the WTF *and* movements along the WTF, but this would require at least one of the three above regularities to be violated. We do not see such departures in our data, but they can potentially be found for different sets of countries (including less developed economies) or for different periods of time.

VII. Robustness

The strength of the DEA method is that it does not require any *a priori* assumptions on the shape of the world's best-practice production function but helps construct it as a piecewise linear function from the efficient observations present in the data. Its weakness is, however, that it would yield only a rough estimate of the true production function if the sample is small or dominated by a few outlying observations.[19]

We addressed this issue in the following way. First, by appending US state-level data to a cross-country dataset, and allowing earlier technologies to span the technology frontier at later dates as well (cf. Henderson and Russell, 2005), we have largely alleviated the small sample size problem. This applies especially to the final year 2000 for which we carry out our development accounting analyses. Second, as far as outliers are concerned, an (inverse) indicator of their presence is the number of frontier observations: the more of them, the ‘smoother’ is the estimated frontier production function, and the less pronounced is the potential outlier problem. In the estimates reported above, there are 38 frontier observations in 2000. Before dropping New Hampshire, there were only 29 of them. Before dropping Colorado, Nevada, Utah on top of that, there were again 29. Before dropping Delaware on top of that, there were 25. Before dropping Alaska, Louisiana, New Mexico, West Virginia, Wyoming on top of that, the WTF was spanned almost exclusively by Alaska, at all periods of time, subsequently lowering the efficiency factor in most other US states by as much as 10–30 percentage points.

The chief reason to drop several states from the current analysis is the extent of their mining activity: resource rents are part of their state GDP but are not accounted for in the estimated production function. Another important reason to drop a few ‘suspicious’ US states from our dataset is their extent of economic specialization. One has to keep in mind that even though US states may be assumed to be local open economies, characterized by their own input mixes and productivity, they are also constituent parts of the entire US which is a large system of free trade and free flows in capital and labour.[20] Hence, some states might have obtained some extra productivity thanks to specializing in more profitable sectors of the economy, leaving the less profitable but necessary activities such as farming to other states, whose productivity was thereby impaired. Hence, excluding such strongly specialized states from the sample is beneficial for the quality of our ‘macro-level’ (i.e. aggregate, not sectoral) WTF estimates.

While the shape of the estimated WTF depends critically on the few efficient observations, potentially outliers, the results of the associated growth and development accounting exercises are more robust to this problem. This was confirmed by comparing the results across different samples of US states, described above. In particular, upon dropping Colorado, Delaware, Nevada, New Hampshire and Utah from the sample, none of the qualitative results of our development and growth accounting exercises was affected. Quantitatively, there have been a few visible changes, of course – most importantly, efficiency levels rose markedly in some countries/states as the aforementioned US states were dropped –

[19]Given this limitation, an important alternative to the DEA method has been proposed in the literature: the stochastic frontier approach (see e.g. Koop, Osiewalski and Steel, 1999, 2000), which sacrifices some flexibility in the functional form – usually a parametric translog production function is assumed there – for more robustness to outliers and the possibility to compute standard errors of all estimates. The last advantage vanishes, however, when the DEA method is augmented with a bootstrap procedure.

[20]Needless to say, all economies in our sample are actually open economies, engaging in international trade and specializing in the production of selected goods and services. Moreover, we have recently observed large increases in the level of economic integration among countries of the European Union, so that the specialization argument might now be applied to European cross-country data with substantial strength as well. There has not been much integration across countries in earlier periods of our study, such as the 1970s and 1980s, though. In contrast, high levels of integration have undoubtedly been present in the US already in the 1970s.

but these level changes affected our sample largely symmetrically, leaving the ratios and growth rate contributions relatively little affected. An analogous conclusion on robustness was also reached by Jerzmanowski (2007).

Finally, we have assessed the magnitude of bias in our estimates by applying the Simar and Wilson (1998, 2000) bootstrap. The results were discussed in section IV.

VIII. Conclusion

The current study has revisited the findings of the literature on the WTF. Thanks to the use of a database consisting of both cross-country and US state-level data, we were able to estimate the WTF with markedly higher accuracy than in the previous literature: the US had been typically found to span the frontier there, but assuming it to be a single data point conceals substantial technological heterogeneity within the US. By relaxing this assumption, we have not only improved the precision of the previous WTF estimates, but also identified the magnitude of upward bias in earlier estimates of countries' technical efficiency.

Our results indicate that the WTF is spanned by a number of US states; the US as a whole falls markedly behind the frontier spanned by its most efficient states. This means that previous estimates of the WTF have been downward biased. Furthermore, the source of bias identified here thanks to the use of (highly relevant) US state-level data alongside international data is decidedly different from the sampling one identified by bootstrap procedures (cf. Simar and Wilson, 1998, 2000). Both these biases might be addressed simultaneously, leading to different results than in the case where only one of them is taken into account.

Our further contribution to the non-parametric cross-country productivity literature is that following Caselli and Coleman (2006), we have split the hitherto homogeneous human capital input into human capital-adjusted stocks of unskilled and skilled labour which might not be perfectly substitutable. This allowed us to obtain further increases in the precision of WTF estimates.

Based on our dataset, which extends the ones used in earlier literature in the two aforementioned ways, we find that technological progress over the period 1970–2000 has been decidedly non-neutral, faster in the range of more capital-intensive technologies. Our results also imply that the WTF (the world's best practice technology) exhibits substantial departures from the Cobb–Douglas production function specification.

Our next step has been to plug our adjusted WTF estimate into a series of development and growth accounting exercises. First, we have used the DEA method to decompose countries' productivity into (i) technical efficiency, and (ii) frontier productivity (potential GDP per worker attainable if the factors were used at 100% efficiency). We have then used this distinction to decompose differences in GDP levels across countries and time. Furthermore, an auxiliary use of the Cobb–Douglas production function structure, present in the 'appropriate technology vs. efficiency' decompositions, enabled us to back out the factor-dependent residual TFP (CDTFP) and therefore to provide a calculation of the extent to which the observed productivity differences were due to differences in efficiency, and the extent to which they were due to differences in 'appropriateness of technology' (Basu and Weil, 1998). When used in growth accounting, this last decomposition enabled us to split the observed productivity improvements into factors attributable to (i) changes in technical efficiency, (ii) shifts of the WTF, and (iii) movements along the WTF. This last distinction is novel to the literature.

What remains on our research agenda is to extend the current investigation to other datasets, preferably including developing economies as well. This would help further increase the precision of WTF estimates and all growth and development accounting exercises based on them. Another idea which looks promising would be to draw some conclusions on the shape of the aggregate production functions, based on our non-parametric estimates. In particular, one could try to identify the empirical patterns behind factor-dependent TFP, partial elasticities and elasticities of substitution, once the assumption of their constancy (implied by the Cobb–Douglas specification) is relaxed. Yet another idea would be to look for an empirical test able to identify the extent to which the 'appropriate technology' term indeed captures endogeneous technology choice, and to which it just mirrors production function misspecification.

Final Manuscript Received: October 2011

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Appendix A: Efficient technologies in 2000

The WTF in 2000, estimated with 1970–2000 data, is spanned by the 38 efficient technologies summarized in Table A1. It might be surprising that old (but not new) technologies from such low-output locations as Portugal, Spain or Nebraska, are still efficient in 2000. This is due to the fact that Portugal and Spain in 1970–1980 relied heavily on

TABLE A1

Efficient technologies in 2000 *and their bias-corrected efficiency scores*

Efficient unit	*Bootstrap*	95% *CI*	
Florida 1970	0.8124	0.7915	0.9911
Georgia 1970	0.7263	0.7109	0.9908
Minnesota 1970	0.7335	0.7160	0.9923
North Carolina 1970	0.7344	0.7175	0.9896
Nebraska 1970	0.7287	0.7184	0.9890
South Dakota 1970	0.7423	0.7215	0.9925
Vermont 1970	0.7367	0.7135	0.9908
Washington 1970	0.8273	0.7806	0.9928
Japan 1970	**0.7321**	**0.7176**	**0.9920**
Netherlands 1970	**0.8641**	**0.8272**	**0.9895**
Portugal 1970	**0.7340**	**0.7186**	**0.9928**
Spain 1970	**0.8130**	**0.7807**	**0.9904**
Idaho 1975	0.7350	0.7175	0.9910
Nebraska 1975	0.7266	0.7167	0.9932
Portugal 1975	**0.7359**	**0.7195**	**0.9902**
Spain 1975	**0.8538**	**0.8186**	**0.9925**
Arizona 1980	0.9162	0.8709	0.9928
Minnesota 1980	0.7299	0.7166	0.9891
Texas 1980	0.9259	0.9036	0.9932
Vermont 1980	0.7295	0.7199	0.9924
Washington 1980	0.7253	0.7125	0.9898
Portugal 1980	**0.8172**	**0.7592**	**0.9919**
Arizona 1985	0.8875	0.8534	0.9920
Minnesota 1985	0.8721	0.8104	0.9911
Vermont 1985	0.7385	0.7210	0.9930
Washington 1990	0.7330	0.7197	0.9920
Arizona 1995	0.9246	0.9004	0.9906
Idaho 1995	0.9122	0.8450	0.9928
Minnesota 1995	0.7329	0.7180	0.9927
Washington 1995	0.7371	0.7170	0.9915
Arizona 2000	0.9439	0.9277	0.9921
Connecticut 2000	0.8537	0.8221	0.9928
Georgia 2000	0.9521	0.9322	0.9919
Minnesota 2000	0.7867	0.7590	0.9929
North Carolina 2000	0.8156	0.7990	0.9908
New Jersey 2000	0.8558	0.8309	0.9914
Washington 2000	0.7285	0.7178	0.9901
Ireland 2000	**0.9680**	**0.9559**	**0.9919**

Notes: CI, confidence intervals. None of the 95% CI contains the respective DEA point efficiency estimate because of its upward bias. OECD countries are indicated in **bold.**

unskilled labour for production, at the same time being relatively undercapitalized and undereducated. In fact, no country was able to use unskilled labour so efficiently later – they all produced *more* but this was mostly due to larger factor inputs. Similarly, Nebraska in 1970–75 was relatively undercapitalized (at least for US standards) but produced a reasonably high output nevertheless.[21] The old Nebraskan technology is thus still efficient, but useful only for sufficiently low capital–labour ratios.

On the other hand, the bootstrap exercise performed on these data suggests that some of the aforementioned findings might have been heavily affected by DEA estimation bias. Indeed, most of the bias-corrected efficiency scores visible in Table A1 are far below unity, and confidence intervals associated with their estimates are relatively wide. This applies particularly to the 1970–85 technologies identified as still efficient in 2000.

Appendix B: Changes in technical efficiency across time

It is also interesting to trace the evolution of technical efficiency (Shephard distance measures) E_{it} across the years 1970–2000. This can be seen in Table B1. An analogue of Table B1 with bootstrap bias-corrected efficiency scores is available from the author upon request.

We see that for each country, there is substantial temporal variability in this variable which could be explained by the arrivals of new frontier technologies (mostly in the US), affecting the relative ranking of each country's technology in an non-uniform way. Some trends are clearly visible, though: technical efficiency in Canada, France, Greece, Italy, Japan, the Netherlands, Spain and Sweden has fallen until 2000 by 10% or more from what it once used to be, indicating that losses in technical efficiency might have been the primary force behind weaker growth performance of these countries as compared to the

TABLE B1

Changes in technical efficiency (Shephard distance measures) E_{it} across time

	1970	1975	1980	1985	1990	1995	2000
Australia	0.8080	0.7696	0.7298	0.7289	0.6814	0.7014	0.7006
Austria	0.7377	0.7719	0.7917	0.8008	0.7910	0.7497	0.7581
Belgium	0.8774	0.8766	0.9002	0.8763	0.9120	0.8693	0.8529
Canada	0.7885	0.7977	0.7236	0.7146	0.6685	0.6652	0.7045
Denmark	0.7762	0.7220	0.7020	0.7273	0.6988	0.7271	0.7367
Finland	0.7541	0.7340	0.6978	0.7028	0.7103	0.5913	0.6647
France	0.8564	0.8087	0.8118	0.8257	0.8395	0.7619	0.7407
Germany	n/a	n/a	n/a	n/a	0.6256	0.6237	0.6202
Greece	0.7801	0.7509	0.7572	0.6756	0.6451	0.5786	0.5764
Ireland	0.8805	0.7733	0.7391	0.6753	0.7503	0.8190	1.0000
Italy	0.9307	0.9033	1.0000	0.9734	0.9801	0.9066	0.8439
Japan	1.0000	0.6467	0.6301	0.6551	0.7068	0.6512	0.6336
The Netherlands	1.0000	1.0000	0.9749	0.8541	0.7977	0.7498	0.7424
Norway	0.7574	0.8207	0.8656	0.9025	0.8474	0.8651	0.9222
Portugal	1.0000	1.0000	1.0000	0.8361	0.9973	0.9249	0.9360
Spain	1.0000	1.0000	0.9580	0.8763	0.9371	0.8238	0.8125
Sweden	0.8027	0.7981	0.7324	0.7239	0.7271	0.6518	0.6582
Switzerland	0.9187	0.8816	0.9532	0.8752	0.8101	0.7122	0.6578
UK	0.7679	0.7408	0.6857	0.7034	0.7573	0.7459	0.7710
USA	0.9045	0.9096	0.8876	0.9082	0.8654	0.8932	0.8946

[21] Temporarily high corn and soy prices in 1975 might have had an impact on this result as well, though.

US. In Ireland, on the other hand, technical efficiency was declining until its minimum in 1985 but quickly increased again since that year, and Ireland eventually came to span the WTF in 2000.

On the other hand, some European countries, as well as Japan, might have lost some technical efficiency as we measure it (i.e. relative to certain US states) in the last considered decade, 1990–2000, due to the surge in ICT investment observed in the 1990s, culminating in the ‘internet bubble’ which burst in the US in 2000/01, which was much less pronounced in European countries such as Germany, France, Italy (Timmer, Ypma and van Ark 2003) and Japan. That is to say, GDP per worker in the US might have actually been temporarily overshooting the fundamentals in 2000. Thus, the decline in technical efficiency between 1990 and 2000 in several countries might have been a transitory phenomenon. More recent data are required to verify this conjecture, though.

In Table B1 we report countries’ efficiency levels only but we refer to the WTF spanned by individual US states as well. One caveat when reading this table is that the precision of estimation of WTF is progressively increasing when we move from 1970 to 2000. For this reason, for example, the sudden drop of efficiency in Japan between 1970 and 1975 might not be a meaningful phenomenon but an artefact of Japanese efficiency being sharply overestimated in 1970 (due to data scarcity).

Appendix C: A comment on computing cross-country productivity distributions

Most macroeconomic contributions based on the non-parametric DEA method (e.g. Kumar and Russell, 2002; Henderson and Russell, 2005) have also emphasized the method’s implications for the evolution of the cross-country distribution of productivity. In line with earlier findings due to Quah (1996, 1997), they showed that in the post-war period, this distribution has evolved from a uni-modal to a visibly bi-modal distribution, thereby providing support for Quah’s ‘twin peaks’ (or ‘club convergence’) hypothesis. They also decomposed this evolution into components attributable to factor accumulation, technological progress at the frontier and changes in technical efficiency.

There is one crucial problem with these analyses, though: their basic unit of observation is a *country*. Although this approach might be justified on many grounds (political, sociological, cultural, etc.), one worry will always remain – namely that countries are very uneven in terms of their size, internal heterogeneity and the degree of economic specialization. Why should Luxembourg, the Netherlands, UK, USA and China be treated on par if their sizes are so vastly different? Analogously, why should for example the US be weighted as one [observation], while the European Union as 27 [observations] if these two entities are comparable in terms of their economic size? Finally, why should an (artificial) splitting of the US into its 50 constituent states shift the productivity distribution so strongly to the right, as it would in these analyses?

These considerations bring us to the conclusion that, while it is absolutely legitimate to do cross-country investigations on the determinants of productivity (e.g. institutions are likely to vary much more across countries than within countries and they are a likely cause for differences in technical efficiency), the concept of a cross-country productivity *distribution* is heavily data-driven. Split a country into a thousand entities and they will swamp the distribution. Another misguided application of this idea would be to try to estimate the productivity distribution within our sample consisting of 70 ‘countries’, among them 50 US states. Of course, we do not do that. Instead, our aim is to use state-level data to recover more precise information about best-practice technologies.