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Jakub Growiec

IBS WORKING PAPER #01/2008

Productivity Differences Across OECD Countries, 1970–2000: The World Technology Frontier Revisited

Jakub Growiec*

November 14, 2008

Abstract. We re-estimate the World Technology Frontier (WTF) non-parametrically, using the Data Envelopment Analysis method, with a dataset covering both OECD country-level and US state-level data on GDP per worker and the stocks of physical capital, unskilled labor, and skilled labor. The WTF 2000 is found to be spanned by a few US states such as Colorado, Connecticut, Delaware, Nevada, Utah, and Washington, while the USA as a whole falls markedly behind these leader states. The auxilliary use of US state-level data adds extra precision to cross-country growth and levels accounting exercises. We also calculate the "appropriate technology vs. efficiency" decomposition, disentangling dynamic shifts of the WTF from movements along the WTF. Our results indicate that previous estimates of the WTF might have been downward biased and previous estimates of technical efficiency might have been upward biased.

Keywords and Phrases: world technology frontier, decomposition, country-level data, US state-level data, development accounting, growth accounting

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

1 Introduction

Is it possible to use production factors more effeciently than in the United States? If your answer is based on aggregate cross-country data (cf. Kumar and Russell, 2002, Henderson and Russell, 2005, Jerzmanowski, 2007, and Badunenko, Henderson and

*Institute for Structural Research, Warsaw, Poland; and Warsaw School of Economics, Institute of Econometrics, Warsaw, Poland. Address: Instytut Badań Strukturalnych, ul. Rejtana 15 lok. 24/25, 02-516 Warszawa. E-mail: jakub.growiec@ibs.org.pl. I am grateful to Aleksandra Iwulska and Łukasz Marć (Institute for Structural Research) for excellent research assistance. I also thank Maciej Bukowski for his useful discussions and comments. All errors are my responsibility.

Zelenyuk, 2007), then it will be negative because the US level of per-worker productivity is high enough to span the world technology frontier.[1] It follows that further improvements in productivity could only be possible thanks to technological progress. Yet, the US is a huge country with substantial internal heterogeneity; considering it a single data point makes you lose a lot of precision in estimating the frontier. Indeed, the folks in Delaware know well how to exceed the average US level of productivity, and so do people in Connecticut, New York, California, and a bunch of other states.

The objective of this paper is therefore to revisit the economic debate on the World Technology Frontier (WTF hereafter) and the question of appropriate technology adoption with the use of US state-level data. By appending a US state-level dataset to an international one, we obtain a great increase in precision of our WTF estimates while remaining within the "cross-country" macro focus. Thanks to a finer approximation of the WTF, we are also able to (i) improve the reliability of standard non-parametric growth and development accounting exercises, (ii) resolve the ambiguity as to which extent productivity changes represent shifts in the WTF or countries' movement along the WTF.

Following the lines of Caselli and Coleman (2006), we also distinguish between skilled and unskilled labor. Allowing for imperfect substitutability between these two production factors leads to a further refinement of the results provided in the established literature.

In our analysis, we allow technologies from earlier years to span the WTF in the given year alongside the current ones (cf. Henderson and Russell, 2005). Indeed, it turns out that even some technologies used back in 1970 remain efficient in 2000 despite substantial technological progress across these years, e.g. because they strongly rely on unskilled labor which has been gradually disappearing in OECD countries in the considered period.

The current study concentrates on highly developed OECD countries located in Europe and North America (plus Australia and Japan), and sets aside all developing economies. This makes it lose some precision in the estimation of the WTF in the region of low capital and/or human capital endowments. On the other hand, this also makes the results less vulnerable to the poor data quality argument (see e.g. the discussion about Sierra Leone spanning the WTF in Kumar and Russell, 2002).

The principal novelty of this paper – to decompose the United States into its 50 constituent states – has a number of interesting features. First, US states are large enough to be directly comparable to OECD countries in terms of productivity (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 is expected to span the

[1]Caselli and Coleman (2006) find however that several countries, notably Italy and Canada, are more efficient in terms of productivity of unskilled labor than the US which makes the US fall behind the frontier slightly.

Table 1: GDP per worker across countries and US states, 2000. Units: US dollars, constant prices (2000).

Rank	State/Country	GDP/worker	Rank	State/Country	GDP/worker
1	**Luxembourg**	114448	37	Wisconsin	59048
2	Delaware	94154	38	**Austria**	58441
3	District of Columbia	89401	39	Missouri	58254
4	Connecticut	87498	40	Tennessee	57655
5	New York	85696	41	**Netherlands**	56691
6	New Jersey	83600	42	South Carolina	56615
7	Alaska	78902	43	Utah	56130
8	Massachusetts	77380	44	Kentucky	55321
9	California	75612	45	**France**	55286
10	Illinois	72162	46	Alabama	54666
11	Washington	72055	47	**Switzerland**	54306
12	Michigan	69065	48	Nebraska	54052
13	Georgia	68550	49	West Virginia	53933
14	Texas	68473	50	Kansas	53903
15	Virginia	68207	51	Iowa	53760
16	Maryland	67263	52	Maine	51721
17	Colorado	67170	53	Oklahoma	51353
18	**USA**	67079	54	South Dakota	51290
19	Nevada	67028	55	Arkansas	51212
20	Rhode Island	66369	56	Idaho	51196
21	Arizona	64829	57	**Germany**	51010
22	Pennsylvania	64418	58	**Italy**	50853
23	North Carolina	64072	59	Vermont	50687
24	New Hampshire	63927	60	**Australia**	50606
25	**Norway**	63909	61	**Denmark**	50448
26	Minnesota	63823	62	**Canada**	49816
27	Louisiana	63068	63	Mississippi	49638
28	Ohio	62742	64	**UK**	49225
29	Oregon	61410	65	**Sweden**	46544
30	Indiana	61021	66	North Dakota	45747
31	Wyoming	60911	67	**Finland**	45192
32	Florida	60828	68	**Japan**	44563
33	Hawaii	60723	69	**Spain**	44361
34	New Mexico	60107	70	Montana	44062
35	**Belgium**	59874	71	**Portugal**	34000
36	**Ireland**	59103	72	**Greece**	32070

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 WTF, one can naturally expect the WTF to be spanned by some above-average performing states. To see how US states fare when compared with OECD countries, please refer to Table 1 which compares GDP per worker in 50+1 US states and 21 OECD countries, measured in 2000. One can thus expect the WTF estimated with the use of country-level data only to be markedly downward biased. Third, US state-level data are of arguably high quality and are relatively easy to obtain.[2]

It must be noted that the decomposition procedure which we apply to the US could also be carried forward to other countries (e.g. Germany consists of 16 *Bundesländer* which are arguably heterogenous in terms of productivity; the UK is composed of England, Scotland, Wales, and Northern Ireland; the European Union authorities decompose the Member States into a total of 121 regions within the NUTS-1 classification, etc.) and to lower levels of aggregation (e.g. counties, townships; sectoral categories within the economy such as the NACE/ISIC sections, etc.). This procedure could even be extended "to the absurd", that is 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.

The text is structured as follows. In Section 2, we describe the methodology. In Section 3, we present the sources of our data. Section 4 discusses the WTF and its evolution from 1970 until 2000. Section 5 uses these results to decompose the differences in productivity across nations into differences in technical efficiency and in the accumulated factors of production. An auxilliary derivation of (factor-dependent) TFP within a Cobb-Douglas production function specification allows us to address the question of "appropriateness" of technology used by each country as well. Section 6 is devoted to decomposing country-level 1970–2000 changes in productivity into (i) changes in technical efficiency, (ii) technological progress shifting the WTF, and (iii) factor accumulation. Section 8 concludes.

2 Methodology

2.1 Data Envelopment Analysis (DEA)

The primary objective of this paper is to construct the best-practice production function nonparametrically, as a convex hull of production techniques (input–output configurations) currently 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 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, Henderson and Zelenyuk (2007). The

[2]Obtaining comparability of the two datasets is however a difficult issue. Please see the discussion in Section 3.

principal idea behind the use of DEA is to envelop all data points in the "smallest" convex cone and to infer the production function as a fragment of the boundary of this cone for which is output is maximized given inputs.

For each observation i, we will thus be able to provide the decomposition of output y_i:

$$y_i = E_i f(\mathbf{x}_i), \tag{1}$$

into a product of the maximum attainable output given inputs $y_i^* \equiv f(\mathbf{x}_i)$ and the efficiency index $E_i \in (0, 1]$. In other words, the efficiency index E_i measures (vertical) distance to the technology frontier, while the frontier itself is computed nonparametrically as $y_i^* = f(\mathbf{x}_i)$. It should be noted that the vector of inputs, $\mathbf{x}_i$, 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, 1994), and (ii) the efficiency levels could be overestimated due to too small a sample size.

Formally, the (output-based) DEA method is a linear programming technique allowing one find the efficiency index E_j for each unit $j = 1, 2, ..., I$ in the sample such that its reciprocal is maximized given a series of feasibility constraints:

$$\begin{aligned}
& \max_{\{\theta_j, \lambda_1, \ldots, \lambda_I\}} \theta_j \\
\text{s.t.} \quad & \theta_j y_j \leq \sum_{i=1}^{I} \lambda_i y_i, \\
& \sum_{i=1}^{I} \lambda_i x_{1i} \leq x_{1j}, \\
& \sum_{i=1}^{I} \lambda_i x_{2i} \leq x_{2j}, \\
& \vdots \\
& \sum_{i=1}^{I} \lambda_i x_{ni} \leq x_{nj}, \\
& \lambda_i \geq 0, \qquad i = 1, 2, ..., I.
\end{aligned} \tag{2}$$

The efficiency index E_j is computed as the reciprocal of θ_i (that is, $E_i = 1/\theta_i$).

Since the data contain a finite number of data points, one for each territorial unit and each year, by construction the DEA–based production function will be piecewise linear and its vertices will be the actually observed *efficient* input–output configurations (i.e. non-dominated by any linear combination of other observed input–output configurations).

2.2 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 to impose any particular functional form on 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. Indeed, 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 total factor productivity (TFP), as argued by Caselli (2005) and Jerzmanowski (2007). As for the predicted shape of the production function, one obvious fact is that due to the characteristics of the method, it will be piecewise linear for any finite data sample. With reasonably large data samples, however, certain parametric forms could be tested formally against the DEA-based nonparametric benchmark, such as the CES or the Cobb–Douglas (presumably leading to a rejection of the latter).

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

Second, the DEA 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; efficiency in nevertheless normalized to 100% for the most efficient units in the sample. A bootstrap method due to Simar and Wilson (2000) could help in this respect by allowing for corrections in the bias as well as for estimating confidence intervals for the actual efficiency levels and the technological frontier. We leave this for further research.

Third, the DEA constructs the production function basing 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 because they spoil the whole subsequent analysis. Systematic mismeasurement associated with some units could be left unnoticed, however, if these units fall short of the frontier. The data have been carefully checked, though, so that one can be confident that the risk of errors has been minimized.

2.3 Implications for TFP

The nonparametric 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.

This is due to the following reasoning. Generically, all functions $f(\mathbf{x}_i)$ could be written as

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

where $A(\mathbf{x}_i)$ captures "total factor productivity" (TFP). As long as f is not precisely Cobb-Douglas, the A factor is a non-trivial function of inputs.

Now, denoting y_i^* as the best attainable (frontier) output given inputs – such that $y_i = E_i y_i^*$ – we can decompose actual output into (i) the efficiency level E_i, (ii) the productivity differentials specific to the observed input configurations (the "appropriate technology" factor, cf. Basu and Weil, 1998), and (iii) the Cobb-Douglas bundle of factor endowments:

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

If by any chance, the actual production function is Cobb-Douglas then from the above equation we would immediately obtain that TFP be equal to a constant $A > 0$; if it is not, however, the "appropriate technology" factor $A(\mathbf{x}_i)$ will co-vary with factor endowments, pointing at the potential TFP gains accruing from a change in the factor mix.

A large strand of contemporary macroeconomic literature aims at quantifying and understanding TFP differences, with TFP computed as a residual value (Solow residual) from the Cobb-Douglas production function. As follows from the preceding discussion, this approach might however lead to a number of artifacts of the assumed functional form. But even articles relaxing the Cobb-Douglas assumption and dealing with different functional forms (cf. Basu and Weil, 1998; Acemoglu, 2003; Caselli and Coleman, 2006) might encounter function misspecification problems. Indeed, the "appropriate technology" factor $A(\mathbf{x}_i)$ could capture not only a meaningful economic phenomenon of optimal technology choice given available inputs (cf. Jones, 2005; Growiec, 2008), but also the error associated with a wrong specification of the production function. Given that in the DEA approach, we do not need any parametric assumptions on the production function, we can judge the extent of the appropriate-technology factor without convoluting it with misspecification error.

2.4 Implications for the direction of technical change

The DEA approach can also help draw important implications for the direction of technical change. This exercise requires the best-practice production function to be derived at (at least) two moments in time to allow intertemporal comparisons.

The procedure is the following. Having computed the "appropriate technology" index $A(\mathbf{x}_i)$ using the nonparametric production function as well as its Cobb-Douglas counterpart for both moments in time, one analyzes the difference between 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.

3 Data

The primary objective of the paper is to estimate the world technology frontier spanned by the world's most developed regions non-parametrically using the DEA method presented above. Our dataset covers 21 OECD countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States as well as 50 US states plus the District of Columbia:[3] AL, AK, AZ, AR, CA, CO, CT, DE, DC, FL, GA, HI, ID, IL, IN, IA, KS, KY, LA, ME, MD, MA, MI, MN, MS, MO, MT, NE, NV, NH, NJ, NM, NY, NC, ND, OH, OK, OR, PA, RI, SC, SD, TN, TX, UT, VT, VA, WA, WV, WI, WY.

We have however decided to drop Luxembourg and the DC from our analysis because of the strong indication that these entities' productivity might be significantly overestimated because of workers commuting from outside of the territory (such as Belgium and France for Luxembourg, or Virginia and Maryland for DC). 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 drop US states whose long-term average mining share in state GDP exceeds 10%. 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, Louisiana, New Mexico, West Virginia, and Wyoming.[4]

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

The production function has been estimated with the DEA method taking physical capital K, unskilled labor L^U and skilled labor L^S as inputs. We have then decomposed total output of each country i in each year t into the efficiency factor and its maximum attainable output given inputs:

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

Unskilled and skilled labor are measured in "no-schooling equivalents", indicating that each worker's labor input is weighted by her educational attainment. Following Caselli and Coleman (2006), we have allowed unskilled and skilled labor to be imperfectly substitutable. This requires us to split the overall level of human capital per worker into "human capital within unskilled labor" and "within skilled labor".[5]

[3]We do not consider U.S. overseas territories.

[4]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.

[5]Empirical evidence of imperfect substitutability between unskilled and skilled labor is provided

The data we are using are set in *per worker* terms. This means that we abstract from the issues of labor market participation which may result in additional *per capita* productivity differences, and of the variation in hours worked per worker which means that our analysis convolutes productivity differences with labor-leisure choice of the employees: ceteris paribus, an increase in hours worked per worker will be reflected by increases in "productivity" as we measure it even though technology as such is unchanged. It is however difficult to find reliable and comparable data on hours worked per capita both across OECD countries and US states which would date back at least until 1970.

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

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

Country-level human capital data have been taken from de la Fuente and Doménech (2006) – D-D hereafter. The raw variables are shares of population aged 25 or above having completed primary, some secondary, secondary, some tertiary, tertiary, or postgraduate education. The considered dataset is of 5-year frequency only and it ends in 1995. Among all possible education attainment databases, the D-D dataset has been given priority due to our trust in its superior quality. The original D-D series has been

by Pandey (2008).

extrapolated forward to the year 2000 using Cohen and Soto (2007) schooling data as a predictor for the trends. Neither Barro and Lee (2001) nor Cohen and Soto (2007) data could be used directly for this purpose because neither of them is (even roughly) in agreement with the D-D dataset – nor with each other – in the period where all datasets offer data points.

US state-level human capital data have been taken from the National Priorities Database. Here, the variables are shares of population aged 25 or above having completed less than high school, high school, some college, college, or having obtained the Associate, Bachelor, or Master degree (the last category covering above-Master education as well). These data are available for 1995-2006 only. We have extrapolated this series backwards using US country-wide trends documented in D-D and state-level differences in the period when the data were available. Cumulative years of schooling at each level of education have been taken from D-D and supplemented with data from country-specific web resources wherever necessary. The US state-level education attainment data have also been adjusted to guarantee comparability with D-D data. We have found a roughly steady surplus of 8 percentage points in the share of population with less than high school completed in the National Priorities Database as compared to D-D, compensated by a shortage of 5.3 pp. in high school graduates, and of 2.7 pp. in the "some college" category. We have thus added/subtracted these values from the US state-level figures to guarantee coherence at the aggregate US level, keeping in mind that this procedure could have introduced some additional error.

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

$$L^U = e^{\phi(s)} \text{ for } s < 12, \qquad L^S = e^{\phi(s)} \text{ for } s \geq 12, \tag{6}$$

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

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

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

Special attention should be paid to the cutoff point of 12 years of schooling delineating unskilled and skilled labor. It is 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 who has – 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 developed economies were to be considered as well (cf. Caselli and Coleman, 2006).

4 The World Technology Frontier revisited: 1970-2000

4.1 The World Technology Frontier in 2000

The production function constructed with the DEA method is piecewise linear in its whole domain. The vertices of the convex feasible production set are the efficient input–output pairs. For all observations, an efficiency level E_{it} is computed. Imposing the Cobb-Douglas structure on this non-Cobb-Douglas production function makes us back out the factor-dependent "appropriate technology" factor:

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

The TFP A_t has been depicted as a function of the K/H ratio for the year 2000 in Figure 1. The frontier has been estimated with both country-level and US state-level data, but using observations from 2000 only. Figure 2 shows the same technology frontier computed with the use of the whole 1970–2000 dataset. A remarkable difference is that the second WTF, computed with markedly higher precision, is smoother. The reason is that it has more data points spanning the frontier because a number of pre-2000 technologies proved to be efficient in 2000 as well. Please note that the WTF itself is a function of three variables but here only its projection on the $K/H = K/(L^U + L^S)$ axis is presented (following Jerzmanowski, 2007).

The WTF in 2000, estimated with 1970–2000 data, is spanned by the following efficient technologies (Table 2).

One result might be particularly surprising here: the efficiency of old (but not new) technologies from Portugal, Spain, and Nebraska. This is due to the fact that Portugal and Spain in 1970–1980 relied heavily on unskilled labor for production, at the same time being relatively undercapitalized and undereducated. In fact, no country was able to use unskilled labor so efficiently later – they all produced *more* but this was due to larger factor inputs. Similarly, Nebraska in 1970–1975 was relatively undercapitalized (at least for US standards) but produced a reasonably high output nevertheless. The old Nebraskan technology is thus efficient, but only for sufficiently low capital–skilled labor ratios.

4.2 Non-neutral technical change

It is worthwhile to show how the WTF evolved during the 30 years between 1970 and 2000. This can be seen in Figure 3. Although technological progress has shifted the WTF in its (almost)[6] whole domain, two effects must be noted: (i) technical change

[6] Remember that Figure 3 does not capture the whole three-dimensional domain of $A_t(K_{it}, L_{it}^U, L_{it}^S)$. The technologies used in 1970 in Colorado, Florida, Nebraska, Japan, Netherlands, Portugal, and Spain remained efficient until 2000 but these countries or states ceased to use them because they accumulated more production factors across the years.

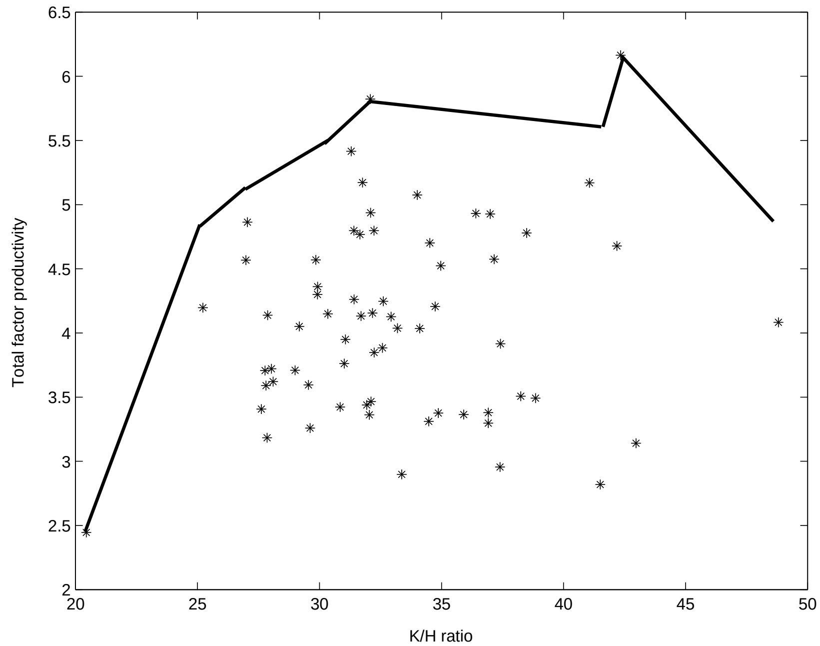

Figure 1: The 2000 World Technology Frontier estimated with 2000 data only. Asterisks denote actual observations, the solid line captures efficient technologies.

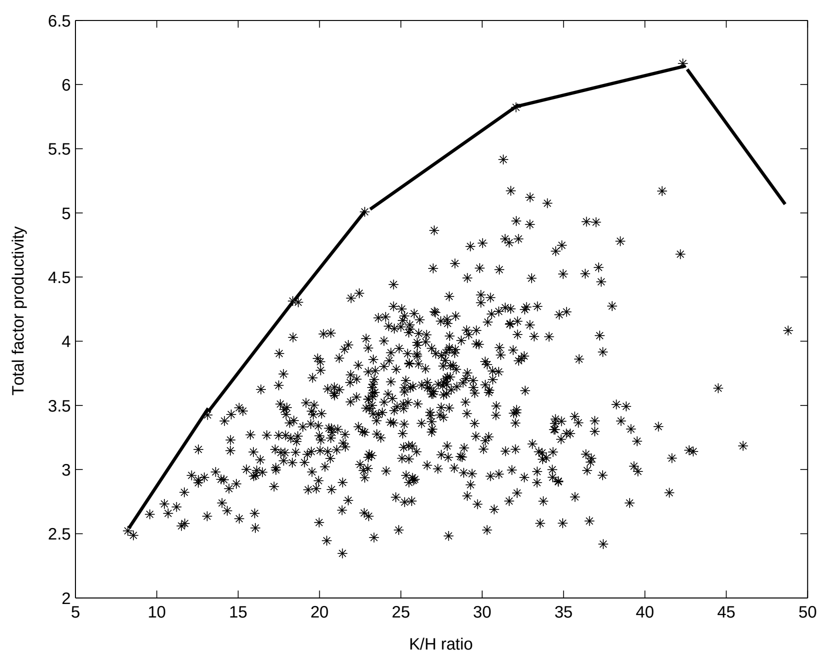

Figure 2: The 2000 World Technology Frontier estimated with 1970–2000 data. Asterisks denote actual observations, the solid line captures efficient technologies.

Table 2: Efficient technologies in 2000.

State / Country	Year	State / Country	Year
Colorado	1970	Texas	1980
Florida	1970	Portugal	1980
Nebraska	1970	Colorado	1985
Japan	1970	Colorado	1990
Netherlands	1970	Nevada	1995
Portugal	1970	Utah	1995
Spain	1970	Colorado	2000
Colorado	1975	Connecticut	2000
Nebraska	1975	Delaware	2000
Portugal	1975	Nevada	2000
Spain	1975	Utah	2000
Colorado	1980	Washington	2000
Nevada	1980		

has been strongest in the area where the K/H ratio is around 25-35, which is "middle range" as for 2000; (ii) continued physical capital accumulation extended the WTF into the range of larger K/H ratios, extending 40. For lower physical/human capital ratios, technical change was less pronounced and for $K/H \approx 7$ (which was the case for Portugal and Spain in 1970), there has been hardly any technical change at all (at least in our data; it is however likely that some technical change for such a low K/H ratio might have occured in developing countries).

It is also interesting to trace the evolution of technical efficiency E_{it} across the years 1970–2000. This can be seen in Table 3. For each country, there is substantial temporal variability in this variable which could be explained by the arrivals of new frontier technologies in the US which affected the relative ranking of each country's technology in an non-uniform way. Some trends are clearly visible, though: technical efficiency in Australia, Canada, Netherlands, Sweden, and Switzerland (since 1980) has been steadily declining throughout the period, indicating that losses in technical efficiency might have been the primary force behind weaker growth performance of these countries as compared to the US. In Ireland, on the other hand, technical efficiency was declining until its minimum in 1985 but quickly increased again since that year.

Another observation is that many European countries, as well as Japan, have lost on technical efficiency (that is, relative to certain U.S. states) in the last considered decade, 1990–2000. One possible explanation for this result is the surge in ICT investment observed in the US in the 1990's, culminating in the "internet bubble" which burst in 2000/01, and which was much less pronounced in European countries such as Germany, France or 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

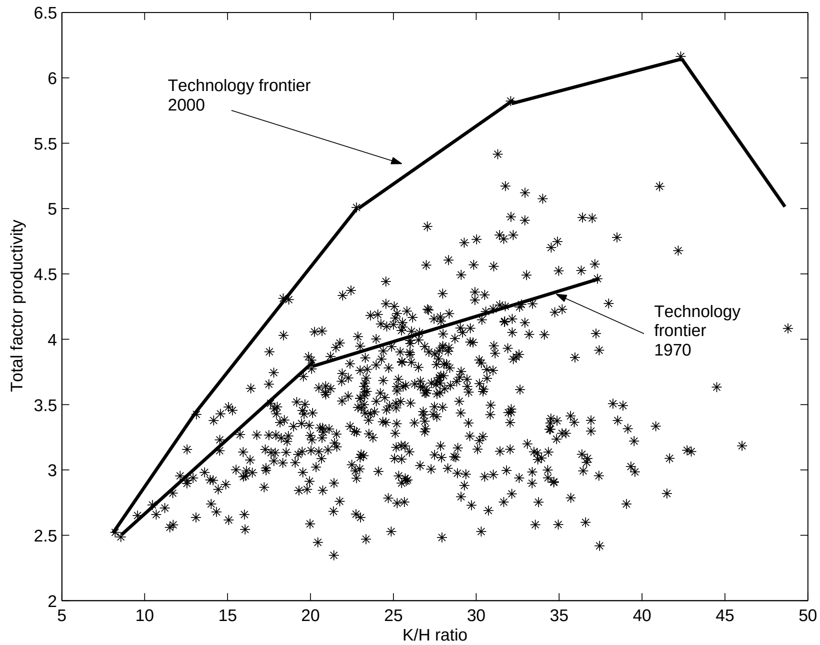

Figure 3: The direction of technical change, 1970–2000. Asterisks denote 2000-efficient technologies given factor endowments.

fundamentals in 2000. Thus, the downfall in technical efficiency in 2000 in several countries might have been a transitory phenomenon. More recent data are required to verify this conjecture, though.

In 3 we report countries' efficiency levels only but it refers to the WTF spanned by individual US states as well.[7] 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, e.g. the sudden drop of efficiency in Japan between 1970 and 1975 might not be a meaningful phenomenon but an artifact of Japanese efficiency being sharply overestimated in 1970 (due to data scarcity in earlier years).

4.3 Have previous WTF estimates been downward biased?

As announced in the introduction, one of the advantages of using US state-level data for estimating the World Technology Frontier is that more precision is gained thanks to this step. Not only is estimation *error* reduced in this process, but also is the magnitude of the *bias* revealed: it turns out that within the U.S., there has been a lot more technological know-how than aggregate data show.

As is visible in Figure 4, the WTF estimate is much lower if only country-level data are used in the estimation procedure. Thanks to US state-level data, the estimate is

[7]The detailed data on state-level efficiency factors and optimal technology choice are available from the author upon request.

Table 3: Changes in technical efficiency E_{it} across time.

Country	1970	1975	1980	1985	1990	1995	2000
Australia	0.8137	0.7690	0.7445	0.7491	0.6874	0.6773	0.6247
Austria	0.7638	0.7646	0.7940	0.7982	0.7949	0.7431	0.6549
Belgium	0.8693	0.8652	0.9020	0.8738	0.9140	0.8629	0.7484
Canada	0.8367	0.8360	0.7588	0.7260	0.6667	0.6212	0.6446
Denmark	0.7729	0.6880	0.7071	0.7351	0.7029	0.7226	0.6381
Finland	0.7475	0.7092	0.6851	0.7023	0.7153	0.5871	0.5795
France	0.8518	0.7977	0.8245	0.8281	0.8424	0.7607	0.6346
Germany	n/a	n/a	n/a	n/a	0.6256	0.6229	0.5487
Greece	0.8020	0.7520	0.7819	0.7045	0.6553	0.5870	0.5664
Ireland	0.9187	0.8107	0.7741	0.7143	0.7706	0.8233	0.9481
Italy	0.9291	0.8962	1.0000	0.9656	0.9827	0.9025	0.7564
Japan	1.0000	0.7124	0.6710	0.6746	0.7123	0.6458	0.4946
Netherlands	1.0000	0.9860	0.9767	0.8471	0.7993	0.7438	0.6326
Norway	0.7466	0.7985	0.8674	0.8957	0.8544	0.8658	0.8074
Portugal	1.0000	1.0000	1.0000	0.8391	0.9989	0.9276	0.8863
Spain	1.0000	1.0000	0.9562	0.8938	0.9455	0.8073	0.7242
Sweden	0.7889	0.7642	0.7343	0.7269	0.7269	0.6541	0.5759
Switzerland	0.8935	0.8736	0.9639	0.8573	0.8108	0.7056	0.5768
UK	0.8128	0.7905	0.7372	0.7617	0.7876	0.7486	0.7195
USA	0.9339	0.9135	0.9131	0.9078	0.8460	0.8359	0.8103

improved and the downward bias is reduced: for many countries it turns out that their efficiency is lower and their potential output is higher.

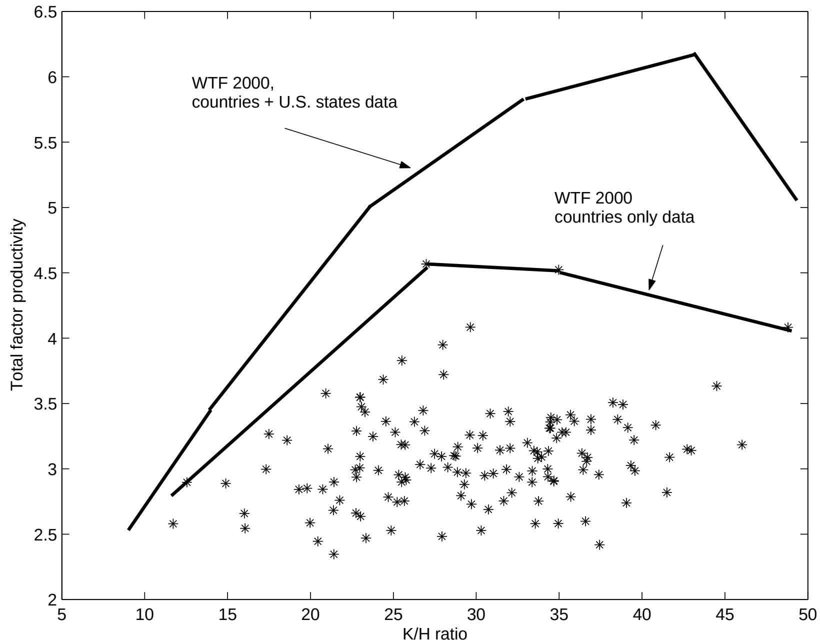

Figure 4: World Technology Frontier in 2000, estimated using countries only data as well as our dataset of both countries and US states.

The main corollary from this analysis is that the downward bias in WTF estimates using country-level data only can be quite substantial, going up to 25% of estimated potential TFP. For 19 OECD countries, efficiencies estimated with and without the auxilliary use of US state-level data are shown in Table 4. The maximum observed difference is 35 percentage points in the case of Canada.

4.4 Optimal technology choice

If knowing a country's efficiency level is the first step, the natural second step would be to learn about its optimal technology choice given its inputs, able to raise its efficiency to one. The DEA method provides the answer to this question immediately: the optimal technology is a convex combination of technologies used by the efficient units in the sample, and the share of each i-th technology is its λ_i multiplier in Eq. (3). We have summarized these findings in Table 5.

One striking feature of Table 5 is that it indicates that most countries could gain efficiency by adopting the Delaware 2000 technology (either fully, as is the case for Germany and Switzerland, or partly). When a given country has a relatively lower capital stock, it could also benefit from the use of the Netherlands 1970, Spain 1970–1975, or Nevada 2000 technology.

Table 4: Efficiency levels in 2000 estimated with and without the use of US state-level data.

Country	With US states	No US states
Australia	0.6247	0.7823
Austria	0.6549	0.8917
Belgium	0.7484	0.9415
Canada	0.6446	1.0000
Denmark	0.6381	0.8220
Finland	0.5795	0.7253
France	0.6346	0.8522
Germany	0.5487	0.7605
Greece	0.5664	0.6416
Ireland	0.9481	1.0000
Italy	0.7564	0.9082
Japan	0.4946	0.6785
Netherlands	0.6326	0.8649
Norway	0.8074	1.0000
Portugal	0.8863	0.9789
Spain	0.7242	0.8235
Sweden	0.5759	0.7644
Switzerland	0.5768	0.8139
UK	0.7195	0.8610
USA	0.8103	1.0000

5 Decomposing the distance between OECD countries and the U.S., 2000

5.1 Development accounting

The non-parametric production frontier approach is very useful for the purposes of development accounting. The ratio of GDP per worker between two countries (here, between each particular OECD country and the U.S.) can be easily 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. 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's 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 case, the best idea would be to decompose the ratio of GDP per worker between country C and USA

Table 5: OECD Countries' optimal technology choice, 2000.

Country	Primary tech.	Share	Secondary tech.	Share
Australia	Delaware 2000	0.5234	Nevada 2000	0.4416
Austria	Delaware 2000	0.9069	Netherlands 1970	0.0931
Belgium	Delaware 2000	0.7326	Netherlands 1970	0.2674
Canada	Nevada 2000	0.5106	Delaware 2000	0.3773
Denmark	Delaware 2000	0.7363	Netherlands 1970	0.1533
Finland	Delaware 2000	0.6955	Netherlands 1970	0.2990
France	Delaware 2000	0.8683	Netherlands 1970	0.1248
Germany	Delaware 2000	1.0000		
Greece	Nevada 2000	0.7219	Portugal 1970	0.2021
Ireland	Nevada 2000	0.4453	Spain 1970	0.2848
Italy	Netherlands 1970	0.5088	Delaware 2000	0.4912
Japan	Delaware 2000	0.9233	Netherlands 1970	0.0767
Netherlands	Delaware 2000	0.9218	Spain 1975	0.0394
Norway	Delaware 2000	0.7173	Netherlands 1970	0.2787
Portugal	Spain 1975	0.5664	Portugal 1980	0.2739
Spain	Delaware 2000	0.4644	Spain 1975	0.4432
Sweden	Delaware 2000	0.6905	Nevada 2000	0.1926
Switzerland	Delaware 2000	1.0000		
UK	Nevada 2000	0.8109	Delaware 2000	0.1351
USA	Delaware 2000	0.5790	Colorado 2000	0.3154

(denoted as U) according to the "Fisher–ideal" decomposition (cf. Henderson and Russell, 2005):

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

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:

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

where

$$\begin{aligned} K \text{ diff} &= \sqrt[6]{\left(\frac{y^*(K_C, L^U_C, L^S_C)}{y^*(K_U, L^U_C, L^S_C)}\right)^2 \frac{y^*(K_C, L^U_C, L^S_U)}{y^*(K_U, L^U_C, L^S_U)} \frac{y^*(K_C, L^U_U, L^S_C)}{y^*(K_U, L^U_U, L^S_C)} \left(\frac{y^*(K_C, L^U_U, L^S_U)}{y^*(K_U, L^U_U, L^S_U)}\right)^2}, \\ L^U \text{ diff} &= \sqrt[6]{\left(\frac{y^*(K_C, L^U_C, L^S_C)}{y^*(K_C, L^U_U, L^S_C)}\right)^2 \frac{y^*(K_C, L^U_C, L^S_U)}{y^*(K_C, L^U_U, L^S_U)} \frac{y^*(K_U, L^U_C, L^S_C)}{y^*(K_U, L^U_U, L^S_C)} \left(\frac{y^*(K_U, L^U_C, L^S_U)}{y^*(K_U, L^U_U, L^S_U)}\right)^2}, \\ L^S \text{ diff} &= \sqrt[6]{\left(\frac{y^*(K_C, L^U_C, L^S_C)}{y^*(K_C, L^U_C, L^S_U)}\right)^2 \frac{y^*(K_C, L^U_U, L^S_C)}{y^*(K_C, L^U_U, L^S_U)} \frac{y^*(K_U, L^U_C, L^S_C)}{y^*(K_U, L^U_C, L^S_U)} \left(\frac{y^*(K_U, L^U_U, L^S_C)}{y^*(K_U, L^U_U, L^S_U)}\right)^2}. \end{aligned}$$

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 results of a numerical computation of decomposition (10) are presented in Table 6. "H diff" is the total impact of human capital differences, being the product of L^U diff and L^S diff.

5.2 Efficiency vs "appropriate technology"

Another advantage of the non-parametric frontier estimation method 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

Table 6: Decomposition of the distance between a given OECD country and the US in 2000.

Country	GDP ratio	Efficiency	K diff	L^U diff	L^S diff	H diff
Australia	0.7544	0.7709	0.9763	1.0179	0.9847	1.0023
Austria	0.8712	0.8082	1.0606	1.0704	0.9495	1.0163
Belgium	0.8926	0.9235	1.0406	1.1296	0.8222	0.9288
Canada	0.7426	0.7955	0.9392	0.9940	1.0000	0.9940
Denmark	0.7521	0.7874	1.0142	1.1193	0.8414	0.9418
Finland	0.6737	0.7152	1.0230	1.1354	0.8110	0.9208
France	0.8242	0.7831	1.0490	1.0775	0.9310	1.0032
Germany	0.7605	0.6771	1.0779	1.0418	1.0001	1.0419
Greece	0.4781	0.6989	0.7581	1.1177	0.8073	0.9023
Ireland	0.8811	1.1700	0.8564	1.1249	0.7817	0.8793
Italy	0.7581	0.9334	1.0090	1.2324	0.6531	0.8049
Japan	0.6643	0.6104	1.0626	1.0676	0.9594	1.0243
Netherlands	0.8451	0.7807	1.0549	1.0640	0.9645	1.0262
Norway	0.9527	0.9964	1.0403	1.1352	0.8097	0.9191
Portugal	0.5069	1.0938	0.8603	1.9676	0.2738	0.5387
Spain	0.6613	0.8937	0.9265	1.2656	0.6311	0.7987
Sweden	0.6939	0.7106	0.9928	1.0619	0.9261	0.9835
Switzerland	0.8096	0.7118	1.0820	1.0537	0.9976	1.0512
UK	0.7338	0.8879	0.8631	1.0341	0.9261	0.9576

maximum attainable production given factor endowments. Backing out the "appropriate technology" part requires an auxilliary assumption of a Cobb–Douglas production function, though. If the Cobb–Douglas assumption is fundamentally wrong then the results of this exercise will be consequently wrong as well.

Referring to the Eq. (4), and adding the assumption of perfect substitutability between skilled and unskilled labor to attain comparability to the established literature, the efficiency vs. appropriate technology decomposition can be written down as:

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

where $\alpha = 1/3$.

The results of such an exercise are presented in Table 7, from which we learn that under the Cobb-Douglas assumption, the role of factor endowments is much smaller than it was in the 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" ratio,

Table 7: Decomposition based on the Cobb-Douglas assumption: efficiency vs. "appropriate technology".

Country	GDP ratio	Effic.	Techn.	K diff	H diff
Australia	0.7544	0.7709	0.9640	0.9857	1.0299
Austria	0.8712	0.8082	0.9243	1.0654	1.0947
Belgium	0.8926	0.9235	0.8051	1.0691	1.1229
Canada	0.7426	0.7955	0.9509	0.9665	1.0157
Denmark	0.7521	0.7874	0.9803	1.0148	0.9601
Finland	0.6737	0.7152	0.9136	1.0255	1.0055
France	0.8242	0.7831	0.9899	1.0411	1.0212
Germany	0.7605	0.6771	0.9461	1.0478	1.1328
Greece	0.4781	0.6989	0.7734	0.8520	1.0381
Ireland	0.8811	1.1700	0.8627	0.9022	0.9675
Italy	0.7581	0.9334	0.7841	1.0086	1.0270
Japan	0.6643	0.6104	1.0210	1.0612	1.0046
Netherlands	0.8451	0.7807	0.9560	1.0417	1.0871
Norway	0.9527	0.9964	0.9057	1.0965	0.9628
Portugal	0.5069	1.0938	0.6950	0.8562	0.7788
Spain	0.6613	0.8937	0.8061	0.9366	0.9801
Sweden	0.6939	0.7106	1.0256	0.9957	0.9562
Switzerland	0.8096	0.7118	0.9752	1.1019	1.0584
UK	0.7338	0.8879	0.9262	0.9166	0.9736

or factor-dependent TFP. 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 actually produce more than the US given their factor endowments (their potential TFP exceeds the US one) but they don't because of markedly lower technical efficiency.

6 Decomposing GDP growth, 1970–2000

6.1 Growth accounting

Analogously to the development accounting exercise described above, we have also conducted a growth accounting exercise where we decomposed the total 1970–2000 increase in GDP per worker into the impacts of (i) change in efficiency relative to the WTF, (ii) technological progress at the WTF, (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^U, L^S, the "Fisher-ideal" (cf. Henderson and Russell, 2005) decomposition of the 2000/1970 productivity ratio is the following (denoting $s = 1970, n = 2000$):

$$\frac{y_n(K_n, L_n^U, L_n^S)}{y_s(K_s, L_s^U, L_s^S)} = \frac{E_n}{E_s} \cdot \frac{y_n^*(K_n, L_n^U, L_n^S)}{y_s^*(K_s, L_s^U, L_s^S)} = \tag{12}$$

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

The decomposition of GDP growth defined by Eq. (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 as in Eq. (10) so that the contribution of each particular factor's accumulation to productivity growth is properly accounted for.

Table 8 presents the growth accounting exercise for OECD countries. Once again, the WTF has been estimated with the use of US state-level data as well, but the decompositions of state-level productivity growth are not presented here. The numbers included in Table 8 (and in all further growth accounting exercises) are 2000/1970 ratios of respective variables, in line with the definitions described in Eq. (12). They can easily be transformed into 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 downfall in technical efficiency. An important group of countries encompasses the Netherlands, Sweden, Finland, and Norway which have 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 Greece which were relatively too undercapitalized and undereducated to take full advantage of the newest developments.

Table 8: Decomposition of the productivity increase in the 1970–2000 period.

Country	GDP	Effic.	Techn.	K diff	L^U diff	L^S diff	H diff
Australia	1.4896	0.7678	1.3935	1.1710	0.9227	1.2885	1.1890
Austria	1.9269	0.8575	1.4597	1.3070	0.9942	1.1846	1.1778
Belgium	1.7902	0.8609	1.3714	1.1884	0.9932	1.2846	1.2759
Canada	1.4426	0.7704	1.4163	1.2588	0.6149	1.7080	1.0503
Denmark	1.4687	0.8256	1.3857	1.1518	0.9861	1.1303	1.1146
Finland	1.8019	0.7753	1.3305	1.1165	0.7220	2.1671	1.5645
France	1.7534	0.7450	1.4171	1.2488	0.7259	1.8320	1.3299
Greece	1.4765	0.7062	1.1909	1.3817	0.9536	1.3325	1.2707
Ireland	2.9088	1.0320	1.2112	2.5160	0.6818	1.3565	0.9249
Italy	1.6992	0.8140	1.2356	1.0840	0.9520	1.6369	1.5584
Japan	1.9971	0.4946	1.4218	2.5008	0.6507	1.7452	1.1356
Netherlands	1.3746	0.6326	1.3326	1.0418	0.4924	3.1786	1.5652
Norway	1.9835	1.0814	1.3542	1.0633	0.6857	1.8577	1.2737
Portugal	1.9022	0.8863	1.1733	1.6664	0.6588	1.6664	1.0977
Spain	1.7849	0.7242	1.2073	1.3288	0.9340	1.6448	1.5363
Sweden	1.3726	0.7300	1.3881	1.0688	0.5015	2.5274	1.2674
Switzerland	1.2044	0.6455	1.6201	1.0530	0.9680	1.1297	1.0936
UK	1.7615	0.8852	1.3124	1.3184	0.8858	1.2983	1.1501
USA	1.6486	0.8677	1.5633	1.2758	0.6247	1.5249	0.9526

6.2 Shifts of the WTF vs. movements along the WTF

Making the auxilliary Cobb-Douglas production function assumption, the 2000/1970 productivity ratio can be decomposed into contributions attributable to (i) efficiency changes (i.e. changes in distance to the WTF), (ii) technological progress shifting the WTF, (iii) changes in factor-specific TFP given a certain WTF (i.e. movements along the frontier), and (iv) factor accumulation. Please note that in principle, the frontier TFP is time-dependent and may increase thanks to new technological developments

– which complicates the current analysis. Formally, the "Fisher-ideal" decomposition, taking full account of technological change, is obtained from the following formula:

$$\frac{y_n(\mathbf{x}_n)}{y_s(\mathbf{x}_s)} = \underbrace{\frac{E_n}{E_s}}_{\text{efficiency}} \cdot \frac{A_n(\mathbf{x}_n)}{A_s(\mathbf{x}_s)} \cdot \underbrace{\frac{K_n^\alpha}{K_s^\alpha}}_{K \text{ diff}} \cdot \underbrace{\frac{(L_n^U + L_n^S)^{1-\alpha}}{(L_s^U + L_s^S)^{1-\alpha}}}_{H \text{ diff}}, \tag{13}$$

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

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

The decomposition summarized in Eq. (13) is, to our knowledge, novel to the literature. The novelty here is that we are able to disentangle *three* characteristics of technological change: 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 have been presented in Table 9. It is clear from this table that shifts of the WTF due to technological progress have been the primary contribution to GDP growth in all considered OECD countries but Portugal (and possibly Greece). For a few interesting cases, movements along the frontier have constituted an important contribution as well: most notably, Ireland and Portugal, and to a slightly 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, covering Japan, Ireland, Portugal, and Spain.

One feature of these results is that the contributions of WTF shifts and movements along the WTF are strongly negatively correlated.[8] Indeed, the raw correlation coefficient between these two contributions (transformed into annualized growth rates) is -0.87. One possible interpretation of this fact could be that there is really just a single factor "technological change" that matters, and decomposing it further is a void exercise.

On the other hand, since all the factor definitions put forward in Eq. (13) are naturally interpretable – these factors indeed measure (i) shifts in the frontier TFP holding factor endowments constant and (ii) changes in factor-dependent TFP holding the WTF constant – one can argue that we have actually uncovered a more general regularity here.

The above mentioned strong negative correlation between the "WTF shift" and the "movement along WTF" factors suggests an approximate "either–or" property: TFP in a country can grow either due to the worldwide technical change increasing

[8] I am grateful to Maciej Bukowski for pointing out this regularity.

Table 9: Decomposition of the productivity increase in the 1970–2000 period. Efficiency, shifts of the World Technology Frontier, and movements along the WTF.

Country	GDP ratio	Effic.	WTF shift	Along WTF	K diff	H diff
Australia	1.4896	0.8276	1.4314	0.9495	1.1699	1.1319
Austria	1.9269	0.8974	1.5078	0.9654	1.3048	1.1305
Belgium	1.7902	0.8680	1.5503	0.9057	1.2705	1.1561
Canada	1.4426	0.7905	1.3638	1.0067	1.1968	1.1105
Denmark	1.4687	0.7984	1.5043	1.0030	1.1731	1.0393
Finland	1.8019	0.8437	1.4444	0.9592	1.2105	1.2734
France	1.7534	0.7970	1.4880	0.9882	1.2843	1.1650
Greece	1.4765	0.7006	1.1977	1.1453	1.2176	1.2619
Ireland	2.9088	0.9631	1.1757	1.5634	1.4202	1.1569
Italy	1.6992	0.8688	1.4732	0.8980	1.1813	1.2515
Japan	1.9971	0.5300	1.4179	1.2990	1.5943	1.2834
Netherlands	1.3746	0.7561	1.6562	0.8597	1.0885	1.1730
Norway	1.9835	1.1016	1.5698	0.9508	1.2051	1.0011
Portugal	1.9022	0.7286	1.0941	1.4893	1.4401	1.1126
Spain	1.7849	0.6260	1.2776	1.2479	1.3645	1.3107
Sweden	1.3726	0.8067	1.4851	0.9286	1.1147	1.1068
Switzerland	1.2044	0.6455	1.6922	0.8559	1.1427	1.1273
UK	1.7615	0.9247	1.2729	1.1120	1.1995	1.1220
USA	1.6486	0.8570	1.4268	1.0345	1.2244	1.0645

TFP at the frontier, or due to movements along the frontier, but not due to both simultaneously. This property relates to the three following facts:

- The maximum attainable (frontier) TFP level 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 the frontier TFP is also low, to high values where the frontier TFP is high. In our current sample, the correlation between the capital accumulation factor and the "movement along WTF" factor is +0.80.

- 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. This implies large technological benefits due to the movements along the WTF in these countries, but not in countries which were highly capitalized initially. In result, the correlation coefficient between the capital accumulation factor and the aggregate "technical change factor" (WTF shift $\times$ movement along WTF) is as high as +0.83.

- Not only is the TFP 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. On the other hand, due to the real convergence mechanism described above, these countries would accumulate capital slower than the catching-up countries, and thus gain less from capital deepening. The correlation coefficient between the capital accumulation factor and the "WTF shift" factor is -0.53, somewhat confirming this intuition.

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

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

6.3 Substitutability between unskilled and skilled labor

How much precision have we gained by allowing skilled and unskilled labor to be imperfectly substitutable? If the technology frontier, estimated with aggregate human capital data, was approximately overlapping with the frontier estimated with skilled and unskilled labor separately, then there would be no gain. On the other hand, the further away from each other are these two estimates, the stronger is the indication of limited substitutability between both types of labor.

In Table 10, we have compared the estimates of technical efficiency (distance to the WTF) obtained with the use of disaggregated unskilled and skilled labor variables to their counterparts computed under the assumption of a homogenous human capital stock ($H = L^U + L^S$).

One lesson here is that the benchmark (L^U, L^S) efficiency estimates are higher or equal than the simpler H–only estimates, and that the benchmark potential TFP estimates are lower or equal than their H–only counterparts, indicating that aggregating human capital to a homogenous stock might lead to an overestimation of potential productivity in all non-frontier countries and states. The extreme cases are the Italy and Portugal, where the efficiency factor increases by 16 percentage points, and potential TFP decreases by 0.9–1.2 when human capital is disaggregated. This is because a relatively large fraction of the Italian and Portuguese workforce is undereducated (less than high school) but their aggregate human capital measures are nevertheless arguably high there (e.g. there are also reasonably large shares of university gradu-

Table 10: Estimated efficiencies and potential TFP (under the Cobb-Douglas assumption). Homogenous vs. heterogenous human capital.

Country	Effic. L^U, L^S	Effic. H	TFP, L^U, L^S	TFP, H
Australia	0.6247	0.6218	5.3817	5.4067
Austria	0.6549	0.6207	5.1601	5.4448
Belgium	0.7484	0.6359	4.4950	5.2898
Canada	0.6446	0.6379	5.3090	5.3647
Denmark	0.6381	0.5831	5.4731	5.9889
Finland	0.5795	0.5099	5.1006	5.7972
France	0.6346	0.6032	5.5264	5.8141
Germany	0.5487	0.5487	5.2823	5.2823
Greece	0.5664	0.5258	4.3179	4.6513
Ireland	0.9481	0.8697	4.8166	5.2512
Italy	0.7564	0.5948	4.3776	5.5665
Japan	0.4946	0.4733	5.7001	5.9569
Netherlands	0.6326	0.6179	5.3371	5.4645
Norway	0.8074	0.7053	5.0566	5.7883
Portugal	0.8863	0.7286	3.8804	4.7202
Spain	0.7242	0.6060	4.5004	5.3788
Sweden	0.5759	0.5607	5.7260	5.8804
Switzerland	0.5768	0.5768	5.4446	5.4446
UK	0.7195	0.7022	5.1712	5.2986
USA	0.8103	0.7993	5.5829	5.6603

ates) implying a heavily unbalanced workforce. An estimate of Italian or Portuguese potential productivity which does not take such large dispersion in their human capital distribution into account is therefore likely to be upward biased.

7 Conclusion

The paper has revisited the literature on the World Technology Frontier (WTF), i.e. the function which assigns the maximum attainable level of GDP per worker to each given mix of factor endowments. Thanks to the use of a database consisting both of cross-country and of U.S. state-level data, we were able to draw the WTF with markedly higher accuracy comparing to previous contributions: the U.S. is consistently a frontier country and considering it to be a single data point conceals substantial technological heterogeneity which could be used to improve the precision of the WTF estimates.

Our analysis was based on the Data Envelopment Analysis (DEA) allowing to estimate the WTF non-parametrically. The method allows one to decompose countries' productivity into (i) technical efficiency, and (ii) the frontier productivity (potential GDP per worker attainable if the factors were used at 100% efficiency). We have used the DEA method also for the purposes of growth accounting and development accounting exercises. An auxilliary use of the Cobb-Douglas functional specification enabled us to back out the factor-specific TFP and therefore to provide an argument whether some productivity differences were due to differences in efficiency or in the appropriateness of technology choice. When used in growth accounting, the Cobb-Douglas assumption 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 – that is, the country's ability to adopt a more "appropriate" technology.

Our results indicate that the WTF is spanned by a number of U.S. states such as Delaware, Massachusetts, Colorado, and Nevada; the U.S. 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.

Our second contribution to the DEA-based productivity literature is that following Caselli and Coleman (2006), we have split the hitherto homogenous human capital input into human-capital adjusted stocks of unskilled and skilled labor which might not be perfectly substitutable. This allowed us to obtain further increases in precision in the estimation of the WTF.

Obviously, the most important vulnerability of the current paper lies at measurement and data comparability issues. What is certainly required in further research is more reliable data, and data covering a wider range of years.

A Technical efficiency and development accounting for European Union's new Member States (NMS12)

Since 2004, twelve new countries, predominantly from the Central and Eastern European region, joined the European Union. These countries were: Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, Slovenia in 2004, and Bulgaria and Romania in 2007. One important characteristic of all these countries is that they produce much less output per worker than the USA or the 21 OECD countries considered in the main part of this paper. Certainly, an important part of this distance comes from their relatively low capital stocks and low educational attainment. But is this decisive? To answer this question, we have decomposed the distance between the NMS12 countries and the USA in terms of GDP per worker into the components attributable to technical efficiency and differences in factor endowments.

We have re-run the estimation of WTF 2000 with NMS12 countries in the sample, and upon this re-running, some changes appear: Bulgaria 1995, Latvia 1995, and Malta 2000 turn out to be efficient and therefore span the WTF, while several observations from 1970–1980 fall behind the frontier. It is clear that NMS12 countries can only

Table 11: NMS' optimal technology choice, 2000.

Country	Primary tech.	Share	Secondary tech.	Share
Bulgaria	Bulgaria 1995	0.9832	Nevada 1995	0.0168
Cyprus	Nevada 2000	0.4651	Spain 1970	0.3749
Czech Republic	Spain 1970	0.6757	Nevada 2000	0.2211
Estonia (1995)	Latvia 1995	0.7360	Nevada 2000	0.0926
Hungary	Portugal 1970	0.3899	Nevada 2000	0.3447
Latvia (1995)	Latvia 1995	1.0000		
Lithuania (1995)	Latvia 1995	0.8359	Nevada 2000	0.0860
Malta	Malta 2000	1.0000		
Poland	Bulgaria 1995	0.5191	Portugal 1970	0.3701
Romania	Bulgaria 1995	0.8276	Portugal 1970	0.1078
Slovakia	Portugal 1970	0.5403	Nevada 2000	0.2386
Slovenia	Spain 1970	0.6567	Delaware 2000	0.2424

add precision to the estimation of WTF at relatively low capital levels (and in fact, dramatically low K/H ratios – Bulgaria 1995, Latvia 1995) or extremely high L^U/L^S ratios (Malta 2000). The optimal technology choices of NMS12 countries in 2000 are presented in Table 11.

Since we do not have reliable data on NMS12 countries for the pre-1990 period when most of them were communist states, we are unable to redo the growth accounting exercise for them. We will thus concentrate on development accounting only.

The ratio of GDP per worker in NMS countries and the U.S. has been decomposed non-parametrically into efficiency ratios and differences in potential GDP due to differences in factor endowments. The results are summarized in Table 12. The educational attainment data for the NMS12 countries have taken from Barro and Lee (2001) and not de la Fuente and Doménech (2006) who do not provide NMS data. The difference in datasets may have an negative impact on data quality and thus lower the reliability of the results presented below. For this reason, and for the fact that L^U/L^S ratios for some NMS countries fall way apart from the ratios observed for the rich OECD countries, we have decided to carry out this decomposition using aggregated human capital data only.

Table 13 presents the auxilliary Cobb-Douglas-based decomposition of the productivity ratio of NMS countries and the U.S., where efficiency is disentangled from "appropriate technology", i.e. factor-dependent TFP.

We learn that there are two principal reasons for which most NMS countries fall behind the U.S. so heavily: first, they are strongly undercapitalized; second, given their factor endowments, there does not exist a technology allowing them to produce as much per unit of capital as the US do. For example, Bulgaria in 1995 used its factors efficiently but it dramatically lacked not only capital, but also a decent tech-

Table 12: Decomposition of the distance between a given NMS and the US in 2000.

Country	GDP ratio	Efficiency	K diff	H diff
Bulgaria	0.2098	1.1161	0.1882	0.9986
Cyprus	0.6206	1.1064	0.6824	0.8219
Czech Republic	0.3617	0.6604	0.7258	0.7547
Estonia (1995)	0.2387	1.0410	0.3519	0.6518
Hungary	0.3546	0.7565	0.6334	0.7401
Latvia (1995)	0.1939	1.2511	0.2365	0.6556
Lithuania (1995)	0.2184	1.0155	0.3176	0.6770
Malta	0.7398	0.9338	0.8803	0.9000
Poland	0.2481	0.9045	0.3413	0.8037
Romania	0.1626	0.6948	0.2449	0.9558
Slovakia	0.2631	0.7500	0.5108	0.6868
Slovenia	0.5288	0.8457	0.7804	0.8013

Table 13: Decomposition of the distance between a given NMS and the US in 2000 under the Cobb-Douglas assumption. Efficiency vs. "appropriate technology".

Country	GDP ratio	Effic.	Techn.	K diff	H diff
Bulgaria	0.2098	1.1161	0.4416	0.4504	0.9449
Cyprus	0.6206	1.1064	0.8472	0.7915	0.8366
Czech Republic	0.3617	0.6604	0.8565	0.7944	0.8050
Estonia (1995)	0.2387	1.0410	0.5265	0.5679	0.7670
Hungary	0.3546	0.7565	0.7836	0.7491	0.7986
Latvia (1995)	0.1939	1.2511	0.4342	0.4616	0.7734
Lithuania (1995)	0.2184	1.0155	0.5089	0.5436	0.7773
Malta	0.7398	0.9338	1.0158	0.8976	0.8689
Poland	0.2481	0.9045	0.5627	0.5865	0.8311
Romania	0.1626	0.6948	0.4996	0.5170	0.9060
Slovakia	0.2631	0.7500	0.6688	0.6752	0.7769
Slovenia	0.5288	0.8457	0.9122	0.8291	0.8269

nology which would allow to produce with such a factor mix: the frontier TFP for the Bulgarian factor mix was only 55% of frontier TFP for the U.S. factor mix.

B A comment on computing 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 the 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 caveat 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 and internal heterogeneity. Why should Luxembourg, Netherlands, UK, USA, and China be treated on par if their sizes are so vastly different? Analogously, why should e.g. the U.S. 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 U.S. 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 the concept of a cross-country productivity distribution is heavily data-driven. Split Luxembourg into a thousand sub-Luxembourgs 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 U.S. states. This is why we don't do that.

Even more worryingly, stepwise disaggregation (countries to provinces) can be extended to consecutive, ever smaller territorial units such as counties or townships. Furthermore, such disaggregation does not have to be done according to spatial criteria: there could be sectoral decompositions of total GDP into agriculture, industry, and services, and further down – into a wide range of sectoral categories.

What to do then? One idea would be to construct samples of regions of comparable size in terms of population, and a comparable degree of internal heterogeneity. The European Union's NUTS classification can act as a guide in this respect. Another idea would be to go all the way down with disaggregation and compute the world distribution of personal incomes (cf. Sala-i-Martin, 2006), having in mind that within countries, the GDP per worker is finally distributed within the population. This requires one to take account of within-country income inequality (neglected when computing the "productivity distribution"), but it also requires one to compute a *weighted* distribution of GDP per worker in the world, the weights being population sizes. As shown by Jones

(1997) and Sala-i-Martin (2006), the weighted distribution is no longer bi-modal: the huge combined weight of China, India, Pakistan, Bangladesh, Brazil, Indonesia, etc., makes the lower mode significantly higher than the upper "mode" which ceases to be a mode anymore. Such an analysis is obviously beyond the scope of the current paper.

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