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Oleg Badunenko, Portsmouth Business School

Daniel J. Henderson, University of Alabama,
Tuscaloosa

Valentin Zelenyuk, University of Queensland

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This paper scrutinizes research on the productivity of nations with a particular focus on the preceding 50 years. First, we briefly synopsise classic studies on economic growth and convergence of nations. The main criticism of these studies is that they did not account for potential inefficiency of countries. The production frontier literature attempts to deal with this issue and we give a brief introduction to it with a focus on data envelopment analysis. One central point of this review is the analysis of sources of productivity growth before and after 1990, a period of time, which appears to be a point of a structural change in growth patterns around the world. The second thread of this paper concerns the forces behind the transformation of the worldwide productivity distribution from a uni-modal to a bimodal distribution during the 1990s. Finally, we emphasize caveats and outline possible directions for future research.

1 Introduction

This paper concerns the patterns and sources of labor productivity (labor productivity) growth of nations, with a focus on the preceding half century.¹ The hallmarks of this review are threefold. First, by patterns we mean changes over time of economic perfor-

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^{*} Economics and Finance Group, Portsmouth Business School, University of Portsmouth, Portsmouth, United Kingdom

[§] Department of Economics, Finance and Legal Studies, University of Alabama, Tuscaloosa, United States

[¶] School of Economics and Centre for Efficiency and Productivity Analysis (CEPA) at The University of Queensland, Australia

¹ GDP is usually used to measure the total output or total income of a country, although some studies argue that GNP is a more appropriate measure (e.g., Abramovitz, 1956; Solow, 1957).

mance for single economies and for all economies jointly. Second, while the economic growth and convergence literatures discuss several economic measures, such as aggregate output, aggregate output per capita, or aggregate labor productivity, we focus on the latter. Specifically, we focus our review on a simple, yet commonly used measure of productivity, namely labor productivity. It is one of the most intuitive indicators of national economic performance since it plainly tells how much a nation produces per unit of labor, given its endowment of other inputs (e.g., capital) and available technology. We will discuss relevant studies whose subject is either growth of labor productivity or other types of productivity change measures, such as a Malmquist Productivity Index. Third, we discuss long-run tendencies and forces behind growth of labor productivity and we pay special attention to the shift over time of the worldwide distribution of labor productivity levels. We will primarily focus on studies that used frontier methods via the so-called Data Envelopment Analysis estimator, yet also briefly mention other popular methods.²

In recent years, there has been a re-emergence of the interest in economic growth. Research on national economic performance may be divided into two main strands. One group is seeking to determine the sources of economic growth. Within this group, there are several approaches used in studies trying to explain why growth rates of per capita or per unit of labor output differ (Fagerberg, 1988). The outdated descriptive analysis of why productivity growth rates differ between countries—typically referred to as ‘catch-up’ analysis—was ascribing differences in productivity levels to various events, such as wars, etc (Maddison, 1984). In these studies, productivity differences are thought of as technological gaps, which less developed economies fill by imitating the technology of more advanced economies, thus ‘catching-up’ to leading economies. The major limitation of ‘catch-up’ analysis is that it does not explain [structural] changes in leading economies, i.e. those that experience large growth rates, existence of those who catch-up, and does not anticipate changes in leadership (Abramovitz, 1986).

Two other popular approaches are ‘level-accounting’ and ‘growth-accounting’ analyses. The former splits aggregate output into components; the latter relates the growth of aggregate output and growth of its components using national accounts. Abramovitz (1956) was first to perform ‘growth-accounting’ analysis for the United States. He measured labor services in man-hours and total volume of capital as land, structures, producers’ durable equipment, inventories and net foreign claims. He used net national product as aggregate output. Over two time periods (1869–1878 to 1944–1953), the author com-

² This review complements Sickles, Hao and Shang (2015), which mainly focused on the regression-based approaches to productivity measurement.

pared growth in aggregate output per capita to the combined growth of per capita labor and capital inputs, weighted proportionally to the base period incomes going to labor and property, respectively. He found that only a small part of net national product growth could be explained by growth in resources (or inputs). [Abramovitz \(1956\)](#) therefore came to the conclusion that almost the entire increase of net national product growth must be contributed to growth of resources productivity. ‘Growth accounting’ analysis studied this unexplained part, which after the seminal work of [Solow \(1957\)](#) was dubbed the ‘[Solow residual](#)’ and routinely attributed as a measure of technological change.³ In the common case with two inputs (capital and labor) and constant returns to scale, the [Solow residual](#) is the difference between the growth rate of labor productivity and the growth rate of capital per unit of labor, the latter being weighted by the fraction of output used to rent capital, known as the capital share ([Barro and Sala-i-Martin, 2004](#)).

[Solow \(1957\)](#) also initiated a regression-based strand of studies trying to explain why growth rates differ. His study inspired a voluminous literature of econometric applications of cross-country production functions. [Chenery \(1986\)](#) summarized this literature emphasizing the Solow-type econometric approach to explaining differences in growth rates of labor productivity is of little help when the sample included less developed and semi-industrialized economies along with developed ones. [Chenery](#) termed such situation ‘disequilibrium growth’ and attributed it to the fact that equilibrium conditions of the neo-classical theory—at the heart of the [Solow \(1957\)](#) approach—are not fulfilled for non-industrialized countries. Most importantly, countries differ by the degree to which they satisfy the assumptions of the underlying model (returns to scale, resource allocation, perfect competition). [Chenery](#) also pointed out that a production function approach can account for different types of disequilibria by adding variables that reveal these disequilibria (see pp. 27–31 in [Chenery, 1986](#)).

The second group studies whether growth rates of labor productivity of national economies converge or polarize over time. The premise that relatively poor and slow growing economies have the potential to grow faster than more developed economies has not been uniformly confirmed. On the one hand, growth rates of labor productivity ([Baumol, 1986](#)) or output per capita weighted by population ([Sala-i-Martin, 2006](#)) tended to equalize. On the other hand, growth rates of labor productivity for narrow samples ([De Long, 1988](#)) and output per capita for a large cross-section of countries ([Pritchett,](#)

³ Note that growth accounting is a mere accounting decomposition; it is not used to identify the sources of growth ([Barro and Sala-i-Martin, 2004](#)).

1997 and Sala-i-Martin, 1996)⁴ failed to converge. Since the factors of production flew to already developed sectors of economies and rich countries (Easterly and Levine, 2001), it suggested even more indication of the divergence of national economies in terms of level and growth of output per capita. Starting from the 1960s, there was a weak tendency for the initially rich economies to grow faster than the poor (Barro and Sala-i-Martin, 1992). The consequence of this tendency was that in terms of labor productivity, economies of the world appeared to form two clubs, the poor and the rich (Quah, 1996, 1997). The worldwide labor productivity distribution had been transforming from having one mode in the 1960s to being bimodal sometime during 1960–2000.

Previous analyses of sources and convergence of growth rates of labor productivity neglected the fact that economies utilize their productive capacities differently. Largely inspired by the works of Caves, Christensen and Diewert (1982) and Färe, Grosskopf, Norris and Zhang (1994b), the next generation of growth studies were taking potential inefficiency of production into account. A new twist in this generation was made by Kumar and Russell (2002), who inspired a literature that combined a version of the Malmquist Productivity Index decomposition with distributional analysis, to analyze sources and evolution of growth of labor productivity taking the change in technology, efficiency and factors of production into consideration. This next generation of the growth literature (Henderson and Russell, 2005, Badunenko, Henderson and Zelenyuk, 2008, Badunenko and Romero-Ávila, 2013 and Isaksson, Sickles and Shang, 2016, Duygun, Isaksson, Hao and Sickles, 2016) presented statistically supported evidence to explain many of the stylized views about differences in productive performance of national economies.⁵

In what follows, we briefly describe some of the key methods and empirical evidence for the analysis of economic growth since the 1960s. Due to space limitations, we consider a sub-sample of the voluminous literature and we are likely missing some interesting papers. The purpose of this review, however, is to provide an overview of major findings that shaped the understanding of productivity growth patterns over half a century, with some remarks on directions for future research. The rest of the paper is structured as following. Section 2 reviews work on proximate causes of economic growth and describes the shift of interest from mere comparison of growth rates of labor productivity across countries to the analysis of the transformation of the entire labor productivity distribu-

⁴ However, Sala-i-Martin (1996) found that growth rates of labor productivity converged for the sub-sample of OECD countries, the states within the United States, the prefectures of Japan, and regions within several European countries.

⁵ Sickles, Hao and Shang (2014, 2016) considered a model averaging approach using various weighting schemes in the TFP decomposition framework.

tion. Section 3 introduces decompositions of Malmquist Productivity Indexes and labor productivity. The core of this paper is Section 4, which summarizes empirical work on sources of productivity growth and the evolution of the worldwide distribution of productivity, most importantly the increased dispersion and the transformation over time from a uni-modal to a bimodal distribution within a production frontier framework. Section 5 makes concluding remarks and a glimpse into possible future directions.

2 Early Works on Economic Growth and Convergence of Labor productivity

2.1 From Within- to Cross-Country Analysis of Sources of Labor productivity Growth

Under a set of relatively restrictive conditions, [Solow \(1957\)](#) showed how to distinguish between movements of the production function from movements along it in an analysis of labor productivity growth. He was the first to decompose labor productivity into components attributable to technical change and increased use of capital. Using U.S. data from 1909–1949, he found that technological progress was on average approximately neutral and that technological change accounted for 87% of U.S. productivity growth.

Since the work of [Solow \(1957\)](#), empirical analysis of economic growth and its sources trended toward the top of the macroeconomics research agenda. The focus of empirical macroeconomists, however, shifted from looking at national economies in isolation to cross-country analyses. One of the triggers was the fact that during the post World War II period, the growth of real national income per worker in 8 European countries with an exception of the U.K., was larger than that of the United States (see Table 2-2, p 18, in [Denison, 1967](#)). In an analysis of sources of national income growth rates for eight European countries and the U.S. from 1950–1962, [Denison](#) also found that the sources vary by place and time-period. While there was no clear answer to the principal driver of the economies, the author identified advances of knowledge, nonresidential structures and equipment, and economies of scale as the sources contributing most to national income per worker growth for the majority of the nine investigated countries.

Following the Solow model, cross-country income difference and economic growth were attributed to improvements in technology, investment in physical capital and accumulation of human capital. These causes, while vital, are only proximate causes of economic

growth (Acemoglu, 2009). The real challenge is to investigate the fundamental causes of differences in income and economic growth, that is, why some nations are not sufficiently improving technology, investing in physical capital and accumulating human capital (Weil, 2014; Acemoglu, 2009). Hall and Jones (1999) for example, found that variables attributable to physical and human capital only partially explained variation of output per worker across countries, while differences in “social infrastructure” (e.g., institutions and government policies) had the largest effect on the variation of economic development. Given the importance of differences in TFP for explaining cross-country differences in output per worker (see e.g., Hall and Jones, 1999), Hsieh and Klenow (2009) analyzed what caused TFP differences. They found that physical capital and labor misallocation at the micro level significantly shrunk aggregate TFP, an argument also put forward by Chenery (1986). Other fundamental causes of productivity and economic growth considered in the literature are cultural and geographical idiosyncrasies (Acemoglu, 2009).

2.2 Evolution of Growth Rates of Labor productivity

Abramovitz (1986) expanded the macroeconomics research agenda by by considering the question of whether growth rates of national economies converge. Convergence studies concentrated on two types of convergence. In the analysis of absolute β -convergence, researchers looked to the sign and significance of the coefficient β in a Baumol (1986) type cross-country regression:

$$\begin{aligned} \text{Growth rate of output per unit of labor (from } b \text{ to } c) = \\ \alpha + \beta \log(\text{Output per unit of labor in } b) + u, \end{aligned} \tag{1}$$

where b and c denote the base period and current period, respectively and u is the disturbance term. The notion of σ -convergence which focuses on the reduction in the dispersion of labor productivity over time goes back at least to Easterlin (1960) and Borts and Stein (1964) (Sala-i-Martin, 1996). β -convergence is a necessary, but not a sufficient condition for the existence of σ -convergence (Sala-i-Martin, 1996). Conditional β -convergence is an extended version of absolute β -convergence, where structural characteristics of countries are taken into account as conditional variables are added to the convergence regression (1). It was noted that a negative β in a Baumol type regression does not necessarily imply convergence (see Bliss, 2000, for discussion of Galton’s Fallacy).

In one of the earliest examinations of long-run economic growth of GDP per worker, Baumol (1986) confirms the convergence phenomenon for eight industrialized countries from 1870–1979. Going beyond the *ex post* chosen sample of countries that are now rich and have successfully developed, yields different results. Using the same variables as Baumol (1986), De Long (1988) found that in a wider sample of 22 nations, rather than exhibiting a tendency to converge in terms of GDP per worker, some of the poorest countries have not been growing faster than rich ones. The argument of De Long is that Baumol’s findings are not informative, since those economies, which have not converged, but were rich back in 1870, have been excluded from the analysis, which only considered economies that belonged to what Baumol termed “convergence club” nations. De Long concluded that such a finding of convergence cannot be trusted because the sample suffers from selection bias.

In the middle 1980s, data on internationally comparable macroeconomic variables compiled by Heston and Summers (1988) from the real national accounts facilitated analyses of an even wider samples of countries. Mankiw, Romer and Weil (1992) confirmed previous results of unconditional convergence⁶ of incomes per worker across rich countries (OECD) from 1960–1985. However, there appeared to be no tendency for the poor economies to perform better than rich ones in a wider sample of countries and the gap between the poor and the rich was not narrowing. Abramovitz (1986) seconds that convergence may take place only within a group of economies. Pritchett (1997) advocates divergence between developed and developing countries, although he concludes that growth rates of GDP per capita in developed economies appeared to converge. In contrast to Pritchett (1997), Sala-i-Martin (2006) argues that if population-weights are used, income per capita tends to converge from 1970–2000 for a wider sample including African, Asian, Latin American and former Soviet Union economies.

Divergence in a wider sample and convergence within a smaller and relatively homogeneous samples required full reconsideration of the approach to study the evolution of growth rates. Quah (1996) introduced alternative models of distribution dynamics to study whether poor economies catch up. These models hinge on the observation that there emerge groups of rich and poor, while a middle-income group vanishes. Standard deviations or any other moment of the cross section distribution, as well as relation of growth rates and per capita levels, which lie at the heart of β - and σ -convergence, cannot adequately explain growth dynamics leading to such twin-peakedness. A combination of β - and σ -convergence is not satisfactory either (see Quah, 1997).

⁶ Sala-i-Martin (1996) calls this type of convergence absolute β -convergence.

Since then, a segment of the convergence literature explicitly focused on the shape of the distribution, more specifically on the observation that the world is moving from a unimodal labor productivity distribution toward a bimodal distribution, the so-called “twin-peaks” distribution.⁷ Jones (1997) centered his attention on the shape of production function, allowing him to investigate the dynamics of income per capita. The author found that economies above the 50th percentile of the income distribution were expected to “catch-up” or even overtake the United States, while economies below the 50th percentile were predicted to remain very close to where they are. Jones (1997) thus reaffirmed previous findings that there is divergence of per capita income at the bottom, while there is convergence at the top of per capita income distribution.

More recently, Andrews et al. (2015) consider national and global productivity frontiers. In their work, national frontiers using micro-level data are formed by choosing the 10 most productive firms by country, industry and year, while the global frontier is formed by the 100 top productivity performers. In a related work, OECD (2016) report considerable divergence between the productivity performance of global frontier firms—whose growth remained stable over time and who are more capital and patent-intensive, have larger sales and are more profitable—and the rest, “non-frontier” firms. From their results, one can see that at the micro level, there is the same tendency as at the macro level: the building of two groups (see, for example, pp. 17–18 in OECD, 2016, for a discussion). Using a different approach, Inklaar and Diewert (2016) use a similar best-practice concept to analyze industry convergence by considering what can be termed “ E -convergence” of multilateral productivity. E measures the gap between the actual world productivity and the potential level of world productivity in a given time-period. If the productivity of each nation is at the potential level, E equals one, indicating 100% efficiency in terms of the world productivity frontier. The dynamics of E over time tells us about shifts away or towards convergence of productivity to best-practice.⁸

The frameworks involving β - and σ -convergence concepts cannot adequately investigate bimodalism in labor productivity distribution. One challenge in reconciling “convergence clubs” and bimodality notions is that bimodality could be a consequence of club convergence, but not vice versa since members can move across clubs. Emergence and persistence of bimodality require revisiting of approaches to analyze the evolution of growth rates.

⁷ Henderson, Parmeter and Russell (2008) showed that twin-peakedness of labor productivity distribution was present throughout or emerged during 1960–2000.

⁸ Also see Henderson and Zelenyuk (2007) for a related discussion and about testing of efficiency convergence.

A major drawback of many of the studies we mentioned in this section, and other studies in the same vein, was that they assumed that economies were producing at their full potential. Market failures, poor legal systems, weak institutions, market power, over-regulation or other reasons lead many national economies to be technically inefficient, in the sense of being below the world technological frontier. The investigation of efficiency changes as a source of economic growth is important for at least two reasons. First, efficiency of countries relative to the best practice may change over time. If this change is neglected, its effect on economic growth will be picked by other proximate causes of economic growth, which will be then estimated with a bias. Second, as will be discussed in this paper, efficiency change (improvement or deterioration) is not a fundamental, but a proximate cause of economic growth. In the late 1990s and 2000s it was becoming *the* force behind emergence of a second (higher) mode of the labor productivity distribution. Hence finding reasons that are preventing nations to improve efficiency becomes a new challenge to the economic growth literature. The relatively new strand of the literature analyses the growth patterns accounting for inefficiency, thus bringing together the macroeconomic and production frontier literatures (the latter being based on the pioneering work of Farrell, 1957), which we move to next.

3 A Nonparametric Construction of Worldwide Technology and Technical Efficiency

3.1 Data Envelopment Analysis

Nonparametric production-frontier methods, based on envelopment of input and output quantity data in the “smallest” or “tightest fitting” convex and free disposal and possibly conical hulls, have been extensively employed over the last several decades in many areas of economics (e.g., manufacturing, agriculture and finance). The principal objective of these methods has been to construct efficiency scores for a given decision making unit (DMU). While traditionally a DMU is a unit such as a firm or an agency, here it is a country-year observation.

Consider a production process in which multiple inputs produce multiple outputs. If vector $\mathbf{x} = (x_1, \dots, x_N)$ denotes N non-negative inputs and vector $\mathbf{y} = (y_1, \dots, y_M)$ denotes M non-negative outputs, the production technology in the period t can be characterized

by a set \mathcal{T}^t , broadly defined as

$$\mathcal{T}^t = \{(\mathbf{x}, \mathbf{y}) : \mathbf{y} \text{ are producible by } \mathbf{x} \text{ in period } t\}. \quad (2)$$

The true technology set \mathcal{T}^t is typically not observed in practice and is usually approximated with the help of activity analysis models and operationalized or estimated via the linear-programming technique, e.g., as

$$\begin{aligned} \hat{\mathcal{T}}^{t, \text{CRS}} = \{(\mathbf{x}, \mathbf{y}) : & \sum_{j=1}^n z_j y_{jm}^t \geq y_m, \quad m = 1, \dots, M, \\ & \sum_{j=1}^n z_j x_{jq}^t \leq x_q, \quad q = 1, \dots, N, \\ & z_j \geq 0, \quad j = 1, \dots, n\}, \end{aligned} \quad (3)$$

where $\mathbf{x}^t = \langle \mathbf{x}_i^t \rangle_{i=1}^n$ and $\mathbf{y}^t = \langle \mathbf{y}_i^t \rangle_{i=1}^n$, $\mathbf{x}_i^t = (x_{i1}^t, \dots, x_{iN}^t)$ and $\mathbf{y}_i^t = (y_{i1}^t, \dots, y_{iM}^t)$ denote data vectors of N inputs and M outputs for country i , ($i = 1, \dots, n$), in time period t , and vector $\mathbf{z} = (z_1, \dots, z_n)$ denotes the intensity variables that help ‘envelop’ the data with the smallest convex free disposal cone. Since no parametric assumptions are imposed on the function, the estimator in (3) is referred to as a nonparametric estimator of technology set \mathcal{T}^t , which satisfies CRS, free disposability and convexity. The roots of this approach go back to at least Farrell (1957) and Afriat (1972), and especially Charnes, Cooper and Rhodes (1978) who branded this approach as Data Envelopment Analysis (DEA hereafter).⁹

The upper boundary of the technology set \mathcal{T}^t defines the (technology) frontier for that period t . How far a given country is from the frontier is referred to as its technical efficiency. Popular measures of technical efficiency for countries are conventional radial Debreu-Farrell measures of technical efficiency (Debreu, 1951; Farrell, 1957), defined for a point $(\mathbf{x}_i, \mathbf{y}_i)$ as

$$OTE(\mathbf{x}_i, \mathbf{y}_i | \mathcal{T}^t) = \max \{ \theta_i : (\mathbf{x}_i, \theta_i \mathbf{y}_i) \in \mathcal{T}^t \}. \quad (4)$$

Intuitively, OTE measures the degree of necessary (equi-proportional) expansion of all outputs to move a country with allocation for a point $(\mathbf{x}_i, \mathbf{y}_i)$ to technology frontier \mathcal{T}^t , while keeping inputs and technology fixed for the particular period t . The true \mathcal{T}^t in (4)

⁹ Other assumptions (non-CRS technology, weak disposability of inputs or outputs, non-convexity, etc.) can also be imposed. For more details see Färe, Grosskopf and Lovell (1994a) and Sickles and Zelenyuk (2017).

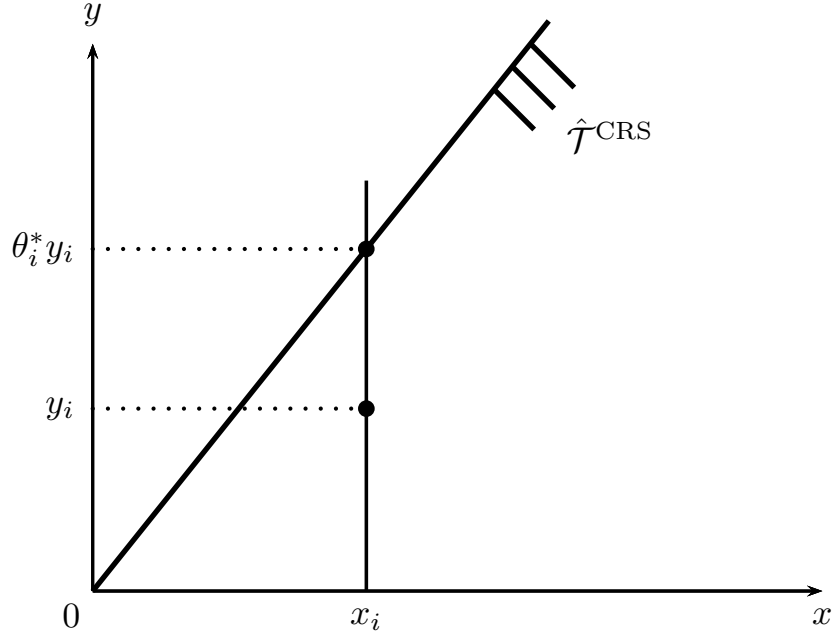


Figure 1: Output Measure of Technical Efficiency

is unobserved and replacing it with its DEA estimate in (3), gives the DEA estimator of this efficiency measure, formulated as

$$\widehat{OTE}(\mathbf{x}_i, \mathbf{y}_i | \hat{\mathcal{T}}^{t, \text{CRS}}) = \max \theta_i \quad (5)$$

$$\text{s.t. } \sum_{j=1}^n z_j y_{jm}^t \geq y_{im} \theta_i, m = 1, \dots, M,$$

$$\sum_{j=1}^n z_j x_{jq}^t \leq x_{iq}, q = 1, \dots, N,$$

$$z_j \geq 0, j = 1, \dots, n,$$

$$\theta_i \geq 0.$$

Figure 1 illustrates an output-based measure of technical efficiency in a hypothetical one-input-one-output production technology. The DMU (x_i, y_i) is inefficient as it is below the frontier. Given its input x_i it could have produced output $\theta_i^* y_i$ were it to exploit the technology, where θ_i^* is the optimal value of θ_i obtained from (5). For ease of interpretation, efficiency is typically calculated as the reciprocal of the Debreu-Farrell measure, $1/\theta_i^*$, multiplied by 100 to obtain a percentage interpretation.

3.2 Malmquist Productivity Index

A Malmquist Productivity Index (MPI hereafter) is a theoretical index that measures the changes in productivity allowing for various useful decompositions of sources of the changes and allowing for multi-input-multi-output production technologies.¹⁰ It makes use of Shephard's distance functions which are reciprocals of the Debreu-Farrell measure of technical efficiency (Färe, Grosskopf and Lovell, 1994a). Output-based MPI from time-period b to time period c for country i is defined as (see Caves, Christensen and Diewert, 1982)

$$MPI_i^{bc} = \left[\frac{OTE(\mathbf{x}_i^b, \mathbf{y}_i^b | \mathcal{T}^{b, \text{CRS}})}{OTE(\mathbf{x}_i^c, \mathbf{y}_i^c | \mathcal{T}^{b, \text{CRS}})} \times \frac{OTE(\mathbf{x}_i^b, \mathbf{y}_i^b | \mathcal{T}^{c, \text{CRS}})}{OTE(\mathbf{x}_i^c, \mathbf{y}_i^c | \mathcal{T}^{c, \text{CRS}})} \right]^{1/2},$$

where $OTE(\mathbf{x}_i^b, \mathbf{y}_i^b | \mathcal{T}^{c, \text{CRS}})$ is the Debreu-Farrell measure calculated for country i observed in time period b relative to the frontier in time period c for technology that satisfies CRS, free disposability and convexity. This index of productivity change for country i can be decomposed as

$$\begin{aligned} MPI_i^{bc} &= \frac{OTE(\mathbf{x}_i^b, \mathbf{y}_i^b | \mathcal{T}^{b, \text{CRS}})}{OTE(\mathbf{x}_i^c, \mathbf{y}_i^c | \mathcal{T}^{c, \text{CRS}})} \\ &\times \left[\frac{OTE(\mathbf{x}_i^c, \mathbf{y}_i^c | \mathcal{T}^{c, \text{CRS}})}{OTE(\mathbf{x}_i^c, \mathbf{y}_i^c | \mathcal{T}^{b, \text{CRS}})} \times \frac{OTE(\mathbf{x}_i^b, \mathbf{y}_i^b | \mathcal{T}^{c, \text{CRS}})}{OTE(\mathbf{x}_i^b, \mathbf{y}_i^b | \mathcal{T}^{b, \text{CRS}})} \right]^{1/2}. \\ &\equiv EFF_i^{bc} \times TECH_i^{bc}, \end{aligned} \tag{6}$$

where EFF and $TECH$ are components attributable to a change in efficiency and change in technology, respectively. If $EFF_i^{bc} \gtrless 1$, contribution of change in efficiency to productivity change from time-period b to time period c was positive/zero/negative for country i . If $TECH_i^{bc} \gtrless 1$, this implies respectively that for country i , technical progress/stagnation/regress has occurred between periods b and c . The empirical estimates of EFF and $TECH$ provide a way to quantify what is sometimes referred to as economic catching up (or falling behind) and forging ahead—the concepts inspired by Abramovitz (1986).

The decomposition in (6) is a theoretical concept. The MPI as well as components EFF and $TECH$ are unobserved and must be estimated, e.g., with DEA as described above

¹⁰ The MPI was introduced by Caves, Christensen and Diewert (1982), and was inspired by related ideas of Malmquist (1953), who dealt with price and quantity indexes based on input distance functions (see Lovell, 2003).

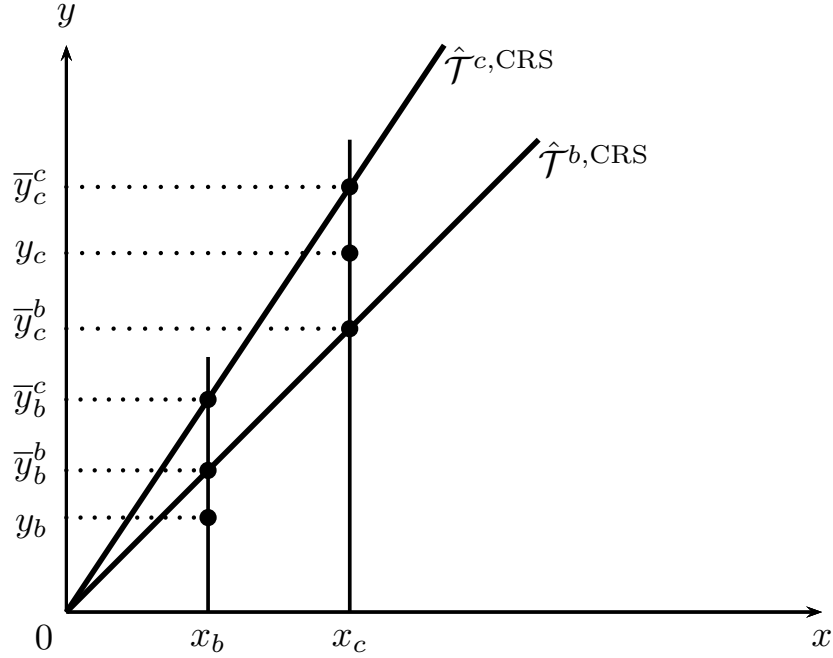


Figure 2: Malmquist Output-Based Productivity Index MPI, a Replication of Figure 1 in Färe, Grosskopf, Norris and Zhang (1994b)

to obtain an empirical version of (6), given by

$$\widehat{MPI}_i^{bc} = \widehat{EFF}_i^{bc} \times \widehat{TECH}_i^{bc}. \quad (7)$$

Figure 2 demonstrates the decomposition of \widehat{MPI} in the one-input-one-output case, the movement from (x_b, y_b) to (x_c, y_c) .¹¹ Denote $\bar{y}_c^b = \widehat{OTE}(x_c, y_c | \hat{\mathcal{T}}^{b,CRS}) \times y_c$ as the potential output in time period c given the estimated technology in time period b . The first term in (7) represents the estimated “catching-up” or how much closer a given country is to the production frontier over time, i.e. movement of \bar{y}_b^b/y_b to \bar{y}_c^c/y_c . The second term in (7) measures shifts in the frontier, from $\hat{\mathcal{T}}^{b,CRS}$ to $\hat{\mathcal{T}}^{c,CRS}$, in the region of input-output space occupied by a given country, and is thus referred to as technical change.

The MPI decomposition is akin to ‘growth accounting.’ It is based on production theory axioms, thus potentially not contradicting economic growth theory. It decomposes an index of productivity change which relates to earlier discussion of productivity sources with an advantage that it takes potential inefficiencies into account and addresses modeling issues raised by Bernard and Jones (1996). The MPI decomposition in (6) imposes CRS,

¹¹ Here and in what follows, we reproduce figures and tables as close as possible to the original studies using publicly available data.

implying that larger economies do not have scale advantage over smaller economies.¹² If they perform better, it is due to adopting better technology and/or being more efficient. Färe, Grosskopf, Norris and Zhang (1994b) were among the first to use the MPI decomposition in (7) to study productivity change and its sources at the macro level. Early empirical study using productivity measurement include among others Färe, Grosskopf, Lindgren and Roos (1989, 1994). See p. 239 of Färe, Grosskopf and Lovell (1994a) for historical remarks.

3.3 Labor Productivity Decomposition

Kumar and Russell (2002) decomposed growth of labor productivity into factors attributable to changes in efficiency, technological change and physical capital deepening. The authors assume that worldwide technology exists and they model it with three macroeconomic variables, aggregate output (Y), labor (L), and physical capital (K) as inputs. They estimated the worldwide technology frontier using DEA, allowing for the measurement of the efficiency of countries. To be consistent with the notation of Kumar and Russell (2002), we let $y = Y/L$ and $k = K/L$ denote labor productivity and capital per unit of labor and drop subscript i for simplicity.¹³ Further, denote $\bar{y}_b(k_b)$ as a potential labor productivity in time period b using capital intensity of time period b . Denote $\bar{y}_c(k_c)$ as a potential labor productivity in time period c using capital intensity of time period c . By definition, $y_b \times \widehat{OTE}_b = \bar{y}_b(k_b)$ and $y_c \times \widehat{OTE}_c = \bar{y}_c(k_c)$, where \widehat{OTE}_b and \widehat{OTE}_c are the values of the estimated efficiency scores in the respective periods as calculated in equation (5). Therefore,

$$\frac{y_c}{y_b} = \frac{\widehat{OTE}_b}{\widehat{OTE}_c} \cdot \frac{\bar{y}_c(k_c)}{\bar{y}_b(k_b)}. \quad (8)$$

By multiplying the numerator and denominator by potential labor productivity at current period capital intensity using base period technology, we obtain

$$\frac{y_c}{y_b} = \frac{\widehat{OTE}_b}{\widehat{OTE}_c} \cdot \frac{\bar{y}_c(k_c)}{\bar{y}_b(k_c)} \cdot \frac{\bar{y}_b(k_c)}{\bar{y}_b(k_b)}. \quad (9)$$

¹² Starting from Solow (1957), CRS is habitually assumed in growth and convergence studies.

¹³ Note in previous section y denoted an output vector. Starting from Section 3.3, y is labor productivity.

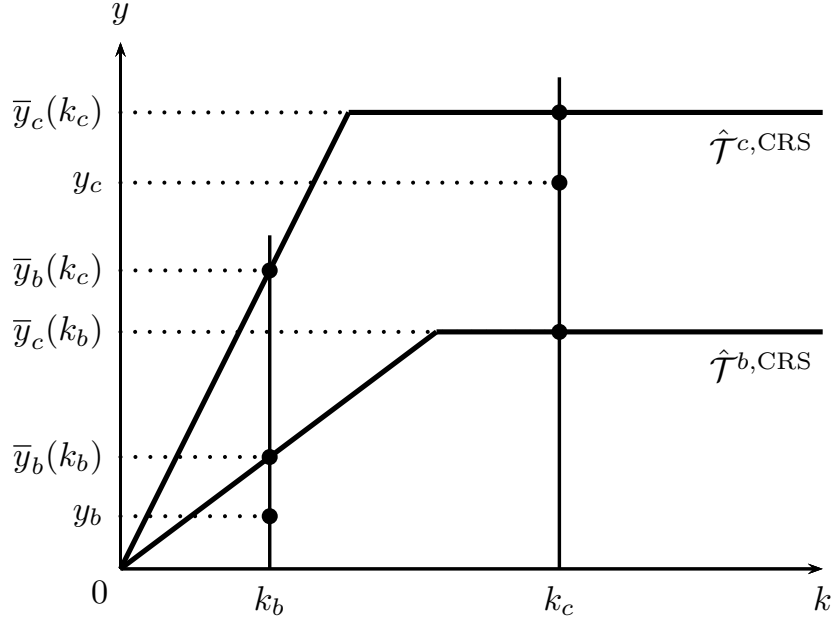


Figure 3: Tripartite Decomposition, a Replication of the Figure 3 in [Kumar and Russell \(2002\)](#)

Alternatively, by multiplying the numerator and denominator by potential labor productivity at base period capital intensity using current period technology, we obtain

$$\frac{y_c}{y_b} = \frac{\widehat{OTE}_b}{\widehat{OTE}_c} \cdot \frac{\bar{y}_c(k_b)}{\bar{y}_b(k_b)} \cdot \frac{\bar{y}_c(k_c)}{\bar{y}_c(k_b)}. \quad (10)$$

These identities decompose the growth of labor productivity in the two periods into changes in efficiency, technology changes and changes in the capital-labor ratio. As shown in Figure 3, the decomposition in (9) measures technological change by the shift in the frontier in the output direction at the current period capital-labor ratios, whereas the decomposition in (10) measures technological change by the shift in the frontier in the output direction at base period capital-labor ratios. Similarly, (9) measures the effect of physical capital deepening along the base period frontier, whereas (10) measures the effect of physical capital deepening along the current period frontier.

The choice between (9) and (10) is arbitrary. [Kumar and Russell \(2002\)](#) found that while the results for many countries differed, the basic results of their study stayed the same when employing either path. They eventually report the “Fisher Ideal” approach ([Persons, 1921](#)), simply by taking geometric averages of the two measures. This results

in the following decomposition of primary interest:

$$\begin{aligned} \frac{y_c}{y_b} &= \frac{\widehat{OTE}_b}{\widehat{OTE}_c} \times \left(\frac{\bar{y}_c(k_c)}{\bar{y}_b(k_c)} \times \frac{\bar{y}_c(k_b)}{\bar{y}_b(k_b)} \right)^{1/2} \times \left(\frac{\bar{y}_b(k_c)}{\bar{y}_b(k_b)} \times \frac{\bar{y}_c(k_c)}{\bar{y}_c(k_b)} \right)^{1/2} \\ &\equiv \widehat{EFF}^{bc} \times \widehat{TECH}^{bc} \times \widehat{KLACC}^{bc}, \end{aligned} \quad (11)$$

where the \widehat{KLACC}^{bc} term represents a contribution to labor productivity growth between time period b and time period c , attributable to change in capital per unit of labor.¹⁴ Note that the components are country specific. We omit the country index for simplicity. The major difference between the approaches of Färe, Grosskopf, Norris and Zhang (1994b) and Kumar and Russell (2002) therefore is distinguishing movements along the frontier as a separate source of the transition of point (k_b, y_b) to point (k_c, y_c) . What is of great importance about MPI and labor productivity decompositions is that they introduce additional, previously neglected by the virtue of the Solow model proximate cause of growth, i.e., the efficiency change. Decompositions illustrate that efficiency change has an effect on labor productivity growth, which is direct, and is not channeled through other proximate causes such as changes in technology and physical capital deepening.

4 Empirical Analysis of Growth and the Evolution of Labor Productivity Using a Production Frontier Approach

In this section, we review some of the cross-country empirical studies of growth and convergence of labor productivity that used a production frontier framework.

¹⁴ The old notation for this component in the literature is $KACC$, which might be incorrectly interpreted as capital accumulation, while in fact it is component indicating (the contribution to labor productivity change from) changes in capital per unit of labor rather than total capital. We therefore hope the addition of L to the old notation will limit confusion. Also note that if $KLACC$ indicates an increase (i.e., $KLACC > 1$), it is interpreted as a positive impact on labor productivity due to physical capital deepening (i.e., due to an increase of capital per unit of labor).

4.1 Data Used in Cross-Country Studies

One of the factors behind the emergence of the voluminous cross-country analyses was availability of data, which allowed making real international quantity comparison both between countries and over time (Heston and Summers, 1988; Feenstra et al., 2015). These data were compiled from the Real National Accounts better known as the Penn World Tables (PWT hereafter).¹⁵ These data are used by numerous authors analyzing growth patterns of labor productivity and therefore deserves some description.

Färe, Grosskopf, Norris and Zhang (1994b); Kumar and Russell (2002) and Henderson and Russell (2005) used PWT, Mark 5 to obtain macroeconomic variables as follows: aggregate output Y is real gross domestic product, obtained by multiplying chain-index of real gross domestic product (RGDPCH) multiplied by population (POP) and aggregate inputs, capital stock K , and employment L are retrieved from capital stock per worker and real GDP per worker (KAPW and RGDPW). Note that the PWT converts gross domestic product (GDP) at national prices to US dollars, making them comparable across countries. Real GDP and the capital stock are measured in billions of US dollars using prices of 1985 as a benchmark. Productivity is aggregate labor productivity. Färe, Grosskopf, Norris and Zhang (1994b) used a sample of 17 OECD countries over the period 1979–1988. Kumar and Russell (2002) and Henderson and Russell (2005) used a wider sample of 57 and 52 countries, respectively, including OECD as well as African, Asian and Latin American nations for 1965–1990. Basic summary statistics for the data used in Kumar and Russell (2002) are given in Table 1. We will describe and mention the sources of variables used in other studies as they come.

4.2 Färe, Grosskopf, Norris and Zhang (1994b) Cross-country Analysis of a Malmquist Productivity Index

In one of the most cited works in the area, Färe, Grosskopf, Norris and Zhang (1994b) used DEA to estimate non-parametrically production frontier for industrialized countries assuming that the technology can be characterized via three macroeconomic variables, aggregate output, labor, and physical capital as inputs, and compare each of the countries in their sample to that frontier. The purpose of their study was to construct the MPI between 1979 and 1988 and perform analysis of productivity change by decomposing the MPI as in (6). *Inter alia*, the authors found that over the period from 1979 to 1988,

¹⁵ PWT have seen many updates, the most recent version 9.0 as of this writing can be downloaded from <http://dx.doi.org/10.15141/S5J01T>.

Table 1: Summary Statistics of Macroeconomic Variables for 57 Countries Used in [Kumar and Russell \(2002\)](#)

Variable	sd	min	p25	mean	p50	p75	max
1965							
Y	313.4	1.2	6.4	110.5	26.2	65.3	2263.5
K	199.2	0.1	4.4	74.8	16.4	55.1	1412.7
L	29.5	0.1	1.4	11.5	3.4	8.8	204.2
1990							
Y	658.2	3.4	15.3	266.0	70.1	194.8	4520.2
K	689.3	0.3	13.0	283.0	60.5	201.9	4266.2
L	46.9	0.1	2.6	17.8	4.7	13.2	331.9

Following the definition used by PWT, Y and K are measured in billions of US dollars at prices of 1985, L is measured in millions of workers (census definition based on economically active population; data from International Labor Organization); sd, min, mean, and max denote the sample standard deviation, the sample minimum, the sample arithmetic mean, and sample maximum, respectively; p# denotes the #th sample percentile.

U.S. productivity was higher than average mainly due to technical change. Interestingly, Japan was found to benefit the most of the industrialized countries from catching up to the world production frontier. By and large, this study together with [Caves et al. \(1982\)](#) inspired a whole new stream of literature that used MPI and its decomposition in general, and for macroeconomic growth analysis in particular, and we discuss some recent studies below.

4.3 Labor Productivity Growth and its Decomposition

Convergence in income is closely related to productivity growth ([Färe, Grosskopf, Norris and Zhang, 1994b](#)). [Bernard and Jones \(1996\)](#) argued that the analysis of convergence should focus more carefully on technology, for example by allowing economies to accumulate technology at different rates. Addressing this issue, [Kumar and Russell \(2002\)](#) were first to put two strands of literatures together: macroeconomic convergence and production frontiers. Their starting point was the stylized fact that during 1965–1990, the countries became divided into two groups, the rich and the poor ([Quah, 1996, 1997](#)). It must be noted that neither [Quah](#) nor [Kumar and Russell](#) tested if multimodality were actually present in 1990. [Henderson, Parmeter and Russell \(2008\)](#) applied calibrated Silverman and Dip tests for multimodality to test worldwide labor productivity distribution and found that it was the period from 1960 to 2000, where the multimodality of the labor productivity distribution was either present or emerged. Figure 4, showing distributions

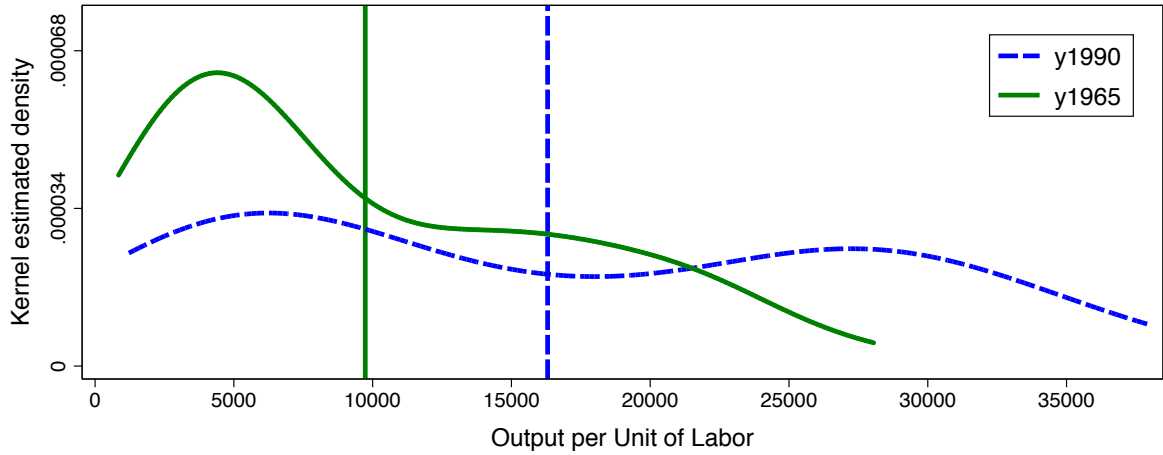


Figure 4: Distributions of Labor productivity, 1965 and 1990, a Replication of the Figure 1 in Kumar and Russell (2002). The Vertical Green Solid Line Represents the Mean of Labor productivity in 1965. The Vertical Blue Dotted Line Represents the Mean of Labor productivity in 1990

of labor productivity in 1965 and 1990,¹⁶ indicated that the distribution of labor productivity shifted from being uni-modal in 1965 to bimodal in 1990.¹⁷ The main interest of Kumar and Russell (2002) thus lied in studying the forces behind emergence of apparent bimodality in the labor productivity distribution, a phenomenon routinely referred to starting from the work of Quah (1996) as “two-club” or “twin-peak” convergence.¹⁸

Among the key findings of Kumar and Russell (2002) was that over the period 1965–1990, labor productivity increased by 75% on average, being primarily driven by physical capital deepening, about 60%, while change in technology and efficiency changes contributed only about 5% each to this growth.¹⁹ Kumar and Russell also used the decomposition (11) to analyze the evolution of the worldwide distribution of productivity, most importantly, the transformation over time from a uni-modal to a bimodal distribution. Figure 5 suggests that physical capital deepening was primarily responsible for the change in the shape of

¹⁶ The sample of 57 countries described in Section 4.1 were used to produce this figure.

¹⁷ This and other replicated figures are very close to those in the original papers, but may not be exact (e.g., potentially different bandwidth parameters for the kernel density estimates).

¹⁸ Also see Zelenyuk (2014), for a related discussion of multi-peak distributions of labor productivity for developed countries, and testing in the growth accounting context.

¹⁹ The contributions are not additive, mainly because the contributions are averages of contributions rather than contributions of the averages. Percent individual contributions are also not additive since they are calculated as an index minus 1 times 100.

Table 2: Distribution Hypothesis Tests (p -values), a Replication of the Results of Table 3 in Kumar and Russell (2002)

H_0 : Distributions Are Equal H_1 : Distributions Are Not Equal	Bootstrap p -value
$g(y_{1990})$ vs. $f(y_{1965})$	0.0022
$g(y_{1990})$ vs. $f(y_{1965} \times EFF)$	0.0074
$g(y_{1990})$ vs. $f(y_{1965} \times TECH)$	0.0366
$g(y_{1990})$ vs. $f(y_{1965} \times KLACC)$	0.3688
$g(y_{1990})$ vs. $f(y_{1965} \times EFF \times TECH)$	0.0502
$g(y_{1990})$ vs. $f(y_{1965} \times EFF \times KLACC)$	0.4012
$g(y_{1990})$ vs. $f(y_{1965} \times TECH \times KLACC)$	0.8780

Notes: We used the bootstrapped Li (1996) Tests with 5000 bootstrap replications and the Sheather and Jones (1991) bandwidth

the distribution. Neither change in efficiency nor technical change contributed to shifting the distribution of labor productivity. Here we use the same data and the bootstrapped version of the Li (1996) test to distinguish the component (set of components) that contributes to overall changes in the distribution of labor productivity.²⁰ Table 2 presents the results of the bootstrapped test of equality of distributions. The distributions of labor productivity in 1965 and 1990 are statistically different. Neither efficiency change nor technological change alone can make the 1965 distribution closer to that of 1990. They can do so only in combination with physical capital deepening. What is remarkable though is that physical capital deepening alone statistically shifts the distribution of labor productivity between 1965 and 1990.

Badunenko, Henderson and Zelenyuk (2008) updated the Kumar and Russell study by considering a more recent time period, 1992-2000 and using a wider sample (approximately 50%) that includes 22 transitional countries. They discovered an apparent structural change in the growth process in the 1990s. By comparing the 1992–2000 results to the 1965–2000 results, Badunenko, Henderson and Zelenyuk (2008) concluded that the major fall in efficiency and rise in technology components happened during the final decade (Table 3). The predominant contribution of physical capital deepening therefore was before 1990. Figure 6, a replication of Figure 6 in Badunenko, Henderson and Zelenyuk (2008) shows that technological change made most countries richer. Table 4

²⁰ Kumar and Russell (2002) used the Li (1996) test with asymptotic critical values. Briefly, the idea of the Li (1996) test is the following: if f and g are two distributions, this statistic tests the null hypothesis $H_0 : f(x) = g(x)$ for all x , against the alternative $H_1 : f(x) \neq g(x)$ for some x .

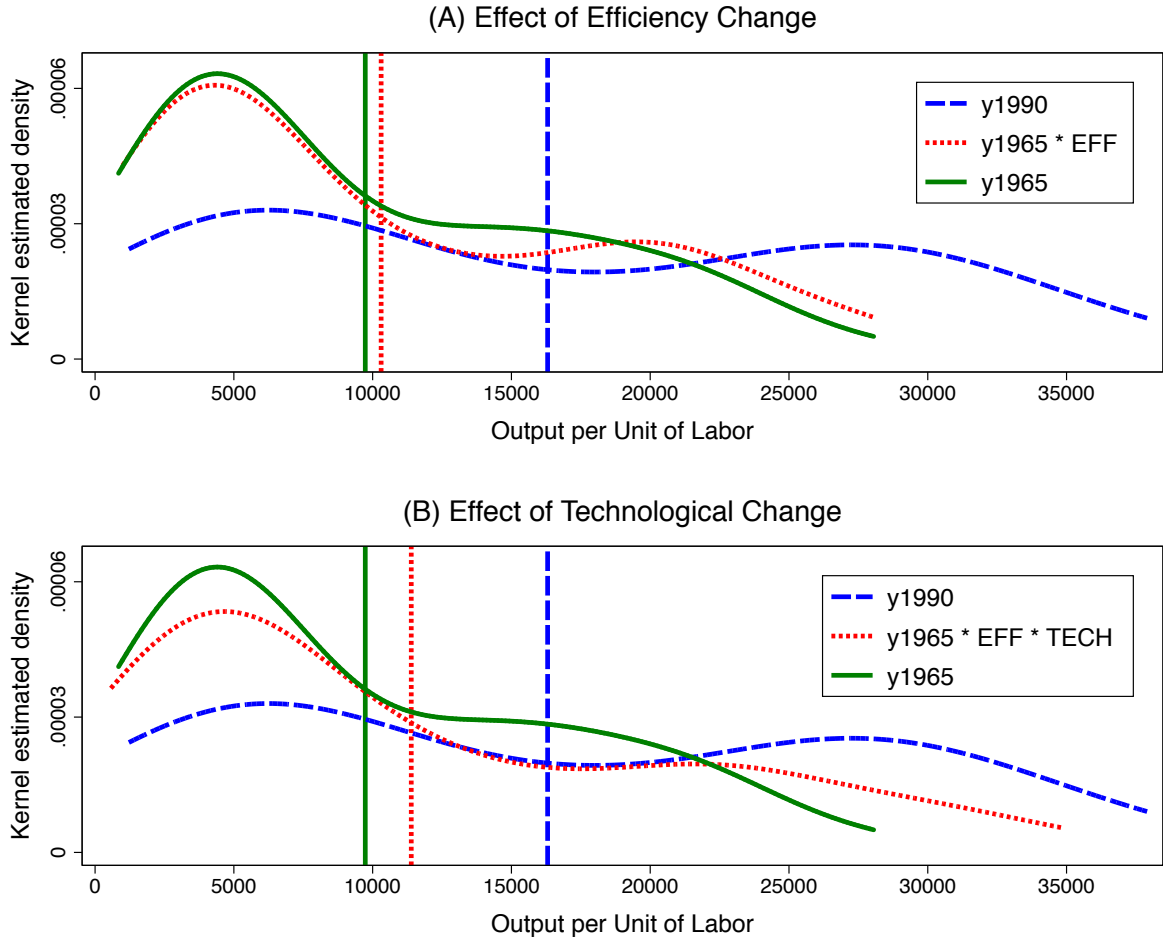


Figure 5: Counterfactual Distributions of Labor productivity, a Replication of Figure 9 in Kumar and Russell (2002)

confirms that it is technological change that shifted the labor productivity of 1992 to that of 2000. Neither efficiency change nor physical capital deepening alone or in combination were responsible for the shift in the sample of countries and the periods they considered.

4.3.1 Role of Human Capital

Many empirical growth researchers have focused on the important role played by human capital in the growth process. This motivated Henderson and Russell (2005) to incorpo-

Table 3: Mean Percentage Change of the Tripartite Decomposition Indexes for Kumar and Russell (2002) Sample, a Replication of the Last Rows of Table A1 and B1 in Badunenko, Henderson and Zelenyuk (2008)

Time period	Labor Productivity change	$(EFF - 1) \times 100$	$(TECH - 1) \times 100$	$(KLACC - 1) \times 100$
1992–2000	13.2	−3.2	7.3	9.0
1965–2000	88.9	−9.7	13.3	84.7

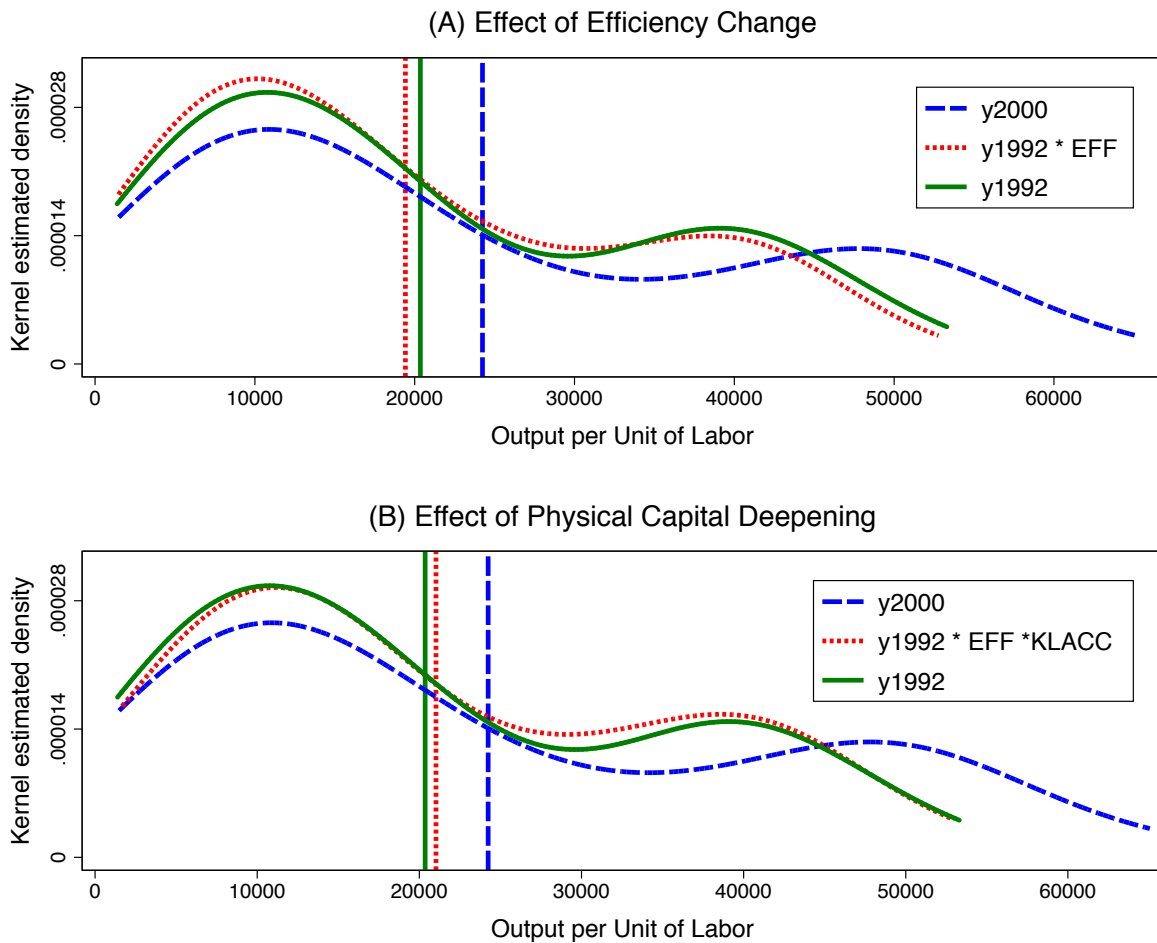


Figure 6: Counterfactual Distributions of Labor productivity, a Replication of Figure 6 in Badunenko, Henderson and Zelenyuk (2008)

rate human capital into the Kumar and Russell framework.²¹ They adopted a standard

²¹ Henderson and Russell (2005) used Barro and Lee (2001) education data and the Psacharopoulos (1994) survey of wage equations evaluating returns to education and followed Hall and Jones (1999)

Table 4: Distribution Hypothesis Tests (p -values), a Replication of Results of Table 4 in [Badunenko, Henderson and Zelenyuk \(2008\)](#)

H_0 : Distributions Are Equal	Bootstrap
H_1 : Distributions Are Not Equal	p -value
$g(y_{2000})$ vs. $f(y_{1992})$	0.0824
$g(y_{2000})$ vs. $f(y_{1992} \times EFF)$	0.0504
$g(y_{2000})$ vs. $f(y_{1992} \times TECH)$	0.9786
$g(y_{2000})$ vs. $f(y_{1992} \times KLACC)$	0.0754
$g(y_{2000})$ vs. $f(y_{1992} \times EFF \times TECH)$	0.9722
$g(y_{2000})$ vs. $f(y_{1992} \times EFF \times KLACC)$	0.0576
$g(y_{2000})$ vs. $f(y_{1992} \times TECH \times KLACC)$	0.8601

approach in the literature (e.g., [Lucas, Jr., 1988](#); [Klenow and Bils, 2000](#); [Hall and Jones, 1999](#)) and assumed that human capital entered the technology as a multiplicative augmentation of physical labor input. This labor-augmenting human capital specification reflects the idea that human capital captures the ‘efficiency units of labor’ embedded in raw labor (see [Weil, 2014](#)). This allowed [Henderson and Russell \(2005\)](#) to decompose labor productivity growth into four components, including human capital deepening (see pp. 1178–1180 in [Henderson and Russell, 2005](#), for details),

$$\frac{y_c}{y_b} \equiv \widehat{EFF}^{bc} \times \widehat{TECH}^{bc} \times \widehat{KLACC}^{bc} \times \widehat{HLACC}^{bc}, \quad (12)$$

where the \widehat{HLACC}^{bc} term represents a contribution to labor productivity growth between time period b and time period c , attributable to human capital deepening.²² The authors also constructed the worldwide technology that precluded technological implosion ([Diewert, 1980](#)) by including past observations in current period frontier estimation.

By accounting for human capital, [Henderson and Russell \(2005\)](#) showed that compared to [Kumar and Russell \(2002\)](#), the mean contribution of physical capital deepening decreased from 58% to 40%. Meanwhile, 16% of productivity growth on average was explained by human capital deepening (Table 5). They also argued that roughly one-third of the

to construct human capital. Data on output, capital stock and labor came from PWT, Mark 5. The data set includes 52 countries, 5 fewer than the [Kumar and Russell \(2002\)](#) data set because data on human capital were not available for some countries.

²² Note a slight change in notation relative to the previous literature: we added L (use $HLACC$ instead of $HACC$), to emphasize the way human capital is accounted for in the model—as a multiplicative augmentation of L (see [Henderson and Russell, 2005](#), for details).

Table 5: Mean Percentage Change of Tripartite and Quadripartite Decomposition Indexes, 1965-1990, a Replication of Two Last Rows of Table 3 in [Henderson and Russell \(2005\)](#)

Decomposition	Labor Productivity change	$(EFF - 1) \times 100$	$(TECH - 1) \times 100$	$(KLACC - 1) \times 100$	$(HLACC - 1) \times 100$
Tripartite	78.6	3.9	9.6	58.0	
Quadripartite	78.6	0.7	7.1	40.5	16.6

growth of productivity attributed to physical capital deepening by [Kumar and Russell \(2002\)](#) was in fact attributable to human capital deepening.

Moreover, [Henderson and Russell \(2005\)](#) confirm that both growth and bimodal polarization are driven by physical capital deepening to a large extent. Specifically, physical capital deepening alone did not change the shape of the labor productivity distribution from uni-modal to bimodal (Figure 7). It did so only in combination with technological change or human capital deepening. The joint contribution of physical capital deepening and human capital deepening in [Henderson and Russell \(2005\)](#) is essentially the contribution of physical capital deepening in [Kumar and Russell \(2002\)](#).

Table 6 contains the results of the bootstrapped [Li \(1996\)](#) test for equality of the counterfactual distributions and the actual 1990 distribution. Table 7 contains results of the [Silverman \(1981\)](#) multimodality test to statistically assess which component (or set of components) causes bimodality in the 1990 productivity distribution. Physical capital deepening does not play the dominant role in overall change in the distribution between 1965 and 1990. Only in combination with technological change or human capital deepening—but not when it is combined with efficiency changes—does physical capital deepening transform the distribution to be bimodal. The hypothesis that the 1990 distribution has one mode is rejected at the 1% significance level. None of the components alone can account for the emergence of bimodality in the distribution at even the 5% significance level. Efficiency changes in combination with physical capital deepening or human capital deepening indicate the emergence of bimodalism. Without efficiency changes and physical capital deepening or efficiency changes and human capital deepening technical change does not add to the transformation of the 1965 productivity distribution from uni-modal to bimodal in 1990.

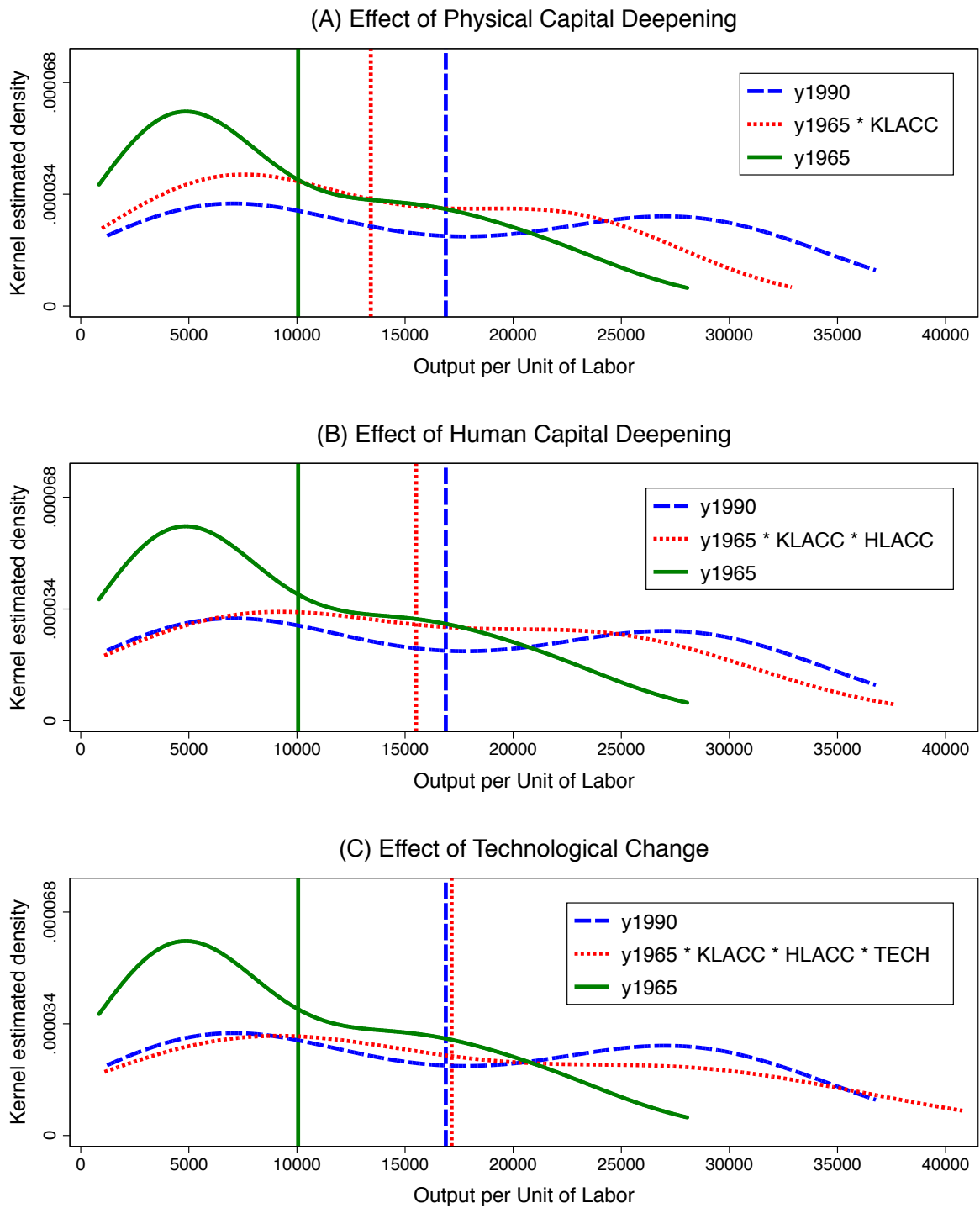


Figure 7: Counterfactual Distributions of Labor productivity, a Replication of Figure 10 in Henderson and Russell (2005)

Table 6: Distribution Hypothesis Tests (p -values), a Replication of the Results of Table 7 in Henderson and Russell (2005)

H_0 : Distributions Are Equal	Bootstrap
H_1 : Distributions Are Not Equal	p -value
$g(y_{1990})$ vs. $f(y_{1965})$	0.0036
$g(y_{1990})$ vs. $f(y_{1965} \times EFF)$	0.0024
$g(y_{1990})$ vs. $f(y_{1965} \times TECH)$	0.0266
$g(y_{1990})$ vs. $f(y_{1965} \times KLACC)$	0.0664
$g(y_{1990})$ vs. $f(y_{1965} \times HLACC)$	0.0348
$g(y_{1990})$ vs. $f(y_{1965} \times EFF \times TECH)$	0.0094
$g(y_{1990})$ vs. $f(y_{1965} \times EFF \times KLACC)$	0.0118
$g(y_{1990})$ vs. $f(y_{1965} \times EFF \times HLACC)$	0.0042
$g(y_{1990})$ vs. $f(y_{1965} \times TECH \times KLACC)$	0.9348
$g(y_{1990})$ vs. $f(y_{1965} \times TECH \times HLACC)$	0.0700
$g(y_{1990})$ vs. $f(y_{1965} \times KLACC \times HLACC)$	0.5156
$g(y_{1990})$ vs. $f(y_{1965} \times EFF \times TECH \times KLACC)$	0.4782
$g(y_{1990})$ vs. $f(y_{1965} \times EFF \times TECH \times HLACC)$	0.2314
$g(y_{1990})$ vs. $f(y_{1965} \times EFF \times KLACC \times HLACC)$	0.0634
$g(y_{1990})$ vs. $f(y_{1965} \times TECH \times KLACC \times HLACC)$	0.8830

Table 7: Modality Tests (p -values), a Replication of the Results of Table 6 in Henderson and Russell (2005)

H_0 : Distribution Has One Mode	Bootstrap
H_1 : Distribution Has More Than One Mode	p -value
$f(y_{1965})$	0.458
$f(y_{1990})$	0.010
$f(y_{1965} \times EFF)$	0.091
$f(y_{1965} \times TECH)$	0.839
$f(y_{1965} \times KLACC)$	0.097
$f(y_{1965} \times HLACC)$	0.338
$f(y_{1965} \times EFF \times TECH)$	0.155
$f(y_{1965} \times EFF \times KLACC)$	0.020
$f(y_{1965} \times EFF \times HLACC)$	0.042
$f(y_{1965} \times TECH \times KLACC)$	0.072
$f(y_{1965} \times TECH \times HLACC)$	0.663
$f(y_{1965} \times KLACC \times HLACC)$	0.076
$f(y_{1965} \times EFF \times TECH \times KLACC)$	0.030
$f(y_{1965} \times EFF \times TECH \times HLACC)$	0.218
$f(y_{1965} \times EFF \times KLACC \times HLACC)$	0.000
$f(y_{1965} \times TECH \times KLACC \times HLACC)$	0.149

In a more recent study, [Badunenko, Henderson and Russell \(2013\)](#) use the [Henderson and Russell](#) decomposition and data for 1965–2007²³ to provide new findings on the causes of polarization (the emergence of bimodality) and divergence (increased variance) of the world productivity distribution. The deterioration of efficiency in the 1990s documented in [Badunenko, Henderson and Zelenyuk \(2008\)](#) continued to an extent that efficiency change has become the unique driver of the emergence of a second mode. This suggests that economies operating at low capital-labor ratios were lagging behind those with high capital intensity, and most of the benefits of technical progress accrued to rich countries that pushed the technological frontier forward.

4.3.2 Preliminary Summary

The reader of this paper might have noticed by now that the conclusions about sources of productivity change as well as driving forces behind the shift and transformation of the distribution of productivity levels vary with decomposition and time period. In particular, several interesting observations are worth summarizing here before going further.

First, irrespective of the decomposition, physical capital deepening seems to be the major proximate cause of productivity growth during 1965–1990. This holds true whether the original sample of 57 nations is considered or wider sample of 98 nations. However, the magnitude of this cause abates by about a third once productivity decomposition accounts for human capital. Moreover, although physical capital deepening remains the strongest force, human capital deepening is a very important cause of productivity growth. Furthermore, physical capital deepening together with efficiency change were responsible for the transformation of the cross-country distribution of productivity levels from being uni-modal in 1965 to bimodal in 1990. On the other hand, neither technological change, nor human capital deepening nor their combination made the 1965 distribution bimodal.

Second, while the predominant contribution of physical capital deepening to productivity growth was before 1990, the 1990s seem to have brought about structural change in the growth process, where technological change started to play a more prominent role (in a statistical sense). Moreover, efficiency change became more substantial contributor to the growth of productivity.

²³ The data on 98 economies for output, capital stock and labor came from PWT, Version 6.3 and for human capital, [Badunenko, Henderson and Russell \(2013\)](#) used [Barro and Lee \(2013\)](#) education data.

Third, during the 2000s, efficiency changes solidified as a unique driver of the emergence of a second (higher) mode. Technological change and human capital deepening were also significant factors explaining this change in the distribution (most notably the emergence of an even longer right-hand tail).

Finally, the reviewed studies indicate that the time-period matters for conclusions. This is encouraging since it helps mark the structural changes in growth patterns.

4.4 Growth and Convergence of Labor Productivity at the Regional Level

In addition to studies that look at performance of national economies, numerous studies investigated performance and within-country convergence of regions. Here we list several examples.

[Henderson, Tochkov and Badunenko \(2007\)](#) analyze growth pattern across Chinese provinces. The distribution of labor productivity is found to be multimodal. Over the period 1978–2000, physical capital deepening was the major driving force behind the growth performance of Chinese provinces and it contributed the most to the shift of the labor productivity distribution, whereas minimal technological progress and human capital deepening were key factors responsible for regional disparities in China.

[Delgado-Rodríguez and Álvarez Ayuso \(2008\)](#) first perform the [Kumar and Russell](#) and MPI decompositions analysis for 15 EU member states, which comprised the integrated European economy over the time period 1980–2001 and then related the components to initial labor productivity level and private, public, and human capital in a panel data setting. Physical capital deepening played the leading role in labor productivity growth throughout, followed by technological improvements in the 1990s. The authors found that in the middle and the end of the observed time period, less productive economies tended to grow faster than more productive counterparts, supporting the convergence of EU member states.

[Badunenko and Tochkov \(2010\)](#) perform a comparative analysis of regional growth and convergence in China, Russia and India over the period 1993–2000 and that wealthy regions were largely responsible for rapid growth in all three countries. For China and India, physical capital deepening was identified as the major determinant of regional growth. In Russia, physical capital deepening impeded positive changes in labor productivity, leaving technological change as the only source of regional growth.

Enflo and Hjertstrand (2009) investigated Western European regional productivity growth and convergence. The authors found that most of the 69 regions in five different countries had fallen behind the production frontier and that physical capital deepening prevented convergence in labor productivity.

Badunenko and Romero-Ávila (2014) found that physical capital deepening was the primary contributor to productivity growth of Spanish regions from 1980–2003, closely followed by human capital deepening and technological change. They also found evidence that many regions fell behind the production frontier and higher efficiency losses exhibited by rich regions in fact drove productivity convergence.

4.5 Statistical Inference

Earlier studies that use nonparametric production frontier measurement have largely ignored the issue of statistical inference when identifying the sources of labor productivity growth. Indeed, the individual and average components found in these papers are point estimates obtained relative to the finite sample DEA estimate of the true and unobserved frontier.

Using the finite sample estimate implies that the efficiency scores and consequently the components of MPI decomposition are subject to sampling variation of the estimated frontier. Simar and Wilson (1999) developed bootstrap methods to provide statistical inference regarding MPI and its components. Jeon and Sickles (2004) extended it for bootstrapping the Malmquist-Luenberger productivity index and its components in OECD and Asian economies while taking explicit account of environmental waste byproducts.

Meanwhile, Henderson and Zelenyuk (2007) used several statistical methods for inference on efficiency scores and convergence of national economies, further extending the framework of Kumar and Russell (2002) and Henderson and Russell (2005). One of the novelties of their approach was to allow for a group-wise heterogeneous data generating process: they assumed that while countries share the same global frontier, the distribution of efficiencies might differ between some groups, such as developed and developing countries. Specifically, the authors first performed a smooth bootstrap to correct for small-sample bias of efficiency estimates in the sample of countries used in Henderson and Russell (2005). Interestingly, such correction of the bias suggested that most countries experienced substantially greater inefficiency than previously reported. For example, the average efficiency dropped from 63% to 53%, and more so for some countries. In-

deed, some surprisingly frontier-defining countries from earlier studies, such as Sierra Leone, appeared with more plausible levels of inefficiency (70% rather than 100%). The second bootstrap-based procedure the authors deployed was for testing distributions of DEA-estimated efficiency, due to [Simar and Zelenyuk \(2006\)](#). Here, the authors concluded that the distributions of efficiencies were statistically and substantially different between groups (developed vs. developing countries) in any considered time periods, yet those distributions did not change significantly over time for any particular group they considered. The third bootstrap-based procedure the authors used was for inference on aggregate (weighted) efficiency scores, due to [Simar and Zelenyuk \(2007\)](#), to allow for an adequate account of the economic weights (in terms of relative GDP) of countries whose efficiency scores were aggregated into a group efficiency. With this procedure, the authors concluded that the developed countries were significantly and substantially more efficient than the developing countries, in both considered periods (1965 and 1990). Moreover, they also found some evidence for what they called ‘efficiency convergence,’ both for the entire sample and within each group.

Recently, [Daskovska et al. \(2010\)](#) extended the bootstrapping methods for MPI further, to account for possible temporal correlation in the data for constructing prediction intervals of the MPI. The authors first consider MPI decomposition where components possess the circularity property, i.e. $I^{t,t+2} = I^{t,t+1} \times I^{t+1,t+2}, \forall t$ ([Pastor and Lovell, 2007](#)). Then they introduce a dynamic procedure for forecasting MPI. Finally, inference on the forecasted MPI was made by extending the smoothed bootstrap procedure in [Simar and Wilson \(1999\)](#) for the sample of industrialized economies used in [Färe, Grosskopf, Norris and Zhang \(1994b\)](#).

More recently, [Badunenko, Henderson and Houssa \(2014\)](#) make use of the bootstrap method in [Simar and Wilson \(1999\)](#) to provide statistical inference regarding the growth components of the [Henderson and Russell \(2005\)](#) quadripartite decomposition to analyze the sources of growth in Africa for the period 1970–2007 using data on 35 African countries.²⁴ On average (Table 8), physical capital deepening seemed to be the largest factor behind growth (contribution of 67%) followed by human capital deepening (60%). However, considering statistical inference, physical capital deepening was not statistically different from 0 even at the 10% level of significance, while human capital deepening was

²⁴ [Badunenko, Henderson and Houssa \(2014\)](#) follow [Simar and Wilson \(1999\)](#) and use a smoothed bootstrap, where the assumption that the density of efficiency scores is independent of the distributions of inputs and outputs needs to be maintained. This assumption can be confirmed using a test of independence ([Wilson, 2003](#)). For the sample of 35 African countries in [Badunenko, Henderson and Houssa \(2014\)](#), the null hypothesis of independence was not rejected.

Table 8: Mean Percentage Change of Quadripartite Decomposition Indexes in African Countries, 1970–2007, a Replication of Table 2 in [Badunenko, Henderson and Houssa \(2014\)](#)

Group	Productivity change	$(EFF - 1) \times 100$	$(TECH - 1) \times 100$	$(KLACC - 1) \times 100$	$(HLACC - 1) \times 100$
Mean	54.18	-38.21	1.53	67.35	60.19

Bold implies significance at 1% level

statistically significant at the 1% level. [Badunenko, Henderson and Houssa \(2014\)](#) showed that ignoring statistical inference leads to falsely concluding that physical capital deepening was a major economic engine in Africa when it was not (see [Pritchett, 2000](#), for discussion of the effect of capital on growth). For other regions of the world, physical capital deepening was a large and significant contributor to productivity growth elsewhere, but not in Africa.

4.6 Growth and Convergence of Labor productivity using Stochastic Frontier Methods

In this review, we have chosen to focus mostly on DEA-based approaches to analyze productivity growth and its convergence. However, we acknowledge that economic growth within a production frontier framework can also be analyzed using a Stochastic Frontier Approach (SFA). We therefore mention a few key studies in this vein.

The first work to note in the area is due to [Hultberg, Nadiri and Sickles \(1999\)](#), who proposed a dynamic model that considers technology diffusion and possible inefficiency caused by institutional rigidities. Applying the model to a total of 40 countries in three regions, Europe, Latin America and East Asia, the authors found that difference to a leader nation in terms of labor productivity was a significant source of growth during the period 1960–1985, which can be interpreted as realizing the catching-up potential described in [Abramovitz \(1986\)](#).

In a related and follow-up study, [Hultberg, Nadiri and Sickles \(2004\)](#) argued that technology transfer from a leading economy effects followers productivity growth in manufacturing sectors in particular, and GDP in general. They also analyzed the catch-up in labor productivity across manufacturing sectors and GDP for 16 OECD nations for the period 1960–1985. *Inter alia*, they found that catch-up rates are underestimated in aggregate studies due to failure to account for heterogeneity of technology levels and

that institutional factors such as bureaucratic efficiency are important determinants of the estimated catch-up rates.

Meanwhile, [Kumbhakar and Wang \(2005\)](#) suggested to decompose TFP growth into technical change, technological catch-up, and scale related components of TFP growth using a stochastic frontier panel data model. One important contribution of the authors is that their specification accounts for country-specific effects, which as econometric analysis suggests, are present. Ignoring heterogeneity tends to underestimate the catch-up rate (see also [Hultberg, Nadiri and Sickles, 2004](#)) and overestimate technical regress. For 82 countries over the period 1960–1987, they estimated the annual average decline in TFP to be about 1.5% (approximately 33% over 27 years). Moreover, their method attributed this drop to technological regress of about 3.1% per year and movement away from optimal scale by 2.5% annually (approximately 57% and 49% over whole period, respectively). They also concluded that countries got closer to the production frontier on average by 4.2% per year (approximately 203% over the entire time period).

Recently, [Sickles, Hao and Shang \(2014\)](#) performed model averaging using various weighting schemes in the TFP decomposition framework for Asian economies for the time period 1980–2000. They found that the TFP changed annually by 1.56% over 31 years, which was driven by technological change of 1.63% and hindered by deteriorating technical efficiency of 0.07% per annum.

Most recently, [Sickles, Hao and Shang \(2016\)](#) consider the period 1960–2010 for 24 OECD countries and revisited the decomposition of the TFP index into components attributable to technical change and catch-up, using a different approach. Specifically, they consider three competing stochastic panel data models and then instead of choosing the best, they combine estimates by weighting them using the method proposed in [Hansen \(2007\)](#).²⁵ [Sickles, Hao and Shang \(2016\)](#) find that the annual TFP growth of 1.13% (approximately 75% over 50 years) occurred mostly due to technological progress of 1.04% per year (approximately 67% over 50 years). Meanwhile, they concluded that catch-up comprised only 0.09% per year or approximately 4.6% over 50 years. Other studies of productivity measurement making use of model averaging approaches include [Isaksson, Sickles and Shang \(2016\)](#) and [Duygun, Isaksson, Hao and Sickles \(2016\)](#). For more discussions and details, see Chapter 16 of [Sickles and Zelenyuk \(2017\)](#).

Finally, a concomitant stream of literature worth mentioning here—as the one that yet to realize its potential for analyzing cross-country productivity change and its decompositions—delves into the theory and estimation of dynamic adjustments in a SFA framework. This

²⁵ A similar approach was suggested by [Sickles \(2005\)](#) for efficiency estimation of panel data.

important segment of literature goes back at least to Chang and Stefanou (1988), Luh and Stefanou (1991) and Sickles and Streitwieser (1998) and revisited more recently by Silva and Stefanou (2003, 2007), Rungsuriyawiboon and Stefanou (2007), Lansink, Stefanou and Serra (2015) and Silva, Lansink and Stefanou (2015). See Chapter 16 of Sickles and Zelenyuk (2017) for further details on dynamic modeling.

5 Concluding Remarks and Future Directions

Measuring productivity and understanding the patterns of its growth is important for connecting a number of macroeconomic trends such as current and potential income levels, poverty, wage determination, social stability, etc. Estimating productivity growth and its sources is not an easy task. Models of differences in performance of national economies depend on assumptions about (the changes in) macroeconomic behavior such as saving rates and technology. Many such approaches exist and the results depend upon the method applied and sample period under investigation.

As is true for virtually any study, the results of the reviewed studies may need to be taken with a grain of salt. First, the decompositions put forward in the literature are not necessarily unique and should labor productivity or MPI be broken down differently, different conclusions might follow (see discussion in Ray and Desli, 1997 and Färe, Grosskopf, Norris and Zhang, 1997). Second, the level of aggregation of variables typically used in cross-country and regional comparisons hide growth patterns at the industry level, where technical change and its dissemination might play a more important role than it does at the aggregate level. Third, average performance is an important benchmark and additional and valuable insights can be gained from using aggregate productivity measures where averaging of individual scores is done with weighting, where weights account for the economic importance of each individual (Zelenyuk, 2006; Henderson and Zelenyuk, 2007; Simar and Zelenyuk, 2007; Mayer and Zelenyuk, 2014). Fourth, as Badunenko, Henderson and Houssa (2014) note, the significance of the components is paramount for making conclusions that are useful for policy makers. Most importantly, the temporal correlation present in the data needs to be taken into account for making consistent statistical inference. Kneip, Simar and Wilson (2015) suggest a method for making inference about mean efficiency levels. A natural extension would be to adopt this method to provide inference regarding the mean of components of the growth decomposition. Moreover, testing for the structure of the technology, such as returns to scale or convexity, cannot be neglected when analyzing differences in growth based on production frontiers (Kneip, Simar and Wilson, 2016). Sixth, Alam and Sickles (2000) developed a time-series

methodology to link efficiency, convergence, and cointegration measures, while [Ahn and Sickles \(2000\)](#) consider frontier model in which firm-specific technical inefficiency levels are autoregressive (applied to the U.S airline industry). These interesting methodologies can be applied to the cross-country analysis as well, thus adding novelty to the stream of literature we focus on.

Furthermore, while the current literature we focused on here gave interesting insights about differences in the productivity of nations, many important aspects have been left out and naturally call for further research. Other important aspects include proper accounting of dynamic adjustments (e.g., [Silva et al., 2015](#)), accounting for the problem of the uneven process of technological diffusion ([Andrews et al., 2015](#); [OECD, 2016](#)), and accounting for the influence of ICT and e-commerce (especially due to ‘Googlization’ and various Internet-based social networks) which have been among the key engines of the recent developments of nations, yet rarely considered directly in productivity studies.²⁶ Finally, the suggested components of growth are proximate causes.²⁷ To better understand the patterns of growth, the fundamental causes should gain more attention. [Mastromarco and Simar \(2015\)](#), for example, use a nonparametric two-step approach on conditional efficiencies to investigate how foreign direct investment (FDI) and time affect the process of catching up. Each of these issues suggests possible areas for fruitful future research.

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²⁶ For related discussion e.g., see [Brynjolfsson and Hitt \(2000\)](#); [Jorgenson \(2001\)](#); [Zelenyuk \(2014\)](#).

²⁷ Exception in this line of research is [Badunenko and Romero-Ávila \(2013\)](#), who investigate the role of changes in financial system, quality of institutions and legal environment in labor productivity growth.

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