Labor Productivity and Technology Heterogeneity*

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Abstract

This paper investigates the role of technology club heterogeneity in economic growth and convergence. To do so, we break up labor productivity change into three factors – efficiency, technological, and capital-labor ratio changes – while distinguishing the impact of technology club heterogeneity respectively. This allows us to observe what is happening within and between clubs; as well as between the world and club technologies. Our labor productivity decomposition is nonparametric in nature and thus overcomes the issue of specifying functional forms for the club technologies. Our results reveal the existence of technology heterogeneity and divergence: the world technology is defined by advanced and rich countries; there exists intra-convergence phenomena (mostly due to capital-labor ratio change), but inter-convergences (owning to capital-labor ratio and technological changes) are not found. Finally, we argue that follower and marginalized countries have adopted imitating strategies, but with respect to different dimensions, namely technological change or capital-labor ratio.

Keywords: labor productivity; economic growth; technology heterogeneity; production-frontier analysis.

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1 Introduction

There has been considerable empirical research on countries' economic growth with the view of answering two questions: first, whether there is a tendency for their respective growth to converge over time, and second, how the sources of economic growth contribute to the convergence process. Besides shedding light on the economic growth process, these questions are relevant to policy targeting. This paper mainly contributes to answering the latter question.

There exist two main conceptual approaches to these questions : exogenous growth theory, initiated by Solow (1956), points out that technological progress is the source of growth, while endogenous growth theory, initiated by Romer (1986) and Lucas (1988), emphasizes differences in technology across countries and over time. Practically, exogenous growth models are easier to deal with as they consider a linear growth process, whereas endogenous growth models consider non-linearities and multiple regimes or clubs. Unsurprisingly, these approaches have contrary answers to the above questions: the former sees convergence resulting from capital accumulation, whereas the latter sees lack of convergence owing to technology heterogeneity.

Endogenous growth theory, however, acknowledges that convergence of countries within technology regime or club is possible (Azariadis and Drazen 1990; Durlauf and Johnson 1995; Bernard and Durlauf, 1996; Galor 1996). Club convergence theory is founded on strong empirical evidence rather than theoretical models as is the case of exogenous growth theory. This strong empirical evidence, starting with Quah (1993), and espoused by Galor (1996), Jones (1997), and Johnson (2005), showed that labor productivity distribution is bimodal, and hence suggested that the world is divided into a poor and a rich 'club'. Yet, since Quah's contribution, advanced and tailored analyses have claimed evidence of more 'clubs'.[1] Whatever, while it is generally admitted that there is a club of rich countries, poor countries would seem to be categorized into sub-groups, namely marginalized, followers, and emerging countries, on the basis of additional variables, such as human capital (Durlauf and Johnson, 1995; Kalaitzidakis et al., 2001; Castellacci and Archibugi, 2008), institutional factors (Alfo et al., 2008), geographical characteristics (Bloom et al., 2003), trade status

[1] Such club heterogeneity is not only true for contemporaneous data. For example, Clark and Feenstra (2001) found evidence that incomes per capita diverged more around the world after than before 1800, due mostly to increasing differences in the efficiency of economies. Allen (2012) also showed evidence of group heterogeneity.

(Rodriket al., 2004), and ownership (Maasoumi et al., 2007; He and Walheer, 2019). The goal is to choose variables that capture initial structures since countries with similar structural characteristics could be expected to converge to a similar steady state equilibrium, despite different initial conditions (Kormendi and Meguire, 1985; Grier and Tullock, 1989).

In many cases, econometric and statistical methods based on the first (or second) moment are used to determine whether countries tend to converge over time, and the relative contribution of economic growth sources to the growth process. Typical examples thereof are cross-section and panel regressions, used by Baumol (1986) and Barro (1991), and followed by increasingly more advanced (and complex but tailored) statistical and econometric tools (e.g. Magnus et al., 2010; Mirestean and Tsangarides, 2016; Moral-Benito, 2016). In the context of club technology heterogeneity, plenty of empirical works have shown that there is strong parameter heterogeneity in cross-country or panel type growth regressions (Durlauf and Johnson, 1995; Desdoigts, 1999; Masanjala and Papageorgiou, 2004; Owen et al., 2009). Advanced and tailored methods have also been used in the context of club heterogeneity (Bloom et al., 2003; Canova, 2004; Alfo et al.,2008). A broad overview of econometric and statistical methods for empirical growth can be found in Durlauf et al. (2005).

In practice, econometric and statistical methods require to specify particular assumptions about the growth process. It is necessary to choose a particular functional form for the technology captured by a specific production function; often, though, more assumptions are needed, such as assumptions about technological change, market structure, market imperfections, returns-to-scale nature. Choosing a functional form for the technology is not insidious and may have important impacts on the empirical analysis. Moreover, empirical evidence has shown that the growth process may be too complex to be captured by methods focusing on the first (or second) moment. This evidence dates to Quah's critique pointing out that empirical works should focus on the entire distribution. Also, the use of more sophisticated statistical methods often requires relatively large samples and, given the limited number of countries in the world, such techniques can 'ask a lot of the available'.[2] In the context of technology heterogeneity, this problem becomes more complex since several production functions have to be specified. Moreover, even when strong arguments are found to choose

[2]Calibration is another alternative method (Graham and Temple, 2006), but it implies subjective judgment.

specific functional forms, it could be computationally cumbersome when the sample size is small and/or the number of parameters is large.

An increasingly popular alternative is to adopt a non-parametric model.[3] This was suggested by Kumar and Russell (2002), who promoted the Farrell's (1957) deterministic production-frontier method to analyze the economic growth process. In practice, data are used to reconstruct a world frontier that may be different over time. These authors' approach is linked with the exogenous growth theory for considering a common world technology, but also with the endogenous one since the world technology differs over time. They obtain a tripartite decomposition of labor productivity into efficiency change, technological change, and capital-labor accumulation without assuming any particular structure for the growth process. Simple as it is, this approach has yielded interesting results: technological catch-up has not contributed to convergence; technological change is decidedly non-neutral; and both growth and bimodal polarization are driven primarily by capital deepening.

Kumar and Russell's initial work has received some attention in the literature and has been extended to include more components in the decomposition: human capital (Henderson and Russell, 2005), financial development (Badunenko and Romero-Avila, 2013), region heterogeneity (Filippetti and Peyrache, 2015), sector heterogeneity (Walheer, 2016), and energy (Walheer, 2018b). These extended specifications have confirmed Kumar and Russell's initial findings, while highlighting the relative contribution of their added component(s) to the economic growth and convergence questions. At this point, it is important to notice that these extended models require specific assumption in order to include their additional variable, such as modeling human capital as an augmented factor of labor, financial inclusion as an augmented factor of physical capital, or energy as a production factor. These additional assumptions often lack theoretical foundation. The initial and extended models have been used, for instance, in Enflo and Hjertstrand (2009), Badunenko and Romero-Avila (2013), Badunenko et al. (2013), and Walheer (2016b).

In this paper, we introduce technology heterogeneity in Kumar and Russell's production-frontier approach. That is, instead of reconstructing a common world technology, we recognize that countries may have access to different technology over time. Our extension is based on the argument that technology difference is a ma-

[3]See, for example, Fiaschi and Lavezzi (2007), Maasoumi et al. (2007), Henderson et al. (2012), Henderson et al .(2013), and the literature cited therein.

jor factor of growth differences across countries (Bernard and Jones, 1996; Prescott, 1998; Hall and Jones, 1999; Gong and Keller, 2003). The argument was taken over in Kumar and Russel's initial work, admitting that their method based on a common world technology fails to capture the true technology for low level of capital per worker. Moreover, we consider the standard production process with labour and capital used to generate output, and recognize the importance of additional variables by using them when defining the technology clubs. By doing so, we follow the common practice in macroeconomic empirics while acknowledging the indirect impact of other important variables. This also avoids making additional (unverifiable) assumption(s) about the growth process.

We obtain a new decomposition of labor productivity distinguishing changes in efficiency, technological, and capital-labor ratio inside the clubs, and the gaps between the clubs and the world technology for these three dimensions.[4] In other words, the new decomposition offers the advantage of making out what is happening within and between clubs. Using our new decomposition enables us to answer several additional empirical questions. First, we can verify each component's effect on economic growth and contribution to the convergence/divergence process within and between clubs. It has been acknowledged that potential economic growth can be drastically different inside each club (Kormendi and Meguire, 1985; Grier and Tullock, 1989). Second, we can investigate whether one club dominates in terms of technology, and whether the other clubs exploit their backwardness position by imitating new technologies produced in the dominant club. It is often argued that advanced countries are the leader in terms of technology, while developing countries with enough technology capabilities adopt imitating strategies. Next, our paper gives more clues about the theoretical foundations of the existence of technology clubs. That is, whether it is capital accumulation, efficiency, or technological change that explains the existence of clubs, and how these dimensions evolve over time (Azariadis and Drazen, 1990; Wang et al., 2018).

The rest of the paper is structured as follows. In Section 2, we decompose labor productivity change into several explanatory components, and investigate the role

[4]Several recent works have considered the connection between a global technology and national ones: Andrews et al. (2015) and OECD (2016) report considerable divergence between the productivity performance of global frontier firms, Inklaar and Diewert (2016) measures the gap between the actual world productivity and the potential level of world productivity in a given time-period, and Walheer (2018a) shows important technology heterogeneity between European sectors.

of each component in the convergence/divergence of countries. In Section 3, we summarize our main findings and present our conclusions.

2 Empirical investigation

Assume we observe a balanced panel of n countries during T periods of time, where each country produces output Y_t using labor L_t and capital K_t at time t. In other words, the production process is defined by $\langle Y_t, L_t, K_t \rangle$. These three variables are constructed according to the common practice. Data are taken from the most recent Penn World Table.[5] We obtain a sample of 81 countries for the time span 1965–2014.

Our aim is to analyze and decompose the change in labor productivity, denoted by $y_t = \frac{Y_t}{L_t}$ at time t, between the initial time period (1965) and the final time period (2014). We start off presenting preliminary results when technology heterogeneity is left out of consideration. We then introduce this option when decomposing labor productivity into different factors, and eventually, study their role in the convergence/divergence process.

2.1 Preliminary results

Figure 1 presents the labor productivity distributions for the initial and final time periods.[6] Here, we see the transformation of the world labor productivity distribution from a uni- to a multi-modal distribution. To formally test whether this observation is statistically true, we rely on the calibrated Silverman's (1981) test for multimodality.[7] We cannot reject the hypothesis that the 1965 labor productivity distribution has more than one mode ($p-$value is 0.69). On the contrary, this hypothesis is rejected for both 1990 and 2014 ($p-$values are 0.02 and 0.01). The world therefore is divided into different groups or clubs. Quah (1993) refers to this stylized fact as "two-club"

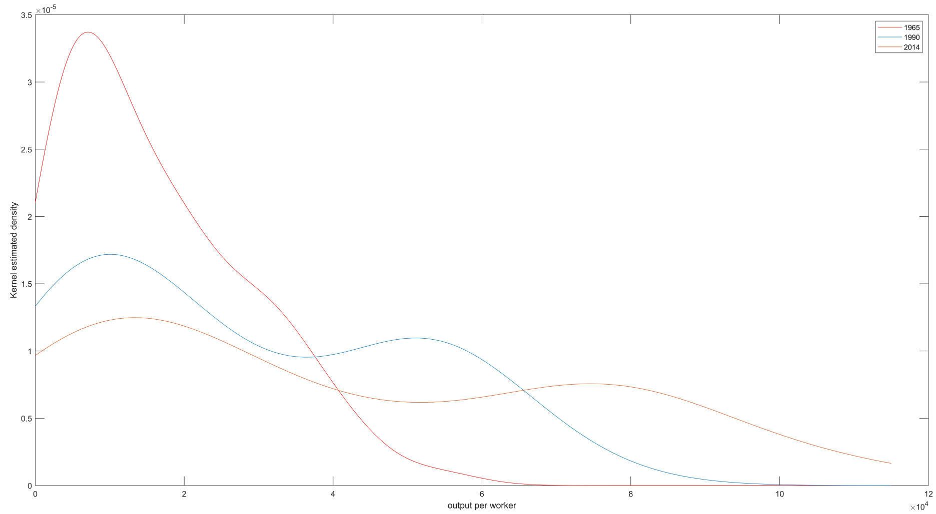
[5]In particular Penn World Table 9.0 is used. See Feenstra et al. (2015) for more detail. Data can be freely downloaded at www.ggdc.net/pwt. See, for example, Badunenko and Romero-Avila (2013), who have considered a setting very close to ours, for detailed explanations about how the three variables are defined and obtained.

[6]For comparison, we also plot the distribution in 1990 which is the last year in the initial work of Kumar and Russell (2002).

[7]H_0: the distribution has one mode; H_1: the distribution has more than one mode. In practice, it is advised to use the bootstrapped version of the calibrated Silverman's (1981) test due to Hall and York (2001). In this paper, we use a level of 5% (unless otherwise stated).

or "twin-peak" convergence.[8]

Figure 1: World labor productivity distributions



A direct implication of this stylized fact is the suspicion of empirical analyses based on the first moment (or even higher moments) of the labor productivity distribution. This implication represents one of Kumar and Russell's major arguments to propose a tripartite decomposition of labor productivity change since, contrary to other (parametric) approaches, it examines the "dynamics of the entire cross-section distribution". This stylized fact has also served as a main reason to partition countries into different groups or clubs since the initial work of Durlauf and Johnson (1995).

Another advantage of Kumar and Russell's labor productivity decomposition is that no functional assumptions are required about the growth process. Instead, a nonparametric reconstruction of the technology, defined by a production possibility set, is adopted. Formally, observed data are used to reconstruct the production process for every time period. It appears that the reconstructed world technology is common to countries, but may vary over time. To avoid a trivial reconstruction and to match with previous works on economic growth modeling, we assume that the reconstructed production possibility set is monotone, convex, and satisfies constant returns-to-scale. In addition, we consider that technological degradation is not possible over time (Henderson and Russell, 2005) by adopting a sequential reconstruction

[8] We observe that this stylized fact is not dependent of the test used. For instance, Krause (2016) used other tests to investigate the existence of multiple modes. This finding remains valid.

of the production process (Diewert, 1980).[9] Formally, the reconstructed production possibility set is given for time t as follows:

$$T_t = \left(\begin{array}{c} (Y, L, K) \mid Y \leq \sum_{\tau=1}^{t} \sum_{j=1}^{n} \lambda_{j\tau} Y_{j\tau}, L \geq \sum_{\tau=1}^{t} \sum_{j=1}^{n} \lambda_{j\tau} L_{j\tau}, \\ K \geq \sum_{\tau=1}^{t} \sum_{j=1}^{n} \lambda_{j\tau} K_{j\tau}, \lambda_{j\tau} \geq 0 \ \forall j, \forall \tau. \end{array} \right). \tag{1}$$

A first reason that could explain the transformation of the labor productivity distribution in Figure 1 is the countries' output generation capacities. That is, whether countries combine their production factors efficiently or whether there are potential output improvements. A natural and well-established indicator to measure the output efficiency behavior of countries is the notion of Debreu (1951)–Farrell (1957) efficiency ratio. It is defined for a specific country operating at (Y_t, L_t, K_t) as follows:

$$e_t(Y_t, L_t, K_t) = \min \left\{ e \mid \left(\frac{Y_t}{e}, L_t, K_t \right) \in T_t \right\}. \tag{2}$$

$e_t(Y_t, L_t, K_t)$ is the inverse of the maximal amount that output Y_t can be expanded while keeping the inputs (L_t and K_t) constant. $e_t(Y_t, L_t, K_t) \leq 1$ and $e_t(Y_t, L_t, K_t) = 1$ means that the maximal amount of output is produced at time t. A smaller value of $e_t(Y_t, L_t, K_t)$ implies more inefficient behavior. Geometrically, it is the distance to the frontier of the reconstructed production possibility set T_t. In practice, it is computed using a linear programming.[10] Empirical distributions are given in Figure 2.

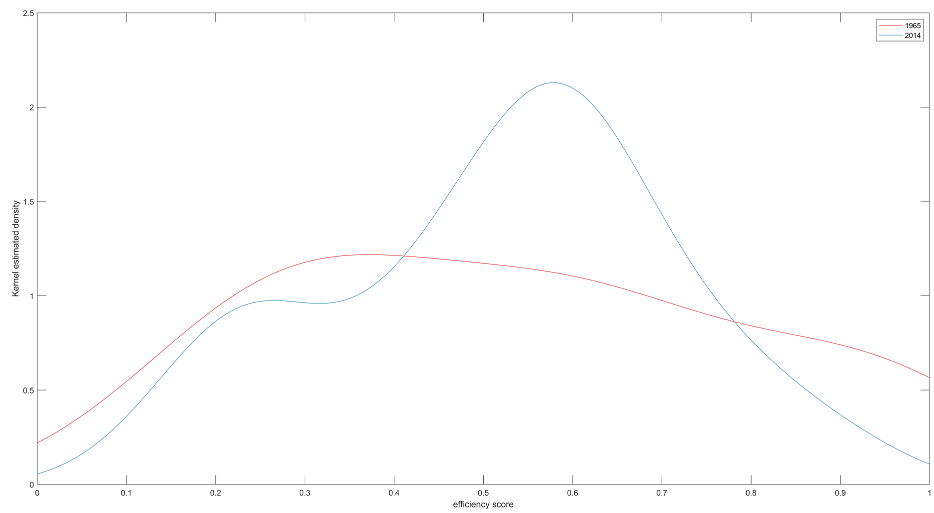
The median has slowly increased from 1965 to 2014 (0.51 to 0.55), while the average is barely smaller (0.54 to 0.52); see Table 1. This reveals that the distribution has moved to the right, but some countries still have a low level of efficiency. The averages and the medians give us two different stories about efficiency change between 1965 and 2014. These results again confirms the Quah's critique that relying on specific statistics/moments of the distribution may hide the true results. This is confirmed by the $p-$values of the Silverman's test (0.36 and 0.06 for 1965 and 2004, i.e. two modes in 2014 and one in 1965). To verify whether the efficiency distribution has moved

[9] We can verify that technological degradation is impossible for T_t by noting that previous observations are included in (1) avoiding an implosion of T_t.

[10] At this point, it is fair to highlight that the deterministic nature of the nonparametric approach makes the results sensitive to the presence of outliers and measurement errors resulting in the potential presence of a (downward) bias. Well-established procedures have been suggested to remove (or, at least, reduce) this bias (Daraio and Simar, 2007). In practice, efficiency scores are computed using sub-samples; the final efficiency scores are obtained as the average of the sub-sample counterparts.

to the right, we make used of the nonparametric Kolmogorov–Smirnov (KS) test.[11] The $p-$value is 0.00 confirming the improvement between the two years. Therefore, although more efficiency behavior may partly explain why labor productivity has improved, we argue in what follows that this is not the main reason.

Figure 2: World efficiency score distributions



Whereas previous works have assumed that clubs have access to the same (world) technology, captured here by the common reconstructed production possibility set T_t, these preliminary results about labor productivity distributions and efficiency behavior overall highlight the existence of groups or clubs. admittedly, if Kumar and Russel (2002) and followers recognized the existence of clubs, they do not propose a systematic way to take this important feature into account. They merely suggest computing averages and medians of the efficiency scores when partitioning countries into different categories using subjective judgments (e.g. OECD, Non-OECD, Latin and Central America, Africa, EU15). While these (a-posteriori) partitions highlight interesting patterns, more can be done.

2.2 Technology clubs

A major departure of our approach is to recognize that clubs may have access to different technologies. Based on our preliminary results, a natural start would be to

[11] H_0: two distributions are equal; H_1: one distribution is larger than another.

partition countries into 'rich' and 'poor' ones. This dualistic partitioning not only lacks foundation but relies on subjective judgment; where indeed lies the cut-off point between 'rich' and 'poor' countries? Studies about technology clubs, besides, have often highlighted the existence of more than two clubs. More precisely, if the distinction between rich and poor countries is hardly contentious, the latter are generally subdivided into sub-groups.

Whereas, in practice, the countries' technology level is not considered, various options are available to partition countries into technology clubs. Makenew sentence anc clarify link with what precedes which, generally, can be synthesized in two steps. Incomplete sentence First step, choosing a particular statistical methodology. Popular methods for that step include various clustering methods: (Canova, 2004; Castellacci and Archibugi, 2008), regression tree method (Durlauf and Johnson 1995), threshold regression (Hansen, 2000), the projection pursuit technique (Desdoigts 1999), techniques based on polynomial functions (Durlauf et al. 2001) or based on multivariate test for stationary (Corrado et al. 2005), latent structures (Alfo et al., 2008), the log t method (Phillips and Sul, 2007; Schnurbus et al., 2017). Second step, selecting variables to quantify the initial structure of the countries (e.g. human capital, GDP per capita, literacy rates).[12]

It has recently been argued that two main dimensions can capture countries' technology level (Howitt, 2000; Howitt and Mayer-Foulkes, 2005; Castellacci, 2008, 2011; Stokke, 2008; Castellacci and Natera, 2016): their innovative ability, measured by the number of patents and the number of scientific articles per capita; and their absorptive capacity, measured by the level of human capital and technological infrastructures (fixed telephony, electricity, computers, Internet users).[13] Note that this approach is theoretically justified within the Schumpeterian multiple equilibria endogenous growth models where three groups are highlighted: an innovation,

[12]Note that several authors have suggested using other variables to identify countries' initial conditions. Examples include institutional factors (Alfo et al., 2008), social conditions (Apergis, 2015), geographical characteristics (Bloom et al., 2003), trade status (Rodriket al., 2004), and group belonging (Maasoumi et al., 2007). As our purpose is to measure countries' technology level, we have left out these additional variables, which can easily be added if needed.

[13]Data for the number of patents are taken from Registered Patent Database of the United States Patent and Trademark Office; data for the number of scientific articles per capita are taken from the World Development Indicators (https://datacatalog.worldbank.org/dataset/world-development-indicators). Data for the literacy rate are taken from World Development Indicators; the other variables to measure human capital come from Barro and Lee (2013). All variables to measure technological infrastructures are taken from the World Development Indicators.

an implementation and a stagnation group (Howitt, 2000; Galor, 2005; Howitt and Mayer-Foulkes, 2005; Acemoglu et al., 2006).

Given our two dimensions and the nonparametric spirit of our empirical approach, we use a classification and regression tree analysis (CART) for each time period. This is a flexible non-parametric method of cluster analysis (Durlauf and Johnson, 1995). Contrary to regression-based techniques, the CART is a data-driven technique as it does not impose any a-priori structure on the data. Moreover, the number of clusters/clubs is identified endogenously and not imposed ex-ante; this is important when we are not sure about the exact number of clubs. Finally, since we run a CART for each time period, the number of clubs may evolve over time and countries are allowed to move from one club to another.

The general idea of CART is to construct a hierarchical classification where each step of the algorithm splits a group into two sub-groups (nodes) based on one single predictor variable. The starting point is to define the largest possible tree without assessing a cost for splitting. Next, the algorithm regroups similar nodes by defining a cost associated with each successive split and by minimizing the misclassification rate. This method has been used, for example, by Castellacci (2008, 2011), Stokke (2008), Castellacci and Natera (2016), in similar contexts. They also obtain three clubs even if our datasets and sample sizes are different.

We obtain three technology clubs for every time period labeled 'Advanced', 'Followers', and 'Marginalized' using the innovative ability and absorptive capacity in the CART.[14] The absorptive capacity highlights the marginalized countries and the innovation ability allows us to distinguish the followers from the advanced countries. The clubs for the starting and ending time periods are given in Table 2. This also specifies when the club switch happens, if at all. Advanced countries perform well in terms of both innovative ability and absorptive capacity; follower countries have low innovative ability but relatively high absorptive capacity; and marginalized economies are poor in both aspects. Club membership is quite stable and club switchers have no important impact on our results since they do not define the club or world frontiers.

Without claiming that this partitioning is the only valid one, it is coherent with the literature and common practice, but also provides interesting results. Nevertheless, relying on a single method and a single specification to define the clubs is clearly risky in this context as cluster methods are known to be rather sensitive techniques.

[14]In practice, these dimensions are obtained using a principal component analysis.

To verify whether our results are robust to a methodology or specification changes, we do our exercise again. First, we keep the CART but use different predictor variables. We select variables that have the largest correlations with the dimensions: literacy rate for the absorptive capacity, and the number of scientific articles per capita for innovative ability. Second, we use two alternative cluster methodologies: the hierarchical agglomerative and the K-means. The main idea of the former is to regroup similar countries based on a similarity matrix, while the latter minimizes within-cluster variances. All these new specifications give us three clubs and a rather stable membership. In fact, countries that define the frontier always belong to the same club. Indeed, given our nonparametric reconstruction of the technologies, only countries that define the frontier can have a direct impact on our overall results.

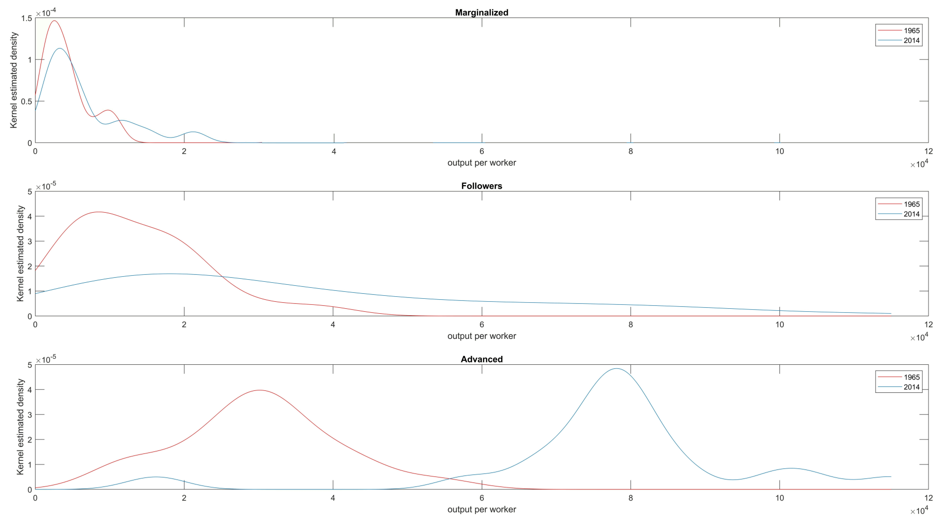
As an initial step, we present the labor productivity distributions of our three technology clubs in Figure 3; descriptive statistics for the three clubs are provided in Table 3. Two main lessons, confirming our grouping choice, arise from these distributions. First, one mode is found for all club-level labor productivity distributions for the initial and ending year. The $p-$values of the Silverman tests are 0.19 and 0.48 for the marginalized club, 0.43 and 0.95 for the followers, and 0.62 and 0.64 for the advanced club, in 1965 and 2014, respectively. Note that the $p-$values increase between both years meaning that countries are more homogeneous in 2014 than in 1965. Next, for advanced countries and the followers ($p-$values of KS tests are 0.00 in both cases), there is a clear labor productivity improvement, while this is not so clear for marginalized countries (the $p-$value is 0.35). It turns out that labor productivity differences seem closely related to technology heterogeneity.

It is fairly straightforward to extend the nonparametric reconstruction approach when countries are partitioned into technology clubs. Let us assume that we have I technology clubs where each club contains n_i countries ($\sum_{i=1}^{I} n_i = n$). In line with our approach to defining T_t in (1), we reconstruct (sequential) club-specific production possibility sets. We obtain for club i at time t:

$$T_t^i = \left(\begin{array}{c} (Y, L, K) \mid Y \leq \sum_{\tau=1}^{t} \sum_{j=1}^{n_i} \lambda_{j\tau} Y_{j\tau}, L \geq \sum_{\tau=1}^{t} \sum_{j=1}^{n_i} \lambda_{j\tau} L_{j\tau}, \\ K \geq \sum_{\tau=1}^{t} \sum_{j=1}^{n_i} \lambda_{j\tau} K_{j\tau}, \lambda_{j\tau} \geq 0 \; \forall j, \forall \tau. \end{array} \right). \tag{3}$$

The corresponding efficiency measurement for a country operating at (Y_t, L_t, K_t)

Figure 3: Club labor productivity distributions



is given at time t by

$$e_t^i(Y_t, L_t, K_t) = \min\left\{e^i \mid \left(\frac{Y_t}{e^i}, L_t, K_t\right) \in T_t^i\right\}. \tag{4}$$

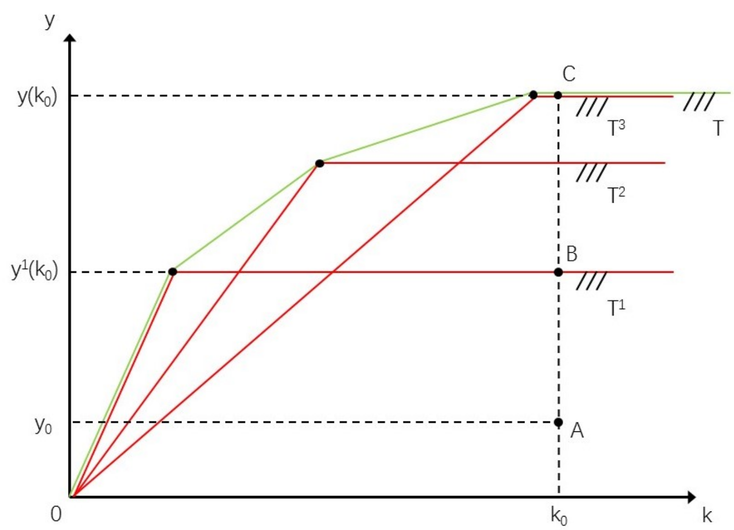
$e_t^i(Y_t, L_t, K_t)$ has to be interpreted as $e_t(Y_t, L_t, K_t)$ but when countries are partitioned into technology clubs. It implies that $e_t^i(Y_t, L_t, K_t) \leq 1$, with $e_t^i(Y_t, L_t, K_t) = 1$ reflects optimal output production, and $e_t^i(Y_t, L_t, K_t) < 1$, potential output improvement with fixed inputs with respect to technology of club i. Descriptive statistics are given in Table 1. This time, both the averages and medians tell us the same story: there is an efficiency progress for the followers, but not for the marginalized and advanced countries. This implies the presence of a catching-up effect for the followers. Next, the efficiency level shows us that the advanced countries are more homogeneous in terms of efficiency. Moreover, the p-values of the Silverman and KS tests for the three efficiency distributions reveal that they have moved to a unimodal distribution reflecting a common change in the club; contrary to the world distribution that is bi-modal as discussed above.[15]

The world- and club-level reconstructed production possibility sets (T_t and T_t^i)

[15]The $p-$values of the Silverman tests are 0.06 and 0.57 for the marginalized club, 0.17 and 0.65 for the followers, and 0.08 and 0.72 for the advanced club in 1965 and 2014, respectively. The $p-$values of KS tests are 0.7699 for the marginalized, 0.03 for the followers, and 0.80 for the advanced.

and efficiency measurements ($e_t(Y_t, L_t, K_t)$ and $e_t^i(Y_t, L_t, K_t)$) are related. First, the reconstructed world production possibility set is fully defined when knowing the club-specific counterparts. This is illustrated in Figure 4 with the case of three distinct technology clubs (named 1, 2, and 3).[16]

Figure 4: World and club technologies



A first and important observation is that the world reconstructed production possibility set is defined as the union of the club counterparts. Indeed, T is defined by T^1 for low capital per worker values, then by T^2 for middle-income, and, finally, by T^3 for higher values. Next, efficiency measurement is always smaller when considering the world than the club technologies. Formally, we obtain the following:

$$T_t = \bigcup_{i=1}^{I} T_t^i. \tag{5}$$

$$e_t^i(Y_t, L_t, K_t) \leq e_t(Y_t, L_t, K_t). \tag{6}$$

To illustrate this result, let us take a particular country that uses k_0 to produce y_0 at point A in Figure 4. Assume also this country belongs to club 1. This country's efficiency measurement with respect to T^1 is therefore captured by the distance AB.

[16]In that Figure, we use our assumption of constant returns-to-scale by redefining the production process as $\langle y_t, k_t \rangle$, where $y_t = \frac{Y_t}{L_t}$ and $k_t = \frac{K_t}{L_t}$ are the output and capital per worker. Also, the potential outputs per worker with respect to the world and club technology are defined as $y(k_t) = y_t/e_t(Y_t, L_t, K_t)$ and $y^i(k_t) = y_t/e_t^i(Y_t, L_t, K_j)$, respectively.

When considering the world technology, efficiency is larger and captured by the distance AC. This implies that when considering the world technology, we exaggerate its inefficiency behavior. The distance between both efficiency measurements is of great interest for economic growth empirics. It captures the efficiency gap due to technology differences. It is given as follows:

$$g_t^i(Y_t, L_t, K_t) = \frac{e_t(Y_t, L_t, K_t)}{e_t^i(Y_t, L_t, K_t)}. \tag{7}$$

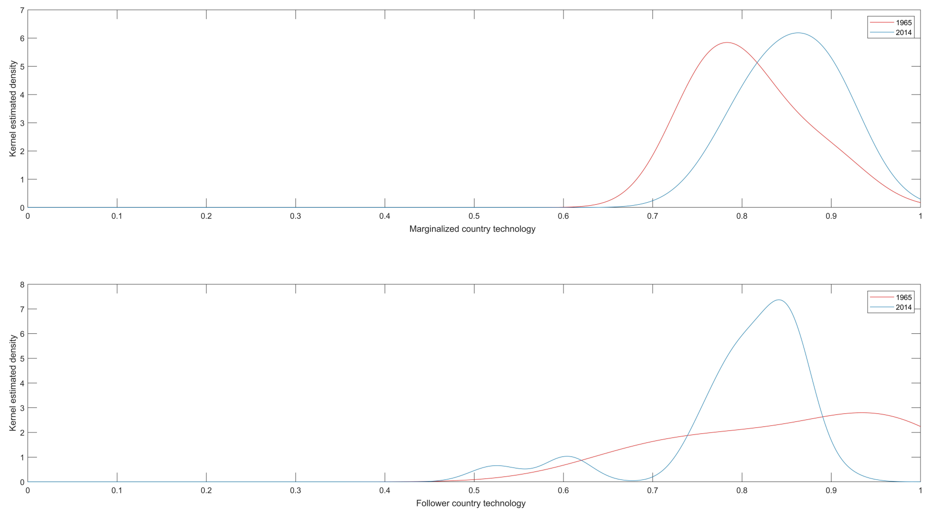
$g_t^i(Y_t, L_t, K_t)$ is the efficiency gap for a country operating at (Y_t, L_t, K_t) at time t. When $g_t^i(Y_t, L_t, K_t) = 1$, it reveals that $e_t(Y_t, L_t, K_t) = e_t^i(Y_t, L_t, K_t)$. That is, it shows an absence of gap. Smaller values imply greater efficiency difference between the club and world technology for a country operating at (Y_t, L_t, K_t) at time t. This gap defines a useful decomposition of the efficiency measurement:

$$e_t(Y_t, L_t, K_t) = e_t^i(Y_t, L_t, K_t) \times g_t^i(Y_t, L_t, K_t). \tag{8}$$

In words, efficiency with respect to the world technology is decomposed into efficiency with respect to the club technology, and the efficiency gap between the club and world technologies. For our fictive country in Figure 4, the efficiency gap is captured by the distance BC. It is thus the part of the inefficiency behavior with respect to the world technology (AC) that is due to the technology available to club 1 (BC). The other part, therefore, is due to the country itself (AB). It appears that the efficiency gap remains even if the fictive country removes its inefficient behavior (and thus will lie at B). The only option in order to remove the efficiency gap is to move the club-level production possibility set T^1 closer to T.

We obtain efficiency gaps of unity in 1965 and 2014 for all advanced countries, i.e. advanced countries define the world technology on the entire time span 1965–2014. We therefore only present the distributions for the followers and marginalized countries in Figure 5; descriptive statistics are provided in Table 1. While both the marginalized and follower countries present a similar level of efficiency gaps (around 0.80), the marginalized group has experienced an improvement of their efficiency gap score, while followers have experienced a regression. These initial results are confirmed by statistical tests: the $p-$values for the Silverman test are 0.51 and 0.29 for marginalized countries, and 0.61 and 0.05 for the followers, in 1965 and 2014, respectively; and for the KS test, we have 0.01 for the marginalized countries and 0.42 for the followers.

Figure 5: Efficiency gap distributions



2.3 Labor productivity decompositions

We pursue our empirical investigation by introducing two additional components: technological change and capital deepening (increases in the capital−labor ratio). We have shown in the previous Section that technology heterogeneity has a clear impact on efficiency change, and suggested a useful decomposition of efficiency. We follow the same procedure for the two additional components. We obtain a new decomposition of labor productivity distinguishing club-specific factors from gaps.

Assume that we want to decompose labor productivity change $\frac{y_c}{y_b}$ between two periods of time b and c (where $b \leq c \leq T$). As an initial step, we discuss the decomposition suggested by Kumar and Russell (2002) when technology homogeneity is assumed. In practice, this is done by considering a common (time varying) world technology. The decomposition makes use of the assumption of constant returns-to-scale of the technology. The decomposition is given as follows:

$$\frac{y_c}{y_b} = EFF \times TECH \times KACC. \tag{9}$$

EFF, $TECH$, and $KACC$ denote the efficiency change, technological change, and capital deepening change between time periods b and c, respectively.

To achieve such decomposition, the starting point is the ratio of potential outputs:

$$\frac{y_c}{y_b} = \frac{e_c(Y_c, L_c, K_c)}{e_b(Y_b, L_b, K_b)} \times \frac{y_c(k_c)}{y_b(k_b)}. \tag{10}$$

As explained in the Introduction, an advantage of this approach is its ease in dealing with counterfactual variables.[17] For instance, $y_c(k_b)$ is potential output where the technology is fixed at period c and inputs at period b. Multiplying equation (10) by $\frac{y_c(k_b)}{y_c(k_b)}$ gives us:

$$\frac{y_c}{y_b} = \frac{e_c(Y_c, L_c, K_c)}{e_b(Y_b, L_b, K_b)} \times \frac{y_c(k_b)}{y_b(k_b)} \times \frac{y_c(k_c)}{y_c(k_b)} = EFF \times TECH_b \times KACC_c. \tag{11}$$

$TECH_b$ is the technological change when using k_b, and $KACC_c$ is the change in capital-labor ratio when the technology is fixed at period c. It turns out that $TECH_b$ and $KACC_c$ are path dependent: they depend on the chosen periods. Alternatively, we can obtain a second decomposition when using the counterfactual variable $y_b(k_c)$. By multiply equation (10) by $\frac{y_b(k_c)}{y_b(k_c)}$, we obtain:

$$\frac{y_c}{y_b} = \frac{e_c(Y_c, L_c, K_c)}{e_b(Y_b, L_b, K_b)} \times \frac{y_c(k_c)}{y_b(k_c)} \times \frac{y_b(k_c)}{y_b(k_b)} = EFF \times TECH_c \times KACC_b. \tag{12}$$

$TECH_c$ is the technological change when using k_c, and $KACC_b$ is the change in capital-labour ratio when the technology is fixed at period b. It turns out that $TECH_b$ and $KACC_c$ are also path dependent. Therefore, equations (11) and (12) do not yield the same results in general. The two decompositions are equal only if the neutrality of technological change is assumed (as in Solow, 1957 and many studies building on his pioneering article). To overcome the path dependence of the decomposition, we adopt the Fisher Ideal decomposition introduced by Caves et al. (1982):

$$\begin{aligned}\frac{y_c}{y_b} =& EFF \times (TECH_b \times TECH_c)^{1/2} \times (KACC_b \times KACC_c)^{1/2}, \\ =& EFF \times TECH \times KACC. \end{aligned} \tag{13}$$

[17] In practice, they are also computed using linear programming (see e.g. Walheer, 2016).

Clearly, a similar decomposition can be made when using the club technologies. Let us denote $y^i_t(k_t) = \frac{y_t}{e^i_t(Y_t,L_t,K_t)}$ for $t = \{b, c\}$ as the club-specific potential output. We obtain our two path-dependent decompositions as follows:

$$\frac{y_c}{y_b} = \frac{e^i_c(Y_c, L_c, K_c)}{e^i_b(Y_b, L_b, K_b)} \times \frac{y^i_c(k_b)}{y^i_b(k_b)} \times \frac{y^i_c(k_c)}{y^i_c(k_b)} = EFF^i \times TECH^i_b \times KACC^i_c. \tag{14}$$

$$\frac{y_c}{y_b} = \frac{e^i_c(Y_c, L_c, K_c)}{e^i_b(Y_b, L_b, K_b)} \times \frac{y^i_c(k_c)}{y^i_b(k_c)} \times \frac{y^i_b(k_c)}{y^i_b(k_b)} = EFF^i \times TECH^i_c \times KACC^i_b. \tag{15}$$

Again the path-independent decomposition is obtained by multiplying both equations and taking the geometric average:

$$\begin{aligned} PROD =& EFF^i \times \left(TECH^i_b \times TECH^i_c\right)^{1/2} \times \left(KACC^i_b \times KACC^i_c\right)^{1/2}, \\ =& EFF^i \times TECH^i \times KACC^i. \end{aligned} \tag{16}$$

The only difference between this decomposition and that in (13) is that it is based on a club technology rather than a world technology. Results for the club technology based decomposition are given in Tables 3 and 4.[18] These Tables yield several interesting findings. First, greater average labor productivity growth and capital-deepening is found for the followers, which confirms that there is a catching-up effect for these countries thanks essentially to capital-labor ratio improvement. Second, marginalized countries have the smallest labor productivity growth for the time period. Third, capital deepening and technological changes have an equal contribution, while efficiency change has a smaller (negative) one. Fourth, advanced countries present important labor productivity improvement due to a combination of positive technological and capital-labor ratio increases. Last, the medians, by contrast, show that advanced countries have the largest labor productivity growth and that technological progress is the main contributor, while efficiency change is negative.

To get a better understanding of the connection between the three clubs, we isolate the technology heterogeneity effect in each of the components in (13), which uncovers a natural and coherent connection between the world and club labor productivity growth decomposition. Let us first consider the decomposition of the efficiency change

[18] Results are presented in percentage changes in Table 4.

component using our definition of the efficiency gap in (8):

$$EFF = \frac{e_c^i(Y_c, L_c, K_c)}{e_b^i(Y_b, L_b, K_b)} \times \frac{g_c^i(Y_c, L_c, K_c)}{g_b^i(Y_b, L_b, K_b)} = EFF^i \times GEFF^i. \tag{17}$$

An overall efficiency improvement therefore can be obtained either from an efficiency improvement at the club level, i.e. $EFF^i > 1$, or when the club frontier is closer to the world one; that is when gap scores between the club and the world frontier increase, i.e. $g_c^i(Y_c, L_c, K_c) > g_b^i(Y_b, L_b, K_b)$ making $GEFF^i > 1$.

Then, to decompose $TECH$ and $KACC$, we need to relate the potential outputs based on the club and world technologies. As both have the same numerator (the actual output value), we can rewrite the gap in (7) as follows:

$$g_t^i(Y_t, L_t, K_t) = \frac{e_t(Y_t, L_t, K_t)}{e_t^i(Y_t, L_t, K_t)} = \frac{y_t/y_t(k_t)}{y_t/y_t^i(k_t)} = \frac{y_t^i(k_t)}{y_t(k_t)}. \tag{18}$$

By isolating $y_t(k_t)$ in the previous equation, we obtain a useful connection to further decompose $TECH$ and $KACC$:

$$y_t^i(k_t) = y_t(k_t) \times g_t^i(Y_t, L_t, K_t). \tag{19}$$

In words, potential output with respect to the club technology can be decomposed into potential output with respect to the world technology times a residual part capturing the gap between both technologies. Using that connection, we can decompose the technological change $TECH$ into two parts:

$$\begin{aligned} TECH &= \left(\frac{y_c^i(k_b)}{y_b^i(k_b)} \times \frac{y_c^i(k_b)}{y_b^i(k_c)}\right)^{1/2} \times \left(\frac{g_b^i(Y_b, L_b, K_b)}{g_c^i(Y_b, L_b, K_b)} \times \frac{g_b^i(Y_c, L_c, K_c)}{g_c^i(Y_c, L_c, K_c)}\right)^{1/2}, \\ &= \left(TECH_b^i \times TECH_c^i\right)^{1/2} \times \left(GTECH_b^i \times GTECH_c^i\right)^{1/2}, \\ &= TECH^i \times GTECH^i. \end{aligned} \tag{20}$$

Technology progress happens either when the club technology experiences progression, i.e. $TECH^i > 1$, or when the technology progress is faster at the club-level than at the world level lowering technology gap ratios at time c, i.e. $g_b^i(Y_c, L_c, K_c) > g_c^i(Y_c, L_c, K_c)$ and $g_b^i(Y_b, L_b, K_b) > g_c^i(Y_b, L_b, K_b)$ making $GTECH^i > 1$.

A similar decomposition can be applied to the capital deepening change $KACC$:

$$\begin{aligned}
KACC = & \left(\frac{y_b^i(k_c)/g_b^i(Y_c,L_c,K_c)}{y_b^i(k_b)/g_b^i(Y_b,L_b,K_b)} \times \frac{y_c^i(k_c)/g_c^i(Y_c,L_c,K_c)}{y_c^i(k_b)/g_c^i(Y_b,L_b,K_b)}\right)^{1/2}, \\
= & \left(\frac{y_b^i(k_c)}{y_b^i(k_b)} \times \frac{y_c^i(k_c)}{y_c^i(k_b)}\right)^{1/2} \times \left(\frac{g_b^i(Y_b,L_b,K_b)}{g_b^i(Y_c,L_c,K_c)} \times \frac{g_c^i(Y_b,L_b,K_b)}{g_c^i(Y_c,L_c,K_c)}\right)^{1/2}, \\
= & \left(KACC_b^i \times KACC_c^i\right)^{1/2} \times \left(GKACC_b^i \times GKACC_c^i\right)^{1/2}, \\
= & KACC^i \times GKACC^i. \qquad (21)
\end{aligned}$$

Capital deepening increases the overall potential output ($KACC > 1$) via two separate possible channels. First, the potential output is increased at the club level ($KACC^i > 1$). Second, as far as the technology gaps are smaller when evaluated at the new input mix (L_c, K_c), the overall potential output increases.

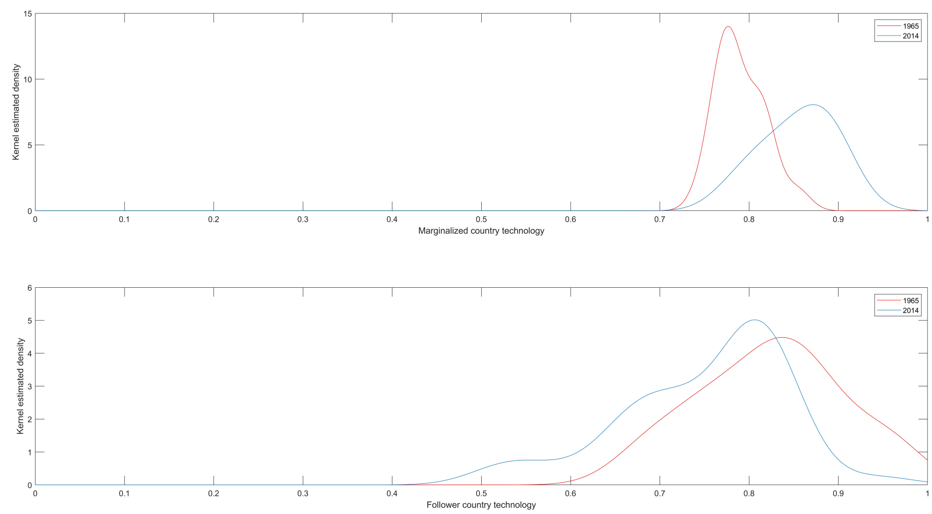
Combining all previous results yields the new extended decomposition:

$$\frac{y_c}{y_b} = EFF^i \times GEFF^i \times TECH^i \times GTECH^i \times KACC^i \times GKACC^i. \qquad (22)$$

In this decomposition EFF^i, $TECH^i$, and $KACC^i$ refer to club specific changes, while $GEFF^i$, $GTECH^i$, and $GKACC^i$ allows us to investigate what is happening between the club and the world technologies, i.e. verifying the role of technology heterogeneity. These are complementary measurements of the distance between the club and the world technologies for empirical studies.

We had found that advanced countries commonly present no gap in the efficiency dimension (Table 1). This is also almost true for the two other components (Table 4). These countries appear to be the uncontested leaders. Moreover, as concerns the technological gap, the marginalized countries show a negative change and the followers a positive one (on average -7.29% and +11.25%; see Table 4). It means that marginalized countries have a worse situation in terms of technology, while followers are closer to the world technology defined by the advanced countries. This also comes clear in Figure 6 where the technology gap distributions have moved to the right for the marginalized countries and to the left for the followers. Indeed, lowering the technology gaps means an improvement of the situation here (see (20)). We may see this finding as followers imitating the world technological progress (as defined by advanced countries). These results are confirmed by statistical tests: the $p-$values of the Silverman test are 0.81 and 0.38 for marginalized countries, and 0.48 and 0.54 for the followers, in 1965 and 2014, respectively; and for the KS test, we have 0.47 for the marginalized and 0.03 for the followers.

Figure 6: Technology gap distributions

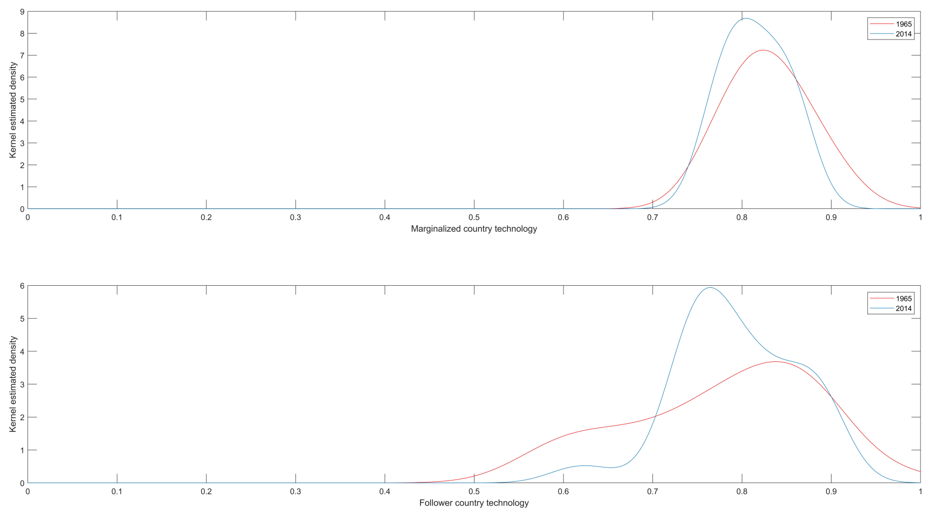


Finally, the capital-labor ratio gap distributions are given in Figure 7. Again, lowering the capital-labor ratio gap means an improvement of the situation (see (21)). There is, on average, a positive change for the marginalized countries and a negative one for the followers in that dimension (+5.65% and -1.51% and the median is +1.91% for the followers, see Table 4). This being said, a clear distribution shift is not observed in Figure 7 as confirmed by the statistical tests: the $p-$values for the Silverman test are 0.72 and 0.54 for marginalized countries, and 0.64 and 0.58 for the followers, in 1965 and 2014, respectively; and for the KS test, we have 0.55 for the marginalized countries and 0.65 for the followers. All in all, it seems that marginalized countries better perform in that dimension. Again, this may be seen as an imitation effect of the best practice in using capital-labor ratio for the marginalized club.

2.4 Convergences

The previous investigations give an overview of how labor productivity changes inside and between technology clubs, and how the efficiency, technology, and capital-labor ratio dimensions contribute to these changes. This last section investigates how each

Figure 7: Capital-labor gap distributions



component contributes to the convergence question. A major advantage of our technique is that it distinguishes the contribution of each dimension to the convergence within (intra-convergence) and between clubs (inter-convergence). In practice, we make use of GLS regressions of efficiency, technology, and capital-labor ratio change against the output per worker level in 1965. A negative (positive) slope coefficient implies that a component has a positive (negative) role in the convergence process.[19] Estimated slope coefficients and the $t-$statistics are given in Table 5.

The results for the advanced countries and followers are very similar: there are strong negative slopes for the efficiency (-0.0001 and -0.0030) and capital-labor ratio changes (-0.0040 and -0.0044), and positive ones for the technological change (0.0002 and 0.0029). Interestingly, the slope for the technological change is not significant for the advanced countries revealing technological consistency in that club (the other slope coefficients have all $p-$values of zero for the $t-$tests). The coefficient slope is significant for the followers implying that some countries are catching-up advanced countries in terms of technology, while others are lagging behind. For marginalized countries, we find that capital accumulation has played a positive role (-0.0084) and,

[19]Note that because lowering the gaps imply an improvement for the technology and capital-labor ratio gaps (it is the opposite for the efficiency gap, see our discussion of (17), (20), and (21)), the inverse values of $GTECH$ and $GKACC$ are used in the regressions to keep a coherent and comparable basis. By doing so, all slope coefficients in Table 5 can be interpreted in a similar fashion.

technological change a negative one (0.0042). It turns out that the same comment made for the followers about technological change applies to the marginalized club. The role of efficiency change is unclear for that club since the slope coefficient is not significant.

To complete our investigation, we perform multi-modality and distribution difference tests between the 2014 labor productivity distribution and counterfactual distributions obtained from adding the components one by one. Our aim is to find the counterfactual distribution that is the closest to the 2014 labor productivity distribution. Results are given in Table 6. Capital accumulation has played the major role alone, but also in combination with efficiency change. Indeed, the counterfactual distributions with capital-labor ratio alone or combined with efficiency change present more than one mode. Next, we compare the counterfactual distributions with the 2014 distribution. The major role of capital-labor ratio (combined with efficiency) is confirmed for the advanced countries, which is not surprising since these countries define the world technology. Next, the major role of capital accumulation is again found for the followers, but this time without the association of efficiency change. Finally, for marginalized countries, it is capital in association with technology change that has played the most important role. The major role of capital-labor ratio is also found in the initial work of Kumar and Russell (2002) and most of the followed works. The important role of technology change is pointed out in Badunenko et al. (2008) and Badunenko et al. (2013).

Finally, we investigate what is happening between clubs. Whereas, for the marginalized club, the efficiency and capital-labor ratio gaps appear to have positively evolved over time, and the technological gap regress over time, it is exactly the opposite for the followers. While this may be interpreted as their ability to imitate the world technology (as defined by the advanced countries), it does not say whether there is a convergence for the gap dimensions: are larger/smaller initial gap values associated with larger/smaller gap growth for each of our three dimensions ? The answer to this question would, in a sense, reveal the inter-convergence/divergence between clubs. As done earlier for labor productivity, we regress the initial value of the gap against its growth for every component. Similar patterns are found for the follower and marginalized countries. As shown in Table 5, there is a positive significant slope for the technology (9.20 and 51.96) and capital-labor ratio (68.91 and 85.42) dimensions, while the slope is negative and significant for the efficiency dimension (-86.42

and -142.80). This implies that inter-convergence is only found for the efficiency dimension.

3 Summary and conclusion

We study labor productivity changes using an original decomposition, which distinguishes club-specific factors from technology heterogeneity gaps. This yields a better understanding of the bi-modality of the world labor productivity and the existence of technology clubs. Our decomposition does not rely on any unverifiable restrictive assumption about the growth process, and, in particular, avoids defining club-specific production functions. We also use our new decomposition to study the intra- and inter-convergence phenomena.

Our exercise answers several important questions. First, we provide several strong empirical facts supporting the existence of technology heterogeneity and divergence. In particular, the world technology is defined by advanced countries, there exists intra-convergence, but inter-convergence is only found for the efficiency dimension. Next, efficiency, technological, and capital-labor ratio changes appear to have affected countries in different manners. Capital-labor ratio and technological changes are the two main factors responsible for the divergence between clubs, while capital-labor ratio is the main explanatory factor of convergence within clubs. In addition, we argue that followers and marginalized countries have adopted imitating strategies: technological change in the case of the former and capital-labor ratio in the case of the latter.

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Appendix

Table 1: Efficiency measurements and gaps

Marginalized	e_{1965}	e_{2004}	e^i_{1965}	e^i_{2004}	g^i_{1965}	g^i_{2004}
average	0.33	0.33	0.41	0.38	0.81	0.86
median	0.27	0.24	0.32	0.29	0.80	0.85
Followers	e_{1965}	e_{2004}	e^i_{1965}	e^i_{2004}	g^i_{1965}	g^i_{2004}
average	0.52	0.52	0.60	0.65	0.86	0.79
median	0.51	0.54	0.58	0.67	0.86	0.82
Advanced	e_{1965}	e_{2004}	e^i_{1965}	e^i_{2004}	g^i_{1965}	g^i_{2004}
average	0.76	0.67	0.76	0.67	1	1
median	0.73	0.64	0.73	0.64	1	1
All	e_{1965}	e_{2004}	e^i_{1965}	e^i_{2004}	g^i_{1965}	g^i_{2004}
average	0.54	0.52	0.60	0.60	0.88	0.86
median	0.51	0.55	0.58	0.63	0.92	0.85

Table 2: Technology clubs: membership and transition

Country	2014	1965	up	down
'Algeria'	Marginalized	Marginalized	-	-
'Bangladesh'	Marginalized	Marginalized	-	-
'Burkina Faso'	Marginalized	Marginalized	-	-
'Côte d''Ivoire'	Marginalized	Marginalized	-	-
'Egypt'	Marginalized	Marginalized	-	-
'Ethiopia'	Marginalized	Marginalized	-	-
'Guatemala'	Marginalized	Marginalized	-	-
'India'	Marginalized	Marginalized	-	-
'Madagascar'	Marginalized	Marginalized	-	-
'Malawi'	Marginalized	Marginalized	-	-
'Mali'	Marginalized	Marginalized	-	-
'Morocco'	Marginalized	Marginalized	-	-
'Mozambique'	Marginalized	Marginalized	-	-
'Niger'	Marginalized	Marginalized	-	-
'Nigeria'	Marginalized	Marginalized	-	-
'Pakistan'	Marginalized	Marginalized	-	-

'Senegal'	Marginalized	Marginalized	-	-
'Uganda'	Marginalized	Marginalized	-	-
'Argentina'	Followers	Followers	-	-
Bolivia'	Followers	Followers	-	-
'Brazil'	Followers	Followers	-	-
'Cameroon'	Followers	Marginalized	1990,1986,1983	1987,1984
'Chile'	Followers	Followers	-	-
'China'	Followers	Followers	-	-
Hong Kong'	Followers	Followers	2007	2009
'Colombia'	Followers	Followers	-	-
'Costa Rica'	Followers	Followers	-	-
'Cyprus'	Followers	Followers	-	-
Congo'	Followers	Marginalized	1983,1975	1976
'Dominican Republic'	Followers	Followers	-	-
'Ecuador'	Followers	Followers	-	-
'Ghana'	Followers	Marginalized	1985,1982,1975	1983,1981
'Greece'	Followers	Marginalized	1969	-
'Indonesia'	Followers	Marginalized	1971	-
Iran'	Followers	Marginalized	1980,1976,1968	1979,1969
'Ireland'	Followers	Followers	-	-
'Italy'	Followers	Followers	-	-
'Jamaica'	Followers	Followers	1974	1967
'Jordan'	Followers	Followers	1985,1974	1979,1971
'Kenya'	Followers	Marginalized	1988,1979, 1971	1987,1975, 1968
'Luxembourg'	Followers	Followers	1992	1994
'Malaysia'	Followers	Followers	-	-
'Malta'	Followers	Followers	-	-
'Mexico'	Followers	Followers	-	-
'Peru'	Followers	Followers	-	-
'Philippines'	Followers	Followers	-	-
'Portugal'	Followers	Followers	-	-
Korea'	Followers	Followers	-	-
'Romania'	Followers	Followers	-	-
'South Africa'	Followers	Followers	-	-

'Spain'	Followers	Followers	-	-
'Sri Lanka'	Followers	Followers	1973	1971
Syria'	Followers	Marginalized	1991,1985	1993,1987
'Taiwan'	Followers	Followers	-	-
'Thailand'	Followers	Followers	-	-
'Trinidad and Tobago'	Followers	Followers	-	-
'Tunisia'	Followers	Marginalized	1977	-
'Turkey'	Followers	Followers	-	-
Tanzania'	Followers	Marginalized	1981	-
'Uruguay'	Followers	Followers	-	-
Venezuela'	Followers	Followers	-	-
'Zambia'	Followers	Followers	-	-
'Australia'	Advanced	Followers	1985,1965	1964
'Austria'	Advanced	Followers	1980	-
'Belgium'	Advanced	Advanced	1991,1988	1990,1987
'Canada'	Advanced	Advanced	-	-
'Denmark'	Advanced	Advanced	-	-
'Finland'	Advanced	Advanced	-	-
'France'	Advanced	Advanced	-	-
'Germany'	Advanced	Advanced	-	-
'Iceland'	Advanced	Followers	1988	-
'Israel'	Advanced	Followers	1971	-
'Japan'	Advanced	Followers	1970	-
'Netherlands'	Advanced	Advanced	-	-
'New Zealand'	Advanced	Advanced	-	-
'Norway'	Advanced	Advanced	-	-
'Singapore'	Advanced	Followers	1986	-
'Sweden'	Advanced	Advanced	-	-
'Switzerland'	Advanced	Followers	1975	-
'United Kingdom'	Advanced	Advanced	-	-
'United States'	Advanced	Advanced	-	-

Table 3: Output and capital per worker

Marginalized	y_{1965}	k_{1965}	y_{2014}	k_{2014}	$PROD$
average	5,936.86	20,908.47	11,758.76	32,199.36	159.00
median	3,259.28	7,614.62	7,164.16	20,118.47	99.85
Followers	y_{1965}	k_{1965}	y_{2014}	k_{2014}	$PROD$
average	13,624.89	57,703.58	42,705.55	174,605.82	283.79
median	11,438.92	39,762.10	36,271.88	124,604.34	164.96
Advanced	y_{1965}	k_{1965}	y_{2014}	k_{2014}	$PROD$
average	29,929.55	108,680.48	86,059.37	332,355.39	216.68
median	30,331.63	106,784.33	87,690.53	341,733.36	186.32

Table 4: Club technology based decomposition (% change)

Marginalized	EFF	$TECH$	$KACC$	$GEFF$	$GTECH$	$GKACC$
Average	10.40	47.35	61.25	6.57	-7.29	5.65
Median	-21.17	52.72	49.66	1.93	-7.15	4.12
Followers	EFF	$TECH$	$KACC$	$GEFF$	$GTECH$	$GKACC$
Average	22.77	52.05	98.23	-5.92	11.26	-1.51
Median	10.96	43.04	66.19	-10.34	7.92	1.91
Advanced	EFF	$TECH$	$KACC$	$GEFF$	$GTECH$	$GKACC$
Average	-8.18	87.12	88.26	-0.01	0.05	-0.04
Median	-14.21	89.48	57.37	0.00	0.00	0.00

Table 5: Convergence regression slope coefficients

Intra-convergence		*efficiency*	*technology*	*capital-labor*
advanced	slope coeff.	-0.0001*	0.0002	-0.004*
	t-statistics	-5.82	1.41	-7.15
followers	slope coeff.	-0.0030*	0.0029*	-0.0044*
	t-statistics	-8.89	11.71	-4.45
marginalized	slope coeff.	-0.0002	0.0042*	-0.0084*
	t-statistics	-1.59	4.49	-1.98
Inter-convergence		*efficiency*	*technology*	*capital-labor*
advanced	slope coeff.	–	–	–
	t-statistics	–	–	–
followers	slope coeff.	-86.42*	9.20*	68.91*
	t-statistics	-4.71	3.38	3.32
marginalized	slope coeff.	-142.8*	51.96*	85.42*
	t-statistics	-4.95	9.01	7.73

Table 6: Multimodality and distribution difference tests

Multimodality tests	marginalized	followers	advanced
$y_{1965} \times EFF^i$	0.3453	0.5725	0.2332
$y_{1965} \times TECH^i$	0.3423	0.3353	0.5625
$y_{1965} \times KACC^i$	0.2232	0.0270	0.1331
$y_{1965} \times EFF^i \times TECH^i$	0.0940	0.2812	0.2762
$y_{1965} \times EFF^i \times KACC^i$	0.2682	0.2242	0.0570
$y_{1965} \times TECH^i \times KACC^i$	0.0150	0.2482	0.2232
Distribution difference with y_{2014}	**marginalized**	**followers**	**advanced**
$y_{1965} \times EFF^i$	0.3175	0.0000	0.0000
$y_{1965} \times TECH^i$	0.8800	0.0065	0.0000
$y_{1965} \times KACC^i$	0.3460	0.2150	0.0000
$y_{1965} \times EFF^i \times TECH^i$	0.8310	0.0120	0.0000
$y_{1965} \times EFF^i \times KACC^i$	0.7400	0.0135	0.0000
$y_{1965} \times TECH^i \times KACC^i$	0.0000	0.0000	0.3250