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This study provides some empirical evidence and quantification of differences in labor productivity among industries and countries. Using a recently available data base of value added per worker, country and time fixed effects are estimated first for various industries. Results are subsequently elaborated, to identify some time trends and sectoral profiles by country, which are in turn employed in a cluster analysis, summarizing some salient characteristics of industrial labor productivity in different economies.

Keywords
Labor productivity, structural change, economic dynamics, cluster analysis

JEL Codes
C23, C82, O11, O47

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1 Introduction

Labor productivity, and productivity in general, does not vary uniformly, neither across sectors, nor across countries (Duarte and Restuccia, 2010). Indeed, differential productivity growth is one key factor of structural change in the economic systems, and probably the most important one (Swiecki, 2017). Several implications of different growth rates have been investigated in the literature, e.g.: relevance and empirics of the so-called "Baumol's disease"(Baumol, 1986; Triplett and Bosworth, 2003; Young, 2014); specialization and international trade (McMillan and Rodrik, 2011; Caron and Markusen, 2014); "premature deindustrialization" (Rodrik, 2016).

However, empirical works aimed at measuring how much (labor) productivity varies by industry and region are quite limited, primarily because of the lack of a consistent data base with sufficient coverage, including developing countries and possibly informal markets. Such an high quality information source is now available (de Vries et al., 2015), and this paper exploits that data source (like in Üngör (2013)) to highlight some key characteristics of differential labor productivity growth among sectors and countries.

This source is the Groeningen Growth and Development Centre GGDC 10-Sector Database, providing a long-run internationally comparable dataset on sectoral productivity performance. It consists of series for 11 countries in Africa, 11 countries in Asia, 2 countries in the Middle East and North Africa, 9 in Latin-America, the US and 8 European countries. From the series of real value added and employment, an unbalanced panel of labor productivity annual variations, covering 10 industries, 42 countries, and ranging from 1949 to 2013, can be readily obtained.

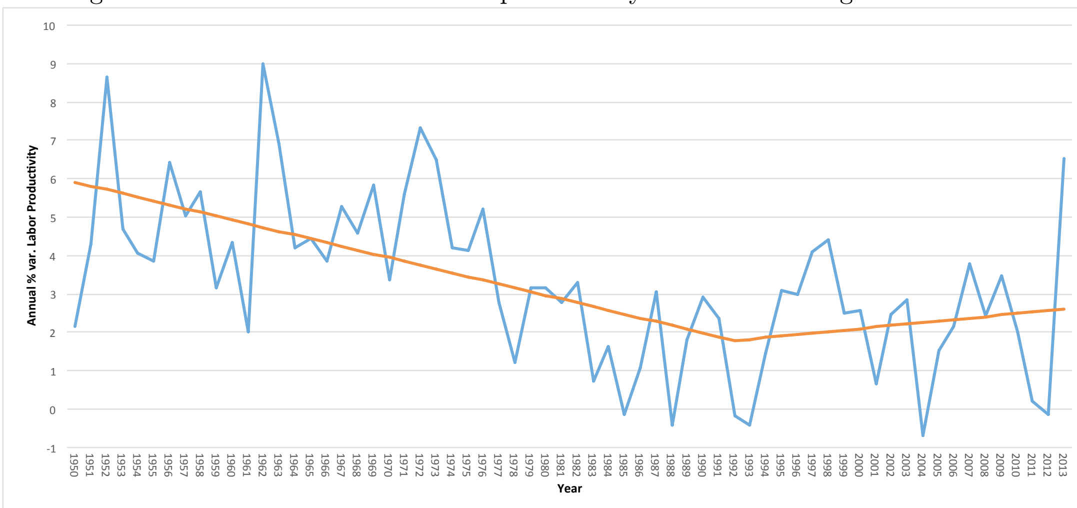
2 Methodology

Ten sectors are considered in the GGDC dataset: Agriculture, hunting, forestry and fishing (AGR); Mining and quarrying (MIN); Manufacturing (MAN); Electricity, gas and water supply (UTI); Construction (CON); Wholesale and retail trade, hotels and restaurants (TRH); Transport, storage, and communication (TRC); Finance, insurance, real estate and business services (FIN); Government services (GOV); Community, social and personal services (SER).

For each sector, an unbalanced panel of annual changes in labor productivity was employed in a fixed effects regression, aimed at deriving two sets of parameters: a series of time variables and a set of intercept parameters by country.[1] Subsequently, the time series were analyzed, to identify some trends in productivity variations. For each sector, a piecewise linear function was interpolated, as shown in Figure 1 for the case of Manufacturing. The break point is endogenously determined in each regression, so as to maximize the goodness of fit. Table 1 presents the findings in terms of: (a) slope coefficient before the break;

[1]Details of the ten panel regressions are available on request.

Figure 1: Semi-linear trend for labor productivity in Manufacturing



(b) slope coefficient after the break; (b) year of the break. A positive (negative) slope coefficient indicates accelerating (decelerating) labor productivity growth.

The fixed effects estimated at the country level account instead for some specific characteristics of the different economies, influencing the labor productivity growth in each sector, in addition to the general worldwide tendency. Therefore, it is a way of indirectly considering factors like the institutional setting, natural conditions, but also the internal composition of the sectors.

Since the fixed effects regression estimates one parameter for all regions in the 10 panels, each country is characterized by a vector of 10 parameter values, expressing its specific "productivity profile". These profiles have been the subject of a cluster analysis, aimed at finding similarities in groups of countries. To this

Table 1: Sectoral trend analysis

Sector	Slope before	Slope after	Break year
AGR	-0.006	-0.006	-
MIN	-0.032	-0.436	2004
MAN	-0.098	+0.040	2002
UTI	-0.060	-0.242	2004
CON	-0.127	+0.338	2001
TRH	-0.140	+0.022	1981
TRC	-0.030	+0.014	1981
FIN	+1.032	-0.054	1954
GOV	-0.299	-0.019	1959
SER	-0.046	+0.032	1979

Table 2: Labor productivity growth rates

Cluster	AGR	MIN	MAN	UTI	CON	TRH	TRC	FIN	GOV	SER
Rising	6.23	13.06	11.93	7.37	10.06	5.00	12.99	1.48	4.27	6.24
Steady	7.00	8.44	8.20	4.36	7.60	3.38	11.41	1.96	5.47	3.88
Lagging	5.17	5.07	5.34	2.68	5.63	0.24	9.34	-0.18	2.94	2.68
Global	*6.04*	*7.55*	*7.42*	*4.02*	*7.04*	*2.16*	*10.68*	*0.90*	*4.12*	*3.67*

end, a measure of vector distance is used, and countries are grouped in the same cluster if the distance among themselves is significantly lower that that between other countries. The data are clustered by the k-means method, using the algorithm by Hartigan and Wong (1979) as implemented in the R statistical package, which aims to partition the points into k groups such that the sum of squares from points to the assigned cluster centres is minimized. At the minimum, all cluster centres are at the mean of their Voronoi sets (the set of data points which are nearest to the cluster centre). The k-means method assumes that the number of cluster is specified beforehand. Of course, the higher the number of clusters, the lower the within-cluster distance. Starting from the case of two clusters, the number of clusters has been progressively increased, stopping the process when no significant decreases in the average internal distance were detected.

In this way, three major clusters have been identified. In one cluster, for illustrative purposes labeled “Rising”, there are several high growth countries of the Far East (including China and South Korea) and Botswana. In the second cluster (“Steady”) there are all European countries, Mauritius, Nigeria, Egypt, India, Indonesia, Japan and other Asian countries. In the remaining group (“Lagging”) we can find the U.S. (suggesting the existence of a global convergence, at least in part), all Latin America and most of the African countries.

3 Results

The primary purpose of the exercise is detecting a (short-run) trend of labor productivity growth at the sectoral level. To this aim, the last estimated values in the linear piecewise regressions, expressing the global trend in each industry, were added to the country fixed effects, and some averages have been computed. Table 2 presents those average labor productivity growth rates for the three clusters[2] and for the whole set of countries.

Since most of the works on labor productivity in the literature focus on the three macro-sectors Agriculture, Manufacturing and Services, the results could be better appreciated after weighted aggregation, using labor income industrial shares in the value added.[3] The results are presented in Table 3, including the

[2]The ten values reported in Table 2 for each cluster correspond to a geometrical “centre” for the cluster, as computed by the k-means algorithm.

[3]The shares have been obtained from the 2011 GTAP SAM, with a consistent aggregation

Table 3: Aggregated productivity growth rates

Cluster	AGR	MAN	SER	*TOT*
Rising	6.23	4.53	2.82	*8.00*
Steady	7.00	2.18	3.28	*5.93*
Lagging	5.17	1.28	1.69	*3.16*

corresponding total economy-wide productivity growth.

Several interesting considerations emerge quite naturally. First, Agriculture is always the fastest growing sector, in terms of value added per worker, at least in the time period considered. This may reflect mechanization, reduced underemployement associated with urbanization in developing countries, diffusion of fertilizers and pesticides (the "Green Revolution"). It is a well established fact that economic development is associated with a very significant reduction of employment in agriculture, whereas output in the same sector does not fall at the same rate, and sometimes it even increases. Second, labor productivity growth in Manufacturing is strongly correlated with productivity growth overall. This may suggests that Manufacturing is still, in a very specific sense, "the engine of growth" (Haraguchi et al., 2017). By contrast, mature economies in the Steady cluster are characterized by stronger productivity gains in the Services, associated with continuing improvements in Agriculture. Lagging regions are distinguished by very slow productivity increases in both Manufacturing and Services.

4 Concluding Remarks

Different economies do not simply grow at different speeds: they do so in different ways. A simple exercise has been presented in this work, where data from the GGDC 10 sectors database has been elaborated, in order to highlight some salient characteristics of the growth processes. Disentangling the contribution of the various sectors to the overall variation of (labor) productivity, and the implied changes in the structure of the economic systems, may be of fundamental importance in many theoretical and empirical studies dealing, for instance, with: conditional convergence (Sorensen, 2001; Castellacci et al., 2014), demand-driven endogenous productivity (Matsuyama, 2017), regional structural change (Fagerberg, 2000; Chen et al., 2011) , skill-based structural change (Buera et al., 2015), to name a few.

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