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The role of human capital in the structural change process

O papel do capital humano no processo de mudança estrutural

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Abstract

The objective of this paper is to verify if human capital is an important determinant of structural change in different sectors of the economy and if it can accelerate the speed of this structural transformation. This paper contributes to the literature by developing an empirical test of the model proposed by Li *et al*. (2019) and by using the GMM methodology. It also uses two proxies for human capital (average years of schooling and the Penn World Table index) and structural change (employment and added value share) in order to verify whether or not they affect the variable of interest. Results showed that human capital has an essential role in the structural transformation process of the economy, since it has an effect on the relative participation of the sectors on total added value or on total employment. Also, human capital proved to be a potential accelerator of this structural transformation.

Keywords

Human Capital, Structural Change, GMM.

JEL Codes J24, O41, C23.

Resumo

O objetivo deste artigo é verificar se o capital humano é um determinante importante da mudança estrutural nos diferentes setores da economia e se este pode acelerar a velocidade dessa transformação. Este artigo contribui com a literatura ao desenvolver um teste empírico do modelo proposto por Li et al*. (2019) e ao utilizar a metodologia GMM. O artigo também utiliza duas* proxies *para capital humano (anos médios de escolaridade e o índice* Penn World Table*) e mudança estrutural (participação do emprego e do valor adicionado), a fim de verificar se elas afetam ou não a variável de interesse. Os resultados encontrados mostraram que o capital humano tem um papel essencial no processo de transformação estrutural da economia, uma vez que afeta a participação relativa dos setores no valor agregado total ou no emprego total. Além disso, o capital humano provou-se ser um potencial acelerador dessa transformação estrutural.*

Palavras-chave

Capital Humano, Mudança Estrutural, GMM.

Códigos JEL *J24, O41, C23.*

1 **Introduction**

The structural change of a country can be understood as a process of transformation of the economy with profound implications for the growth and development of society. As industrialization and modernization take place, countries cease to be based on low-productivity agriculture and become urbanized with modern, dynamic and more technological sectors. The service sectors develop and start to play an important role in the economy, as they account for the largest share of the gross domestic product. Martins (2019) points out that generalized relocation of labor from agriculture to the service sectors has been the main driver of structural change. Human capital plays an important role in this process, since, as the educational level and the skills of the population increase, the labor productivity and the capacity for innovation exponentially develops, which accelerates the process of structural transformation of the economy. However, there is still much to be studied about the role of human capital in this process of structural transformation. As such, this assessment is the main objective of this paper.

Structural change is a process linked to the growth and development of nations as experienced over time. As countries grow richer, secular shifts can be observed in their allocation of labor and expenditure across broad sectors (Święcki, 2017). As a rule, when countries get urbanized, they first reallocate employment, production and consumption of the agricultural sector to the industrial and service sectors. Subsequently, resources are often reallocated from industry to services[1].

The reallocation of labor happens when countries begin to shift their development patterns toward more technological levels, thereby changing the participation (and importance) of agriculture, manufacturing and services in the country's economy. Not only does structural change stimulate economic growth, it can also lead to a sustained growth path (Martins, 2019). Countries that undergo changes in their productive structures, obtaining a greater participation of technology/knowledge-intensive activities, tend to observe higher economic growth (Teixeira; Queirós, 2016).

1 This is the classical definition of structural change and can be seen in more detail in the works of Kuznets (1966, 1971), Chenery and Syrquin (1975), Chenery, Robinson and Syrquin (1986).

Martins (2019) uses a data panel of 160 countries from 1991 to 2013 to analyze the determinants of structural change in the countries (dependent variable used is the between-sector productivity effect). Through a panel fixed-effects estimator, the author finds a positive effect of human capital for both the complete sample and when dividing the sample by regions. In addition, the author points out that the pace of structural change is significantly shaped by human and physical capital and that investments in education and economic infrastructure are crucial to accelerating the structural change.

In addition to sector breakdown, consideration should also be given as to how to measure structural change at the sector level. The most common measures in the literature of activity are employment shares and added value shares, two production-side measures (Van Neuss, 2019). This work follows the literature by using both proxies to analyze structural change.

Most of the literature focuses on analyzing the role of structural change in economic growth, but there is also a large body of literature that examines how this process happens and what are its main determinants. There is theoretical and empirical evidence that structural changes are driven by technological progress (Freeman *et al.*, 1982; Święcki, 2017), openness to international trade (Matsuyama, 2009; Uy *et al.*, 2013; Rodrik, 2016), changes in the demand structure as a result of income effects (Gollin *et al.*, 2007), and relative price effects (Grossmann, 2013). Chenery (1960) draws attention to the fact that, in addition to factors related to demand, changes in supply conditions, such as the stock of capital per worker and levels of qualification, must be considered when analyzing the determinants of structural change. Human capital, which is one of the main determinants of economic growth (Schultz, 1961; Becker, 1964; Barro, 1991), has been overlooked in the literature as a determinant of structural change. A large body of literature in growth theory is dedicated to examining human capital accumulation and structural change separately, but few works focus on their empirical and theoretical relationship (Li *et al.*, 2019). One way to advance in the understanding of the effects of human capital on growth is to focus on channels through which such effects can happen (Ciccone; Papaioannou, 2009) and one of these channels is through structural change.

Kongsamut *et al.* (1997, 2001), seeking to explain the Kuznets facts, developed a three sectors nonbalanced growth model and concluded that structural change occurs due to the difference in income elasticity of demand for the final goods of the three main sectors – agriculture, manufacturing and services. In order to investigate the relationship between human capital and structural change, Li *et al*. (2019) developed a theoretical model proposing the combination of the structural change model developed by Kongsamut *et al*. (1997, 2001) with the endogenous growth model proposed by Romer (1990). The authors suggest that by introducing Romer's (1990) endogenous technological change into the multi-sector growth model pioneered by Kongsamut *et al*. (1997, 2001), human capital can accelerate the structural change of the economy.

Ciccone and Papaioannou (2009) found evidence of a positive relationship between human capital and structural change because added value and employment growth in school-intensive industries were significantly faster in economies with higher initial levels of schooling. Also, according Li *et al*. (2019), there is a positive and statistically significant relationship between the stock of human capital and the speed of structural change. One of the reasons is that accumulation of human capital expands the role of Research and Development (R&D) in the economies and affects the technological progress of countries (Romer, 1990; Caselli; Coleman, 2006; Bodman; Le, 2013). Thus, as the stock of human capital of the countries increases, the productivity and skill of the workers increase, leading to an acceleration of the structural change of the country.

Human capital can be defined as the stock of knowledge, skills and other personal characteristics embodied in people that allow them to be more productive (Botev *et al*., 2019; Goldin, 2016). This set of intangible resources is associated with knowledge and skills gained through education, experience, health care and migration (Schultz, 1961; Becker, 1964; Teixeira; Queirós, 2016). According to Acemoglu (2009), the term was coined because many of those attributes are accumulated by workers through investments.

The literature points to two mechanisms through which human capital can affect economic growth. First, education increases the human capital of the workforce, which increases labor productivity and, consequently, leads to a higher level of equilibrium production (Romer, 1990; Bodman; Le, 2013). Second, following endogenous growth theories, a higher educational level increases the capacity for innovation in the economy, leads to the development of new technologies, products and processes, and thus promotes economic growth (Romer, 1990; Hanushek; Woessmann, 2008).

Despite advances in empirical research on the role of human capital, there is still no consensus on which measure of human capital is the most appropriate and that is the reason why this article uses more than one human capital measure, as it seeks to verify whether different human capital measures can generate similar results, bringing robustness to the analysis. The most commonly used proxy of human capital is the average years of schooling provided by Barro and Lee (2013), particularly because of its wide country coverage.

However, Sala-i-Martin and Mulligan (1995) showed that the average years of schooling is a weak proxy for human capital as it assumes that workers are perfect substitutes regardless of the sector in which they work, that productivity differences between workers are proportional to years of schooling without considering their wage differences, that one year of study generates the same increase in qualification, regardless of the quality of education or field of study; and assume a constant elasticity of substitution among workers.

In recent years, numerous other measures of human capital have emerged. Nevertheless, according to Benos and Zotou (2014), most of these proxies use quantitative data and do not give an indication of the skill level of the workforce. According to the authors, one solution to this problem is to focus on education measures of quality, such as educational expenditures, student-to-teacher ratios, and test scores. Nevertheless, data available that address the quality of education is limited to a few countries or a few time periods, which makes cross-country analysis difficult.

Considering that there are few papers devoted to studying human capital as a source of structural change and that empirical works usually use only three sectors in the analysis, it is believed that this article, when testing a theoretical model that discusses those connections, fits within the literature in a novel way to offer insights on how to enhance the structural change of the economy. Given the important role of human capital and structural change in the economic growth of countries and that little is discussed about the impact of human capital on structural change, the question this article seeks to answer is: Is human capital an important determinant of structural change in the different sectors of the economy and can it accelerate the speed of this structural transformation?

Considering that the objective of the article is to study the role of human capital in the structural transformation process of the economy, this paper used the theoretical model proposed by Li *et al*. (2019), where the author introduces Romer (1990)'s endogenous technological change into the multi-sector growth model pioneered by Kongsamut *et al*. (1997, 2001).

The authors start from an economy with three sectors (a final-goods sector, an intermediate-goods sector, and a research sector) and show that the rate of economic growth depends on the total stock of human capital, time discount rate and technological parameters of the research and final-goods sectors (LI *et al*., 2019). The results show that the larger the total stock of human capital in the economy, the greater the human capital employed in the research sector becomes, and the faster knowledge accumulates. Consequently, the rate of economic growth will be higher.

They demonstrate that there are aggregate effects of human capital on structural change. Thus, an increase of human capital accelerates the shrinkage of the agricultural sector and the expansions of the manufacturing and services sectors, concluding that an increase of human capital accelerates the structural transformation of the economy (LI *et al*., 2019).

The objective of the paper is to estimate the direct effects of human capital on structural change, considering two different measures of human capital, while controlling for other determinants found in the literature. More specifically, this paper contributes to the literature by: a) developing an empirical test of the model proposed by Li *et al*. (2019); b) expanding on previous work by broadening the analysis by using ten sectors of the economy[2] and, when using the generalized method of moments (GMM) instead of the fixed effects panel used by the author, it also considers the problem of endogeneity found in human capital variables; c) using two proxies for human capital: the main purpose of using two different measures of human capital is to perform an exploratory analysis of these alternative measures in order to verify whether or not they affect the variable of interest and also to provide robust results.

Seeking to meet these objectives, this paper uses system GMM estimates to examine the model proposed by Li *et al*. (2019). The dynamic

2 The sectors used in this paper follow the ten main sectors of the economy as defined in the International Standard Industrial Classification, Revision 3.1 (ISIC rev. 3.1): agriculture (includes agriculture, hunting, forestry and fishing); mining (includes mining and quarrying); manufacturing; utilities (includes electricity, gas and water supply); construction; trade services (includes wholesale and retail trade, hotels and restaurants); transport services (includes transport, storage, and communication); financial services (includes financial, insurance, real estate and business services); government services and personal services (includes community, social and personal services).

panel data model was chosen due to the problems of endogeneity and heterogeneity that can be found in human capital empirical studies (Zhang; Zhuang, 2011; Teixeira; Barros, 2019). The data used comes from several sources: GGDC 10-Sector Database; Penn World Table; World Development Indicators from World Bank and schooling data from Barro and Lee (2013) and covers 40 countries with annual data from 1950 to 2013. Results showed that human capital has an essential role in the structural transformation process of the economy, since it has an effect on the relative participation of the sectors on total added value or on total employment. In addition, human capital proved to be a potential accelerator of this structural transformation.

The rest of the paper is structured as follows: section 2 presents the model and the methodology used, section 3 presents the results and discussion, and section 4 concludes and summarizes the paper's results.

2 **Methods and data**

This section provides the general methodology used in this paper, which is the dynamic panel data model and the databank collected in order to do so.

2.1 **General method**

This section presents an empirical model that seeks to test the predictions of the theoretical model proposed by Li *et al*. (2019)[3]. Due to the possible problems of endogeneity and heterogeneity that can be found in human capital empirical studies (Bond *et al*., 2001), this paper uses a dynamic panel data model, where differences between countries are captured across and over time (Cameron; Trivedi, 2005). The parameters of the following dynamic specification are estimated:

$$sc_{it} = \delta sc_{i,t-1} + \beta' X_{it} + \lambda hcap_{it} + \theta' D_{it} + u_{it} \tag{1}$$

3 For a detailed analysis of the theoretical model used in this paper, see Li *et al*. (2019).

where sc_{it} is the structural change variable in any of the ten sectors used in this paper: two different measures of structural change were used: the employment share and the added value at constant 2005 national prices share. X_{it} is a $K \times 1$ vector of the linear explanatory variables (physical capital per worker, population density, international trade). The variable $hcap_{it}$ represents the variable of interest and shows the impact of a changing proportion of human capital (considering the two different measures proposed) on the structural change variable in any of the ten sectors. Besides that, D_{it} is a vector of the cross-sectional fixed effects, $sc_{i,t-1}$ is the first lag of the dependent variable, which was included in order to consider its temporal correlation, and u_{it} is the component error vector.

Nickell (1981) points out that, in the presence of fixed effects, the estimation of the parameters of the dynamic panel data model is subject to estimation bias. As a solution, Anderson and Hsiao (1982) proposed the instrumental estimator method, which uses the first difference of the data to eliminate fixed effects. Arellano and Bond (1991) expanded the Anderson and Hsiao (1982) estimator and found that there are many more instruments available within the GMM framework than used by conventional instrumental variable estimation (Siliverstovs *et al.*, 2011). The GMM estimator of Arellano and Bond (1991) is the two-step estimator: in the first step, the parameters are estimated using the identity matrix for weighting the moment conditions, and in the second step, an asymptotically more efficient estimation is conducted by optimal weighting of the moment condition using the first-step estimation results (Siliverstovs *et al.*, 2011).

The second equation that forms the system is the following difference equation:

$$\Delta sc_{it} = \delta \Delta sc_{i,t-1} + \beta' \Delta X_{it} + \lambda \Delta hcap_{it} + \Delta u_{it} \tag{2}$$

where Δ is the first-difference operator. As highlighted by Dias and Tebaldi (2012), the instrument quality problem is minimized by using lags of the dependent variable as instruments for the first equation and the lags of the variables in differences for the second equation as suggested by Arellano and Bond (1981), Arellano and Bover (1995) and Blundell and Bond (1998).

In addition to the difference-GMM, which can show persistence in the series, rendering the level variables to become weak instruments for the difference equation, suggesting bias and low precision in finite samples (Blundell; Bond, 1998), the system-GMM can be used. In the system-GMM estimation, the model itself and the first difference of the model are estimated as a “system”. Thus, system-GMM is formed by the level equation, which uses difference lags as instruments, and the difference equation, which uses level-lagged variables as instruments. Blundell and Bond (1998) present evidence that this estimator, for finite samples, would perform better than the difference-GMM estimator in terms of both bias and efficiency[4].

Furthermore, as one of the main goals of this paper is to verify whether human capital, in addition to affecting structural change, is able to accelerate the speed with which such change occurs, after initial estimates new estimates are made from the primary results obtained, that is, the second derivative of the model is obtained, which makes it possible to verify the rate of change (speed) of the structural transformation. The rate of change is calculated according to the following equation (14):

$$g_{sc_t} = \frac{ln\left(sh_{sc_{i,t}} \,/\, sh_{sc_{i,t-5}}\right)}{5} \tag{3}$$

where g_{sc_t} is the speed of the structural change (rate of change), g_{sc_t} is the share of each sector on total employment or added value and $sh_{sc_{i,t-5}}$ is the share of each sector on total employment or added value in time t – 5.

2.2 **Data**

Considering that one of the objectives of this paper is to work with a larger number of sectors besides the three normally used in the literature (agriculture, manufacture and services), the main dataset we used is the GGDC 10-Sector Database (Timmer *et al.*, 2015), which provides a long-run internationally comparable dataset on sectoral productivity perfor-

4 For a practical and intuitive exposition of the one-step system-GMM estimator, see Roodman (2009).

mance for 40 countries[5] and includes a 5-year interval data from 1950 to 2013 (due the data availability). This dataset covers the ten main sectors of the economy as defined in the International Standard Industrial Classification, Revision 3.1 (ISIC rev. 3.1): agriculture; mining; manufacturing; utilities; construction; trade services; transport services; financial services; government services and personal services.

Physical capital per worker (capital stock at constant 2011 US$ divided by the total workers) and population density (people per square km of land area) data were collected from Penn World Table 9.1. International trade (sum of exports and imports of goods and services measured as a share of gross domestic product) data comes from the World Development Indicators database of the World Bank. These variables were chosen because they are commonly used in the literature and are used as control variables.

Due to the fact that there is no consensus in the literature on which would be the most appropriate measure for human capital, another aim of this paper is to use and test two different measures of human capital in order to verify which one is the most appropriate to explain the process of structural change. The first measure used is the average years of schooling provided by Barro and Lee (2013). The second measure of human capital is the Penn World Table index based on the average years of schooling from Barro and Lee (2013) and Cohen and Soto (2007) and a presumed rate of return to education, based on Mincer equation estimates around the world (Psacharopoulos, 1994). This is a relatively new measure of human capital – however, is considered a superior measure in capturing multidimensional facets of human capital (Feenstra *et al.*, 2015). Murphy and O'Rilley (2019) and Bruns and Ioannidis (2020) are examples of papers that used this proxy.

The structural change variables (employment share and added value share) come from the GGDC database, which provides country-level data from 1950-2013 for numerous countries. However, considering that human capital data provided by Barro and Lee (2013) has a 5-year interval between observations, the same interval for the Penn World Table index data was used, making it possible to compare the results and the control

5 The countries in the sample are: Argentina, Bolivia, Botswana, Brazil, Chile, China, Hong Kong (China), Colombia, Costa Rica, Denmark, Egypt, Ethiopia, France, Ghana, India, Indonesia, Italy, Japan, Kenya, Malawi, Malaysia, Mauritius, Mexico, Netherlands, Nigeria, Peru, Philippines, Republic of Korea, Senegal, Singapore, South Africa, Spain, Sweden, Taiwan, Thailand, Tanzania, United Kingdom, United States, Venezuela and Zambia.

variables were linearized. The number of observations used in this paper was 344, resulting in an unbalanced panel.

3 Results

This section shows the results found in this paper and includes the discussion about those findings, in addition to comparing it with the literature.

3.1 The human capital role on the structural change of the sectors

As the first aim of this paper it is to analyze the human capital role in the structural transformation of the sectors, Table 1 shows the results of the GMM model for the Added Value share of the ten sectors analyzed considering the Penn World Table index as a proxy for human capital. All GMM results were obtained using GMM-style instruments that were replaced with their main components using the method developed by Mehrhoff (2009), Kapetanios and Marcellino (2010) and Bai and Ng (2010) and all models include time dummies[6].

Importantly, although the models for each sector are independent[7], they all have satisfied all the requisites of the Arellano-Bond AR(1) and AR(2) tests. The AR(1) correlation is positive and statistically significant in all models, but the AR(2) correlation is not significant at standard levels. In addition, the Sargan Overidentification test presented the expected results. Thus, the results of these three tests suggest that the instruments are valid for all regressions reported in Table 1[8]. Considering the results in Table 1, it is possible to verify that, of the 10 sectors analyzed, six sectors presented significant results for the human capital index: Mining, Manufacturing, Utilities, Construction, Trade and Financial services.

6 A 5-year interval was used in all regressions since it is understood in the literature that human capital does not change sharply from one year to another, thus, a longer period allows a more concrete analysis of the impact of this variable on structural transformation.

7 The models are considered independent because they were run separately, where each model structure (number of lags and/or orthogonality condition) is unique for each sector.

8 Among all the regressions run, only two models did not pass the validity tests of the instruments: mining sector and utilities sector considering employment share and PWT as human capital index, both are in the Table 2.

Table 1 **Dependent Variable: Added Value share of each sector, human capital index: Penn World Table, 1950-2010 (5-year interval) (GMM-style instruments replaced with their principal components)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
L.Employment share	0.792***	0.837***	1.076***	0.990***	0.674***	0.871***	1.025***	0.798***	0.842***	0.919***
	[11.38]	[10.03]	[25.59]	[13.52]	[9.09]	[10.74]	[11.30]	[17.76]	[15.16]	[28.77]
Human capital index	−0.486	−10.46**	3.616**	−0.488**	1.518*	2.852**	−1.107	2.559**	2.101	0.662
	[−0.22]	[−2.28]	[2.06]	[−2.22]	[1.96]	[2.00]	[−1.62]	[2.15]	[1.37]	[0.55]
Ln physical capital	−0.409	1.158	−2.658***	0.301**	−0.529	−1.105	0.328	0.229	0.0386	0.750
	[−0.37]	[0.61]	[−2.72]	[2.36]	[−1.08]	[−1.33]	[1.24]	[0.52]	[0.05]	[0.85]
Ln Population density	0.725	0.403	0.408	0.0353	−0.442*	−0.234	0.296	−0.0398	−0.191	−0.549**
	[1.28]	[0.51]	[1.29]	[0.58]	[−1.81]	[−0.72]	[1.52]	[−0.43]	[−1.37]	[−2.48]
Ln Exportation	−1.255	−0.542	0.503	−0.0853	−0.272	1.854**	−0.446*	0.182	0.0448	1.038
	[−1.52]	[−0.48]	[1.07]	[−0.87]	[−0.51]	[2.31]	[−1.87]	[0.75]	[0.17]	[1.32]
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	326	326	336	336	336	336	325	305	235	315
# Instruments	47	49	44	47	46	50	37	38	37	49
p-values for										
AR(1)	0	0	0	0	0	0	0	0	0	0
AR(2)	0.583	0.545	0.843	0.299	0.804	0.460	0.836	0.128	0.872	0.953
Sargan Overid	0.152	0.568	0.375	0.127	0.390	0.395	0.378	0.162	0.402	0.367

Source: Author's elaboration.

Notes: Each model refers to the added value share of a sector: (1) Agriculture; (2) Mining; (3) Manufacturing; (4) Utilities; (5) Construction; (6) Trade; (7) Transportation services; (8) Financial services; (9) Government and (10) Community and personal services.

t *statistics in brackets,* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

All regressions are estimated using a one-step system GMM estimator and include time dummies. Also, GMM-style instruments are replaced with their principal instruments components using the methods developed by Mehrhoff (2009); Kapetanios and Marcellino (2010) and Bai and Ng (2010) and are implemented in Stata using the command xtabond2.

Specifications: Models (1) and (2): 1 lag for the share variable, 1 lag for the explanatory variables (human capital, physical capital and populational density), time variable and exportation considered exogenous and with 1 lag. Models (3), (4), (5) and (6): 1 lag for the share variable, 1 lag for all the explanatory variables, time variable considered exogenous e with 1 lag. Model (7): 1 lag for the share variable, 1 lag for the explanatory variables (human capital and populational density), time variable, physical capital and exportation considered exogenous with 1 lag. Models (8) and (9): 1 lag for the share variable, 1 lag for the explanatory variables (human capital and physical capital), time variable, populational density and exportation considered exogenous with 1 lag. Model (10): 1 lag for the share variable, 1 lag for the explanatory variables (human capital, physical capital and exportation), time variable and populational density considered exogenous e with 1 lag.

Table 2 **Dependent Variable: Employment share of each sector, human capital index: Penn World Table, 1950-2010 (5-year interval) (GMM-style instruments replaced with their principal components)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
L.Employment share	1.024***	0.903***	0.925***	0.868***	0.580***	1.091***	1.039***	0.904***	0.986***	1.032***
	[12.32]	[24.32]	[16.86]	[16.01]	[6.52]	[15.62]	[12.89]	[17.65]	[15.50]	[9.39]
L2.Employment share	–	–	–	–	0.243***	–	–	–	–	−0.147
	–	–	–	–	[2.75]	–	–	–	–	[−1.63]
Human capital index	−5.222	−0.151	−0.466	0.178**	−1.590*	3.257***	1.321**	1.200	2.880*	−2.455***
	[−1.64]	[−0.68]	[−0.30]	[2.56]	[−1.89]	[2.97]	[2.15]	[1.20]	[1.81]	[−2.60]
Ln physical capital	2.217	−0.0997	−1.828**	−0.109***	0.855*	−1.750***	−0.752**	0.242	−0.267	0.276
	[1.63]	[−0.67]	[−2.11]	[−2.89]	[1.90]	[−3.00]	[−2.15]	[0.41]	[−0.35]	[0.43]
Ln Population density	2.459***	0.0238	0.224	−0.0145**	0.0320	−0.794**	−0.403*	0.0727*	−0.237	−0.0746
	[3.32]	[0.38]	[0.73]	[−2.17]	[0.45]	[−2.57]	[−1.72]	[1.87]	[−1.56]	[−0.55]
Ln Exportation	−1.905	0.204	2.295**	0.0749***	−0.131	1.644**	1.075***	0.182	−0.134	0.0847
	[−1.22]	[1.62]	[2.46]	[3.44]	[−0.53]	[2.41]	[3.34]	[0.68]	[−0.24]	[0.15]
Time Dummies	Yes	Yes	Yes	yes	yes	yes	Yes	Yes	yes	yes
Observations	335	335	335	307	298	335	335	307	251	289
# Instruments	55	63	54	50	49	42	43	40	43	53
p-values for										
AR(1)	0	0	0	0	0	0	0	0	0	0
AR(2)	0.853	0.469	0.954	0.449	0.847	0.181	0.304	0.545	0.297	0.336
Sargan Overid	0.530	0	0.932	0	0.181	0.284	0.912	0.332	0.504	0.142

Source: Author's elaboration.

Notes: Each model refers to the employment share of a sector: (1) Agriculture; (2) Mining; (3) Manufacturing; (4) Utilities; (5) Construction; (6) Trade; (7) Transportation services; (8) Financial services; (9) Government and (10) Community and personal services.

t *statistics in brackets,* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

All regressions are estimated using a one-step system GMM estimator and include time dummies. Also, GMM-style instruments are replaced with their principal instruments components using the methods developed by Mehrhoff (2009); Kapetanios and Marcellino (2010) and Bai and Ng (2010) and are implemented in Stata using the command xtabond2.

Specifications: Models (1), (2) and (3): 2 lags for the share variable, 1 lag for all the explanatory variables, time variable considered exogenous and with 1 lag. Models (4), (5), (8) and (10): 2 lags for the share variable, 1 lag for the explanatory variables (human capital and physical capital), time variable, populational density and exportation considered exogenous e with 1 lag. Models (6) and (7): 1 lag for the share variable, 1 lag for all the explanatory, time variable considered exogenous e with 1 lag. Model (9): 1 lag for the share variable, 1 lag for the explanatory variables (human capital, physical capital and exportation), time variable and populational density considered exogenous e with 1 lag.

The coefficients of the mining and utilities sectors were both significant and negative, showing that, for these sectors, human capital is an important element to explain structural change but its impact is negative, that is, the increase in the level of human capital is contributing to the reduction of structural change in these sectors.

The sectors that showed a positive sign and were statistically significant were Manufacturing, Construction, Trade and Financial services. For these four sectors, human capital is relevant to explain the structural change that they underwent during the analysis period. The control variables, for the most part, did not present significant coefficients. The negative or positive impacts of human capital on each sector separately show the general transformation that the countries underwent in the analyzed period. The sectors with negative impact are those that have become less important in the productive sphere, while those that have had a positive impact are those that, over time, have demanded more human capital: in general, the service sectors.

One sector that is important to highlight is the agricultural sector, where human capital was not significant. A possible explanation for this is that with technological advances, we have important changes in this sector, such as mechanization, which “save” labor. Thus, although the sector employs less labor over time, its importance in terms of participation in the economy's output or in added value may increase.

When considering the structural change of the sectors from the perspective of employment share (Table 2), it can be seen that the Construction and Community services sectors presented negative and significant coefficients while Trade, Transportation and Government sectors presented positive and significant coefficients – these three sectors maintained the benchmark results. Thus, it is possible to affirm that human capital has a positive effect on the structural change occurred in these sectors.

The results show that the human capital role on the structural change of the sectors has some specific trends, regardless of the human index used: the relative participation of each sector in the economy is affected by human capital in different ways. When the regressions have sectors with negative impact it means that they are losing relative participation in the economy and when the sectors have positive impact it means that they had an increase in their relative participation in the added value or in the employment. Thus, in the analyzed period, the countries showed a tendency to lose the relative participation of the primary and secondary sectors and to increase the relative participation of service sectors.

It is important to highlight the results of the manufacturing sector: although the results of Table 2 were not statistically significant, they showed a sign contrary to that of Table 1. Thus, there seems to be a disparity in the results when considering different proxies for structural change: for the Added Value share of each sector proxy, the human capital had a positive impact on the manufacturing sector, showing that the increase in this variable resulted in an increase in the added value of the sector, that is, as the total number of workers increased its stock of human capital, the sector benefited positively, which allowed it to increase its share. When considering the employment share proxy, this effect was reversed, although not statistically significant.

In addition, there is the issue of deindustrialization that has occurred in most countries (mainly developing countries) in recent decades. With globalization and specialization, many countries ended up "skipping" the industrialization stage, moving from agriculturally based economies to service economies, so that countries that increased their participation in world manufacturing, such as China and other Asian countries, ended up specializing in this sector, in order to capture most of the human capital. As highlighted by Atolia *et al*. (2020), the manufacturing sector is able to lead to a widespread distribution of strong, dynamic gains of enhanced skill levels of the workforce, upgrades of technology, and product and process innovation. Therefore, it is necessary that countries pay due attention to the manufacturing sector, which is of great importance in the countries' growth process.

As highlighted by Mensah *et al*. (2016), the results are in line with the structural change ideology of Chenery (1960) and Lewis (1954) that a growing literate society will result in a gradual shift from low technology requirement economic activities such as agriculture toward the industrial and service sectors. Święcki (2017) points out that the sector-biased technological progress is important for explaining the net movement of labor from manufacturing to services and is, thus, crucial for understanding structural change occurring in countries.

In addition, structural transformation is important in the context of increasing and sustaining growth, reducing poverty, as well as supporting the sustainability of development (Puspitowati; Iskandar, 2020). Thus, the results show that, in addition to increasing the economic growth of the countries, human capital acts indirectly through the channel of structural change, which allows for even stronger economic growth and development.

These results come from encounters with other works in the literature that have shown that the global trend is for a drop in relative participation in the agriculture and manufacturing sectors and an increase in the service sectors (*e.g.*, Alonso-Carrera; Raurich, 2018; Mcmillan; Rodrik, 2011; Herrendorf *et al.*, 2014). Additionally, authors such as Dabla-Norris *et al.* (2013), Martins (2019), Jha; Agrin (2017), Lee; Malin (2013), Mensah *et al.* (2016) and Puspitowati; Iskandar (2020) also found similar results concerning the role of human capital in the structural transformation of sectors.

The results also reinforced the need to use a dynamic panel to perform the analysis, given that in all models the lagged dependent variable was significant (Tables 1.1 and 1.2), pointing to a persistence effect over time. Additionally, the use of two proxies for human capital and for structural change showed that there is no "one proxy better than the other", the appropriate use depending on the researcher's objectives and the availability of the data.

However, the control variables used in this paper showed few significant results. We can highlight the positive effect of the "Exportation" variable on the Trade and Utilities sectors and the negative effect of the "Population Density" variable on the Utilities and Personal Services sectors.

Analyzing the set of results, it is possible to verify that, in general, the results found are disparate, that is, human capital may not be affecting only the level of structural change, but rather the speed of this transformation, so that the next subsection presents the results of regressions in GMM considering the speed of structural change in the sectors as a dependent variable.

3.2 **The human capital as an explanatory factor for the speed of structural change in the sectors**

This subsection presents the results of regressions in GMM considering the speed of structural change as a dependent variable (considering employment share and added value share) and, again, using two indices for human capital: data from Penn World Table and Barro and Lee (2013). The speed was calculated as the second derivative of the model proposed. Table 3 presents the results of the GMM regression for speed of the employment share of each sector using the Penn World Table data as a proxy for human capital. The other regressions are included in the supplementary files attached to this paper.

The results show that, when considering the impact of the level of human capital on the speed of structural change, the sectors of Mining, Construction, Trade and Financial Services present positive and significant coefficients. In other words, for these sectors, human capital impacts by accelerating their structural transformation. The Manufacturing sector was the only sector that presented a negative and significant coefficient; in this case, the increase in the level of human capital would be contributing to slow down the structural change in that sector. The other sectors were not significant.

Comparing the results of Table 3 with the other model (Table 4), it is possible to reach some conclusions: when the speed of the added value is used as a proxy for structural change, both the human capital indices of the Penn World Table and that of Barro and Lee (2013) presented the same results, meaning that the models are robust. In addition, the Manufacturing sector presented a negative and significant coefficient in three of the four models. Thus, it is possible to affirm that in fact there is a decrease in the speed of structural change with the increase of human capital in this sector. The financial sector, on the other hand, presented a positive and significant coefficient in the four specifications, so it is possible to affirm that, in this sector, the increase in the level of human capital accelerates its structural transformation.

This positive impact of human capital (regardless of which human capital index is used) in Financial Services is important because it shows that, as human capital in this sector increases, its structural change accelerates. In other words, there seems to be a movement in the analyzed period in favor of the service sectors to the detriment of the primary and secondary sectors. This movement is expected when it comes to structural change, since, with the passage of time and evolution of human capital, it is expected that the employment share and the added value share of the service sectors will increase, as these results show that, in general, countries are on a path that leads to developed and modern economies. These results corroborate those found by Martins (2019): the author emphasizes that services are the main driver of economic performance and the key catalyst for structural change.

Table 3 **Dependent Variable: Speed of the employment share of each sector, human capital index: Penn World Table, 1950-2010 (5-year interval) – (GMM-style instruments replaced with their principal components)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
L.Employment share	0.428**	0.0225	0.538**	0.0788	–0.0167	0.188	0.172	–0.0539	0.254	0.157
	[2.52]	[0.10]	[2.40]	[0.47]	[–0.11]	[0.99]	[1.26]	[–0.29]	[1.39]	[0.79]
L2.Employment share	0.0647	–	0.00352	0.0718	0.00259	–	–0.163*	0.116	–	–
	[0.38]	–	[0.03]	[0.68]	[0.03]	–	[–1.88]	[1.08]	–	–
Human capital index	–0.137	0.872***	–0.199*	0.0575	0.300*	0.180*	–0.0970	0.295**	0.116	–0.158
	[–1.40]	[2.80]	[–1.67]	[0.46]	[1.81]	[1.83]	[–0.88]	[2.07]	[1.40]	[–1.30]
Ln physical capital	0.0949*	–0.417***	0.0359	–0.0392	–0.204**	–0.102**	–0.00442	–0.0797*	–0.0244	0.104
	[1.79]	[–2.94]	[0.71]	[–0.58]	[–2.43]	[–2.47]	[–0.08]	[–1.76]	[–0.48]	[1.59]
Ln Population density	0.0340	–0.0330	0.0210	–0.0242	0.00648	–0.0157	0.0372	–0.0141	–0.0119	0.00829
	[1.13]	[–1.31]	[0.87]	[–1.53]	[0.37]	[–1.27]	[1.26]	[–1.24]	[–1.54]	[1.00]
Ln Exportation	–0.0933**	–0.00483	–0.0407	0.104	0.0431	0.0440	–0.0204	0.0433	0.00931	–0.0881**
	[–2.56]	[–0.04]	[–1.22]	[1.35]	[0.52]	[0.91]	[–0.55]	[1.52]	[0.42]	[–2.52]
Time Dummies	Yes	Yes	yes	Yes	yes	Yes	yes	Yes	yes	yes
Observations	290	308	289	288	288	308	290	281	235	289
# Instruments	43	40	44	51	50	39	45	42	36	35
p-values for										
AR(1)	0	0	0	0	0	0	0	0	0	0
AR(2)	0.273	0.937	0.913	0.664	0.233	0.420	0.955	0.150	0.144	0.143
Sargan Overid	0.346	0.549	0.915	0.240	0.711	0.779	0.113	0.365	0.113	0.680

Source: Author's elaboration.

Notes: Each model refers to the speed of the added value share of a sector: (1) Agriculture; (2) Mining; (3) Manufacturing; (4) Utilities; (5) Construction; (6) Trade; (7) Transportation services; (8) Financial services; (9) Government and (10) Community and personal services.

t *statistics in brackets,* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

All regressions are estimated using a one-step system GMM estimator and include time dummies. Also, GMM-style instruments are replaced with their principal instruments components using the methods developed by Mehrhoff (2009); Kapetanios and Marcellino (2010) and Bai and Ng (2010) and are implemented in Stata using the command xtabond2.

Specifications: Models (1) and (7): 2 lags for the share variable, 1 lag for all the explanatory, time variable considered exogenous and with 1 lag. Models (2) and (6): 1 lag for the share variable, 1 lag for the explanatory variables (human capital, physical capital and exportation), time variable and populational density considered exogenous e with 1 lag. Model (3): 2 lags for the share variable, 1 lag for the explanatory variables (human capital and populational density), time variable, physical capital and exportation considered exogenous with 1 lag. Models (4) and (5): 2 lags for the share variable, 1 lag for the explanatory variables (human capital, physical capital and exportation), time variable and populational density considered exogenous with 1 lag. Model (8): 2 lags for the share variable, 1 lag for the explanatory variables (human capital and physical capital), time variable, populational density and exportation considered exogenous e with 1 lag. Models (9) and (10): 1 lag for the share variable, 1 lag for the explanatory variables (human capital and physical capital), time variable, populational density and exportation considered exogenous e with 1 lag.

Table 4 **Dependent Variable: Speed of the employment share of each sector, human capital index: Barro and Lee (2013), 1950-2010 (5-year interval) – (GMM-style instruments replaced with their principal components)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
L.Employment share	0.346	−0.378	0.359**	0.0550	−0.270	0.0187	0.0517	−0.0499	0.269**	0.0557
	[1.63]	[0.02]	[2.18]	[0.32]	[−1.55]	[0.12]	[0.47]	[−0.31]	[2.36]	[0.29]
L2.Employment share	–	–	–	0.0877	–	–	−0.147*	0.0832	0.0681	−0.00507
	–	–	–	[0.81]	–	–	[−1.67]	[0.76]	[0.73]	[−0.04]
Human capital index	−0.0480	0.013	0.00595	−0.0292	0.0673*	0.0539**	−0.0238	0.0529**	0.0174	−0.0499
	[−1.43]	[0.70]	[0.23]	[−1.09]	[1.74]	[2.06]	[−1.25]	[2.00]	[1.37]	[−1.56]
Ln physical capital	0.0389	−0.122	−0.111**	−0.0270	−0.209***	−0.179***	−0.0301	−0.133***	−0.0407*	0.0524
	[0.81]	[0.09]	[−2.46]	[−0.56]	[−3.05]	[−3.25]	[−0.78]	[−3.27]	[−1.74]	[1.12]
Ln Population density	0.0166	−0.005	−0.0142	0.0734**	−0.00724	−0.00667	−0.00498	−0.00301	0.00315	0.0723**
	[0.70]	[0.89]	[−1.29]	[2.40]	[−0.47]	[−1.12]	[−0.53]	[−0.23]	[0.52]	[2.51]
Ln Exportation	−0.0527*	0.004	0.101**	0.0176	0.189**	0.0835***	0.0582	0.105*	0.0111	−0.109***
	[0.08]	[0.95]	[0.02]	[0.77]	[0.03]	[0.00]	[0.13]	[0.09]	[0.39]	[0.00]
Time Dummies	yes	yes	yes	yes	Yes	yes	yes	yes	yes	Yes
Observations	291	291	291	282	289	281	273	273	213	266
# Instruments	38	38	46	57	42	34	52	55	46	45
p-values for										
AR(1)	0	0	0	0	0	0	0	0	0	0
AR(2)	0.153	0.153	0.975	0.740	0.772	0.701	0.697	0.495	0.547	0.400
Sargan Overid	0.135	0.135	0.318	0.228	0.265	0.148	0.344	0.127	0.119	0.417

Source: Author's elaboration.

Notes: Each model refers to the speed of the employment share of a sector: (1) Agriculture; (2) Mining; (3) Manufacturing; (4) Utilities; (5) Construction; (6) Trade; (7) Transportation services; (8) Financial services; (9) Government and (10) Community and personal services.

t *statistics in brackets,* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

All regressions are estimated using a one-step system GMM estimator and include time dummies. Also, GMM-style instruments are replaced with their principal instruments components using the methods developed by Mehrhoff (2009); Kapetanios and Marcellino (2010) and Bai and Ng (2010) and are implemented in Stata using the command xtabond2.

Specifications: Model (1): 1 lag for the share variable, 1 lag for the explanatory variables (human capital, physical capital and populational density), time variable and exportation considered exogenous and with 1 lag. Model (2): 1 lag for the share variable, 1 lag for all the explanatory variables, time variable considered exogenous and with 1 lag. Model (3): 1 lag for the share variable, 1 lag for the explanatory variables (human capital, physical capital and exportation), time variable and populational density considered exogenous and with 1 lag. Model (4): 2 lags for the share variable, 1 lag for all the explanatory variables, time variable considered exogenous and with 1 lag. Model (5): 1 lag for the share variable, 1 lag for the explanatory variables (human capital and exportation), time variable, physical capital and populational density considered exogenous and with 1 lag. Model (6): 1 lag for the share variable, 1 lag for the explanatory variables (human capital and physical capital), time variable, exportation and populational density considered exogenous and with 1 lag. Models (7) and (8): 2 lags for the share variable, 1 lag for all the explanatory variables, time variable considered exogenous and with 1 lag. Model (9): 2 lags for the share variable, 1 lag for the explanatory variables (human capital and physical capital), time variable, exportation and populational density considered exogenous and with 1 lag. Model (10): 2 lags for the share variable, 1 lag for the explanatory variables (human capital and populational density), time variable, exportation and physical capital considered exogenous and with 1 lag.

Source: Author's elaboration.

In addition, Dabla-Norris *et al*. (2013) reinforce that strengthening of human capital and greater flexibility in the labor market, especially in countries with high participation of services, can have a significant positive impact on the growth of productivity in the service sectors, driving the acceleration of economic growth in these countries. This productivity growth takes place via R&D, which enhances the innovation and technological progress of the economy. Therefore, the more educated the workforce of a country, the greater the benefits of the R&D activities in terms of economic growth (Teixeira; Queirós, 2016).

The results altogether demonstrate that the human capital level proved to be very important to explain the structural transformation that occurred in the period as well as its rate of change. Thus, human capital shows itself as an important driver of the structural change that occurred in the period, which implies that countries that wish to accelerate their structural transformation must invest in increasing the levels of human capital, because following this path they not only foster economic development but also reach it faster.

4 **Final conclusions**

The determinants of the process of structural change that occurs in the economy have been the subject of an increasing portion of the economic literature. Human capital is among these determinants, whose role in explaining structural changes in the economy is still insufficiently studied. Considering this, this paper sought to find evidence to determine whether human capital is an important determinant of structural change in different sectors of the economy and whether it can accelerate the speed of this structural transformation. To answer this question, this article developed an empirical test of the model proposed by Li *et al*. (2019) using two proxies for human capital and applied the generalized method of moments to correct the endogeneity problem.

First of all, the results showed the importance of using GMM when working with human capital. By correcting the problem of endogeneity present in this variable, the results became more consistent and reliable. Also, the regressions showed that the use of different proxies for the human capital variable and for the measurement of structural change were able to present satisfactory results, which means that the results were consistent regardless of which proxy was used. Therefore, it is possible to state that the choice of different proxies for the variables does not significantly alter the results, so the choice of one or the other becomes indifferent.

Human capital has shown to have an essential role in the structural transformation process of the economy, since this has an effect on the relative participation of the sectors on total added value or on total employment. Also, human capital proved to be a potential accelerator of this structural transformation.

Based on these conclusions, the important role of human capital is reinforced in allowing this acceleration of structural change, which indirectly leads countries to economic growth and development. Also, considering that the results were robust due to the use of various proxies for human capital, the main policy implication of this paper is that what decision makers need to consider is what kind of structural transformation they want to make in their respective countries. This is not an easy task and begins with deciding which sectors need to accelerate or decelerate structural change most. Based on this decision, investment in human capital in specific sectors is important for the effectiveness of this planned structural change.

In addition, this paper contributes in the area of public policies, as the results show to the decision-makers the different effects of human capital on the various sectors of the economy, indicating directions that can be taken by them depending on what type of growth they want for their countries. If the objective is to fully develop more technologically advanced sectors, such as the financial sector, investment in human capital must be carried out in R&D, through incentives to Universities and students, as well as private research. However, if the country aims to develop sectors that demand more technical personnel, such as Manufacturing, Transport and Communication, for example, investment in technical courses seems to be more appropriate. Based on this decision, investment in human capital in specific sectors is important for the effectiveness of the structural change planned by the country, which will lead it to achieve the desired economic growth and achieve it faster.

Among the suggestions for future research would be the inclusion of squared human capital variables, as they are important and necessary to allow the capturing of non-linear relationships. Also important would be the inclusion, in the model, of the demand variables of the economy, as a way to expand the analysis, ensuring results that better explain the real world. In addition, it would be interesting to create an index of structural change that covers both employment share and added value share in a way that permits a unified empirical analysis.

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