Human capital, technology and productive structure

Deyvid W. Leite[1] and Leonardo C. B. Cardoso[2]

[1]Graduate Program in Applied Economics, Universidade Federal de Viçosa
[2]Department of Rural Economics, Universidade Federal de Viçosa

Abstract

Recognizing a relationship between productive structure and growth is important but not enough to screening policies. For policy purposes, the second natural step is to understand how structural change proceeds, which variables explain the productive structure. Here, we shed light on this debate, analyzing the relation between productive structure, human capital, and technology investment at the national level. We use a new measure of the productive structure with progress in objectivity and comparability – the Economic Complexity Index. We use a two-way fixed-effects panel with data for 97 countries from 1996 to 2015. Results indicated that a more complex structure is related to higher levels of human capital, investment in technology, and trade openness. Regarding human capital, not only does the democratization of education play a role, but its quality is also fundamental to structural change. Measured by PISA scores, education quality made the quantity of education lose its relevance to explaining the structure. (JEL: I25; O11; F43)
Keywords: Productive structure, Human capital, Economic complexity.

Resumo

O reconhecimento da relação entre estrutura produtiva e crescimento é importante, mas não suficiente para a seleção de políticas. Para fins de política, o segundo passo natural é entender como ocorre a mudança estrutural, quais variáveis explicam a estrutura produtiva. Aqui, lançamos luz sobre esse debate, analisando a relação entre estrutura produtiva, capital humano e investimento em tecnologia em nível nacional. Utilizamos uma nova medida da estrutura produtiva com avanços em objetividade e comparabilidade - o Índice de Complexidade Econômica. Usamos um painel de efeito fixo de países e de período com dados de 97 países de 1996 a 2015. Os resultados indicaram que uma estrutura mais complexa está relacionada a níveis mais elevados de capital humano, investimento em tecnologia e abertura comercial. Em relação ao capital humano, não só a democratização da educação desempenha um papel, mas sua qualidade também é fundamental para a mudança estrutural. Medida pelas pontuações do PISA, a qualidade da educação fez com que a quantidade de educação perdesse sua relevância para explicar a estrutura. (JEL: I25; O11; F43)
Keywords: Estrutura produtiva, Capital humano, Complexidade econômica.

1 Introduction

Lall et al. (2006) inferred export sophistication of some countries by looking at their export basket and income levels, understanding export sophistication as a result of exporting both high-technology and diversified products. In this context, Hidalgo (2009), Hidalgo and Hausmann (2009) and Hausmann et al. (2014) introduced the idea of economic complexity, a measure of export sophistication, which may reflect a nation's productive structure.

Economic complexity considers the levels of diversity and ubiquity of exports as well as the share in international market of each product and country. Looking at export basket provides an acceptable notion of what is happening in a country and indicates an indirect measure of competitiveness. Thus, economic complexity has gained visibility as a per capita income determinant.

The debate on the importance of productive structure in cross-country income differences has contributions regarding the correlation between diversification and per capita output, *e.g.* Nelson and Pack (1999), Peneder (2003), Cimoli (2005) and Felipe et al. (2012). Moreover, a few studies argued there is a causal relationship between the exported products and per capita output (Rodrik, 2006; Hausmann et al., 2007). In line with those investigations, Hausmann et al. (2014) found that a country's export basket, which expresses the productive structure, is a strong and robust predictor of the subsequent economic growth. If an economy has a high level of export sophistication but not a high level of per capita income, it means the economy will grow faster in order to have a level of per capita income that corresponds to its level of export sophistication.

The pattern of productive specialization matters to explain even intra-country income differentials. Jarreau and Poncet (2012) investigated the relation between sophisticated product exports and the economic growth of 33 Chinese regions. Where the exports were composed of highly sophisticated products, income growth was faster. However, gains in income growth came only when exports were composed of ordinary products and undertaken by domestic firms because it indicates positive technology adoption and capacity building.

Given the relation between complexity and growth, a second step could be to investigate the determinants for increasing complexity. In this regard, Hidalgo (2009) affirmed that differences in productive structure lead to differences in products. After that, Hausmann et al. (2014) stated that the products a nation makes have a particular relation to its inhabitants' knowledge and the possibilities an economy holds. Promoting the choice of our first candidate for determining complexity: human capital.

Beyond the relevance of human capital, some studies have underlined the interaction between technological progress and economic growth (Solow, 1957; Romer, 1990; Lichtenberg, 1992). Moreover, Grossman and Helpman (1994) affirmed that gains from trading with other economies might take place where technological advantages exist, and the learning process is dynamic. They also suggested investment in technology presents increasing returns to scale. Considering that, technology seems to play an important role in economic growth as well as in productive structure. Justifying the choice of investment in technology as our second determinant candidate for economic complexity.

This investigation aims to expand the knowledge of productive structure at national level and verify whether there is any direct relation between productive structure and both the quantity and the quality of human capital. Furthermore, if productive structure is influenced by technology.

Associating human capital and investment in technology with productive structure is not new (Ciccone and Papaioannou, 2009; Bravo-Ortega and de Gregorio, 2011; Teixeira and Queirós, 2016). However, we use a new measure of productive structure. The economic complexity index is this measure, and it presents important progress, given the enhancements in terms of objectivity and comparability.

Although Hausmann et al. (2014) explained the process of how complexity and growth are correlated, no indication is given of which variables are associated with the increase in economic complexity. This study contributes to the literature as it pursues the economic complexity determinants, once complexity may reflect an economy's productive structure. Our contribution is of practical importance for screening policies addressed to promote structural change.

Results indicated human capital and investment in technology explain productive structure. The quantitative measure of human capital showed a positive and significant effect on complexity as well as investment in technology. However, when PISA scores, the qualitative measure of human capital, are included, the quantitative measure showed less relevance or, in most cases, none. PISA 75th percentile score exhibited the largest and significant effect on economic complexity.

The remainder of this study proceeds as follows. Framework presents the economic complexity index. Methodology displays the empirical model, data source, and summary statistics. After that, Results and Discussion expose the core outcomes. Finally, Conclusion presents the study limitations and the suggestions for further researches.

2 Framework

2.1 The concept of economic complexity

Hausmann et al. (2014) introduced the concept of economic complexity. It is based on the amount of knowledge an economy holds. According to that approach, the amount of knowledge is embedded in the products a nation exports, and it is revealed in an analysis of the export basket. The more diversified and less ubiquitous the products in an export basket are, the more complex an economy is.

A ubiquitous product is found everywhere. Using the level of ubiquity seems to be a better measure for economic complexity than technology intensity – the level of ubiquity is more objective than the level of technology. Also, using data on exports is preferred over data on domestic consumption. Hausmann et al. (2014) explained that if a country can export a product, it has mastered the necessary capabilities to produce that product. They also stated that data on exports are more available and comparable than other national-specific economic measures. The connectedness level between products is also taken into account. The economic complexity is measured at the product level and at the national level.

At the product level, a product exported by many countries may be easier to be produced, while a product that is exported by a few may be harder to make. On the other hand, the capabilities required may be used to making different products. So, certain products present more connections than others.

In this context, if a product is not ubiquitous but low connected to other products, it indicates little knowledge required for manufacturing. If a ubiquitous product is highly connected to other products, it suggests this product requires much knowledge, but the kind of knowledge that is somehow explicit, *e.g.* paper products. The less ubiquitous and more connected a product is, the higher its complexity, *e.g.* optical instruments. At the national level, a country is more complex as more knowledge is required to make its products. This amount of knowledge is indirectly measured by the ability to produce and export non-ubiquitous and a wide variety of products.

The interplay between nations and products leads us to calculate each country's diversity level and the ubiquity level of each exported product in a single measure. This measure is the economic complexity index (ECI). It takes into account the revealed comparative advantages[1] that a country has in exporting a product.

Using the country's export basket, the products in which it has advantages, its product space can be constructed to visualize the productive structure. The product space is a net relating products according to the capabilities required to make each product. The proximity of products in this net results from the co-exportation probability. It means a specific capability is linked to both products. For instance, a nation with a comparative advantage in cocoa butter has a high probability of exporting cocoa paste with advantages. In the product space, these two products are close to each other, and there is a line connecting them.

The ECI is a comparative index, which means an increase in ECI indicates an improvement in the capability ranking. The country (region) is learning new capabilities faster than the average.

Furthermore, Hausmann et al. (2014) expect the higher the level of economic complexity is, the more sophisticated exports are, then, larger per capita income is expected as well. Following Hausmann et al. (2014), we relate the normalized data[2] of both per capita output and economic complexity index in order to check for the relation between the two variables.

In Figure 1 each point represents normalized per capita output (on the vertical axis) and normalized economic complexity (on the horizontal axis) for nations in the years at the top of each graph. Economic complexity and per capita output is significantly correlated with each other $(r = 0.6248, p - value < 0.01)$. The relation holds for each of the chosen years between 1964 and 2014.

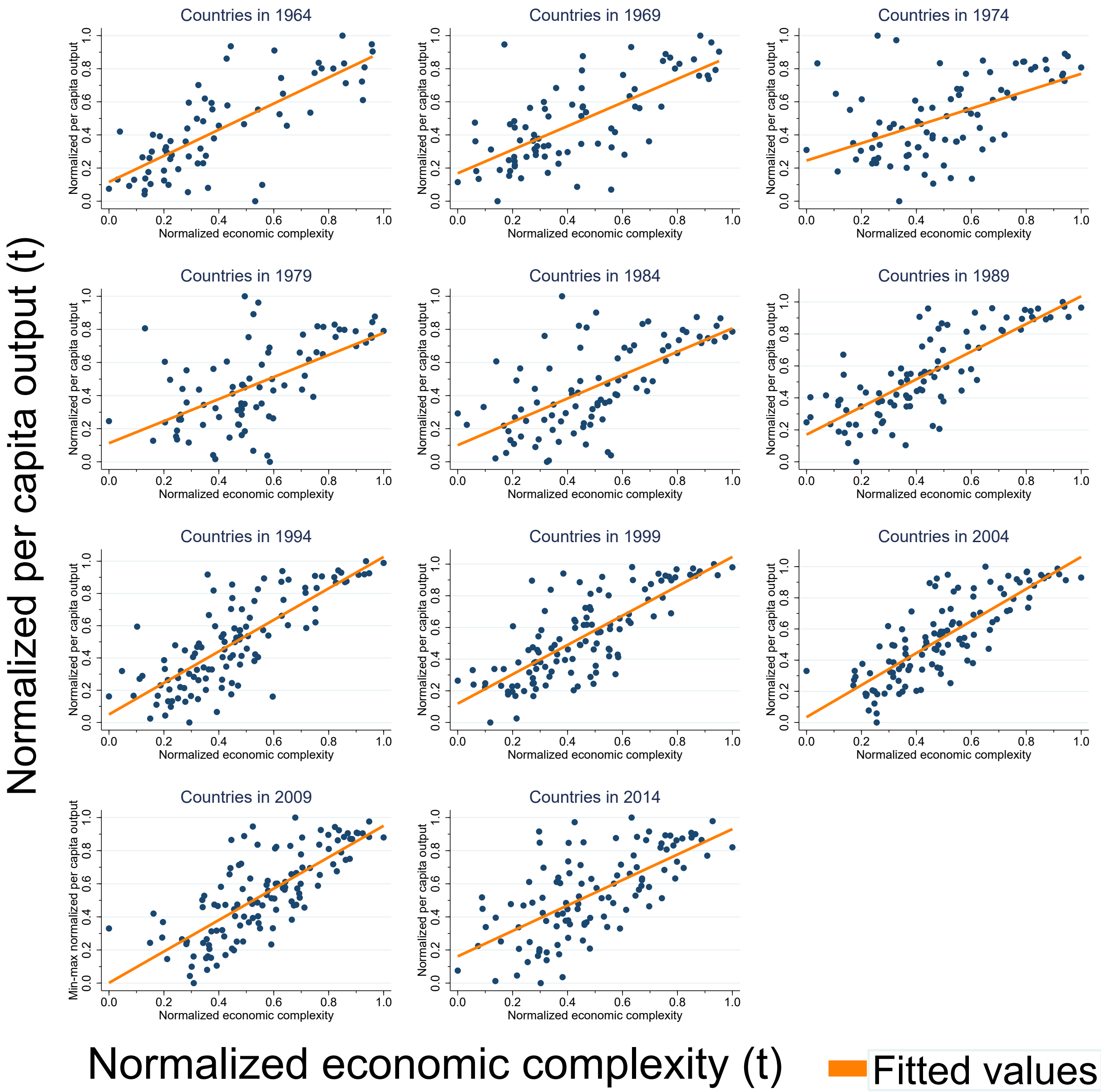
As exposed above, nations with high economic complexity levels but still low levels of per capita income tend to present an accelerated growth. Hausmann et al. (2014) expect that relation, especially when nations presenting similar per capita income levels are compared. On the other hand, countries with a high per capita income level but a comparatively low economic complexity level tend to present diminishing growth.

Lall (2000), Cimoli (2005), and Hausmann et al. (2014) stated that labor-intensive and natural resource-intensive economies tend to present diminishing rates of income growth over time. In the beginning, producing resource-abundant goods yields compar-

[1] Balassa (1965) affirmed that revealed comparative advantage (RCA) exists when the ratio of product p in a country's export share to the world's export share of the same product is higher than the unity $(RCA \geq 1)$. For example, in 2016, with exports of \$30.1 billion, coffee represented 0.20% of world trade. Of this total, Brazil exported \$5.08 billion, and since Brazil's total exports in 2016 were \$191 billion, coffee accounted for 2.65% of Brazil's exports. Since $RCA_{Brazil,coffee} = 13.25$ (2.65% divided by 0.20%), coffee is a product in which Brazil has revealed comparative advantage. RCA is a measure of the relevance of a product in a nation's export basket that controls the size of the nation's economy and the size of each product's market.

[2] The normalization process was: $a'_{it} = \frac{a_{it} - min_t}{max_t - min_t}$, where i means the country and t the period; a'_{it} is the normalized value; a_{it} is the initial value; min_t is the minimum value of a_t, and max_t is the maximum value of a_t.

Figure 1: Normalized per capita output and normalized economic complexity

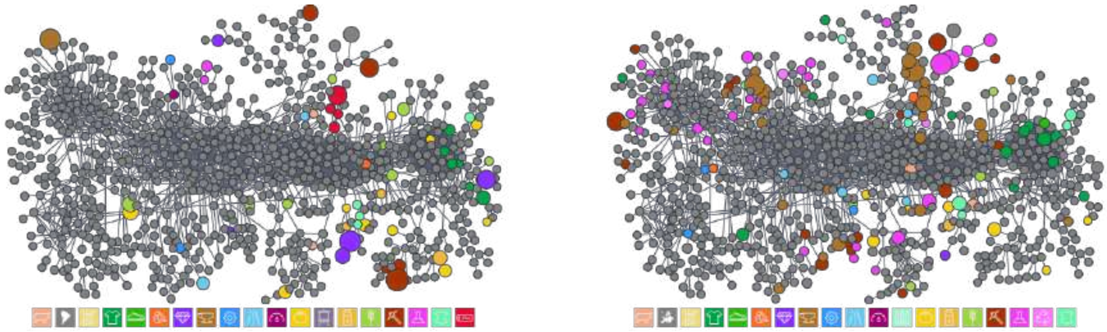


Source: Elaborated by authors

ative advantages; however, it turns toward a loss of competitiveness in the international market over time. Beyond the low-income elasticity that kind of product presents, the capacity to adapt and to recognize new opportunities are the central point to understand the difference between the dependence of an abundant resource and the growth generated by knowledge and technology.

Besides, the product space is used to check for the causal relationship between economic complexity in a year and income growth in the following decade. The product space is the economic complexity visualization of the productive structure. In a product space, each node represents a product; the colorful nodes are the products that an economy exports with comparative advantages. The larger the node is, the higher the share of that product in international trade is. The colors and the icons at the bottom of the image represent the groups of products.

Figure 2: Product Space in 1995



(a) Bolivia (ECI = -0.7848)

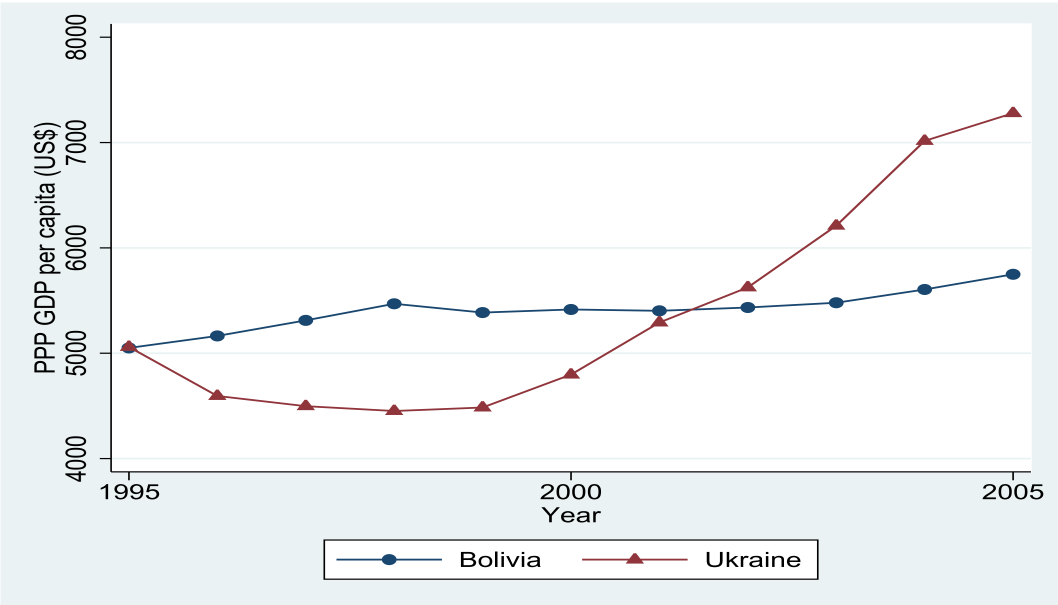
(b) Ukraine (ECI = 0.0623)

Source: Adapted from Simoes and Hidalgo (2011).

Figure 2 displays the product space of Bolivia and Ukraine in 1995. In that year, Bolivia's ECI was -0.7848, and its per capita income was $5,050, while Ukraine's ECI was 0.0623, and its per capita income was $5,059. The Figures 2a and 2b are a bit different.

In Bolivia's product space, the nodes are more scattered and related to four groups of products: mineral products (in dark brown), metals (in light brown), precious metals (in purple), and wood products (in red). In Ukraine's product space, the nodes are less scattered and related to four groups of products: the mineral products (in dark brown), metals (in light brown), chemical products (in pink), and textiles (in green).

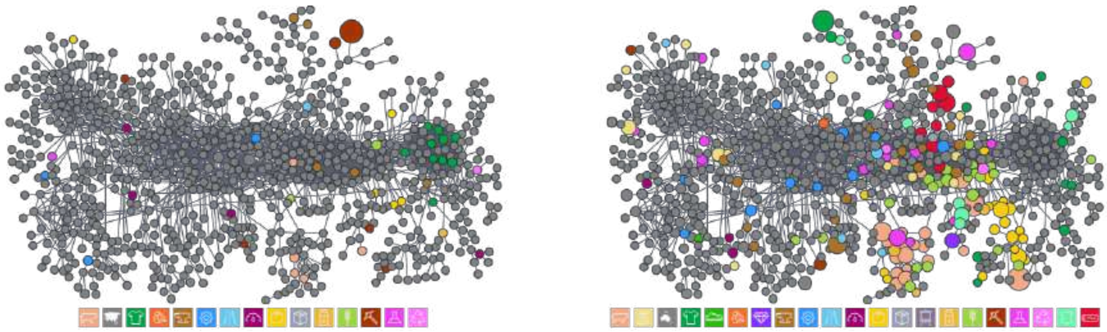
Figure 3: Per capita GDP growth



Note: Per capita GDP is at purchase power parity in 2017 constant international dollars.
Source: Elaborated by authors.

Figure 3 exhibits per capita income of Bolivia and Ukraine from 1995 until 2005. The accumulated growth in the decade after 1995 was 13.85% in Bolivia and 43.86%

Figure 4: Product space in 1995



(a) Oman (ECI = -0.6775) (b) New Zealand (ECI = 0.4412)

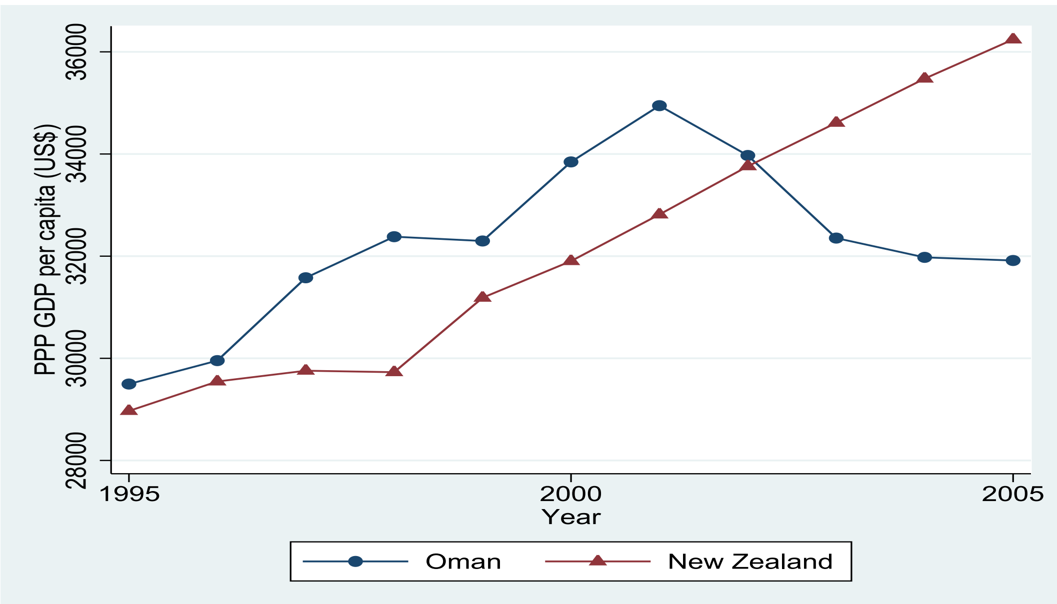
Source: Adapted from Simoes and Hidalgo (2011).

in Ukraine. The average annual growth rate between 1995 and 2005 was 1.32% in Bolivia and 3.91% in Ukraine.

Figure 4 shows Oman and New Zealand's product space in 1995. In that year, Oman's ECI was -0.6775, and its per capita income was $29,496, while New Zealand's ECI was 0.4412, and its per capita income was $28,969. The Figures 4a and 4b are quite different.

In Oman's product space, the nodes are sparsely distributed and related to two groups of products: mineral products (in dark brown); and textiles (in green). In New Zealand's product space, the nodes are more concentrated and related to five groups of products: animal products (in salmon); wood products (in red); vegetable products (in yellow); chemical products (in pink); and textiles (in green).

Figure 5: Per capita GDP growth



Note: Per capita GDP is at purchase power parity in 2017 constant international dollars.
Source: Elaborated by authors

Figure 5 presents Oman and New Zealand's per capita income from 1995 until 2005. The accumulated growth in the following decade was 8.2% in Oman and 25.11%

in New Zealand. The average annual growth rate between 1995 and 2005 was 0.84% in Oman and 2.27% in New Zealand.

In 1995, Bolivia and Ukraine presented similar per capita income; it also occurred between Oman and New Zealand. Though their similarity in per capita income, the difference in product space and economic complexity, productive structure measures, may have played a major role in shaping their income growth in the following decade.

2.2 Human capital and investment in technology

Diversifying the set of products and exporting products that only certain economies export are tasks that require education and technology. Thus, human capital and investment in technology seem to play an important role in economic complexity determination. Moreover, Nelson and Pack (1999) and Cimoli (2005) stated that investments in human capital are the key to increase the learning capacity that predicts a change in productive structure. Technological knowledge cannot be accessed only by having machines, equipment, and blueprints. The learning capacity and the entrance into new sectors depend upon the set of new capabilities.

If an economy presents entrepreneurship, innovation, and learning capacity, the more productive sectors will progressively raise their share of output, capital, and labor. After such changes, the level of national productivity increases as a result of investments in human capital and the expansion of the more productive sectors (Nelson and Pack, 1999).

Furthermore, Romer (1990) introduced the notion that human capital also influences technology growth by being a factor of technical progress that may boost the innovative capacity. He suggested that some skilled people work for expanding technology rather than producing final-output products. Those people's outcomes may be related to cognitive skills instead of the quantity of education.

Nelson and Pack (1999), Cimoli (2005), and Romer (1990) agreed human capital is relevant and presents positive effects on income growth, but they diverge in the size of the effects. They also take technology into account. Given that, a high-skilled worker may follow, understand and cause technical progress.

Hanushek and Kimko (2000) observed the most important limitation left from the studies between labor-force quality and economic growth was to take only schooling attainment as human capital proxies. They affirmed the quality of human capital presents a consistent and stable positive relation to growth rates. Therefore, in the third section, we attempt to separate these two components of human capital, the quantity and the quality of education, to analyze the effects of both on productive structure changes.

According to Gould and Ruffin (1995) and Chen and Feng (2000), international trade leads to economic growth. Rodrik and Subramanian (2005) and Hausmann et al. (2007) indicated government policy is relevant in shaping productive structure. Yanikkaya (2003) affirmed that the previous level of income may also be assumed as the stock of capital in the lagged period.

There is no widely accepted framework for economic growth determinants (Levine and Renelt, 1992; Sala-i Martin, 1997; Barro, 2003). Hence, we follow Gould and Ruffin (1995), Chen and Feng (2000), Rodrik and Subramanian (2005), Hausmann et al. (2007), and Yanikkaya (2003) and introduce trade openness, government expenditure and initial income into our conceptual model.

3 Methodology

In methodological terms, comparing human capital and productive structure at the country level would yield inconsistent estimates, once there may be an endogenous relation between them. Endogeneity comes from the fact that nations with better productive structures also present higher levels of human capital. And, countries with worse productive structures tend to have lower levels of human capital as well. Given that, it seems that those two variables affect one another, which indicates a simultaneity between them.

In order to cope with the simultaneity between productive structure and human capital, we start stating the ideal experiment. The ideal experiment to estimate the effect of human capital on productive structure would be to improve human capital randomly in some countries and not in others. Hence, we should compare productive structure between the countries that had their human capital improved and the ones that did not. Although such experiments would show how human capital influences productive structure, they are not normally held given its practical difficulty.

Without the ideal experiment, the productive structure may be explained by human capital and a group of observable and non-observable variables. As observable variables we outline government spending, investments in technology and trade openness. As non-observable variables we outline cultural and political issues related to economic activities such as entrepreneurship, political system or tax system.

Even though all the observable variables are considered, the non-observable ones would still need to be treated and controlled. Thus, we have developed an identification strategy to deal with the non-observable variables. The identification strategy is to consider two possible characteristics of the non-observable variables. The first characteristic is that the non-observable variables are constant over time. The second characteristic is that the non-observable variables are constant over time when the year-specific changes are removed.

3.1 Identification strategy

Our identification strategy is based on two assumptions: the non-observable variables are constant over time; and the non-observable variables are constant over time only if the year-specific changes are removed. Thus, non-observable variables affecting productive structure are generally country-specific, and do not change much over time, or period-specific, and do not change much in countries given the same period. So, controlling that type of characteristics would yield consistent results when all the observable variables that matter are used. So, the change in human capital causes the variation in productive structure. Therefore, the proper way to try to capture the effect of human capital on productive structure is using a two-way fixed-effect (TW-FE) panel. We use a TW-FE panel due to it allows us to control the non-observable characteristics that are fixed at country level or at the period level.

According to our identification strategy, using the observable variables and a TW-FE panel, we will come close to the effect of human capital on productive structure. We have used one proxy for each observable variable except for human capital. For human capital, we have used two proxies: a quantitative and a qualitative measure. Given methodological issues, we have run two estimates to use both proxies for human capital. The first estimate uses only the quantitative measure of education, the second estimate includes both the quantitative and the qualitative measures of human capital.

Data are for 97 countries from 1996 to 2015 averaged over five-year periods. Furthermore, the availability of data restricted the number of nations and the period analyzed. Five-year intervals and period dummies are used to remove a correlation that comes from business cycle effects (Fölster and Henrekson, 2001). By doing that, we also attempted to eliminate the influence of government changes or economic crises. The dependent variable is productive structure over four periods: 1996-2000, 2001-2005, 2006-2010, and 2011-2015. The specified regression is:

$$Pro.Stru_{it} = \beta_1 Hum.Cap_{it} + \beta_2 Phy.Cap_{it-1} + \beta_3 Inv.Tec_{it} + \beta_4 Tra.Op_{it} + \beta_5 Gov_{it} + v_i + \alpha_t + \omega_{it} \tag{1}$$

where i means the country and t the period. $Pro.Stru$ is productive structure; $Hum.Cap.$ is human capital; $Phy.Cap$ is physical capital; $Inv.Tec$ is investment in technology; $Tra.Op$ is the level of trade openness; Gov is government expenditure; v is the intercept of each country; α is the intercept of each period; and ω is the error term.

The measure of productive structure is the economic complexity index (ECI). The ECI is based on the products each country is able to produce and export with advantages. The ECI also takes into account the share of products in the international trade and the income level of their exporters.

There are two proxies for human capital, one based on the quantity of human capital and another one based on the quality of human capital. The first measure is an education index. The human capital index is used because it combines different databases on education attainment and has more observations than any other human capital measure. The second proxy for human capital is based on a qualitative measure. According to Hanushek and Kimko (2000), educational quality measures may come from two sources: schooling inputs or cognitive skill tests. We used a cognitive skill test as the quality of human capital because it is an output of education system.

The proxy for physical capital is lagged per capital output. We follow Yanikkaya (2003) and take lagged per capital output as a measure of the stock of capital. The proxy for investment in technology is the share of output spent on research and development (R&D).

A measure is constructed to access the trade openness level of an economy. It is based on the sum of imports and exports as a percentage of output, country's area, and country's population. The sum of imports and exports as a percentage of output is regressed on the country's area, and population and the error term are separated. The estimate's residual is about all the other variables related to trade openness, excepting country's area and population. Afterwards, the residual of the mentioned estimate is multiplied by a measure of trade terms, which is a ratio of an export price index to an import price index. Thus, the trade openness variable is controlled for differences in international prices, population, and country's area[3].

The proxy for government expenditure is the share of output spent on general government final consumption. This measure includes all current government expenditures for purchases of products and services. It also contains most expenditures on national defense and security. Nevertheless, it drops government military spending, which is part of the government's capital formation.

We expect human capital to be positively related to productive structure. Furthermore, we expect physical and investment in technology to have positive effects on

[3] Barro (2003) used a similar approach to capture the impact of trade openness on economic growth.

productive structure. And, we also expect a positive relation between trade openness and productive structure, once a more open nation may access better inputs and bigger markets. However, we have no expectation for the relationship between government expenditure and productive structure. We expect that because public spending may be used to favor the production and export of highly complex products and promote opportunities to increase capabilities. On the other hand, the government may complicate some issues and bring a worse economic environment to business.

3.2 Data source

The value of the ECI is a time-varying measure, which has 0 average, 1 as standard deviation and lies between -∞ and ∞. All of the product data used to elaborate the ECI come from the Standard International Trade Classification (STIC) or Harmonized System (HS). Data on complexity goes from 1964 to 2018 and is available on observatory economic complexity (Simoes and Hidalgo, 2011). Per capita output based on purchasing power parity is in constant 2017 international dollars and comes from the World Development Indicators.

The quantitative proxy for human capital is the human capital index in the Penn World Table 9.1(Feenstra et al., 2015). This index takes into account data on the average years of schooling from Cohen and Soto (2007), Barro and Lee (2013) and Cohen and Leker (2014) and also the rates of return to education for each level of schooling estimated by Psacharopoulos (1994). The human capital index is used because it combines different databases on education attainment and has more observations than any other human capital measure.

The qualitative measure for human capital comes from the national scores in the Programme for International Student Assessment (PISA) executed by the Organisation for Economic Co-operation and Development (OECD)[4]. PISA is an international survey that collects data on student's performances in the 30 members of the OECD and some partner countries. Surveys take place every three years and assess the 15-year-old students' knowledge in reading, mathematics, and science.

PISA provides detailed information on students' backgrounds and school factors. Results of the surveys were transformed to a scale that had 500 as mean and 100 as standard deviation. PISA database presented important issues, such as testing students on three subjects while the other international tests do not have a broad result of the education process; and outcomes are internationally comparable (Fuchs and Wößmann, 2007).

International surveys, such as PISA, aim to assess the knowledge or skills of a population. However, it is not easy to evaluate the population's performance by testing a sample of it. A statistical technique for doing that is to use plausible values. According to Wu (2005), plausible values represent the range of abilities that a student might have, and they perform well in estimating population parameters. Plausible values were used to estimate the population mean score and the population scores of the percentiles 75th, 90th, and 95th of PISA surveys in 2000, 2003, 2009 and 2012[5].

[4]Jakubowski and Pokropek (2013) facilitated the OECD databases approach by developing a Stata module to access such information.

[5]Although PISA surveys have a three-year interval and our database has a five-year interval, we could use PISA surveys because they matched our five-year periods: PISA 2000 for the interval 1996-2000; PISA 2003 for the interval 2001-2005; PISA 2009 for the interval 2006-2010; and PISA 2012 for the interval 2011-2015.

R&D is compounded by current and capital spending from both the public and private sectors in activities that systematically increase knowledge of humanities, culture, and society. That spending covers basic and applied research as well as experimental development. R&D are from United Nation Educational, Scientific and Cultural Organization (UNESCO). Data on R&D are available from 1996 until 2016.

Data on import, export, and government expenditure come from the OECD. Data on population and land area come from United Nations (UN). The World Bank made all data available[6], excepting economic complexity and human capital. Table I shows the summary statistics of the data.

Table I: Summary statistics between 1996 and 2015 (five-year intervals)

	Observation	Mean	Std.Dev.	Minimum	Maximum
Economic Complexity Index	482	-0.01907	0.9942	-2.4411	2.5391
GDP per capita	470	19536.6	19229.3	582.61	101304.7
Human Capital	442	2.5212	0.6627	1.1232	3.7265
PISA mean Score	184	472.20	49.007	327.08	546.47
PISA 75th Score	184	538.00	50.413	392.28	613.75
PISA 90th Score	184	588.82	49.135	452.18	667.90
PISA 95th Score	184	617.76	48.259	485.44	698.30
R&D	357	0.9019	0.9222	0.009205	4.1977
Trade openness	465	-3404.2	5304.8	-29966.6	28798.0
GOV	463	15.362	5.0763	1.3413	27.934

Note: GDP per capita based on purchasing power parity is in constant 2017 international dollars; R&D is the research and development (% of GDP); GOV is the government expenditure (% of GDP).
Source: The World Bank; The OECD; The Penn World Table 9.1; Simoes and Hidalgo (2011).

For the regression, we use the natural logarithm of both per capita output and human capital index, the square root of R&D, and the others variables were not transformed. All variables were standardized[7], except ECI data. The ECI come already in a standardized form.

4 Results and Discussion

4.1 Core outcomes

Table II displays the results of the specification presented in Equation 1.

Hereafter, we consider the significance level at 0.10. According to Table II, initial per capita output, human capital, investment in technology, and trade openness presented significant effects on economic complexity. The possibility of diminishing returns of R&D to human capital was tested, but it exhibited insignificant effects.

Government expenditure showed no significance. We believe cross-country differences in public spending explain the absence of a significant effect on complexity. An

[6] Azevedo (2014) facilitated the approach to the World Bank databases by developing a Stata module to access such information.

[7] The standardization process was: $X^*_{it} = \frac{(X_{it}-\mu_t)}{\sigma_t}$,where i means the country and t the period; X^*_{it} is the standardized value; X_{it} is the initial value; μ_t is the mean of X_t; and σ_t is the standard deviation of X_t.

Table II: Economic complexity between 1996 and 2015 (five-year intervals)

	Economic Complexity Index
GDP per capita	0.41***
	(0.135)
Human Capital	0.47***
	(0.612)
R&D	0.14*
	(0.142)
Trade openness	0.14***
	(0.00001)
GOV	-0.03
	(0.00668)
Observation	318
Adj. R^2	0.27

Standardized beta coefficients; standard errors in parentheses; all standard errors clustered at country level; * $p < .1$, ** $p < .05$, *** $p < .01$

Note: R&D is the research and development (% of GDP); GOV is the government expenditure (% of GDP); GDP per capita is in period t-1, all other regressors are in period t.

Source: Elaborated by authors.

important difference between countries is the government's attitude toward production and exports.

The coefficients are in standard deviation terms. A one-standard-deviation increase in lagged per capita output is associated with a 0.4038 standard-deviation increase in the ECI. A one-standard-deviation increase in the human capital index is associated with a 0.4964 standard-deviation increase in the ECI. While for R&D and Trade openness, a one-standard-deviation increase is associated with a 0.1308 and 0.1369 standard-deviation increase in the ECI, respectively.

To depict what a one-standard-deviation increase means, certain examples are given. From 1990 to 2014, a one-standard-deviation in the human capital index occurred in Singapore, Brazil, and Qatar. It took seven years in Singapore and 13 years in the other two countries.

From 1996 to 2016, a one-standard-deviation increase in R&D took place in Estonia, Iceland, Slovenia, South Korea, and Denmark. It happened in periods of three, four, four, five, and ten years, respectively. Furthermore, most of the observations showed a R&D level smaller than the full sample's standard deviation. It makes a one-standard-deviation increase even more difficult for those countries.

From 1980 to 2016, a one-standard-deviation increase in trade openness occurred in Liberia, Iraq, Panama, Qatar, Angola, and other 15 nations. It took a period of a year to happen. It suggests a one-standard-deviation increase in trade openness is somehow less difficult to happen. From 1964 to 2016, and considering at most 20-year periods, a one-standard-deviation increase in the ECI took place in 35 countries. The time average for such change was 6.25 years.

As an attempt to test the validity of the results, different samples of countries were used. Countries were separated into seven groups according to their geographical region. The geographical regions were: East Asia and Pacific; Europe and Central Asia; Latin America and Caribbean; Middle East and North Africa; North America; South Asia; and Sub-Saharan Africa. Equation 1 was run on seven different samples; for each estimate, one region was left out[8].

Comparing the estimates of the seven different region samples to the results presented in Table II, trade openness and government expenditure showed similar outcomes. When countries of East Asia and Pacific were left out, lagged per capita output displayed no significance. Human capital and investment in technology showed no significance when countries of either East Asian and Pacific or Europe and Central Asia were left out.

Focusing on the coefficients' size and their significance among the estimates of the seven different region samples and the full sample estimate, we believe human capital has smaller effects on economic complexity in countries of Latin America and Caribbean. We suppose that because human capital displayed the largest coefficient when Latin America and Caribbean countries were left out. Moreover, we believe investment in technology presents smaller effects on complexity in Middle East and North Africa countries as well as in countries of Sub-Saharan Africa. We assume that due to R&D showed the two largest coefficients when countries of these two regions were left out.

In this context, we believe human capital and investment in technology have larger effects on economic complexity in countries of two regions, East Asia and Pacific and Europe and Central Asia. We presume that because human capital and R&D exhibited the two smallest coefficients when countries of these regions were left out[9].

4.2 Focus on human capital

Alternative proxies for human capital were used to test the robustness of the relationship between human capital and economic complexity. Gross and net enrollment rate in primary, secondary, and tertiary education[10] served as human capital proxies. Running the Equation 1 on these alternative proxies yielded that only gross, and net enrollment rates in secondary showed significance. We believe these results happened because the human capital index partly uses average schooling years, which generally follows enrollment rate trends. These alternative proxies for human capital presented either a smaller number of observation or insignificant coefficients.

Holsinger and Cowell (2000) affirmed that there are three sorts of secondary school: the general or academic secondary; the vocational or technical secondary; and the diversified or comprehensive secondary. Although no data on these differences are available at the country level, secondary education plays an essential role in a nation's productive structure.

Other alternative proxies for human capital were considered: the share of the population aged 25 or over with completed primary, secondary or tertiary education, the

[8]We did it to prevent losing more degrees of freedom.

[9]We tested other two alternative samples, one made only of countries of East Asia and Pacific, and another one compounded only of countries of Europe and Central Asia. For countries of Europe and Central Asia, human capital and investment in technology displayed larger and significant coefficients. For countries of East Asia and Pacific, only human capital presented a larger and significant coefficient.

[10]All data on enrollment rate come from UNESCO.

average years of total schooling[11], and another human capital index[12]. Running the Equation 1 on these alternative proxies resulted that only the share of the population with completed primary education presented significance, while trade openness showed no significance and R&D exhibited a smaller and significant coefficient. We suppose completing primary education is the threshold for human capital that Azariadis and Drazen (1990) explained. All these alternative proxies displayed a loss in degrees of freedom.

Barro (2003) presented different returns of education to economic growth according to gender. Given that, a sample with only female students and a sample with only male students were considered. Gross and net enrollment rate on the three levels of education, the share of the population with completed primary, secondary and tertiary, and the average years of total schooling were used with different gender samples. Running the Equation 1 on these different gender samples yielded outcomes similar to the results without gender differentiation, though each gender samples presented a smaller number of observations.

To improve the analysis, a qualitative measure of human capital was included in the estimate. PISA data was used as the quality of human capital. PISA surveys were limited to a set of countries smaller than our core estimate. Thus, we believe a loss in the degrees of freedom exists as well as a selection bias[13]. It biased the results toward an underestimate of the relation proposed here. Although including the quality of education makes the sample smaller, the coefficients performed well to this new specification.

Data on PISA 2000, 2003, 2009, and 2012 surveys were used[14]. The performance in reading[15] was used for the PISA surveys mentioned. We used PISA mean score and PISA scores of the percentiles 75th, 90th, and 95th in the estimates[16].

Equation 1 was run again, but now the quality of human capital was included. Hence, human capital presents two components, the human capital index, and PISA scores. Results of this specification are displayed in Table III.

According to Table III, initial per capita income, the quantity or the quality of human capital, investment in technology, and trade openness presented significant effects in all five estimates. At the same time, the government size showed no effect at all. Including PISA scores alters only the human capital's relevance; all other coefficients stood slightly the same.

Comparing the quantity and quality of human capital draws that PISA scores' inclusion makes the human capital index lose its significance, except when PISA 95th

[11] Data on the share of the population with a completed level of education and average years of schooling come all from Barro and Lee (2013).

[12] This alternative human capital index is developed by Cohen and Soto (2007).

[13] The selection bias comes from the similarity of countries compounding the OECD group. The average of their human capital index might be higher than the other countries. Thus, the effect of education on economic complexity within this group may be lowered. It may also happen with the R&D. Only 56 nations participated in PISA surveys; our core estimate without PISA data is compounded of 97 countries.

[14] Data are in 5-year intervals from 1996 to 2015. We considered for each interval the PISA survey collected within that interval. We used PISA 2009 for the interval 2006-2010, once two new countries were included in that survey. Using PISA 2006, instead of PISA 2009, yields coefficients and signs similar. However, standard errors are different, which causes divergences in terms of significance.

[15] We made use of reading performance because it presented a smaller standard deviation, which results in significant coefficients.

[16] The scores were chosen arbitrarily.

Table III: Economic complexity between 1996 and 2015 (five-year intervals)

	(1) ECI	(2) ECI	(3) ECI	(4) ECI	(5) ECI
GDP per capita	0.40***	0.38**	0.38**	0.39**	0.39***
	(0.175)	(0.175)	(0.177)	(0.180)	(0.179)
Human Capital	0.47*	0.41	0.40	0.41	0.43*
	(1.285)	(1.272)	(1.260)	(1.267)	(1.280)
R&D	0.41***	0.41***	0.42***	0.43***	0.43***
	(0.198)	(0.196)	(0.187)	(0.183)	(0.184)
Trade openness	0.24***	0.23***	0.21***	0.20***	0.21***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
GOV	0.04	0.09	0.08	0.06	0.05
	(0.0161)	(0.0171)	(0.0163)	(0.0160)	(0.0161)
PISA Mean Score		0.18**			
		(0.001)			
PISA 75th Score			0.20**		
			(0.00144)		
PISA 90th Score				0.16*	
				(0.00131)	
PISA 95th Score					0.12
					(0.00118)
Observation	175	175	175	175	175
Adj. R^2	0.50	0.53	0.53	0.52	0.51

Standardized beta coefficients; standard errors in parentheses; all standard errors clustered at country level; $^{*}\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .01$

Note: R&D is the research and development (% of GDP); GOV is the government expenditure (% of GDP); GDP per capita is in period t-1, all other regressors are in period t.

Source: Elaborated by authors.

score is included. Among PISA scores, PISA 75th score presented the largest coefficient. Adding PISA scores to the estimate yielded lower coefficients of the human capital index. Lower coefficients suggest human capital relies on the quality of education.

Hanushek and Kimko (2000) stated that educational quality improves the power to explain economic growth. Thus, considering a qualitative measure of education causes the quantitative measure to lose its relevance a bit. Outcomes indicated that achieving higher PISA scores is associated with presenting higher levels of economic complexity, reflecting an improvement in the nation's productive structure.

5 Conclusion

This investigation contributes to the debate on the importance of human capital and investment in technology on a country's productive structure. Once export sophistication reflects productive structure, this study focused on finding export sophistication determinants and related them to productive structure, per capita output, and income growth.

The economic complexity index was used as a measure of export sophistication. This index is based on the levels of ubiquity and diversity of exports, the share of international trade, and connections between products. Our estimate is from 1996 to 2015 with a sample of 97 countries.

According to results, given data, and the methodology used, human capital, investment in technology, lagged per capita income, and trade openness are important factors in explaining productive structure. The four factors showed positive effects on economic complexity. On the other hand, government expenditure is not a key element in determining a country's productive structure. We checked for any differences in female and male education affecting economic complexity, none was found.

We also included a qualitative measure of human capital in our main estimate and presented promising outcomes. PISA mean score and PISA scores of 75th, 90th, and 95th percentiles were used as the quality of human capital. Three of the four PISA scores showed relevance in explaining productive structure. PISA mean, 75th, and 90th scores displayed a positive effect on economic complexity. The percentile of 75th showed the largest and significant coefficient.

Our findings suggest expansions in human capital are conducive to enhancements to a country's productive structure. So, investments in increasing both the average years of schooling and the quality of education should be promoted. And, given that the quantity of human capital matters only when its quality is not taken into account, countries should invest more in the quality of education. Moreover, the efforts to raise the human capital stock, besides aiming to increase economic complexity, are direct income growth factors.

The learning and innovative capacities lead to improvements in productive structure. Both capacities come from investing in technology. Hence, rises in R&D should be encouraged. Furthermore, R&D also aims to increase the economy's level of knowledge. Trade openness promotes upgrades in productive structure as well. Thus, investments in opening international trade should receive certain incentives. On the other hand, we cannot indicate the influence of government expenditure on the productive structure.

The main limitation of the study is the availability of data, particularly on human capital and R&D. Furthermore, a suggestion for further researches is to analyze R&D according to its resource, given that public and business enterprise investments cause different effects on the productive structure. Another suggestion is to analyze R&D according to its objectives, given that basic and applied research may vary their effects on the productive structure.

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