Human capital, technology, and productive structure

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Area 6 - Crescimento, Desenvolvimento Econômico e Instituições

Abstract

Understanding the factors that shape productive structure leads us to the causes of income growth, given that several studies have associated growth with productive structure. This study analyzes the relation between productive structure, human capital and investment in technology at national level. The economic complexity index is used as a proxy for productive structure. The quantity and the quality of education were considered. The scores of the Programme for International Student Assessment were used as the qualitative measure of human capital. We used a fixed-effects panel with data for 97 countries from 1996 to 2015. Results indicated a positive effect of human capital on economic complexity, although including the quality of education made the quantity of it lose its relevance. These results suggested the quality of education improves the power of human capital to explain productive structure. We conclude that human capital and investment in technology should be promoted, especially the quality of education. (JEL: I25; O11; F43)
Keywords: Productive structure, Human capital, Technology, Economic complexity.

Resumo

Compreender os fatores que moldam a estrutura produtiva nos leva às causas do crescimento da renda, dado que muitos estudos associaram crescimento e estrutura produtiva. Este estudo analisa a relação entre estrutura produtiva, capital humano e investimento em tecnologia a nível nacional. O índice de complexidade econômica é usado como *proxy* da estrutura produtiva. A quantidade e a qualidade da educação foram consideradas. As notas no PISA foram usadas como a medida qualitativa do capital humano. Utilizamos um painel de efeitos fixos com dados para 97 países, de 1996 a 2015. Os resultados indicaram um efeito positivo do capital humano na complexidade econômica, embora a inclusão da qualidade da educação fizesse com que a quantidade perdesse sua relevância. Esses resultados sugeriram que a qualidade da educação melhora o poder do capital humano de explicar a estrutura produtiva. Conclui-se que o capital humano e o investimento em tecnologia devem ser promovidos, especialmente a qualidade da educação. (JEL: I25; O11; F43)
Keywords: Estrutura produtiva, Capital humano, Tecnologia, Complexidade econômica.

1 INTRODUCTION

Lall et al. (2006) analyzed the export structure of some countries by looking at their export basket and their level of income, and inferring their levels of export sophistication. Furthermore, the sophistication of exports is a result of a set of characteristics that include exporting higher-level of technology products as well as 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. Given that, we aim to explain productive structure using economic complexity as its proxy and human capital and investment in technology as its possible determinants.

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 a country's export basket, which expresses the productive structure, is a strong and robust predictor of the subsequent rate of 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 sophistication in ordinary exports 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 to 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 indicative 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 thereby indicating future income growth.

Results indicated human capital and investment in technology explain productuve 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 as well as 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 reavealed 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, once the level of ubiquity is more objective than the level of technology. Also, using data on exports is preferred than data on domestic consumption. Hausmann et al. (2014) explained that if a country is able to 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 measure. The connectedness level between products is also taken into account. The economic complexity is measured at product level and at national level.

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

In this context, if a product is not ubiquitous, but low connected to other products, this indicates little knowledge required for manufacturing. If a ubiquitous product is highly connected to others 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 is, *e.g* optical instruments. At national level, a country is more complex the 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 lead 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) and it takes into account the revealed comparative advantages[1] that a

[1] Balassa (1965) affirmed that revealed comparative advantage (RCA) exists when the ratio of product p in a coun-

nation has in exporting a product.

Using the country's export basket, the products in which it has advantages, its product space can be contructed as a visualization of 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 is a consequence of the probability of some products to be co-exported by the same country. It means a specific capability is linked to both products. For instance, a nation that has the comparative advantage in cocoa butter has a high probability of exporting cocoa paste with advantages too. 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 not only learning new capabilities, but it is doing that faster that 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 year between 1964 and 2014.

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

Lall (2000), Cimoli (2005), and Hausmann et al. (2014) stated that economies mainly based on natural resources and labor-intensive products tend to present diminishing rates of income growth over time. In the beginning, producing resource-abundant goods yields comparative advantages, however, over time it turns toward a loss of competitiveness in international market. 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 as an attemption to check for the causal relation 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 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.

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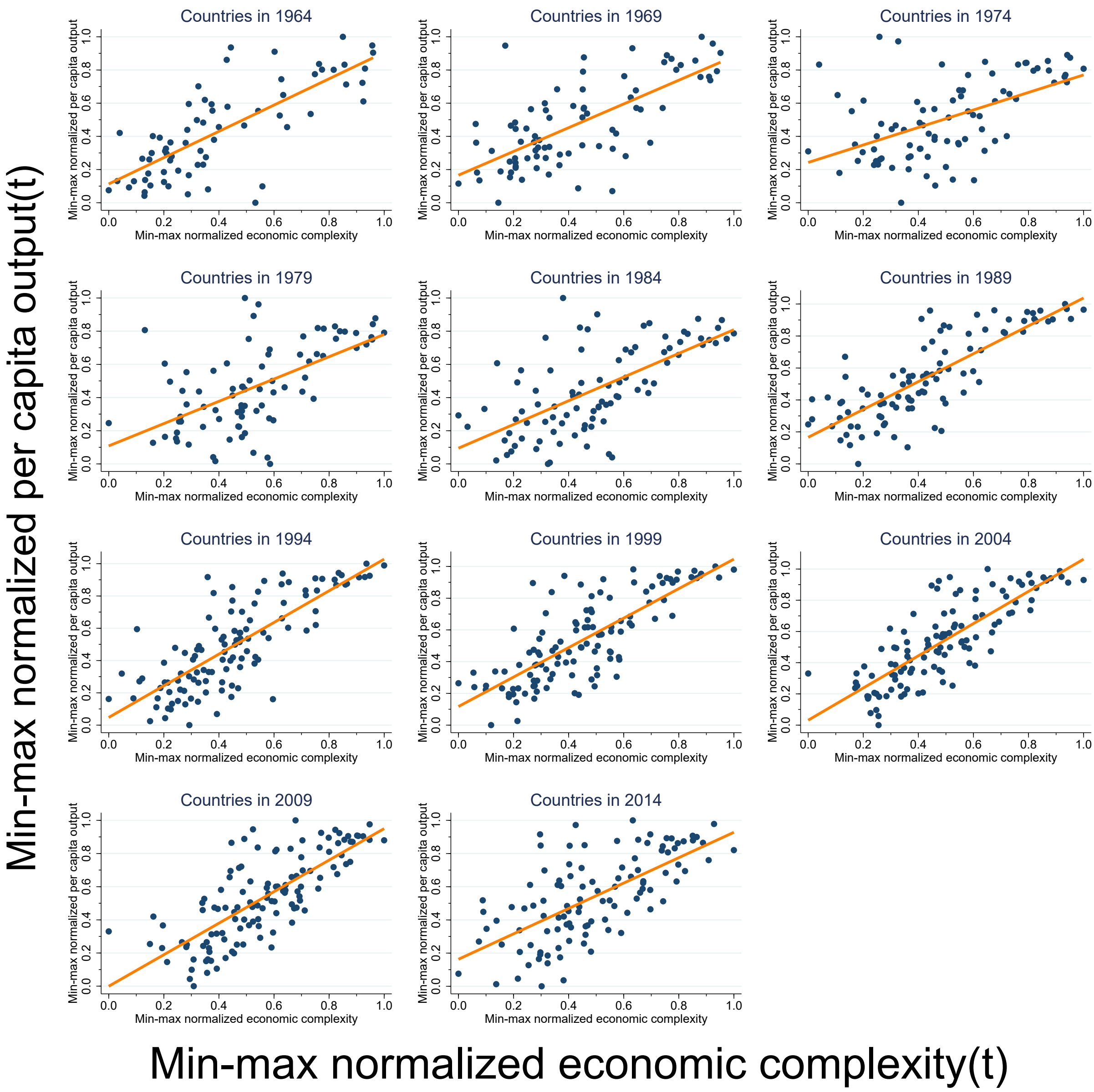
try's export share to the world's export share of the same product is higher than the unity $(RCA \geq 1)$. For example, in 2016, with exports of \$30.1 billion, coffee represented 0.20% of world trade. Of this total, Brazil exported \$5.08 billion, and since Brazil's total exports in 2016 was \$191 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 for the size of the nation's economy as well as the size of the market of each product.

[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

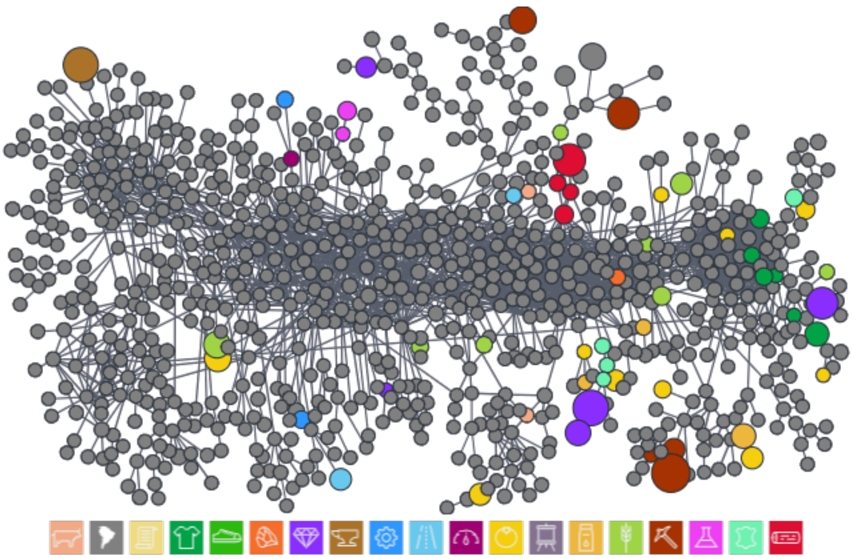
In Bolivia's product space the nodes are more scattered and related to four groups of products: mineral products (in dark brown); metals (in light brown); precious metals (in purple); and wood products (in red). In Ukraine's product space the nodes are less scattered and related to four groups of products: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

Figure 3 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% in Ukraine. The average annual growth rate between 1995 and 2005 was 1.32% in Bolivia and 3.91% in Ukraine.

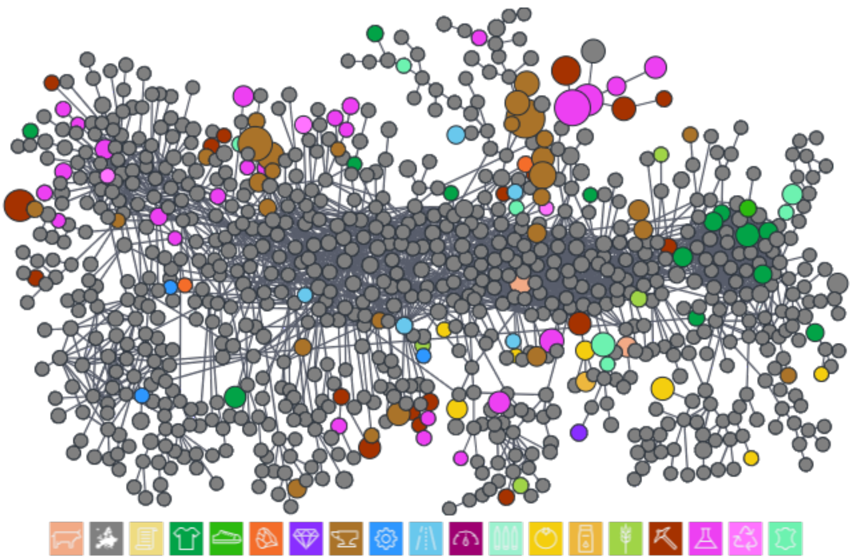
Figure 4 shows the product space of Oman and New Zealand in 1995. In that year Oman's ECI was -0.6775 and its per capita income was $29,496, while New Zealand's ECI was 0.4412 and its per capita income was $28,969. The Figures 4a and 4b are quite different.

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

Figure 2: Product Space in 1995



(a) Bolivia (ECI = -0.7848)



(b) Ukraine (ECI = 0.0623)

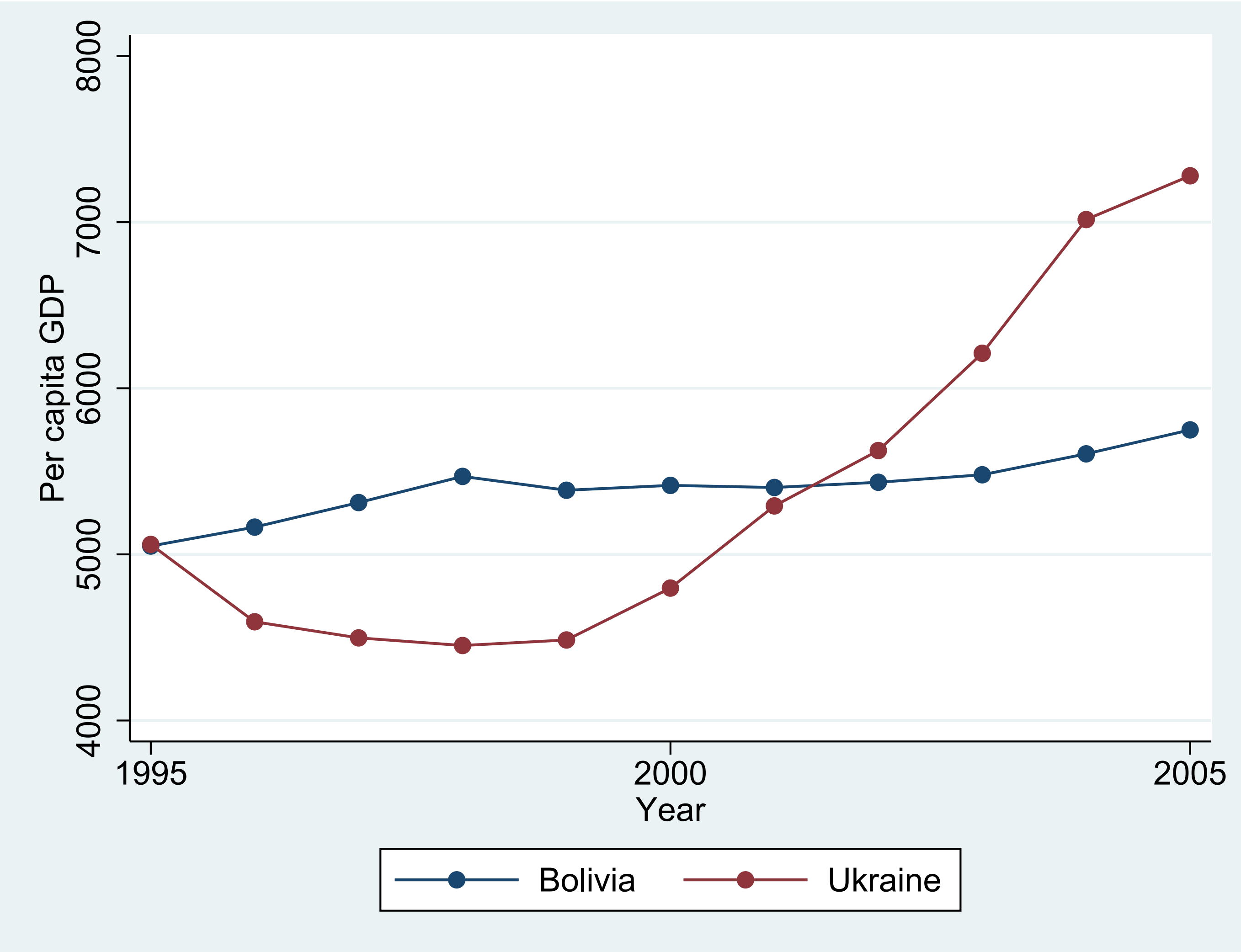
Source: Adapted from Simoes and Hidalgo (2011).

space the nodes are more concentrated and related to five groups of products: animal products (in salmon); wood products (in red); vegetables products (in yellow); chemical products (in pink); and textiles (in green).

Figure 5 presents per capita income of Oman and New Zealand 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 occured between Oman and New Zealand. Though their similarity in per capita income, the difference in product space and in economic complexity, measures of productive structure, may have played a major role in shaping their income growth in the following decade.

Figure 3: Per capita GDP growth



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

2.2 Human capital and investment in technology

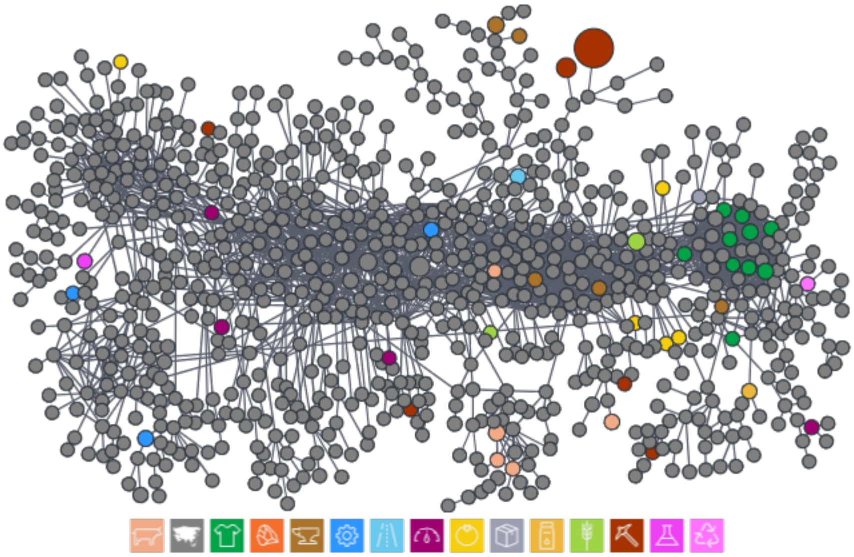
Diversifying the set of products and exporting products that only certain economies export are tasks that require education and technology. Thus, human capital and investment in technology seem to play an important role in economic complexity determination. Moreover, Nelson and Pack (1999) and Cimoli (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 the learning capacity, the more productive sectors will progressively rise their share of output, capital and labour. 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).

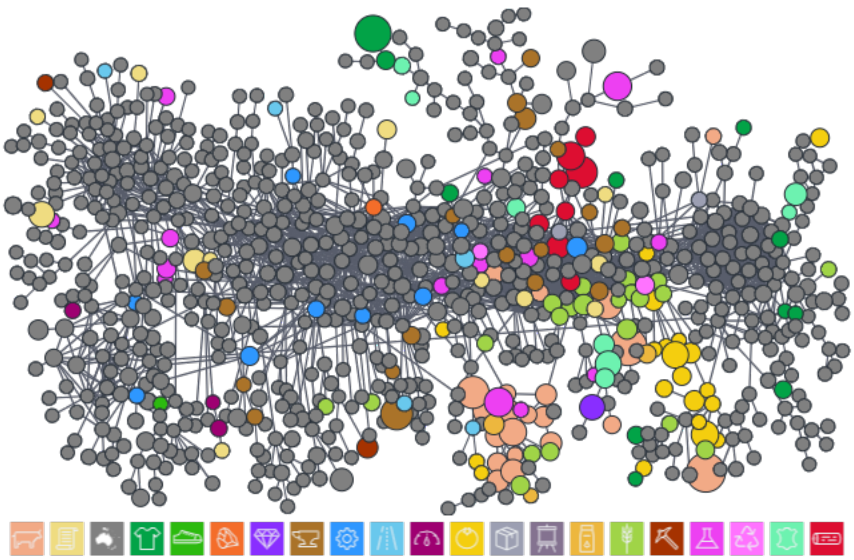
Furthermore, Romer (1990) introduced the notion that human capital also influences technology growth by being a factor of technical progress that may boost the innovative capacity. He suggested some skilled people work for expanding technology, rather than producing final-output products. Those people's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

Nelson and Pack (1999), Cimoli (2005), and Romer (1990) agreed human capital is relevant

Figure 4: Product space in 1995



(a) Oman (ECI = -0.6775)



(b) New Zealand (ECI = 0.4412)

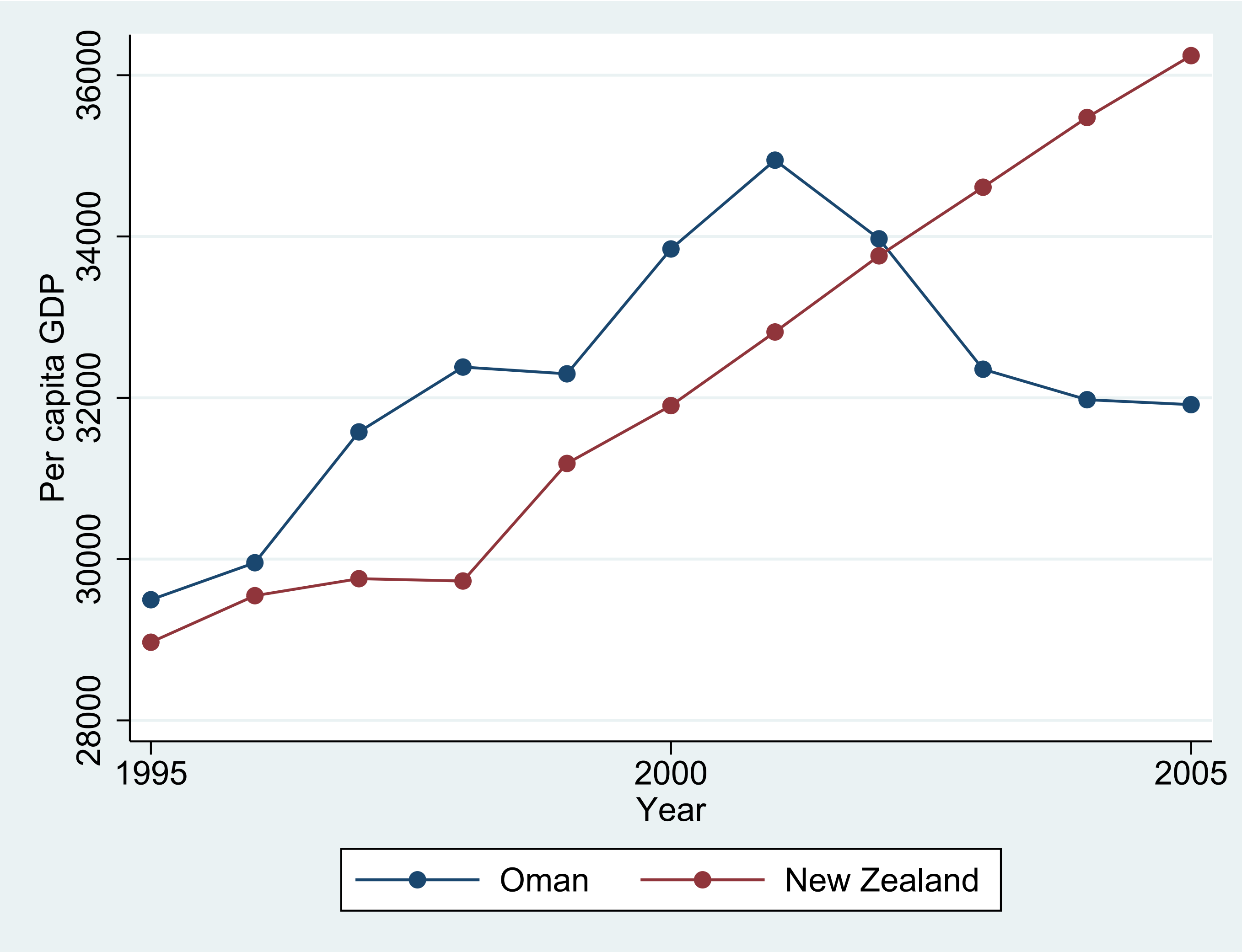
Source: Adapted from Simoes and Hidalgo (2011).

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 attainament 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.

Figure 5: Per capita GDP growth



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

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.

$$ECI = GDP_{initial} + HC + R\&D + TRA + GOV \tag{1}$$

where ECI is economic complexity; $GDP_{initial}$ is initial income; HC is human capital; R&D is investment in technology; TRA is trade openness and GOV is government expenditure.

3 METHODOLOGY

3.1 Empirical Model

The empirical model estimates the relationship between economic complexity and human capital, previous level of income, investment in technology, trade openness, and government expenditure.

We have used one proxy for each variable, excepting for human capital. For human capital, we have firstly analyzed only a quantitative measure of it, afterward we used both, the quantity and the quality of education.

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 in order 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 crisis.

We made use of a fixed-effects panel, because it allowed us to control the non-observable fixed part of the heterogeneity at country level. The dependent variable is the economic complexity index over four periods: 1996-2000, 2001-2005, 2006-2010, and 2011-2015. The specified regression is according to the following fixed-effects panel:

$$ECI_{it} = \beta_1 GDP_{it-1} + \beta_2 HC_{it} + \beta_3 R\&D_{it} + \beta_4 TRA_{it} + \beta_5 GOV_{it} + \upsilon_i + \omega_{it} \quad (2)$$

where i means the country and t the period. ECI is the economic complexity index; GDP is initial per capita output; HC is human capital; $R\&D$ is investment in technology; TRA is trade openness; GOV is government expenditure; υ is the intercept of each country; and ω is the error term.

Lagged per capita output is used as a control for the past economic growth. Also, Yanikkaya (2003) took that measure as a proxy for the stock of capital. In the first estimate, a quantitative measure of education is used as a proxy for human capital. The second estimate included a qualitative measure of human capital. The proxy for investment in technology is the share of output spent on research and development (R&D).

To access the trade openness level of an economy, a measure is constructed. 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 country's area and population, and the error term is separated. The residual of the estimate is about all the other variables that are related to trade openness, excepting country's area and population. Thus, 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. By doing so, 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 government current expenditures for purchases of products and services. It also contains most expenditures on national defense and security, however, it drops government military spending, which are part of government's capital formation.

We expect that lagged per capita output, human capital, and investment in technology have positive effects on the complexity index. Our expectation for the relation between trade openness and complexity is a positive relationship, since the ECI is based on the sophistication of exports and a more open nation may access better inputs and bigger markets.

We have no expectation related to the sign of government expenditure in economic complexity regressions. It is difficult to expect a negative contribution of government on complexity, given that public spending may be used to favor production and export of highly complex products as well as to promote opportunities to increase capabilities. On the other hand, 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 either from

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

the Standard International Trade Classification (STIC) or from Harmonized System (HS). Data on complexity goes from 1964 to 2018 and is available on the observatory of 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 9.0[4](Feenstra et al., 2015), that 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). That index is used because it combines different datasets on education attainment and has more observations than other human capital measures. The qualitative measure[5] 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)[6].

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' background and school factors. Results of the surveys were transformed to a scale that had 500 as mean and 100 as standard deviation.

PISA dataset presented important issues, such as, testing students on three subject 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 population's performance by testing a sample of it. A statistical technique for doing this 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 populational mean score and the populational scores of the percentiles 75th, 90th and 95th of PISA surveys in 2000, 2003, 2009 and 2012[7].

R&D are compounded by current and capital spending from both public and private sector in activities that aim to 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[8], excepting economic complexity and human capital. Table 1 shows the summary statistics of data.

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[9], except ECI data. The ECI come already in a standardized form.

[4]Our period of investigation is from 1996 to 2015, but the Penn World Table 9.0 presents data until 2014. Thus, the human capital index for the interval between 2010 and 2015 considers a four-year averaged period and not a five-year averaged period as the previous periods.

[5]Hanushek and Kimko (2000) stated that educational quality measures may come from two sources, schooling inputs or cognitive skill tests.

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

[7]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.

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

[9]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 1: 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	2.5185	0.6621	1.1232	3.7226
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	0.9023	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 9.0; Simoes and Hidalgo (2011).

4 RESULTS AND DISCUSSION

4.1 Core Outcomes

Table 2 displays the results of the specification presented in Equation 2.

Table 2: Economic complexity between 1996 and 2015 (five-year intervals)

	(1) Economic Complexity Index
GDP per capita	0.40377***
	(0.136)
Human Capital	0.49641***
	(0.640)
R&D	0.13083*
	(0.151)
Trade openness	0.13690***
	(0.00000813)
GOV	0.00050
	(0.00846)
Observation	318
Adj. R^2	0.2629

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.

Hereafter, we consider the significance level at 0.10. According to Table 2, 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 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 a period of 7 years in Singapore and a period of 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 Denmank. It happened in periods of three, four, four, five and ten years, respectively. Furthermore, most of the observation showed a R&D level smaller than the standard deviation of the full sample. 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. And, 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 attemption to test the validity of the results, different samples of countries were used. Countries were separated into 7 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 2 was run on 7 different samples, for each estimate one region was left out.

Comparing these 7 region estimates to the results presented in Table 2, trade openness and government expenditure presented 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 size of the coefficients and their significance among the 7 region estimates 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 countries of Latin America and Caribbean are left out. Moreover, we believe investment in technology presents smaller effects on complexity in countries of Middle East and North Africa 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[10].

[10]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

4.2 Focus on human capital

To test the robustness of the relation between human capital and economic complexity, alternative proxies for human capital were used. Gross and net enrolment rate in primary, secondary and tertiary education[11] served as human capital proxies. Running the Equation 2 on these alternative proxies yielded that only gross and net enrolment rates in secondary showed significance. We believe these results happened because the human capital index partly uses the average years of schooling, which normally follows the trends of enrolment rates. 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 country level, secondary education seems to play an important role in a nation's productive structure.

Other alternative proxies for human capital were considered: the share of population aged 25 or over with completed primary, secondary or tertiary education, the average years of total schooling[12], and another human capital index[13]. Running the Equation 2 on these alternative proxies resulted that only the share of population with completed primary education presented significance, while trade openness showed no significance and R&D exhibited a smaller and significance 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 taken into account. Gross and net enrolment rate on the three levels of education, the share of population with completed primary, secondary and tertiary, and the average years of total schooling were used with different gender samples. Running the Equation 2 on these different gender samples yielded outcomes similar to the results without gender differentiation, though each gender samples presented a smaller number of observations.

As an attemption 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[14]. 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[15]. The performance in reading[16] was used for the PISA surveys mentioned. We used PISA mean score and PISA scores of the

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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.

[11] All data on enrolment rate come from UNESCO.

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

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

[14] 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.

[15] 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.

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

percentiles 75th, 90th, and 95th in the estimates[17].

Equation 2 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 3.

Table 3: Economic complexity between 1996 and 2015 (five-year intervals)

	(1) ECI	(2) ECI	(3) ECI	(4) ECI	(5) ECI
GDP per capita	0.39630***	0.38493***	0.38310***	0.39164***	0.39583***
	(0.172)	(0.173)	(0.175)	(0.178)	(0.177)
Human Capital	0.50284*	0.43326	0.42214	0.43879	0.45903*
	(1.356)	(1.343)	(1.333)	(1.339)	(1.352)
R&D	0.43378***	0.43221***	0.44433***	0.45306***	0.45522***
	(0.196)	(0.194)	(0.186)	(0.182)	(0.182)
Trade openness	0.23615***	0.22397***	0.20691***	0.20064***	0.20449***
	(0.00000857)	(0.00000786)	(0.00000799)	(0.00000806)	(0.00000823)
GOV	0.04020	0.08685	0.07715	0.06259	0.05546
	(0.0161)	(0.0171)	(0.0163)	(0.0160)	(0.0161)
PISA Mean Score		0.18144**			
		(0.00139)			
PISA 75th Score			0.19989**		
			(0.00145)		
PISA 90th Score				0.16034*	
				(0.00132)	
PISA 95th Score					0.11600
					(0.00118)
Observation	175	175	175	175	175
Adj. R^2	0.5090	0.5321	0.5336	0.5274	0.5193

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.

According to Table 3, initial per capita income, the quantity or the quality of human capital, investment in technology and trade openness presented significance in all the 5 estimates. While government showed no significance at all. Including PISA scores alters only the significance of the human capital, all other coefficients stood slightly the same.

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

[17]The scores were chosen arbitrarily.

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 scores in PISA is associated with presenting higher levels of economic complexity, which reflects and improvement in nation's productive structure.

5 CONCLUSION

This investigation contributes to the debate on the importance of both human capital and investment in technology on country's productive structure. Once export sophistication reflects the productive structure, hence, 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. The index is based on the levels of ubiquity and diversity of exports, the share of international trade, and connections between products. Our estimate is for the period of 1996-2015 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 education of female and male affecting economic complexity, none was found.

In addition, we included a qualitative measure of human capital in our main estimate and it 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 explaing 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 the quality of it is not taken into account, countries should invest more in the quality of education. Moreover, the efforts used to rise the human capital stock, besides aiming to increase economic complexity, are direct factors of income growth.

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 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 productive structure. Another suggestion is to analyze R&D according to its objectives, given that basic and applied research may vary their effects on productive structure.

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