Sección general

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Are Science Students Missing in South America? Productivity and the Labor Market Say Yes

¿Faltan estudiantes de ciencias en América del Sur? La productividad y el mercado laboral dicen que sí

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Abstract

During 2002–2011, inequality in South American decreased substantially, in large part because the wage gap between unskilled and skilled professionals narrowed. A feasible generalized least squares model shows that skilled workers contribute less to productivity and thus receive smaller wages increases. We study if this outcome is because of a mismatch between labor market needs and knowledge of professionals with higher education. We use the cluster methodology applied by Izquierdo, et al. (2019) to show how the number of publications in science, as a proxy for the number of science professionals, affects productivity. The results demonstrate that the lack of science professionals is the main constraint on productivity in South American countries. These results help explain the contradiction between high demand for skilled workers, which firms fail to meet, and low compensation among employees with higher education.

Keywords: Inequality, skill premium, skill mismatch, higher education, science

Resumen

Durante 2002–2011, la desigualdad en América del Sur disminuyó sustancialmente, en gran parte debido a que se redujo la brecha salarial entre profesionales calificados y no calificados. Un modelo factible de mínimos cuadrados generalizados muestra que los trabajadores calificados contribuyen menos a la productividad y, por lo tanto, reciben aumentos salariales menores. Estudiamos si este resultado se debe a un desajuste entre las necesidades del mercado laboral y los conocimientos de los profesionales con educación superior. Utilizamos la metodología de cluster aplicada por Izquierdo, et al. (2019) para mostrar cómo el número de publicaciones científicas, como proxy del número de profesionales de la ciencia, afecta la productividad. Los resultados demuestran que la falta de profesionales de la ciencia es la principal limitación a la productividad en los países de América del Sur. Estos resultados ayudan a explicar la contradicción entre la alta demanda de trabajadores calificados, que las empresas no satisfacen, y la baja compensación entre los empleados con educación superior.

Palabras Clave: desigualdad, prima de habilidades, desajuste de habilidades, educación superior, carreras de ciencia.

JEL Classification / Clasificación JEL: O3, O33, O36, O38, O5, O54.

1. Introduction

The Gini index decreased by almost 10 points in South America in 2002–2011, marking a period of historically low inequality in this region. During this period, the process is countercyclical (i.e., it decreases in a context of economic growth). Contributors to this phenomenon included simultaneous decreases in labor income inequality and skill premiums (i.e., the wage difference decreased between people with low and high education, as measured by the academic degree achieved). This phenomenon did not occur in other reference economies.

The decline in skill premiums in South America, in terms of the limitations on qualified wages, coincided with an increase in heterogeneity between the number of years studied and the remuneration received thereafter. The latter is explained by the literature for the low academic levels of students with higher education, as well as for non-academic skills related to the capacity for innovation and adaptation to change. The analysis of the content of higher education is consistent with the findings on the relationship between productivity and wages. Moreover, a feasible generalized least squares model confirms that productivity variations have greater impact on unqualified wages than on qualified wages. Skilled workers contribute less to productivity increases than unskilled workers, so they in turn receive lower wage increases.

In this paper, we assess whether skilled workers are less productive because they lack the relevant skills needed in the labor market. We also assess how this lack of skills training affects productivity. In particular, we consider the relationship between science careers and productivity. We use the number of scientific publications to proxy for the number of academic professionals with higher education in science. We can thus compensate for the lack of data and capture not only the number of people with science educations but also the performance effectiveness of those people in their respective fields.

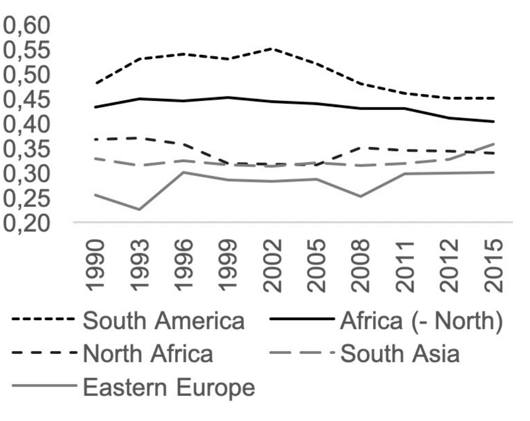
We follow the cluster methodology of Izquierdo, *et al*. (2016), which groups different countries into different groups based on a chosen measure (in our case, productivity). Specifically, we study how the fundamental variables affecting variations in productivity (e.g., capital and labor market behavior, education, health, infrastructure, innovation, integration, trade, telecommunications, and in our case, number of science publications) influence their ability to move to another group with better productivity. We find that the number of professionals with science educations determines the ability of South American countries to move to another group with higher productivity rates. A lack of science professionals is consistent with a lack of compensation among skilled workers and with high demand among firms for workers with higher education.

2. Why did inequality decrease in South America in 2002–2011?

To measure inequality, we use the World Bank Gini index of Ravallion and Chen (1996). Between 1990 and 2015, there was an average difference of almost eight points between the region that follows, Sub-Saharan Africa. However, from 2002 to 2011, South America experienced a period of unprecedented growth, and inequality decreased steadily by almost ten points for the first time in recent history. Since then, South American inequality has stagnated. Figure 1 shows inequality rates in five regions between 1990 and 2015, as measured by the Gini index, with similar or lower development indicators.

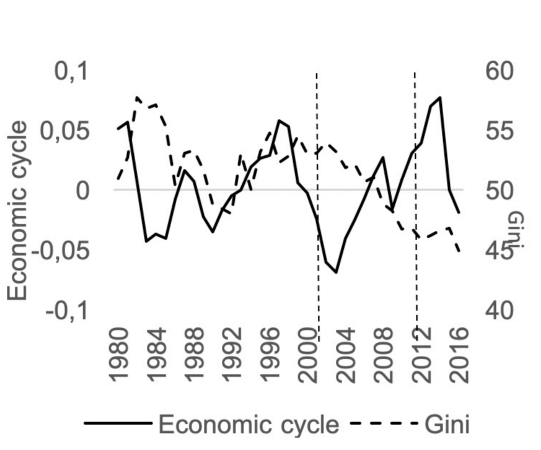
The 1980s and 1990s were characterized by increasing economic instability and inequality. The growth of the South American economy from 2002 to 2011 and its accompanying decrease in inequality thus represents a novel countercyclical trend, which ended in 2012 as the economy declined again along with inequality. To calculate the business cycle, we applied the Hodrick-Prescott (1980) methodology, which decomposes a series into a trend component and a cyclical component and identifies the trend component that minimizes deviations from the center of the series. The decrease in inequality in South America is downward in a context of growth, which can be explained only by an increase in income among the lowest deciles (i.e., those with less income, greater than the growth in the highest deciles). Figure 2 shows the relationship between income inequality and the South American economic cycle during 1980 to 2016.

Figure 1. Gini by regions



Source: Own elaboration. The World Bank (2019).

Figure 2. Inequality and economic cycle in south america



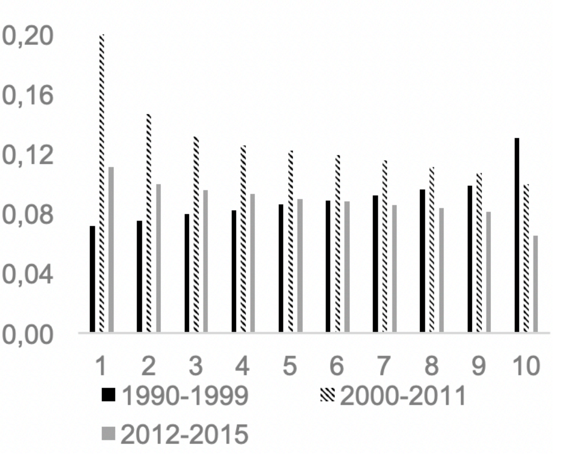
Source: Own elaboration. The World Bank (2019) and United Nations (2019).

Figure 3 shows the average annual variations in income, by decile, during 1990–2001, 2002–2011, and 2012–2016. As expected, in 2002–2011, the behavior of the extremes, particularly the first decile, explains the decrease in inequality. In the highest decile, a progressive reduction in income increases occurs, period after period. To understand what boosted income in the first decile and moderated growth in the last, it is necessary to identify the channels that made it possible, that is, the main sources of income. For Alejo, *et al*. (2013), changes in labor incomes explain about 75% of income variations in Latin America during 2002–2011. Among causes of the decline in the labor income gap, social and cultural variables are fundamental influences (Ferreira, *et al*., 2017). The weight of the decrease in the skill premium also is a factor (i.e., the reduction of the wage difference between workers with low and high skillsets). Skill premium is measured in terms of the academic degree achieved. In Latin America, a 64% decrease in wage inequality is attributed to the skill premium (Azevedo, *et al*., 2013).

The data for South America shows the same relationships as in the case of Latin America between income inequality, labor income, and skill premium. In South America, the correlation between income and labor income is greater than 80%. Between income or labor income and the skill premium, the correlation is greater than 70%. When studying the decline in South American inequality in the period, most of the literature focuses on the increase in unskilled wages. The causes are indirectly related to changes in commercial structure (Robertson, 2004; Ferreira, *et al*., 2007) and the input market (Acosta and Gasparini, 2007; Gallego, 2010) and directly related to the minimum wage. Whereas the minimum wage increase could explain up to 20%

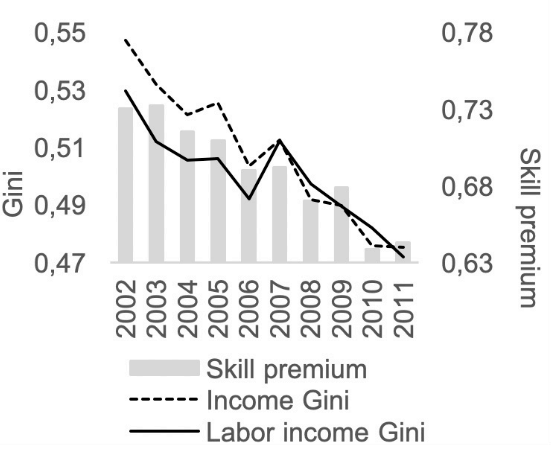
of the decline in skill premium in Brazil (Ferreira, *et al.*, 2017), it could explain up to 50% (Guzmán, 2018) in Ecuador. Figure 4 illustrates the relationship between income, labor income, and skill premium.

Figure 3. Variation of income per decile (annual average)



Source: Own elaboration. SEDLAC (CEDLAS and The World Bank) (2019).

Figure 4. Income gini, labor income gini and skill premium



Source: Own elaboration. SEDLAC (CEDLAS and The World Bank) (2019).

In this paper, we examine the behavior of less qualified wages, but first we look at the behavior of the highest deciles to understand what caused qualified wages to increase less than unqualified wages and why increases in qualified wages have slowed.

3. Why did wages for skilled workers plateau in South America during 2002–2011?

The percentage of highly qualified people under age 34 in South America increased by 16 points from 1995 to 2011 (Aedo and Walker, 2012). In theory, this oversupply of workers could have led to decreased wages. In practice, however, the number of highly qualified persons remained insufficient. In 2009, 55% of adults up to 34 years of age and 76% of adults between 55 and 64 years of age had not completed a secondary education, compared to an average 37% and 18%, respectively, for member countries in the Organisation for Economic Co-operation and Development (OECD).

South America may have required fewer workers with higher education than OECD countries. For example, an excess of highly qualified people would cause wage moderation in France, as argued by Guironnet and Peypoch (2007), and in Germany, as argued by Jensen, *et al*. (2010). In South America, however, nearly one-third of companies report that a low-skilled workforce is the main obstacle to their operational development (OECD, 2014) and innovation (World Bank, 2011). The main challenge for these companies is to find workers with appropriate knowledge (World Bank, 2011). If there is no excess of skilled workers, then what causes skilled wages to increase less than unskilled wages? Why does the increase in skilled wages slow over time? From the related literature, the behavior of skilled wages in South America is related to improvements in technology, which increase the demand for skilled workers to manage it. This scenario has occurred in Chile (Gallego, 2019; Pavcnik, 2003), in the capital goods market of Peru (Mazumdar and Quispe-Agnoli, 2002), and in Argentina (Acosta and Gasparini, 2007).

Changes in production factors that complement skilled labor influence the demand for skilled employees and wages. The workforce thus can lead productivity improvements on its own. Changes in employees' ability to affect productivity are expected to be rewarded with increased wages. To the extent that the wage is the payment for the work, the ability of workers to contribute to productivity is a wage variable. If the ability to contribute to productivity increases, wages also increase. If it decreases, the increase in wages also decreases. In this case, unskilled wages increase more than skilled wages, because they contribute more to productivity. Thus, productivity gains pay more to unskilled workers, because they contribute most. Consequently, an inverse relationship occurs between productivity and skill premium.

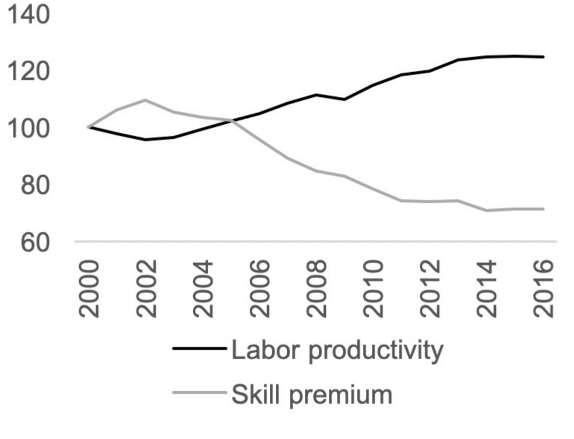
We analyze this relationship between productivity and the skill premium by considering the interannual variation of the South American natural logarithm index of labor productivity and the average of unskilled and skilled wages, in terms of purchasing power parity (PPP), in the year 2000. South American productivity is the natural logarithm of the average of each country, calculated as the contribution to production, as expressed in equation (1).

$$\textit{labor productivity}_{it} = \frac{GDP_{it}}{H_{it}} = \frac{GDP_{it}}{h_{it}L_{it}} \tag{1}$$

where represents each South American country, is the year, is the Gross Domestic Product, is the human capital, is the workforce, and is the average years of schooling.

Figure 5 shows the inverse relationship between productivity and skill premium, a phenomenon that does not occur in other reference economies, as shown in Figure 6 for Europe and the United States. In both cases, there is a direct, albeit moderate, relationship between the upward trends in skill premium and labor productivity.

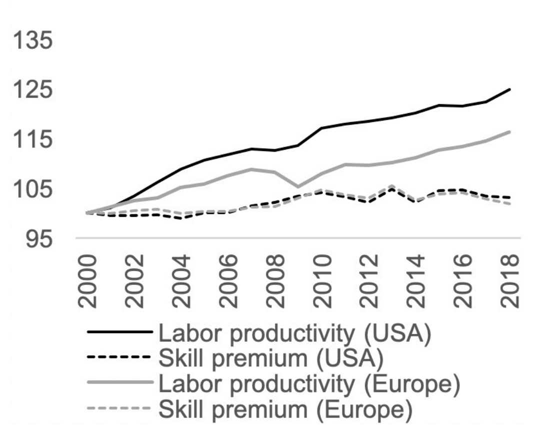
Figure 5. Labor productivity and skill premium for South America



Source: Own elaboration. Labor productivity data in ILOSTAT (2019) and wages in SEDLAC (CEDLAS and The World Bank) (2019).

We ascertain the relationship between unskilled and skilled real wages and productivity by applying a feasible generalized minimum squares model for nine South American countries during 2000–2016, following equations (2) and (3), for unskilled and skilled wages. Wages are expressed in real terms, based on the PPA conversion factor. The dependent variables are unskilled and skilled wages. The independent variables are the variation of labor productivity, production, unemployment, minimum wage, and inflation. To interpret the elasticity, we take the natural logarithm of the variables, with the exception of the unemployment rate and inflation, due to the nature of the data. Due to

Figure 6. Output index per worker and wages (EEUU and Europe)



Source: Own elaboration. US labor productivity data in ILOSTAT (2019) and wages in US Department of Labor (2019). Labor productivity data for 27 countries of the European Union in ILOSTAT (2019) and wages in EUROSTAT (2019).

the lagged impact that some independent variables have on the dependent variable, we consider lags in some explanatory variables (ECLAC, 2018).

$$log\ wage_{it}^{ns} = \alpha + \gamma^{ns}\ log\ A_{it} + X_{it}\beta + u_{it} \qquad (2)$$

$$log\ wage_{it}^{s} = \alpha + \gamma^{s}\ log\ A_{it} + X_{it}\beta + u_{it} \qquad (3)$$

Where represent unskilled, represent skilled, represents each South American country, is the year, is the constant term, is the coefficient associated with productivity, is the productivity, is the vector of estimated coefficients of the control variable matrix , and is the error term. Table 1 shows the results of the two equations.

Both the significance and the sign are as expected for each case. The productivity coefficient is higher when applying the model that considers unskilled wages as an independent variable. Productivity gains translate into higher incomes for uneducated professionals than for skilled workers.

4. What limits the relationship between skilled wages and productivity?

The literature suggests that containment of the increase in qualified wages explains the behavior of the skill premium. This containment has been linked to quality limits that decrease the lower cognitive and non-cognitive capacity of professionals with higher education. Lustig (2015) hypothesis of "degraded

TABLE 1. REGRESSION RESULTS BY FEASIBLE GENERALIZED MINIMUM SQUARES

	Equation (2)	Equation (3)
Variable		
Δ labor productivity$_{t-2}$	0.759**	0.138**
Δ log productivity	0.651***	0.279**
Δ log productivity$_{t-2}$	0.575***	0.452***
Δ unemployment rate$_{t-2}$	-1.475**	-1.372*
Δ log minimum wage	0.352*	0.184*
inflation	0.260*	0.172
Constant	-0.0262*	-0.0276
Observations	93	93

Note: Significance level at ***p<0.01, **p<0.05, *p<0.1.

tertiary" postulates that the remarkable expansion of coverage in post-primary education was accompanied by a growing dispersion in the quality of educational centers, which reduced the average quality of post-primary studies, especially at the tertiary levels (bachelor's, master's, and doctorate). The extension of tertiary education coverage is mainly applied in the margin to students coming from the lower end of income distribution. The quality of education among the highest and middle deciles determines the capacity that universities and higher technical training centers can demand, hoping that a majority will graduate, so it is expected that a majority will graduate.

Using data from the World Economic Forum and Programme for International Student Assessment, we show that the overall quality of education is 43% lower in South America than in OECD countries. Despite improvement from 2006 to 2012, as recorded by the World Economic Forum, this gap decreased only by two percentage points. In a more detailed analysis, the difference in performance of South American and U.S. youth in the areas of pure science, mathematics, and reading has narrowed. However, 50% of South American youth still do not reach the required levels in reading, and 65% do not reach the required levels in mathematics to solve basic real-life problems (IADB, 2011).

To ensure that a significant number of students can complete tertiary education, the level of higher education must remain below the OECD average. If the quality of university education is low, the capacity to contribute to productivity also will be low, thus exerting downward pressure on remuneration, which explains the reduction in the skill premium. To the extent that a limited number of South American students achieve grades comparable to the OECD average, the capacity of professionals with higher education to improve productivity also is limited. Moreover, reduced performance of non-academic skills has a larger effect on productivity than academic performance, as shown in Canada (Krahn and Lowe, 1998), Mexico (Ardila, *et al.*, 2000), and the United States (Bowles and Gintis, 2002).

The World Bank (2018) measured three independent knowledge skills in Chile and Argentina. These skills include metacognitive strategies, or the ability to organize and plan cognitive tasks; social and leadership skills, or the individual's ability to relate to others; and self-efficacy, or the ability to perceive oneself as an effective student or worker. The averages are similar for university graduates who finished and did not finish university, lower than that of professionals with higher technical education, and three points higher than those with primary education. University students had lower cognitive skills than workers with a higher education, which is consistent with the special downward pressure on wages by high skilled workers within the most qualified group. This finding reveals a difference between the level of training of a worker with higher education and that of a graduate of higher education, as shown in the United States (Hofler and Murphy, 1992), Canada (McClure, *et al*., 1998), and China (Zhan, *et al*., 2008). Based on social and self-efficacy criteria, students with higher technical training had the highest participation, employment rates, and wages.

The lack of high-quality cognitive and non-cognitive skills among workers must be considered. However, it also is necessary to review whether students leaving academia are effectively responding to the needs of the labor market. It may be that certain skills are not compensated as expected, because they do not meet the needs of companies in the region, and thus are not maintained by workers. Workers with these irrelevant skills are not in demand and therefore take lower paying jobs, which reduces the skill premium. This interpretation could explain why entrepreneurs in the region continue to complain about the lack of sufficient professionals.

The increase in the number of employees with higher education makes sense when it is directed at economic sectors with the greatest capacity to generate development for the country. Such an increase does not occur in sectors that generate added value in the GDP. The number of public and private centers increased in all countries, and the number of economics-related courses that, for the most part, are not traditionally linked to improved development also increased. Although the number of South American workers with higher education has increased, they have not yet been able to transform their knowledge into better development capacity. Professionals trained in careers with greater added value still prefer to work abroad, where their fields of expertise are much more developed than they are at home.

We observed a simultaneous increase in exports of high-value-added goods and the price of raw materials, but these increases failed to significantly improve the region's position in the share of global exports. Improvements in the capacity of South American workers were below expectations. This skill mismatch between workers and labor market needs leads to an oversupply of workers in low-demand careers as these workers accept jobs for which they are overqualified and employers' labor requirements increase. For example, in both Chile and Colombia, there is a strong relationship between higher education and its heterogeneous return (González-Velosa, *et al*., 2015). In Peru, Lavado, *et al*. (2014) confirm that in 2012, four out of ten university professionals had jobs in non-professional and underpaid fields.

We suggest that although participation in higher education in South America increased significantly during the studied period, this increase was not distributed across careers with high productivity. To test this assumption, we account for fields of study with high productivity, such as science, technology, engineering, and mathematics (STEM) fields. The ILO (2008) highlights that a shortage of skilled workers in STEM limits economic growth by suppressing firms' ability to act on opportunities and the generation of higher wages. Several organizations, policy makers, and authors recommend increasing the number of students and workers in STEM fields to increase innovation and competitiveness in global markets (Gordon, 2007; NSF, 2007; OIT, 2008; Beede, *et al*., 2011; Myers, *et al*., 2011; Kier, *et al*., 2014). Kisselburgh, Berkelaar, and Buzzanell (2009) emphasize the importance of STEM disciplines, mainly because of the scope of technology in production, domestic work, and education.

STEM fields increase total factor productivity and, in turn, economic growth (Antonelli, Crepax, and Fassio, 2013; Antonelli and Fassio, 2016). In an empirical investigation, Griliches (1991) found that STEM careers determine endogenous growth through spillover effects on productivity of different industries and their contribution to innovation. Jones (1995) found that scientists and engineers are responsible for about 50% of long-run growth in U.S. productivity. In a more recent study, Peri, Shih, and Sparber (2015) determined that STEM fields stimulate economic growth by increasing the productivity and innovation of the labor force, especially among workers with tertiary educations. The academic community widely agrees that STEM education is important to secure the U.S. advantage in the global economy (White, 2014). STEM careers significantly affect the U.S. labor force by influencing economic competition, innovation, and productivity (NSF, 2015). Villarán and Golup (2010) found that careers in science and technology increased workforce productivity in Singapore, China, Taiwan, South Korea, and Japan. They highlight the importance of establishing high-quality education standards in science-related fields and conclude that emphasizing STEM-related fields is more important than the absolute number of graduates.

5. Methodology

We use the methodology proposed by Izquierdo, *et al*. (2016) to measure how the number of people graduating with STEM degrees affects productivity in the South American region and thus wages of skilled workers. As in Izquierdo, *et al*. (2016), we consider South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) and OECD member countries (Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, Turkey, United Kingdom, and the United States). Each South American country is included in a cluster of countries with similar levels of productivity. We then study the key variables of sector indicators that determine a country's production, according to the literature (Duval et al, 2011). These indicators include capital markets, education, health, infrastructure, innovation, integration and trade, the labor market, and telecommunications. We assess how the key variables of these indicators change with respect to the average of each cluster. Table A1 of the Appendix shows the list of variables and their sources.

The data source for 2000–2012 is the Priorities for Productivity and Income (PPI) database (Izquierdo, *et al.*, 2016). To cover 2000–2016, the database was updated from the original sources. To construct sectoral variables, we normalize each variable and consider the total number of observations for the countries and years available. In cases of missing observations, we conduct a linear interpolation and fill before data normalization. Then, the sign of the observations of those variables that theoretically negatively affect productivity is inverted. Finally, we calculate a simple average of the variables of the sectoral indicator, by country and by year, and normalize each indicator.

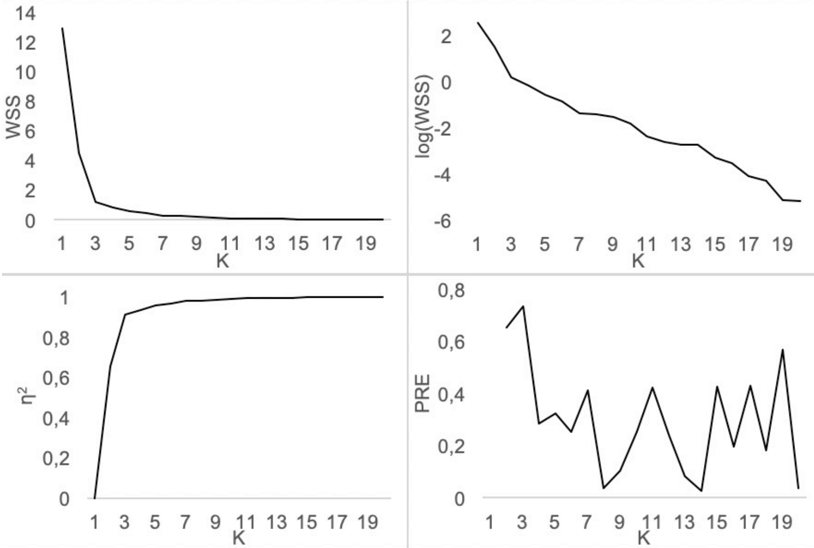
We also include the number of academic publications in each STEM field (mathematics, physics, astronomy, engineering, computer science, materials science, chemistry, chemical engineering, Earth and planetary sciences, biochemistry, genetics, and molecular biology) to proxy for the number or distribution of students in the fields that contribute most to a country's productivity. This measure assesses participation in research and development to capture the number of educated workers in an academic field and their effectiveness in that field.

Our measure covers 2013 to 2016 due to the availability of observations. The correlation coefficient is approximately 0.95 between the number of academic publications from selected OECD countries (from OECD Stat) and the number of undergraduate students; between 0.96 and 0.97 for master's degree students; 0.98 for doctoral students; and 0.98 for the total number of students in tertiary education. The correlation coefficient is 0.9 between the number of academic publications in mathematics and the total number of mathematics students in tertiary education, and it is 0.87 between the number of technology-related papers and the number of students in technology fields. Thus, the number of academic publications of a country is an appropriate measure to represent the number of students in those fields.

Before estimating the model, we estimate production clusters per worker to classify each country by its level of productivity. To obtain the number of optimal clusters, we apply the -means clustering procedure, where is determined via the elbow method. As shown in Figure 7, the and fall drastically when . At , there is a kink. When , there is no major change in either measure. Similarly, when , explains a reduction of approximately 91% in . Thus, the optimal number of clusters is three. We then use a hierarchical clustering method to form the clusters.

Figure A1 of the Appendix shows the evolution of each country with respect to its level of productivity per cluster. In this productivity segmentation, countries are distributed in different clusters depending on the year. Due to this

Figure 7. Determination of the number of optimal clusters using the elbow method



Note: is the within sum of squares, is the percentage of variance explained or reduced in , and is the proportional reduction error coefficient.
Source: Own elaboration.

non-linearity, the model to be applied is based on an ordered probit model. For this model, the Brant test suggests that the parallel regression assumption is not satisfied; hence, we estimate the model via a generalized method to relax the parallelism assumptions (i.e., the applied method of estimation is a generalized ordered probit, which estimates the sectors with more influence on productivity). In this case, the positive coefficients of the regression determine those sectors that increase the probability that a country in cluster will jump to cluster , and the negative coefficients determine those sectors that cause the country to stay in the same cluster or decrease its productivity.

To account for endogeneity problems between productivity and sector variables, we apply a Granger causality test. The results suggest that all explanatory variables cause, in the Wiener-Granger sense, the dependent variable (i.e., a unidirectional relationship). To avoid an endogeneity problem undetected by the test, we use the first lag of each explanatory variable. To control for other types of exogenous variables, we use the VIX volatility index (Izquierdo, *et al.*, 2016). The VIX index estimates the expected value of volatility regarding the U.S. stock market in the next 30 days and accounts for S&P 500 reference prices (Comelli, 2012). This index is considered a main indicator of investor confidence and intrinsic market volatility (CBOE, 2019). Finally, we estimate the model using robust standard errors and clustered standard errors due to the possible presence of autocorrelation in the error term between countries.

6. Results

Table 3 presents the results of the estimation. McFadden's pseudo R2 is 0.577, and the adjusted McFadden's pseudo R2 is 0.555. Count R2 is 0.863, and its adjusted value is 0.594, similar to McFadden's pseudo R2. Additionally, we estimate the same regression 5,000 times, randomly dropping one year-country observation each time. Table A2 of the Appendix displays the results of this process. Table A3 in the Appendix shows the results of the estimated regression in Table 2 but with the first lag of the VIX index. In this way, the estimated coefficient shows consistency and robustness.

Table 3. Results of the estimation of generalized ordered probit model

	Robust standard errors		Clustered standard errors	
Productivity	Cluster 1	Cluster 2	Cluster 1	Cluster 2
STEM	19.665***	0.386**	19.665***	0.386
	(5.041)	(0.181)	(7.016)	(0.323)
Capital markets	-0.970***	0.452***	-0.970**	0.452**
	(0.288)	(0.135)	(0.389)	(0.225)
Education	-0.105	-0.105	-0.105	-0.105
	(0.113)	(0.113)	(0.173)	(0.173)
Health	0.802***	0.312*	0.802***	0.312
	(0.190)	(0.186)	(0.280)	(0.334)
Infrastructure	0.620***	0.620***	0.620***	0.620***
	(0.149)	(0.149)	(0.267)	(0.267)
Innovation	-0.032	-0.032	-0.032	-0.032
	(0.107)	(0.107)	(0.176)	(0.176)
Integration and trade	0.494***	0.494***	0.494**	0.494**
	(0.125)	(0.125)	(0.218)	(0.218)
Labor market	1.273***	-0.265**	1.273***	-0.265
	(0.324)	(0.116)	(0.383)	(0.213)
Telecommuni-cations	-0.236	0.447***	-0.236	0.447**
	(0.25)	(0.145)	(0.410)	(0.202)
VIX	0.034***	0.034***	0.034***	0.034***
	(0.013)	(0.013)	(0.005)	(0.005)
Constant	12.337***	0.019	12.337***	0.019
	(2.672)	(0.271)	(3.718)	(0.232)
Pseudo R2		0.587		0.587
Observations		640		640

Note: Significance levels at $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. Standard errors in parentheses.

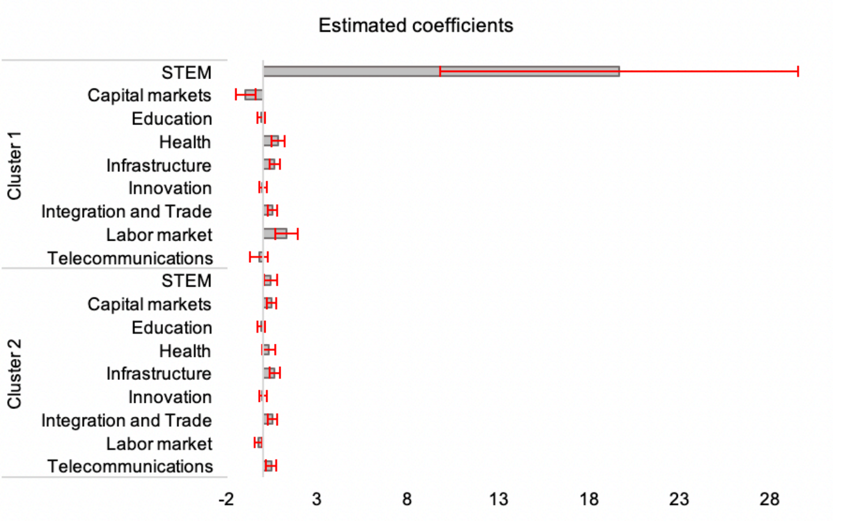
Based on Table 2, the results of the estimation with robust standard errors suggest that STEM publications, health, infrastructure, integration, and trade and labor markets are statistically significant sectoral variables (at the 1% confidence level) that improve productivity in countries in cluster 1. With respect to countries in cluster 2, the variables with positive effects on productivity are STEM publications (at the 5% confidence level), capital markets, infrastructure and telecommunications (at the 1% confidence level), and health (at the 10% confidence level). Capital markets seem to have a negative influence on productivity of cluster-1 countries, in terms of their growth or stagnation (significance level of 1%), and labor markets have negative effects on productivity of cluster-2 countries (significance level of 5%).

With respect to estimation by clustered standard errors, the impact of variables has the same magnitude and sign; however, the significance changes. Infrastructure, integration, and trade increase in significance from 1% to 5% confidence for cluster-1 countries. Capital markets, infrastructure, integration, trade, and telecommunications become statistically significant from 1% to 5% for cluster-2 countries. STEM and health variables lose their significance. With respect to the variables that negatively affect productivity, capital markets become significant at 5% for cluster 1, and the labor market loses its significance in cluster 2.

These results show that the priority given to each cluster depends on the productivity group being analyzed. Thus, in general terms, the priorities for cluster-1 countries are based on the increase of publications in the STEM field and improvements in health, infrastructure, integration, and trade and labor markets. For cluster-2 countries, the priority is based on improving capital markets, infrastructure, integration, trade, and telecommunications. Due to the standardized form of the explanatory variables used, the estimated coefficients can be directly interpreted to establish the order of sectoral priorities, by cluster, based on their magnitude. Figure 8 presents the results corresponding to the coefficients, estimated using the methodology previously applied.

Figure 8 shows that the STEM variable has the greatest impact on improving productivity in cluster-1 countries; that is, those less productive that are, in relation to the OECD countries, the South American countries. The results suggest that an increase of one standard deviation in the STEM field increases the probability, by more than one standard deviation, that cluster-1 countries will reach cluster 2 in all variables that positively affect productivity in this group. In turn, despite having a smaller magnitude, the results suggest that the STEM variable also is important to increase the probability that countries in cluster 2 reach cluster 3. Due to the aforementioned relationship between the number of students in STEM fields and the number of corresponding publications, the results indicate that South American students should pursue STEM-related degrees to improve productivity in their region.

Figure 8. Estimated coefficients of generalized ordered probit model



Source: Own elaboration.

7. Conclusion

The reduction in inequality that occurred in South America during 2002–2011 has been widely applauded, as it was the first time that inequality decreased in a countercyclical way. We observe that not all factors contributing to this trend were positive. Inequality decreased mainly because the income gap narrowed. The income gap narrowed because the wage gap narrowed. Wages for skilled jobs increased less than those for low-skilled jobs, thus reducing the skill premium. One reason for this slower increase in high wages was an insufficient cognitive and non-cognitive qualification of workers with higher education, leading to unsatisfied demand among entrepreneurs for professionals with higher education and poor compensation in several countries of the region. Workers with higher educations did not have sufficient capacity to respond to the needs of the labor market, so they were less recognized and, in turn, their remuneration increases slowed. This finding is more consistent with a weaker relationship between skilled wages and productivity than with unskilled wages and productivity. Unskilled wages contributed more to productivity and thus received better remuneration in terms of percentage increases.

In this paper, we demonstrate that the weak relationship between qualified wages and productivity results from the lack of professionals in careers that are traditionally linked to productivity improvement (in this case, STEM careers). Future study should assess how economic and social policies in a region might increase the number of professionals in STEM careers and thus enhance productivity.

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9. Annex

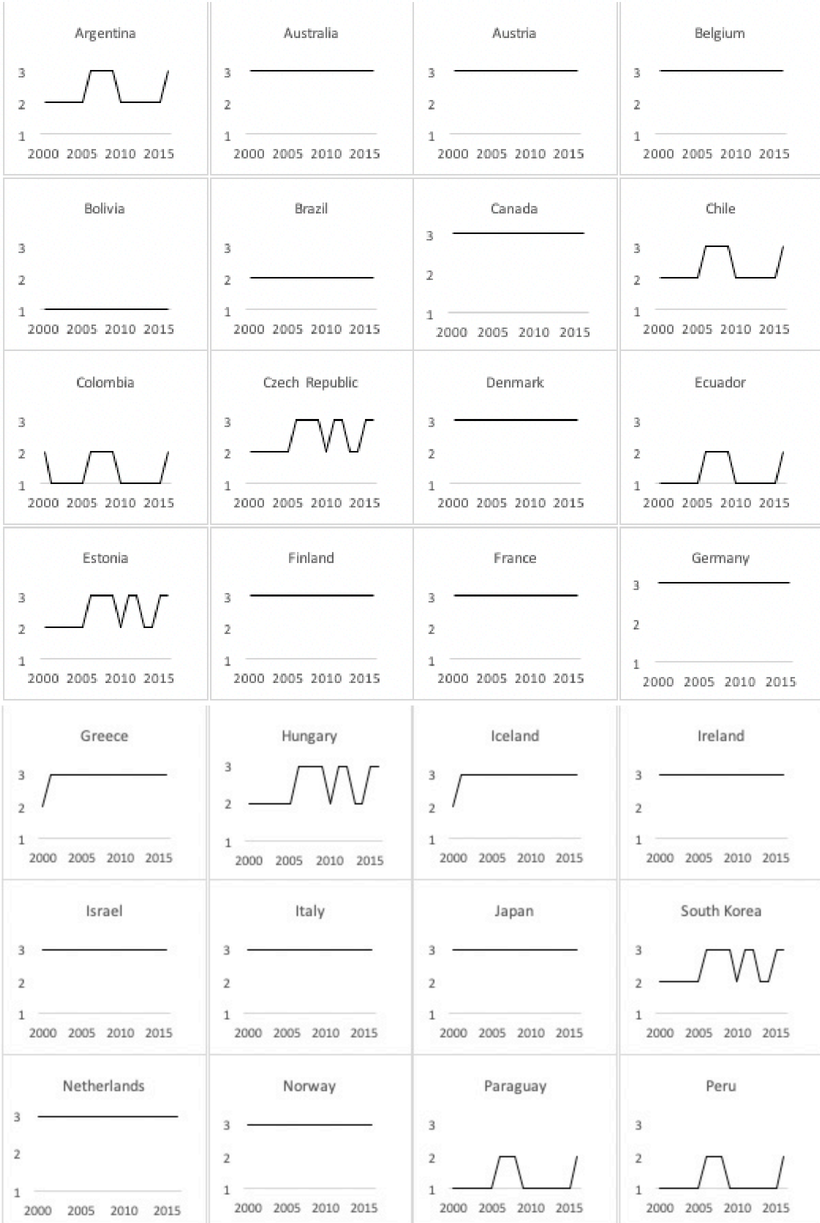
Table A1. List of variables used together with their sources

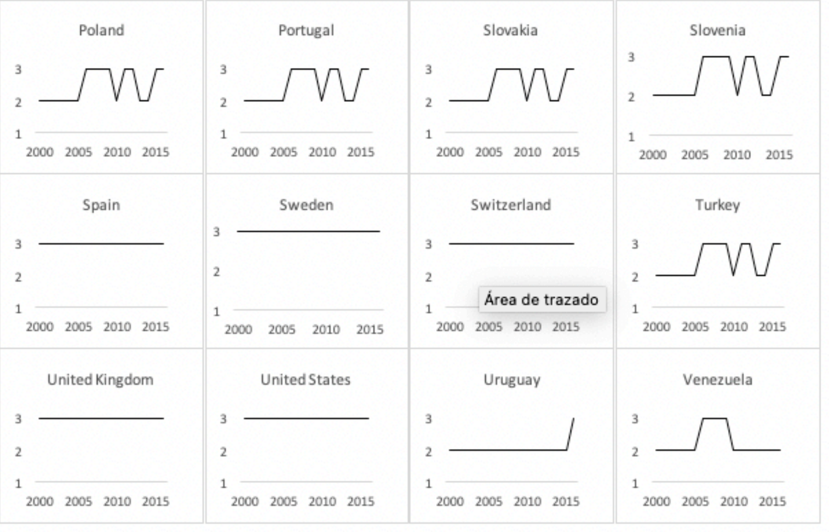
Sector	No.	Indicator	Source
		Productivity: Output per worker (GDP constant 2011 international $ in PPP)	ILOSTAT, ILO
STEM	1	Country rank in mathematics, physics, astronomy, engineering, computer science, material science, chemistry, chemical engineering, planetary and earth sciences, biochemistry, genetics, and molecular biology	Scimago Journal & Country Rank
Capital markets	2	Domestic credit to private sector by banks (% of GDP)	WDI, World Bank
	3	Real interest rate (%)*	Database PPIs (Izquierdo, *et al.*, 2016)
	4	Market capitalization of listed domestic companies (% of GDP)	WDI, World Bank
	5	Property Rights Index	Economic Freedom of the World Index Database, Fraser Institute
	6	Rule of Law	WDI, World Bank
Education	7	Education expenditure (% of GNI)	WDI, World Bank
	8	Net enrollment rate, pre-school	UIS, UNESCO
	9	Population age 25+ with secondary or tertiary schooling (% completed)	Barro and Lee dataset (2018)
	10	Population age 25+ with no education (% of total population)*	Barro and Lee dataset (2018)
Health	11	Life expectancy at birth	WDI, World Bank
	12	Public expenditure on health (% GDP)	WDI, World Bank
	13	Infant mortality rate under 1 years (per 1000 live births)*	WDI, World Bank
	14	Mortality rate under 5 years (per 1000 live births)*	WDI, World Bank
	15	Immunization, measles (% of children ages 12–23 months)	WDI, World Bank
	16	Maternal mortality rate (modeled estimate, per 100.000 live births)*	WDI, World Bank
Infrastructure	17	Road density (km of road per 100 sq. km of land area)	Database PPIs (Izquierdo, *et al.*, 2016)
	18	Road safety (number of fatalities per 100,000 people)*	Database PPIs (Izquierdo, *et al.*, 2016)
	19	Electric power transmission and distribution losses (% of output)*	WDI, World Bank
	20	Energy use (kg of oil equivalent per capita)	WDI, World Bank
	21	Electric power consumption (kWh per capita)	WDI, World Bank
Innovation	22	Exports of high and medium technology (share of total exports)	Database PPIs (Izquierdo, *et al.*, 2016)
	23	Scientific and technical journal articles (per total population)	Database PPIs (Izquierdo, *et al.,* 2016)
	24	Quality Management Certificates (number of Certificates per billion PPP$ GDP)	Database PPIs (Izquierdo, *et al.*, 2016)

Integration and Trade	25	Foreign direct investment, net inflows (% of GDP)	WDI, World Bank
	26	Hummels-Klenow extensive margin index: markets	Database PPIs (Izquierdo, *et al*., 2016)
	27	Hummels-Klenow extensive margin index: products	Database PPIs (Izquierdo, *et al*., 2016)
	28	Trade openness (% GDP in PPP)	Database PPIs (Izquierdo, *et al*., 2016)
Working market	29	Formal employment ratio: Active contributors to an old age contributory scheme (% of labor force)	Database PPIs (Izquierdo, et al., 2016)
	30	NEETS youth 15–24 (labor)*	Database PPIs (Izquierdo, *et al*., 2016)
	31	Unemployment ratio, total (% of full participation in the labor force)*	WDI, World Bank
	32	Workers with low education levels as a percentage of total workers (15+)*	Database PPIs (Izquierdo, *et al*., 2016)
Telecom-munica-tions	33	Internet users (per 100 people)	International Telecommunication Union
	3. 4	Mobile lines (per 100 people)	International Telecommunication Union
	35	Telephone lines (per 100 people)	International Telecommunication Union

Source: Own elaboration.

Figure A1. Productivity development of countries, by cluster





Source: International Labour Organization.

TABLE A2. BOOTSTRAPPING ESTIMATION RESULTS

	Cluster 1	Cluster 2
STEM	19.665*	0.386*
	(11.481)	(0.23)
Capital markets	-0.970**	0.452***
	(0.443)	(0.151)
Education	-0.105	-0.105
	(0.126)	(0.126)
Health	0.802**	0.312
	(0.335)	(0.231)
Infrastructure	0.620***	0.620***
	(0.163)	(0.163)
Innovation	-0.032	-0.032
	(0.112)	(0.112)
Integration and trade	0.494***	0.494***
	(0.137)	(0.137)
Labor market	1.273***	-0.265**
	(0.46)	(0.127)
Telecommunications	-0.236	0.447***
	(0.377)	(0.163)
VIX	0.034**	0.034**
	(0.014)	(0.0149)
Constant	12.337**	0.019
	(6.116)	(0.293)
Pseudo R2		0.587
Observations		640

Note: Significance levels *p<0.1, **p<0.05, ***p<0.01. Robust standard errors in parentheses. Estimation with 5,000 repetitions.

Table A3. Results of the estimation with the first lag of the VIX index

	Robust standard errors		Standard errors clustered	
	Cluster 1	Cluster 2	Cluster 1	Cluster 2
STEM	19.534***	0.328**	19.534**	0.328
	(5.269)	(0.160)	(7.821)	(0.281)
Capital markets	-1.039***	0.445***	-1.039***	0.445*
	(0.281)	(0.139)	(0.371)	(0.241)
Education	-0.17	-0.17	-0.17	-0.17
	(0.110)	(0.110)	(0.183)	(0.183)
Health	0.826***	0.351**	0.826***	0.351
	(0.191)	(0.179)	(0.278)	(0.342)
Infrastructure	0.668***	0.668***	0.668**	0.668**
	(0.152)	(0.152)	(0.283)	(0.283)
Innovation	-0.078	-0.078	-0.078	-0.078
	(0.105)	(0.105)	(0.198)	(0.198)
Integration and trade	0.622***	0.622***	0.622**	0.622**
	(0.132)	(0.132)	(0.241)	(0.241)
Labor market	1.331***	-0.191*	1.331***	-0.191
	(0.300)	(0.111)	(0.370)	(0.216)
Telecommunications	-0.295	0.324**	-0.295	0.324
	(0.238)	(0.141)	(0.386)	(0.203)
VIX	-0.032**	-0.032**	-0.032***	-0.032***
	(0.013)	(0.013)	(0.007)	(0.007)
Constant	13.619***	1.334***	13.619***	1.334***
	(2.835)	(0.287)	(4.130)	(0.220)
Pseudo R2		0.587		0.587
Observations	640		640	

Note: Significance level *p<0.1, **p<0.05, ***p<0.01. Standard errors in parentheses.