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Capturing the drivers of social SDGs: An econometric analysis of the dimensions of health and education.

Abstract

With the changing policy landscape, the monitoring of human development in terms of the three pillars of sustainability (i.e., economic, social, environmental) has gained considerable traction in recent years. As a tool for conducting economic impact assessments, CGE simulation modelling is a workhorse member of the standard toolbox of modelling applications available to policy-makers, think tanks and academics alike. Notwithstanding, whilst simulation modelling is adept (in differing degrees) at handling issues relating to two of the three dimensions of sustainability, the social dimension remains neglected. Indeed, with their reliance on strictly market driven concepts, the task of including social indicators in economic models relating to, for example, health or education, necessitates a linkage with historical observation and statistical rigour. This paper sets out to provide an initial step toward filling this gap. More specifically, employing panel datasets and econometric model specifications based on searches of the relevant literature, this paper provides parametric linkages between identifiable indices in economic simulation models and a selection of six indicators covering health and education.

One of the conclusions drawn from this paper is the significant effect of per capita GDP on health and education indicators. Nevertheless, the impact of other drivers, such as the food intake or the share of the agricultural sector on GDP, have a similar or even a greater magnitude than the income level. We also found a close relationship between health and education, since all health indicators tend to improve as the years of schooling increase. In contrast, the impact of pollution, trade openness and inequality on the selected indicators is much more reduced and, in most cases, not statistically significant.

1. Introduction

With a view toward coordinating policy initiatives across environmental, economic and social domains, the Sustainable Development Goals (SDGs) provides an internationally recognisable series of targets in 2030 with metrics for identification and monitoring purposes. Rooted within the principle of efficient resource allocation within a world of unlimited wants, the economics discipline can make an important contribution to the analysis of the SDGs, by examining some of the key drivers of SDG trends and identifying those areas where potential SDG inconsistencies arise. Ultimately, the use of computable general equilibrium (CGE) ex-ante economic modelling frameworks for detailed foresight studies is proving to be a useful tool of analysis (Philippidis et al., 2018, 2020). Indeed, CGE models are particularly adept in this area when one considers the SDG trade-offs and synergy effects arising from the interaction of different policy measures. To a large degree, the enumeration of SDG indicators in CGE models is typically restricted to market driven indicators of, for example, food security, production, income inequality, economic prosperity, employment, energy and climate. On the other hand, mathematical simulation market models are found wanting when one is interested in examining the more abstract 'social' concepts relating to (*inter alia*) health and wellbeing (SDG 3), education quality (SDG4), gender equality (SDG5), or peace, justice and strong institutions (SDG16).

The aim of this research is to provide an initial step toward improving the "social SDG" coverage of CGE modelling. More concretely, we seek to establish plausible econometric models of drivers for health and education SDGs with a view to providing parametric inputs to a global CGE simulation model. Thus, in a first phase, we examine the literature to identify relevant drivers for each indicator. In a subsequent stage, we construct a global panel dataset by merging different sources of secondary data for our selected drivers and indicators. Finally, we estimate econometric models to determine the magnitude and direction of these drivers across broad regional groupings.

After this introduction, Section 2 describes the process to select the most suitable SDGs indicators and drivers, Section 3 present the methodology used and Section 4 shows and discuss the results obtained. Finally, main conclusions are exposed in Section 5.

2. Data

2.1. Selection of SDGs indicators

The selection of indicators to measure the progress of SDGs 3 and 4 was based on the Global indicator framework for the Sustainable Development Goals and targets of the 2030 Agenda for Sustainable Development developed by United Nations (UN, 2017). Among the proposed indicators, three indicators were selected to measure health SDGs, two for the education SDGs, and two for inequality SDGs (see Table 1).

Table 1. Description of selected SDGs indicators.

Indicator	Description	SDG	Target	Data source	No. Countries	Years
LifeExp	Life Expectancy at birth (years)	3 - Health	Global	Wittgenstein HCDE	202	1950-55/1955-60/…/2095-2100
SurvivalNB	Age-Specific Survival ratio for newborn (%)	3 - Health	3.2 - End preventable deaths of newborns and children	Wittgenstein HCDE	202	1950-55/1955-60/…/2095-2100
Survival4	Age-Specific Survival ratio for ages 0-4 (%)	3 - Health	3.2 - End preventable deaths of newborns and children	Wittgenstein HCDE	202	1950-55/1955-60/…/2095-2100
Fertility	Age-Specific Fertility rate for ages 15-19 (%)	3 - Health	3.7 - Sexual and reproductive health-care services	Wittgenstein HCDE	202	1950-55/1955-60/…/2095-2100
School	Mean years of Schooling for ages 20-24 (years) for both male and female	4 - Education	Global	Wittgenstein HCDE	202	1950/1955/…/2100
SchoolM	Mean years of Schooling for ages 20-24 (years) for male	4 - Education	4.5 - Eliminate gender disparities in education	Wittgenstein HCDE	202	1950/1955/…/2100
SchoolF	Mean years of Schooling for ages 20-24 (years) for female	4 - Education	4.5 - Eliminate gender disparities in education	Wittgenstein HCDE	202	1950/1955/…/2100

With respect to health indicators, the following ones have been selected:

1. *Life Expectancy at birth.* This indicator measures the number of years a newborn is expected to live, and was taken as a global measure of health conditions, as usually done in the literature (among others, Valkonen et al., 1997; Mackenbach and Looman, 2013; Novak et al., 2016; Cardona and Bishai, 2018; Lutz et al., 2018). The other three health indicators are devoted to capture more specific but relevant goals.

2. *Age specific survival ratio*. Taken as a measure of neonatal mortality, two mortality indicators examine the ratio between (i) successful newborns and the total population of registered newborns and (ii) the population of living children aged between zero and five years and the total registered

births for this age group. These ratios have been chosen to measure Target 3.2. that pursues the 'reduction of deaths of newborns and children under 5 years of age'[1].

3. Age-specific fertility rate. This indicator measures the number of births occurring to women in a particular age group divided by the number of women in that age group. In this case, the fertility rate (in %) for women between 15 and 19 years was taken to measure Target 3.7.[2] aiming at 'ensuring sexual and reproductive health-care services, including family planning and reduced adolescent birth rate'.

Regarding the two indicators selected to assess education goals, one of them was selected to measure global education, whereas the other seeks to evaluate gender disparities in the access to education. Specifically:

1. *Mean years of schooling* (by five-year age groups) was taken for ages between 20 and 24 years, trying to cover the school-age population. This indicator was considered both for male and female population.

2. Gender gap in mean years of schooling (by five-year age groups). This is calculated as the difference between the mean years of schooling (the previous indicator) between males and females. This indicator relates to Target 4.5., which seeks to eliminate gender disparities in education[3].

The data source for the health and education indicators is the Wittgenstein Human Capital Data Explorer (HCDE) database (see Lutz et al., 2018). Table 1 shows the county and temporal coverage for each indicator. Note that the health indicators from the Wittgenstein HCDE database are available for five-year periods starting in 1950 (including projections up to 2100), whereas education indicators from this database are annual data every five years (including projections up to 2100).

Figures 1-5 present the geographical pattern for the main indicators[4]. At the outset, one can observe the existence of correlations across neighbouring regions and the presence of spatial clusters of regions with similar values for all the indicators.

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[1] Specifically, Target 3.2. is described as follows: "By 2030, end preventable deaths of newborns and children under 5 years of age, with all countries aiming to reduce neonatal mortality to at least as low as 12 per 1,000 live births and under-5 mortality to at least as low as 25 per 1,000 live births".

[2] Target 3.7. states that "By 2030, ensure universal access to sexual and reproductive health-care services, including for family planning, information and education, and the integration of reproductive health into national strategies and programmes".

[3] Target 4.5. states that "By 2030, eliminate gender disparities in education and ensure equal access to all levels of education and vocational training for the vulnerable, including persons with disabilities, indigenous peoples and children in vulnerable situations".

[4] The map for the survival ratio for children between 0-4 years is not presented because the geographical pattern is practically the same as for the newborns. The map for the gender gap in mean years of schooling is not presented because the indicator can be obtained based on the information of Figures 4 and 5.

Figure 1. Life expectancy at birth (years). Year 2015.

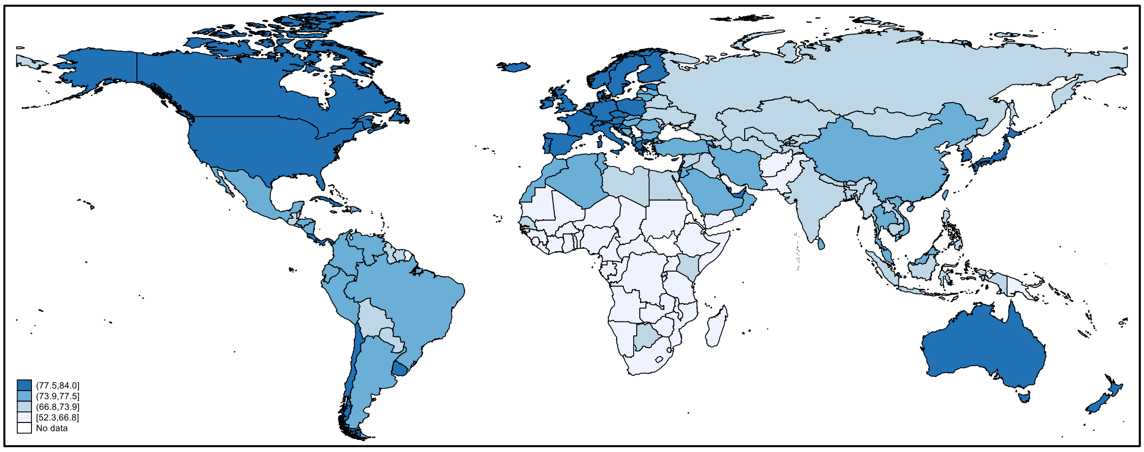


Figure 2. Survival ratio (%) for newborns. Year 2015.

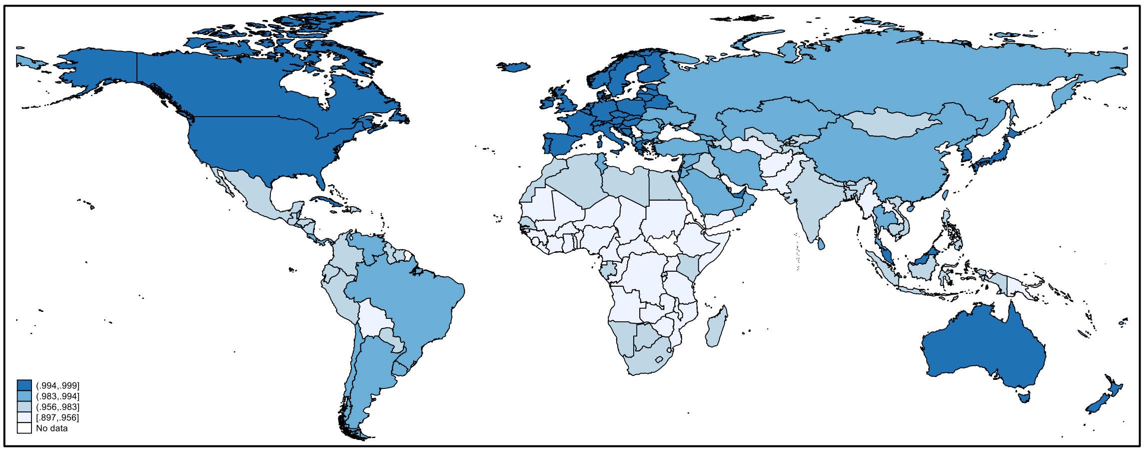


Figure 3. Fertility rate (%) for women between 15 and 19 years. Year 2015.

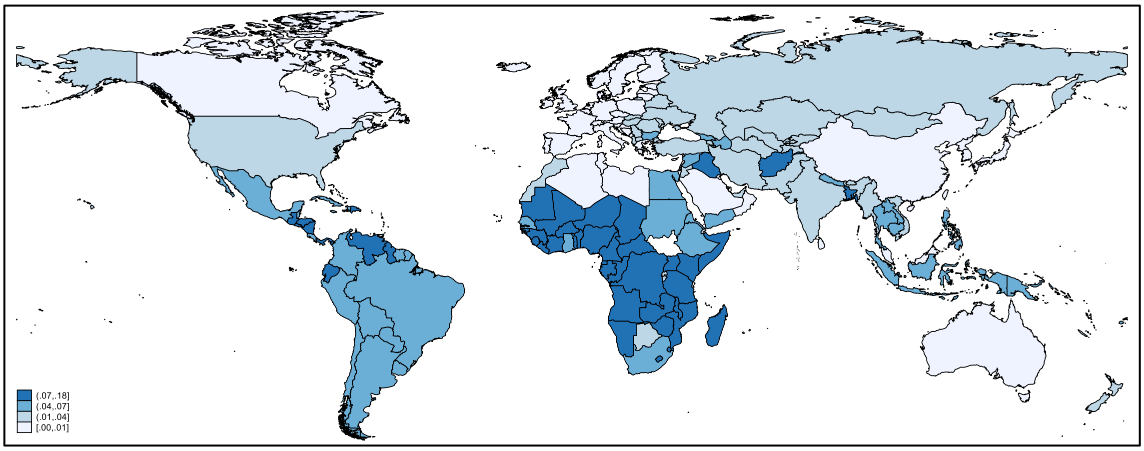


Figure 4. Mean years of schooling (years) for men between 20 and 24 years. Year 2015.

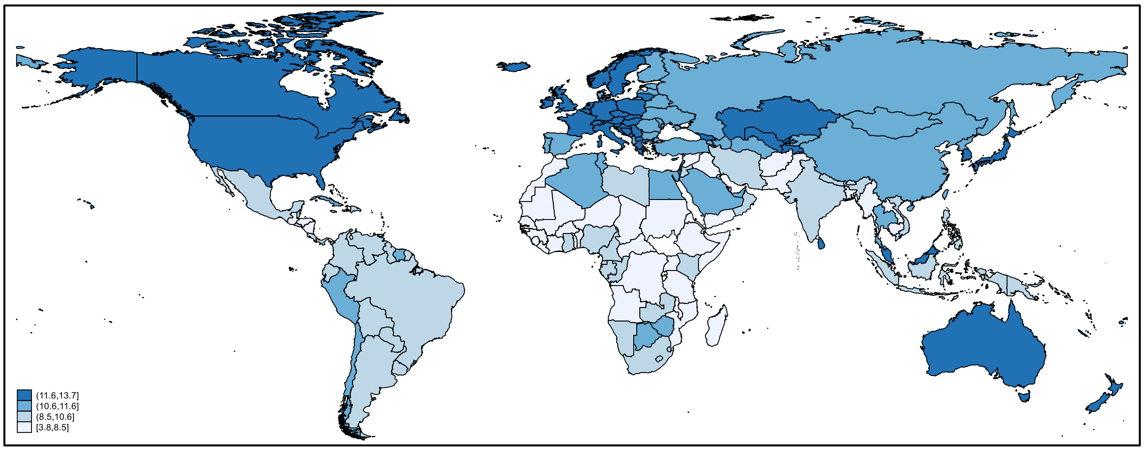
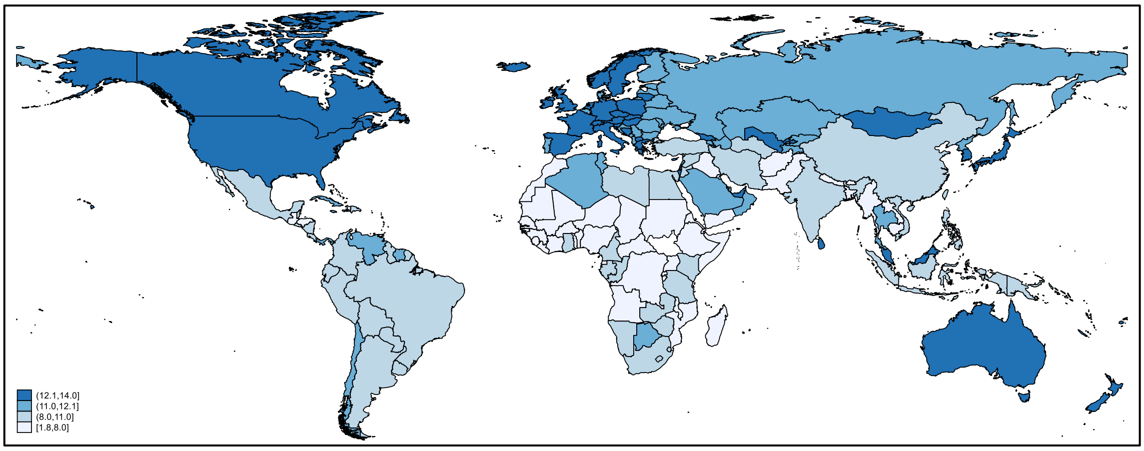


Figure 5. Mean years of schooling (years) for women between 20 and 24 years. Year 2015.



As a result, global spatial association tests have been implemented to confirm whether the general behaviour of the indicators exhibits global spatial autocorrelation. In particular, the Moran's I test (Moran, 1950) has been applied to test for the null of spatial randomisation, in other words, data are randomly distributed in space with no spatial associations or clusters. If the test statistic is statistically significant positive, data show positive autocorrelation with spatial clustering around similar values. If the test is statistically significant but negative, data show negative autocorrelation suggesting dissimilar neighbours. Finally, if the test is not statistically significant there is absence of spatial autocorrelation.

Table 2 presents the results of the application of this test. For all the indicators, the test confirms the existence of a positive autocorrelation with spatial clustering. According to that, results obtained in this study are presented for the following four clusters. These clusters were formed taking into account the countries' proximity and the level of development (especially in Africa), as usually done in other country classifications (such as the World Bank Country Classification). But also the availability of enough observations for the estimations was considered, which forced us to aggregate some non-bordering countries in the OECD and RAAP clusters.

- OECD cluster: including Europe, USA, Canada, Japan, Australia, and New Zeeland.

- LAC cluster: formed by Latin America and Caribbean countries.
- SSA cluster: including Sub-Saharan countries, except South Africa.
- Rest of Africa, Asia and Pacific (RAAP) cluster: including all the African, Asian and Pacific countries not included in the other clusters.

Table 2. Results of the test for spatial correlation.

Indicator	Moran test	p-value
LifeExp	191.88	0.00
SurvivalNB	216.41	0.00
Fertility	200.08	0.00
SchoolM	158.78	0.00
SchoolF	171.82	0.00

2.2. SDGs drivers

Once the indicators of SDGs targets were selected, an array of drivers needed to be considered. Table 3 presents a summary of drivers chosen based on two stages. The first stage follows a thorough review of the literature to identify health and education drivers. In a second stage, a final set of drivers were selected based on this review of the literature, but also in the availability of relevant variables in the CGE model to proxy these drivers. The drivers can be classified into socioeconomic, nutritional, environmental, and institutional factors.

Among the socioeconomic determinants, income level was identified as the most relevant factor (Filmer, 2000; WHO, 2008). In the case of health, this is illustrated by the so-called Preston curve that relates economic development and life expectancy at birth (Preston, 1975; Mackenbach and Looman, 2013; Lutz and Kebede, 2018). Moreover, income level is not only expected to influence general health conditions, but also specific indicators such as newborn and child mortality (Lutz and Kebede, 2018), or adolescent birth rate (Santelli et al., 2017). The relationship between economic development and education is also clear in the literature (Filmer, 2000). Therefore, in our application, per capita GDP (in constant 2010 US$) was used as an explanatory variable for both health and education indicators.

The quality of public services is also shown in the literature as a key factor influencing people's health and education; an aspect that macroeconomic studies usually have proxied with per capita expenditure (Halicioglu, 2011; Bergqvist et al., 2013; Amuka et al., 2018) or the share of these expenditures in GDP (Kabir, 2008; Fayissa and Gutema, 2005). The latter specification is more suitable, since the use of per capita health or education expenditure may lead to multicollinearity problems due to the high correlation between these expenditures and per capita GDP (Kabir, 2008; Fayissa and Gutema, 2005). Therefore, we include the share of public education expenditure in GDP (%) as a driver of education. We have also tried to include the share of health expenditure in GDP (%) as a driver of health, leading to non-significant coefficients with changeable signs. This result is in line with the ambiguous effect of this variable observed in the literature (Fayissa and Gutema, 2005; Halicioglu, 2011; Baltagli et al., 2012; Benos et al., 2019). Note that, although one would expect that an increase in health expenditure may help to improve health services and hence health status, this is only true if the marginal effect of this increase is greater than the forgone benefits that would have accrued had these financial resources from taxes been allocated for other purposes with beneficial impacts on health. So, given this ambiguity and the reduced time coverage we have for this variable (only since the year 2000), we opted for not considering share of health expenditure in GDP as a driver.

In contrast, the chosen model specification does consider the positive effect that better education services could have on life expectancy, as recognised by international organizations (WHO, 2008) and the empirical literature (Valkonen et al., 1997; Fayissa and Gutema, 2005; Halicioglu, 2011; Bayati et al., 2013; Novak et al., 2016; Lutz and Kebede, 2018). Previous literature also finds that education has a significant impact on specific indicators such as adolescent birth rate (Santelli et al., 2017) or child survival (Kabir, 2008). Consequently, in our application, mean years of schooling of the population between 20 and 24 years was considered to drive health indicators. This age interval was considered to account for people of school-leaving age that are therefore eligible active additions to the workforce.

In addition to the quality of public services, the accessibility to such services is also critical. The concept of accessibility is highly conditioned by the share of the population in urban/rural areas (Kabir, 2008; Bayati et al., 2013; Monsef and Mehrjardi, 2015; Novak et al., 2016). However, some authors have pointed out that urbanisation can also be associated with congestion and pollution, thereby having an adverse effect on health status (Fayissa and Gutema, 2005; Halicioglu, 2011). Accordingly, there is no *a priori* sign associated with this driver. In our model specification, it is proxied though the share of the agri-food sector in GDP (in %).

The literature also establishes a clear relationship between food and health, since malnutrition (both undernutrition and obesity) is shown as a crucial factor influencing life expectancy (for a literature review, see Zheng et al., 2014). In general, the literature has used food availability (Fayissa and Gutema, 2005; Halicioglu, 2011; Bayati et al., 2013) or caloric deficiency (Kabir, 2008; Amuka et al., 2018) to explore this nexus. In studies focused on developed countries, fat consumption (Baltagli et al., 2012) or obesity (Allen et al., 2016; Benos et al., 2019; Dobis et al., 2020) are also used. In our case, per capita food consumption (in kcal/capita/day) was considered as a possible driver of general health. Here, again, the links between health and education need to be considered, since malnutrition also conditions education (Jukes et al., 2002).

A further factor identified as a health driver is environmental conditions (Fayissa and Gutema, 2005; Monsef and Mehrjardi 2015; Amuka et al., 2018; Cardona and Bishai, 2018; Naik et al., 2020). For example, air pollution can cause respiratory diseases, lung cancer, and cardiovascular diseases, which might particularly affect the youngest segments of the population (OECD, 2017). The relationship between pollution and these diseases is corroborated by the empirical literature, both in the adult population (see, for example, Cai et al., 2014; Chen et al., 2017) and in children and newborns (see, as an example, Coneus and Spiess, 2012). In this study, we construct an aggregate pollution per capita measure (in Kilograms/capita) that includes ozone precursor gases, such as Carbon Monoxide (CO), Nitrogen Oxides (NOx), Non-Methane Volatile Organic Compounds (NMVOC) and Methane (CH4); acidifying gases, such as Ammonia (NH3), Nitrogen oxides (NOx) and Sulfur Dioxide (SO2); and Fine Particulate Matter, as PM10, PM2.5 and Carbonaceous specification (BC, OC).

Finally, institutional factors such as globalisation, governance, or corruption can be considered when analysing health and education determinants (Stroup, 2007; WHO, 2008; Smith et al, 2015; Mackey et al., 2018; Shahba et al., 2019; Mialon, 2020). Among these factors, globalisation was considered, measured as the ratio between the county's share of trade (exports and imports) on GDP and the world's share of trade on GDP, rendering a relative openness index. The effects of openness on health has been discussed in the literature and the sign of these effects remains indeterminate. On the one hand, openness can benefit health status through the increased trade of medical supplies, drugs and vaccines, and the increased mobility of medical staff, technologies and knowledge. On the other hand, trade can deteriorate health through (*inter alia*) the deterioration of working conditions, the transfer of diseases or the adoption of unhealthy consumer practices (Owen and Wu, 2007, Bergh and Nilsson, 2010).

To capture social inequalities, the Palma ratio is also included as a driver for the health and education indicators. Note that this variable is constructed as the ratio of the richest 10% of the population's share of gross national income divided by the poorest 40%'s share. Other authors explored the relationship between inequality and health status through the Gini Index (Rodgers, 1979; Flegg, 1982; Filmer and Pritchett, 1999; Szwarcwald et al., 2002), the poverty rate (Crémieux et al., 1999; Kirby et al., 2001; Kumar et al., 2012; Gunaratne et al., 2015; Dobis et al., 2020), the share of national income received by the richest 5% population (Waldmann, 1992), or the 90:10 income decile share ratio (Gold et al., 2001). We opted for the Palma ratio because it is easy to calculate and reduces oversensitivity to income in the middle of the distribution of other inequality measures such as the Gini Index (Campagnolo and Davide, 2017). Moreover, the Palma ratio captures the essence of the SGD 10.1. "By 2030, progressively achieve and sustain income growth of the bottom 40 per cent of the population at a rate higher than the national average" (UN, 2017).

Table 3 describes the selected SDG drivers. Data for these variables is drawn from the World Bank Development Indicators database (World Bank, 2020), except for food consumption that comes from the Food Balances of the FAOSTAT database (FAO, 2020) and the air pollutants information that comes from the EDGARv5.0 air pollutant database (https://edgar.jrc.ec.europa.eu/overview.php?v=50_AP) (see Crippa et al., 2019).

Table 3. Description of selected SDGs drivers.

Driver	**Description**	**SDG**	**Data source**	**No. Countries**	**Years**
GDPpc	GDP per capita (constant 2010 US$)	Both	WorldBank Data	206	1960/1961/…/2019
School	Mean years of Schooling for ages 20-24 (years) for both male and female	Health	Wittgenstein HCDE	180	1950-1955/1955-1960/…/2095-2021
EducShare	Share of government education expenditures on GDP (%)	Education	WorldBank Data	169	1970/1971/…/2019
Agri	Share of agricultural sector on GPD (%)	Both	WorldBank Data	204	1960/1961/…/2019
Food	Food consumption (kcal/capita/day)	Both	FAOSTAT Database	167	1961/1962/…/2019
Pollutantspc	Pollutants per capita (Kg/capita)	Health	WorldBank Data	198	1970/1971/…/2015
Openess	Relative Openness Index (%)	Both	WorldBank Data	200	1960/1961/…/2019
Palma	Palma ratio (%)	Both	WorldBank Data	164	1967/1968/…/2018

Although we have information for all drivers and indicators since 1970, only the period 1990-2015 is considered in this analysis because we have few observations for the previous years (specially for the Palma ratio). Moreover, since for most SDG indicators information is available for five-year time intervals, we adapted the drivers database to this structure. Table 4 shows the descriptive statistics of the variables included in the database.

Table 4. Descriptive statistics of the explanatory variables.

Variable	Observations	Mean	Standard Deviation	Min.	Max.
GDPpc	1,535	9,850.79	14,950.57	154.27	105,761.90
School	1,980	7.38	3.50	0.01	14.86
EducShare	968	4.26	1.95	0.79	26.37
Agri	1,304	17.91	15.02	0.03	86.26
Food	1,562	2,563.96	513.71	1,410.25	3,766.20
Pollutantspc	1,571	200.46	180.47	1.19	2,316.22
Openess	1,426	2.82	4.60	0.004	86.35
Palma	617	2.11	1.28	0.73	8.33

3. Estimation of SDGs drivers

A panel data approach with country fixed effects is used to assess the impact of SDG drivers, allowing us to measure the relationship between variables after controlling for country heterogeneity. Among the possible model specifications for the continuous indicators (life expectancy at birth and mean years of schooling), the double-logarithmic model is selected because it permits non-linear relationships amongst the original variables and because the parameters of the explanatory variables can be directly interpreted as elasticities.

For life expectancy at birth, the chosen regression specification is:

$$\begin{aligned} \ln LifeExp_{i,t} = \ & \beta_0 + \beta_1 \ln GDPpc_{i,t} + \beta_2 \ln GDPpc_{i,t}^2 \\ & + \beta_3 \ln School_{i,t} + \beta_4 Agri_{i,t} + \beta_5 \ln Food_{i,t} + \beta_6 \ln Food_{i,t}^2 \\ & + \beta_7 \ln Pollutpc_{i,t} + \beta_8 Openess_{i,t} + \beta_9 \, Palma_{i,t} + u_{i,t} \end{aligned} \quad (1)$$

Where i refers to the country and t=1990-1995,…,2010-2015. The description of the variables is detailed in Tables 1 and 3, and u is the error term assumed to be identically and independently distributed across countries. Note that the HCDE database provides information about the life expectancy at birth for males and females, but not for both sexes, so the variable $LifeExp$ is obtained as the average of male and female life expectancy weighted according to the population of each gender. All variables are in logarithms, except rates or percentage variables since in these cases coefficients can be also interpreted as elasticities. Per capita GDP and food consumption are also introduced in the model in quadratic form to capture the different effect that can have for different values of the variable. For example, although an increase of food consumption could enhance life expectancy, an excessive caloric intake could reduce it. Similarly, the literature maintains that life expectancy rises at a declining rate as income grows (Rodgers, 1979; Kabir, 2008). Nevertheless, in those estimations where the coefficients of the quadratic terms are not statistically significant or have a counterintuitive sign, then the quadratic terms are excluded. This should not pose a problem in the estimation since the list of variables may not necessarily be uniform across different regions (Fayissa and Gutema, 2005; Halicioglu, 2011).

For male and female mean years of schooling, the regression specification is as follows:

$$\begin{aligned} \ln SchoolM_{i,t} = \ & \beta_0 + \beta_1 \ln GDPpc_{i,t} + \beta_2 \ln GDPpc_{i,t}^2 + \beta_3 Agri_{i,t} + \beta_4 \ln Food_{i,t} \\ & + \beta_5 \ln Food_{i,t}^2 + \beta_6 Openess_{i,t} + \beta_7 \, Palma_{i,t} + u_{i,t} \end{aligned} \quad (2)$$

$$\ln SchoolF_{i,t} = \beta_0 + \beta_1 \ln GDPpc_{i,t} + \beta_2 \ln GDPpc_{i,t}^2 + \beta_3 Agri_{i,t} + \beta_4 \ln Food_{i,t} + \beta_5 \ln Food_{i,t}^2 + \beta_6 Openess_{i,t} + \beta_7\ Palma_{i,t} + u_{i,t} \quad (3)$$

For percentage indicators (survival ratio and fertility rate), a beta regression model (Ferrari and Cribari-Neto, 2004; Smithson and Verkuilen, 2006) is used because of its flexibility for modelling continuous dependent variables between 0 and 1 and because its predictions are confined to the same range. Beta regression is a model of the mean of the dependent variable y conditional on covariates x, which is usually denoted by μ_x. The dependent variable y is in the space (0; 1), which means that we must ensure that μ_x is also in the space (0; 1). We do this by using the link function for the conditional mean. For the logit link function[5], this implies that:

$$\ln\{\mu_x/(1-\mu_x)\} = x\beta \quad (4)$$

And that:

$$\mu_x = E(y|x) = exp(x\beta)/\{1 + exp(x\beta)\} \quad (5)$$

The conditional variance of the beta distribution is:

$$Var(y|x) = \{\mu_x(1-\mu_x)\}/(1+\psi) \quad (6)$$

Where the parameter ψ is the scale factor that rescales the conditional variance to ensure that $\psi > 0$.

Let us note that, in our case study, when $y = SurvivalNB$ or $y = Survival4$; then $x\beta = \beta_0 + \beta_1 \ln GDPpc_{i,t} + \beta_2 \ln GDPpc_{i,t}^2 + \beta_3 \ln School_{i,t} + \beta_4 Agri_{i,t} + \beta_5 \ln Food_{i,t} + \beta_6 \ln Food_{i,t}^2 + \beta_7 \ln Pollutpc_{i,t} + \beta_8 Openess_{i,t} + \beta_9\ Palma_{i,t}$. And, when $y = Fertility$; then $x\beta = \beta_0 + \beta_1 \ln GDPpc_{i,t} + \beta_2 \ln GDPpc_{i,t}^2 + \beta_3 \ln School_{i,t} + \beta_4 Agri_{i,t} + \beta_5 Openess_{i,t} + \beta_6\ Palma_{i,t}$.

4. Results

Results of estimation are shown in Tables 5-10, for all countries in the sample and for the different geographical clusters described in Section 2.1. Results reveal that, in general, elasticities obtained are statistically significant and have the expected sign. Moreover, these results appear to be consistent when the model is estimated for different geographical clusters. Below, the results for each indicator are presented and discussed in consecutive sections.

Life expectancy at birth

As expected, Table 5 shows that income level and education positively influence life expectancy and are the variables that have a greater impact on this indicator. Specifically, a 1% increase in GDP per capita and in mean years of schooling leads to an increase in life expectancy of 0.21% and 0.16%, respectively. These results are consistent with previous literature on the relationship between economic development and life expectancy (Crémieux et al., 1999; Fayissa and Gutema, 2005; Owen and Wu, 2007; Bayati et al., 2013; Mackenbach and Looman, 2013; Ebstein et al., 2015; Monsef and Mehrjardi, 2015; Allen et al., 2016; Amuka et al., 2018; Dobis et al., 2020) and between education and life expectancy (Valkonen et al., 1997; Fayissa and Gutema, 2005; Owen and Wu, 2007; Halicioglu, 2011; Bayati et al., 2013; Novak et al., 2016; Lutz and Kebede, 2018; Benos et al., 2019; Dobis et al., 2020). Results by regions show a greater impact of these variables in low-income regions than in more developed counties. The implication is that at the margin, efforts in less developed countries lead to greater increases in life expectancy. Lower

[5] Other link functions were considered (probit, log-log, and complementary log-log), but logit function was selected based on the BIC selection criterion.

impacts of rising income on life expectancy in developed countries is also observed by Benos et al. (2019), who obtained a non-significant coefficient for the US States. Similarly, Rodgers (1979) find a slightly higher income coefficient for the estimation for the less developed countries in comparison with all countries. Cardona and Bishai (2018) only obtained positive and significant income effects in countries with lower life expectancy.

Table 5. Results of estimation for the life expectancy at birth.

	All countries	OECD	LAC	SSA	RAAP
$\ln GDPpc$	0.206*	0.0822*	0.106	0.177**	0.0121
$\ln GDPpc^2$	-0.0100	-0.00074	-0.00473	-	-
$\ln School$	0.160***	0.0813*	0.278***	0.119**	0.159***
$Agri$	-0.206***	0.0280	-0.0336	-0.362***	-0.275***
$\ln Food$	0.0418	0.00786	0.0842	0.0415	0.0214
$\ln Food^2$	-	-	-	-	-
$\ln Pollutpc$	-0.0342***	-0.0316***	0.00603	-0.0844	0.0143
$Openess$	0.00513	0.00418	0.0129	0.0384	-0.0108*
$Palma$	-0.00333	0.00407	-0.000280	-0.00118	-0.00671
No. Observations	483	150	93	103	139
No. Groups	138	40	22	36	41
R2	0.58	0.86	0.86	0.58	0.72

***p<0.01, **p<0.05, *p<0.10. Definition of the variables was detailed in Table 3.

The quadratic term of GDP per capita is not statistically significant, but has the expected negative sign indicating that as income level increases, the effect of income increases is decelerating. This non-linear effect of income is also observed in the previous literature (Rodgers, 1979).

Results also corroborated the assumed hypothesis regarding the greater accessibility to public services on urban areas than in rural ones. Specifically, a 1% increase in the share of agricultural sector on GDP reduces life expectancy by 0.21%; this 'accessibility effect' being more pronounced in less developed such as Subsaharan Africa. Similar results were obtained by Fayissa and Gutema (2005), Bayati et al. (2013), Monsef and Mehrjardi (2015) and Novak et al. (2016) that found a positive relationship between urban population and life expectancy at birth. However, other authors obtained an adverse impact of urbanization on health status (Halicioglu, 2011; Dobis et al., 2020).

Environmental conditions also have a significant effect on life expectancy. An increase in the quantity of pollutants per capita has a negative effect on life expectancy at worldwide level and in the OECD countries (with elasticities of -0.03). However, in the other regional clusters, the coefficient is not statistically significant. The negative relationship between pollution and health was also confirmed by other authors, such as Ebstein et al. (2015), Allen et al. (2016), and Cardona and Bishai (2018). But another strand of the literature obtained a non-significant effect of environmental variables (Fayissa and Gutema, 2005; Monsef and Mehrjardi, 2015).

The other drivers considered (food consumption, relative openness index and Palma ratio) do not exhibit a statistically significant effect on life expectancy. However, the coefficients indicate that an increase in food consumption or in commercial openness could enhance life expectancy, whereas greater economic inequality could reduce it. The sign of these coefficients are consistent with the effect observed by the previous literature regarding food (Fayissa and Gutema, 2005;

Kabir, 2008; Bergh and Nilsson, 2010; Halicioglu, 2011; Bayati et al., 2013, Amuka et al., 2018) and inequality (Rodgers, 1979; Dobis et al., 2020). The lack of significance of the relative openness index is consistent with the ambiguous effect between trade and health pointed out by the literature, although the positive sign obtained for the majority of regions is in line with a number of studies (Owen and Wu, 2007; Stroup, 2007; Bergh and Nilsson, 2010). In contrast, the significant negative effect of the coefficient for the RAAP countries reveals that the negative effects discussed in Section 2.2. outweigh the beneficial effects.

Newborn and child survival ratio

Table 6. Results of estimation for the newborn survival ratio.

	World	LAC	SSA	OECD	RAAP
$\ln GDPpc$	0.0104***	0.0033*	0.0343	0.0092***	0.0135***
$\ln GDPpc^2$	-0.0016***	-	-0.0102*	-0.0024**	-0.0008
$\ln School$	0.0425***	0.0548***	0.0691***	0.0075	0.0463***
$Agri$	-0.0525***	-0.0198	-0.0857**	-0.0179***	-0.0904***
$\ln Food$	0.1369*	0.0385***	0.6828*	0.0179	-0.0099
$\ln Food^2$	-0.0509	-	-0.2930*	-0.0035	-
$\ln Pollutpc$	-0.0044	-0.0022	-0.0330	-0.0008	0.0020
$Openess$	-0.0006	0.0013	-0.0050	0.0009	-0.0024
$Palma$	-0.0010**	-0.0007*	-0.0016	-0.0013**	-0.0007
No. Observations	483	93	103	150	139
No. Groups	138	22	36	40	41

***p<0.01, **p<0.05, *p<0.10. Definition of the variables was detailed in Table 3.

Table 7. Results of estimation for the under 5 years old survival ratio.

	World	LAC	SSA	OECD	RAAP
$\ln GDPpc$	0.0018*	0.0001	0.0192	-0.0001	0.0027**
$\ln GDPpc^2$	-0.0003*	-	-0.0063**	-	-0.0002
$\ln School$	0.0150***	0.0106***	0.0330***	0.0035***	0.0147***
$Agri$	-0.0196***	-0.0086	-0.0442**	-0.0039***	-0.0245***
$\ln Food$	0.0939***	0.0215	0.4658**	0.0215	0.0155
$\ln Food^2$	-0.0377**	-0.0050	-0.2012**	-0.0090	-0.0081
$\ln Pollutpc$	-0.0019	-0.0008	-0.0138	-0.0001	0.0011
$Openess$	-0.0008	-0.0001	-0.0040	0.0002	-0.0010**
$Palma$	-0.0005**	-0.0002*	-0.0014	-0.0001	-0.0006**
No. Observations	483	93	103	150	139
No. Groups	193	31	47	44	68

***p<0.01, **p<0.05, *p<0.10. Definition of the variables was detailed in Table 3.

Tables 6 and 7 present the results for the survival ratio of newborns and children under 5 years of age. The first observation is that corresponding elasticities tend to be more pronounced in the newborn model specification, although the levels of significance are quite similar in both model specifications (except for per capita GDP, where most coefficients for the under 5 model are not statistically significant).

Caloric intake is the main driver of child survival rates, with an elasticity at worldwide level of 0.14 and 0.09 for newborn and children under five years of age, respectively. This effect is particularly pronounced in Sub-Saharan countries, although the impact of this variable is progressively weaker as per capita consumption of calories increases. In the other regions analysed, the magnitude and significance of this variable is not as clear as in Sub-Saharan countries. The strong relationship between caloric intake and infant survival in Sub-Saharan countries is also confirmed by the previous literature (Akachi and Canning, 2010; Abrahams et al., 2011; Lu et al., 2019).

The variables with the next highest impact are education and the share of the agricultural sector, which exhibit a similar magnitude but are of opposite sign. Thus, a 1% increase in mean years of education leads to a 0.04% and 0.015% increase in the survival ratio of newborn and children under five years of age, respectively. For the agricultural share driver, the corresponding indicator elasticities are -0.05 in both model specifications. Comparing across regions, we observe a higher impact in developing countries than in developed ones, with elasticities ten times higher in Sub-Saharan countries than in OECD ones. Results are consistent with previous studies, both for the education (Flegg, 1982; Filmer and Pritchett, 1999; Alves and Belluzzo 2004; Amouzou and Hill, 2004; Owen and Wu, 2007; Barufi et al., 2012; Kumar et al., 2012; Lutz and Kebede, 2018) and the agricultural variable (Amouzou and Hill, 2004; Barufi et al., 2012; Kumar et al., 2012).

A positive relationship between per capita income levels and child survival ratios is observed, although this effect tends to soften as per capita GDP increases (as also found in Rodgers, 1979). However, as mentioned above, this positive effect on survival ratios for children under the age of five year is almost negligible. The effect of this variable in the previous literature is ambiguous, with some authors obtaining very small effects for this variable (Flegg, 1982; Barufi et al., 2012; Lutz and Kebede, 2018), and other studies finding a large positive impact of income (Filmer and Pritchett, 1999; Alves and Belluzzo, 2004; Amouzou and Hill, 2004; Owen and Wu, 2007).

Similarly, we observe a negative relationship between inequality and survival ratios in children, but with a very limited effect. These results are supported by previous literature, where a positive relationship between the under-five mortality rate and the Gini Index (Rodgers, 1979; Flegg, 1982; Filmer and Pritchett, 1999; Barufi et al., 2012), the percentage of people below the poverty line (Kumar et al., 2012), or the share of national income received by the richest 5% population (Waldmann, 1992).

At the global level, the other drivers considered (pollution and openness) are not statistically significant. In the case of the RAAP countries, however, we find a negative and statistically significant coefficient indicating that, as for life expectancy, the negative effects of globalisation on health status outweigh its beneficial effects (contrary to the results obtained by Owen and Wu, 2007; Stroup, 2007). A non-significant effect of pollution on neonatal mortality is also found by Arceo et al. (2016), although other studies obtain a negative and significant impact of pollution on infant mortality rates (Chay and Greenstone, 2003; Knittel et al., 2011).

Adolescent birth rate

The main factor driving adolescent birth rate is education (see Table 8). On average, a 1% increase in mean years of schooling leads to a 0.05% decrease in the fertility rate for women between 15 and 19 years. The magnitude of this variable is quite similar for all the regions, except for the OECD countries where the effect is more reduced and statistically non-significant. A relevant impact of education (and with the same sign) is also found in the previous literature (Kirby et al., 2001; Gupta and Mahy, 2003; Alemayehu et al., 2010; Chiavegatto Filho and Kawachi, 2015; Gunaratne et al., 2015; Avellaneda and Dávalos, 2017; Santelli et al., 2017; Chuang et al., 2018).

Table 8. Results of estimation for the fertility rate for women between 15 and 19 years.

	World	LAC	SSA	OECD	RAAP
$\ln GDPpc$	-0.0078***	-0.0017	-0.0345***	-0.0136***	-0.0021
$\ln GDPpc^2$	0.0005		0.0053*	0.0015	
$\ln School$	-0.0545***	-0.0791***	-0.0614***	-0.0079	-0.0563***
$Agri$	0.0397***	0.0385	0.0333*	0.0619***	0.0407***
$Openess$	0.0012	0.0043	0.0039	-0.0028*	0.0004
$Palma$	0.0001	0.0021*	-0.0013*	0.0064***	-0.0004
No. Observations	509	93	113	156	149
No. Groups	149	22	40	43	45

***p<0.01, **p<0.05, *p<0.10. Definition of the variables was detailed in Table 3.

Rurality is another factor that seems to have a relevant impact on the adolescent birth rate, since it tends to increase as the agricultural share on GDP increases. The previous empirical literature regarding the effect of rurality or urbanisation on adolescent fertility rate is scarce and somewhat inconclusive, with most papers obtaining greater birth rates in rural areas (Gupta and Mahy, 2003; Alemayehu et al., 2010), and other papers in urban ones (Avellaneda and Dávalos, 2017).

As for the child survival ratio, the effect of per capita GDP is statistically significant but its magnitude is limited in comparison with other variables (as found in Crosby and Holtgrave, 2004; Alemayehu et al., 2010; Chiavegatto Filho and Kawachi, 2015; Avellaneda and Dávalos, 2017). Moreover, this effect tends to soften as the income level increases. Only in Sub-Saharan countries do we find a high elasticity that is comparable to the magnitude of the elasticity of the agricultural share. A negative relationship is also found in the literature (see, for example, Gold et al., 2001; Santelli et al., 2017; Zhuang et al., 2020).

The other factors (openness and Palma ratio) are not statistically significant at worldwide level. Globalisation only has a significant and negative impact on adolescent birth rate in OECD countries, whereas in middle and low-income countries we find a positive but reduced impact (as shown in Zhuang et al., 2020). The results of inequality by regions are inconsistent. For example, in OECD and LAC countries, a 1% increase of the Palma ratio implies an increase in the fertility rate for women between 15 and 19 years of 0.006% and 0.002%, respectively. In contrast, in Sub-Saharan Africa, grater inequality is associated with lower fertility rates in women between 15 and 19 years. One explanation is that in the Sub-Saharan countries where family planning and cultural attitudes to childbirth are different, a more pertinent measure of fertility rates might be found in a younger age group. In fact, whereas in most countries the number of births per 1,000 girls aged 10 to 14 is less than 1, in some Sub-Saharan countries there are 10 or more births per 1,000 girls under 15 (UN, 2020). A positive relationship between inequality and teen pregnancy was also found in the literature for developed countries (Gold et al., 2001; Kirby et al., 2001; Crosby and

Holtgrave, 2004; Gunaratne et al., 2015), in LAC countries (Szwarcwald et al., 2002; Chiavegatto Filho and Kawachi, 2015), and at worldwide level (Santelli et al., 2017).

Mean years of schooling

Table 9. Results of estimation for the mean years of schooling of males.

	World	LAC	SSA	OECD	RAAP
$\ln GDPpc$	1.061***	1.436*	1.562*	0.0667	0.249**
$\ln GDPpc^2$	-0.0547***	-0.0784*	-0.0916		
$EducShare$	1.879**	1.773**	1.436	1.797*	1.438
$Agri$	0.758***	-0.607*	0.880***	0.0584	0.508*
$\ln Food$	0.551**	0.118	1.202**	-0.197	0.258
$Openess$	-0.0343*	-0.0233	-0.0324	-0.0179	-0.0354
$Palma$	-0.0135	-0.0109	-0.0165	0.0119	-0.00191
No. Observations	401	75	85	133	110
No. Groups	127	21	33	39	35
R2	0.46	0.75	0.56	0.16	0.52

***p<0.01, **p<0.05, *p<0.10. Definition of the variables was detailed in Table 3.

Table 10. Results of estimation for the mean years of schooling of females.

	World	LAC	SSA	OECD	RAAP
$\ln GDPpc$	2.035***	2.172***	3.622***	0.102**	3.437**
$\ln GDPpc^2$	-0.107***	-0.120***	-0.228***		-0.171**
$EducShare$	3.130***	2.390**	3.405	1.968*	3.307
$Agri$	1.044***	-0.848**	0.896*	0.0865	2.190***
$\ln Food$	0.837**	0.174	1.897***	-0.158	-0.538
$Openess$	-0.0521*	-0.0258	-0.0759	-0.0123	-0.0467
$Palma$	-0.0246	-0.0153	-0.0427	0.0188	-0.0240
No. Observations	401	75	85	133	110
No. Groups	127	21	33	39	35
R2	0.48	0.82	0.64	0.30	0.52

***p<0.01, **p<0.05, *p<0.10. Definition of the variables was detailed in Table 3.

Tables 9 and 10 present the results of estimation of mean years of schooling for the male and female population. A first comparison of results shows that elasticities obtained for females are higher and have a greater level of statistical significance than for males. This suggests that future socioeconomic development would tend to reduce the existing education gender gap. A similar conclusion is drawn in Handa (1996), Glick and Sahn (2000) and Tansel (2002).

With an elastic order of magnitude, the main drivers of the education indicator are the share of public education expenditure on GDP and the income level, although the latter effect is found to weaken as per capita GDP increases. In both variables, we observe a higher impact in developing countries than in developed ones. The positive effect of income is in line with the results of the previous literature (Glick and Sahn, 2000; De Gregorio and Lee, 2002; Grupta et al., 2002; Tansel, 2002; Baldacci et al., 2003; Al-Samarrai, 2006; Raijkumar and Swaroop, 2007; De Mello and Pisu, 2009; Sánchez and Sbrana, 2009; LaFleur and López, 2014). Similarly, some authors also observe, as in our case, a non-linear effect of the income variable (De Gregorio and Lee, 2002; Al-Samarrai, 2006; Ulubasoglu and Cardak, 2007). For the education expenditure variable, the evidence is inconclusive, where several commentators observe a positive incidence on education outcomes (Grupta et al., 2002; Baldacci et al., 2003; De Mello and Pisu, 2009), whereas other studies obtain a non-significant coefficient (Al-Samarrai, 2006; Raijkumar and Swaroop, 2007; Craigwell et al., 2012; LaFleur and López, 2014).

The share of agriculture on GDP and per capita food intake also have a positive effect on education at the global level, although the signs of the coefficients across the regions are inconsistent. An increase in the share of agriculture on GDP leads to an increase in mean years of schooling in all regions except in LAC countries (where we obtain a negative coefficient) and in OECD countries (where the positive effect is not statistically significant). An undetermined effect of this variable is also found in the previous literature, with evidence of non-significant coefficients (Al-Samarrai, 2006; Raijkumar and Swaroop, 2007; Craigwell et al., 2012), whilst other studies obtain coefficients with a different sign depending on the school grade (Kabubo-Mariara and Mwabu, 2007; Sánchez and Sbrana, 2009; Sbrana, 2009).

For the driver of per capita food consumption, we only obtain a significant effect in Sub-Saharan countries where a 1% increase in caloric intake leads to a 1.2% and 1.9% increase in male and female education, respectively. To the best of our knowledge, there are no previous studies that analyse the relationship between food consumption and education outcomes, although several papers have considered other health status variables (e.g., longevity, infant mortality or the presence of disabilities), obtaining a positive effect of health on education (Grupta et al., 2002; De Mello and Pisu, 2009; Craigwell et al., 2012).

The other two variables (openness and Palma ratio) have a very limited effect on mean years of schooling. Al-Samarrai (2006) and Raijkumar and Swaroop (2007) also obtain a non-significant relationship between inequality and school enrolment. Although the openness variable has a negative and significant effect on education at worldwide level, its magnitude is very moderate and the coefficient is not statistically significant for the regional estimates. In contrast, the previous literature has usually found a positive relationship between economic globalisation and educational attainment outcomes (Stroup, 2007).

5. Conclusions

This paper aims at assessing the drivers of a few indicators of health and education SDGs. Results obtained provide valuable information about the rationale that guides the evolution of these indicators at global level and for different regions. Elasticities obtained also serve as a first step for the integration of education and health indices into CGE simulation models.

One of the conclusions drawn from this paper is the significant effect of per capita GDP on health and education indicators. Nevertheless, the impact of other drivers, such as the food intake or the share of the agricultural sector on GDP, have a similar or even a greater magnitude than the income level. We also found a close relationship between health and education, since all health indicators tend to improve as the years of schooling increase. In contrast, the impact of pollution, trade openness and inequality on the selected indicators is much more reduced and, in most cases, not statistically significant.

These results imply that, although income level has been traditionally seen as the main driver of health and education outcomes, other drivers should also been taken into account when analysing these SDG indicators. In particular, agricultural policies and food access measures could have a relevant impact on health and education, especially in sub-Saharan countries. The results also confirm the relevant impact that measures to enhance educational attainment could have on health outcomes though better work conditions, greater economic development and greater health awareness.

Comparing across regions, greater elasticities are obtained for developing countries than for developed ones, especially for sub-Saharan countries. Therefore, at the margin, efforts in less developed countries could lead to greater increases in health and education outcomes. Elasticities for the food intake and the share of the agricultural sector for sub-Saharan countries are particularly high in comparison with other regions. This highlights the importance of adequate food and agricultural policies in this continent for ensuring food supply and food security.

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