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Government expenditure, education, and productivity in the European Union: Effects on economic growth

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Government expenditure, education, and productivity in the European Union: Effects on economic growth[1]

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Abstract

In this paper we will analyse the effects of public spending on education on productivity, wages, and growth at European Union (EU) level. We are trying to find out to what extent education expenditures and human capital contribute to improving productivity, achieving higher wages, and enhancing the standard of living of the population, as measured by per capita growth.

Key words: government expenditure, education, human capital, productivity
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1. Introduction

Among the areas in which equality should be a primary objective is education, since the development of human capital favours wage redistribution and the satisfaction of people (Albert and Davia, 2005). This is achieved, basically, through the improvement of the opportunities for insertion in the labour market, the economic position, and the social condition of the individual, reducing income disparity and social inequality (Lathapipat, 2016). In this sense, investing in education is important to achieve positive results in terms of redistribution and equality, but it has received limited attention in comparative research on welfare states (West and Nikolai, 2013).

In this paper we will analyse the effects of public spending on education on productivity, wages, and growth at European Union (EU) level. We try to find out to what extent spending on education and human capital contributes to improving productivity, achieving higher wages, and improving the standard of living of the population, measured by per capita growth. As far as we know, empirical studies do not analyse the effects of education spending simultaneously with productivity, wage gains and per capita growth. Therefore, we will address these issues in this paper.

First, the academic literature will be reviewed focusing on the impact of public spending on education on human capital development. Later, to perform the quantitative analysis, we will use the methodologies for cointegrated panel data: Dynamic Ordinary Least Squares (DOLS) and Fully Modified Ordinary Least Squares (FMOLS), that solve the problem of endogeneity and eliminate small sample bias. In this study, data on the variables of interest shall be obtained from Eurostat.

The structure of the paper is as follows. The literature on the subject will be reviewed in section 2. The methodology and exploratory analysis of the data are presented in section 3. The empirical application and results will be discussed in section 4. Finally, section 5 shows some conclusions, limitations, and extensions of the work.

2. The determinant drivers: some literature on the issue

To guide the literature review, we will group the studies into four blocks. The first of these provides an overview of the analyses relating human capital to economic growth. In the second, those that relate the development of human capital to the reduction of inequalities. Finally, the third and fourth blocks review the studies that link the educational level of the population with productivity and those that try to measure the efficiency of spending on education.

2.1 The relationship between human capital and economic growth

The acquisition of knowledge and skills by individuals is a form of capital holding that, like other types of capital, is acquired through an investment process. As Becker (2009) said, education and training are the most important investments in human capital.

A large number of studies focusing on the theory of human capital confirm its relevance. The relationship between human capital and economic growth has been studied by authors such as Mincer (1984), Frank (1960), Romer (1986), Lucas (1988), Romer (1989), Stockey (1991), Mankiw et al. (1992), Becker et al. (1999), De la Fuente and Domenech (2006) or Krueger and Lindahl (2001).

Among the results obtained, it is found that education generates positive externalities that give rise to private and social returns. Denison (1985) showed that the schooling of the average worker has significant effects on their income. Angrist and Krueger (1991) found a 7% return to schooling. Bassani and Scarpetta (2001) found that one more year of schooling increased GDP per capita by 6 per cent in OECD countries between 1971 and 1998. Card (2001) noted an increase in the estimated school enrolment yield of 7.3 per cent.

Regarding the fact that education can promote both private and social benefits, Krueger (1999) stressed that the literature shows two important conclusions. First, the initial stock of human capital is more relevant than that of physical capital. And second, secondary and post-secondary education are more important than primary education.

Along these lines, Funke, Holger and Strulik (2000) observed that physical capital contributes greatly to the growth of per capita income in the early stages of development, but it is through the accumulation of knowledge (through continuing education and training) that progress is made towards higher stages of economic development. And later, Krueger (2001) showed that technological progress is related to an expansion of human capital when starting from high levels of it, while crime reduction or well informed political decision-making are related to the development of human capital from lower levels.

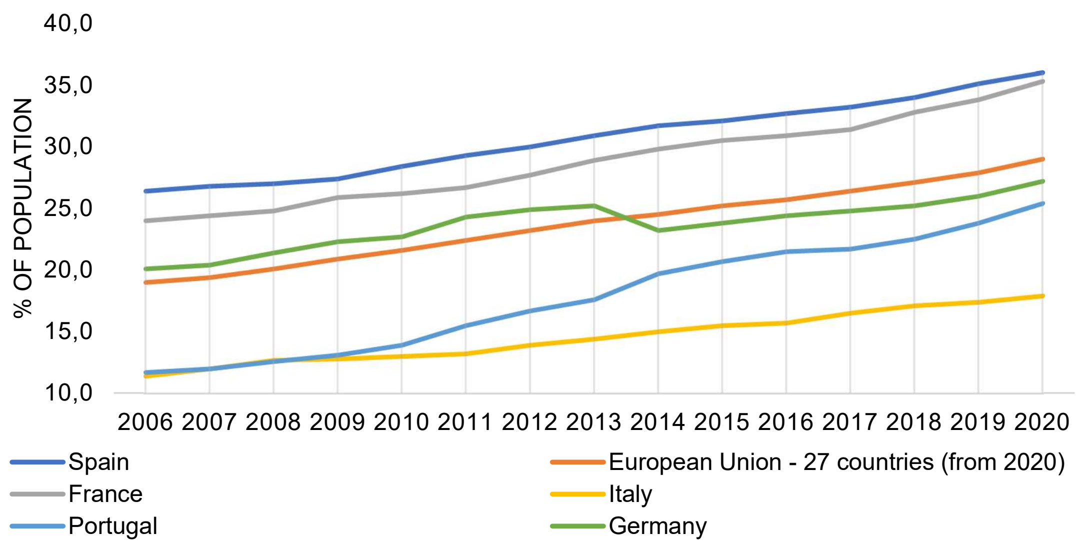
Nelson and Phelps (1966) showed that a 1% increase in capital stock leads to a 0.13% increase in the growth rate. This is closely related to technology, which in turn has a close relationship with the development of human capital. Jenkins (1995) studied the case of the United Kingdom, where a one per cent increase in highly skilled workers led to an increase in annual production from 0.42 to 0.63. On the other hand, the number of highly educated people has increased significantly in the last 50 years, which has translated into significant economic growth. Griliches (1997) found that improving the educational level of the workforce led to a 33% increase in productivity in the US. In the same vein, Englander and Gurney (1999) revealed that growth in OECD countries rose from 70 per cent in 1960 to 95 per cent of school enrolment in 1985, resulting in a 0.6 per cent annual increase in labour productivity.

Bassani and Scarpetta (2001) found that an additional year of schooling leads to a 6 per cent increase in GDP per capita in OECD countries between 1971 and 1998. According to Pritchett (2001), the impact of education on development varied widely among countries and did not meet expectations for three possible reasons: the institutional environment, the possible fall in the marginal performance of education as the supply of skilled labour expanded while demand remained stagnant, and third, low educational quality.

As Barro (2002) states, the difference between prosperity and poverty for a country depends on how fast it grows in the long run. This author revealed that for a specific level of initial per capita GDP obtained with a higher proportion of human capital than physical capital, it tends to promote higher growth through two channels: the absorption of more developed technologies facilitated by more developed human capital and the difficulty of adjusting human capital, as opposed to physical. This implies that countries with a higher proportion of human capital relative to physical capital tend to grow faster by adjusting the amount of physical capital upwards.

In Figure 1, we represent the data on the highest educational level successfully completed by individuals from some European countries and the EU average:

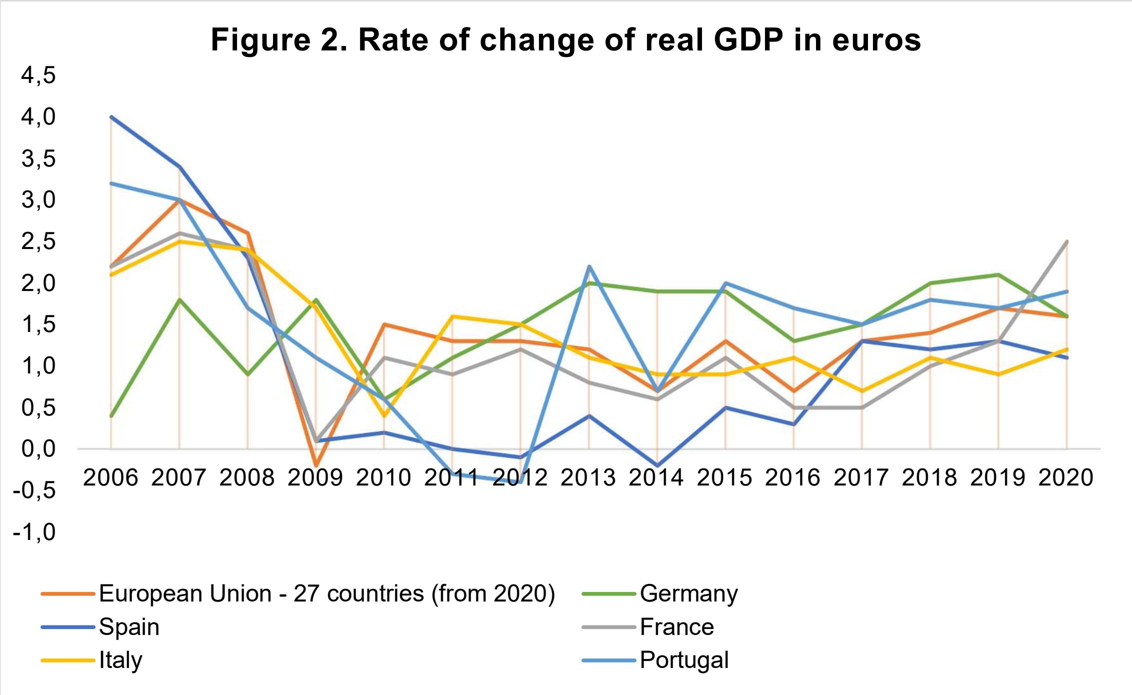
Figure 1. Share of attainment of tertiary education level



Source: Own elaboration based on Eurostat data.

As can be seen in the illustration, Spain has the best record of educational success in higher education, followed by France. Germany remains close to the European average, while Portugal and Italy have lower percentages. However, the proportion of success increases permanently over the years.

Figure 2 shows the growth rate of the same economies.



Source: Own elaboration based on Wold Bank Data

Figure 2 shows that growth rates are heterogeneous. On the one hand, Germany's growth is slightly above the European average, which is similar to that of Portugal. Country that showed a good recovery in the post-crisis period of 2008. On the other hand, France, Italy, and Spain have shown low growth in recent years. The case of the latter is worrying, as since 2009 it has shown a growth rate below the European average on a continuous basis.

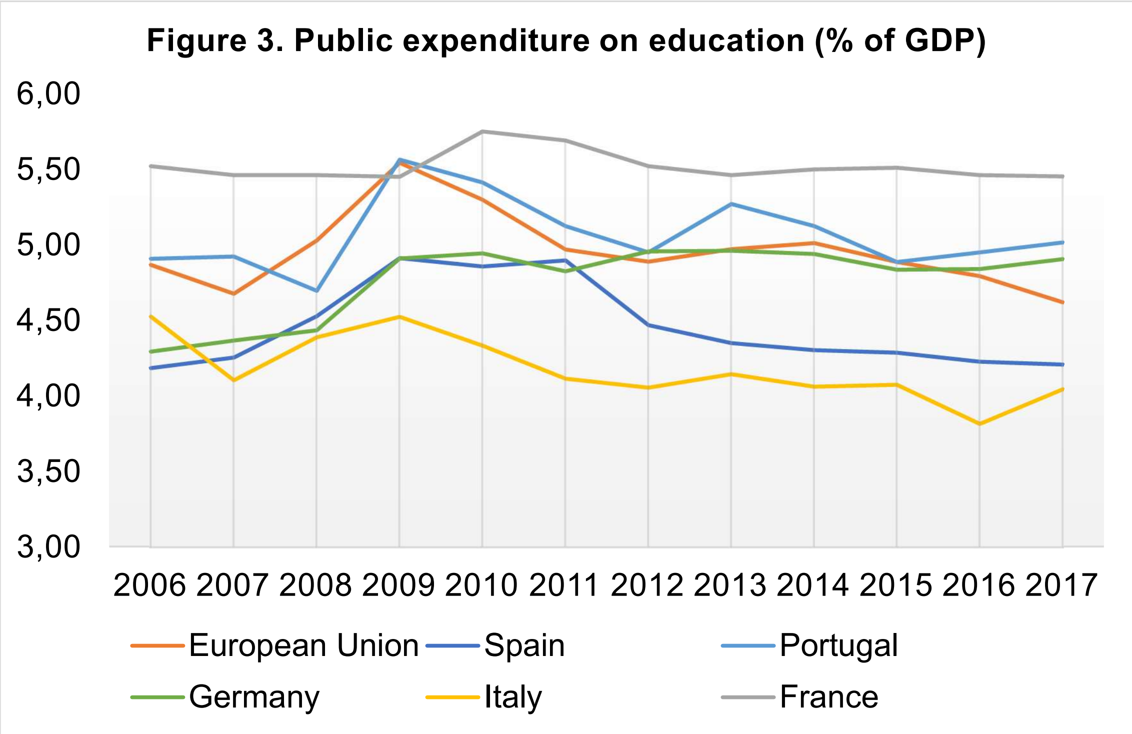
2.2 The human capital and the reduction of inequalities

Barro and Lee (2013) argued that the level and distribution of educational achievements also have effects on social progress. Hence, the acquisition of human capital and its contribution to reducing inequalities has also been studied by various authors such as Glomm and Ravikumar (1992), Benabou (1996), Checchi (2006), Castello and Domenech (2014), Chiani et al. (2014) or Murphy and Topel (2016). According to Le Grand (2018), education is the great equalizer of the conditions of men and women.

But despite the enormous development of economies achieved by many countries, manifested in aspects such as convergence in the increase in life expectancy, or the accumulation of human capital, there are still notable differences between rich and poor. Schultz (1961) stated that investment in human capital accounts for most of the impressive increase in real income per worker. As Castello and Domenech (2008) showed, while the secondary school enrolment rate was almost 100% in rich countries, more than 70% of children in sub-Saharan Africa were not enrolled in secondary school and, therefore, entered the labour market as unskilled persons, workers since childhood. This led to significant differences in terms of the Gini coefficient, where the coefficient for sub-Saharan Africa is more than double that for OECD countries.

On this subject, Becker (2009) addressed that the incomes of the most educated people are almost always much higher than the average, although profits are generally higher in the least developed countries. This could be explained by the greater inequality of this group of countries. The starting assumption is that human capital development contributes to the reduction of inequality, which directly influences economic growth. Moreover, investment in human capital is closely linked to spending on education. In this sense, influenced by this relationship, many countries have undertaken reforms in recent years, where spending per student has grown significantly since the mid-1990s, reaching 3% of GDP on average in OECD countries.

If we look at the European case, we can see in Figure 3 that spending on education in Portugal and especially in France is higher than the European average. As for Germany, since the 2010s, it has evolved towards convergence with European average values. Spain and Italy have values significantly lower than the rest of countries, maintaining a trend below the average.



Source: Own elaboration based on Wold Bank Data.

One of the main objectives of growth in education spending is to reduce inequality, which has a significant impact on aggregate output. Coady and Gupta (2012) revealed that income inequality has been expanding in many advanced economies since 1980. This is due to an array of variables such as the effects of globalisation on the wages of low-skilled workers, which are also adversely affected by technological change. In addition, the bargaining power of labour has been reduced. And inequality in the EU has increased substantially since the mid-1980s due to their countries' poor growth performance. One explanation is the enlargement of the region. However, inequality has increased within a "core" of 8 European countries, where large income increases, among the top 10% of those earning, appear to be the main driver of this evolution (Fredriksen, 2012). Along the same lines Fournier and Johansson (2016) showed that public investment and education boost potential growth, while other social expenditures such as pensions and public subsidies reduce it. In addition, reforms aimed at improving the efficiency of the public sector, as well as educational reform that promotes completion of secondary education, would contribute to reducing income inequality. In this sense, Gradstein (2003) found that inequality in the distribution of public spending on education slows down long-term growth, and that income inequality is also harmful in this sense.

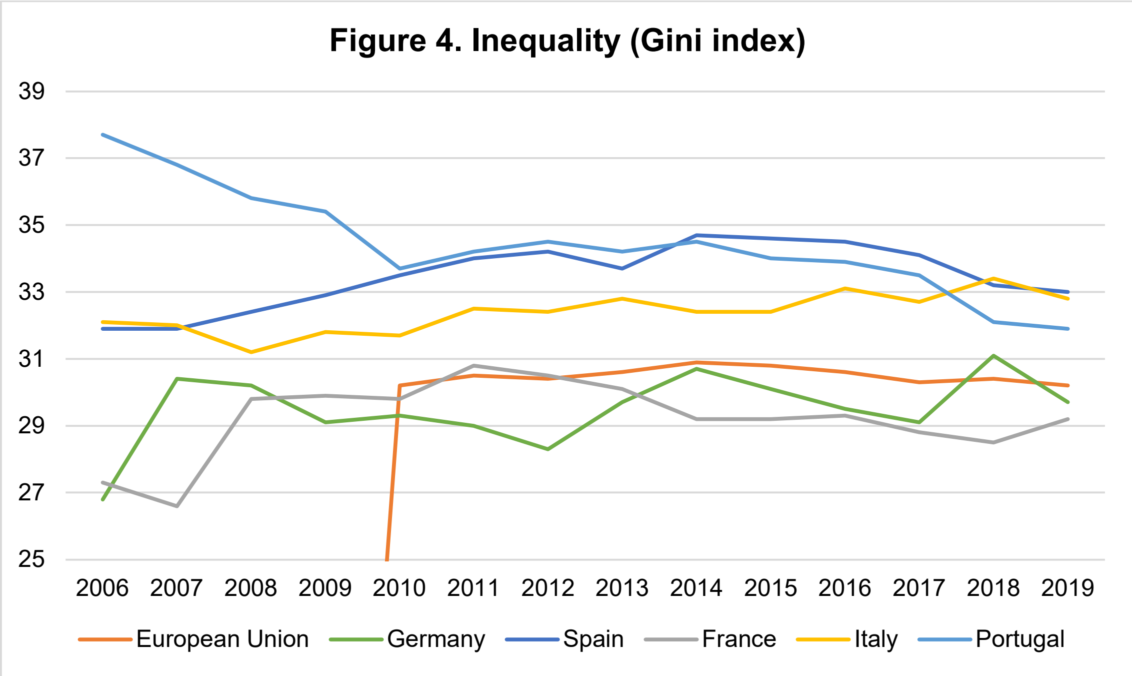
Education is a powerful tool for achieving social inclusion, which leads to a decrease in income inequality, promoting intergenerational mobility. The United Nations Sustainable Development Goals (UN, 2022) promote Quality Education as Goal No. 4, closely linked to No. 5: Gender Equality, No. 8: Decent Work and Economic Growth, and No. 10: Reducing Inequalities.

When studying inequality, most authors focus on wages as the variable to be analysed. But there are also many authors who have found that education has important returns. Angrist and Krueger (1991) found a return to schooling of 7%. Card (2001) observed an increase in the estimated return to school of 7.3%. And Dickson (2013) suggested that an additional year of schooling increases wages by 4.6%. However, the variable return of education is commonly used as an indicator, not as a goal. When measuring wages, the concentration of graduates in public sector employment is identified as a problem in growth studies. This problem lies in the fact that public sector wages do not normally reflect market wages (Pissarides 2000).

On the other hand, Psacharopoulos and Patrinos (2004) pointed out the growing concern of governments and other agencies in the educational reforms on returns, to guide macro-political decisions on the management and financing of educational reforms.

Although wages are an indicator of well-being, it is useful to analyse other factors such as job quality and satisfaction. In this sense, Albert and Davia (2005) found a strong relationship between education and satisfaction, explained by the link between education and job quality. However, the authors pointed out that this link is not conclusive due to salary expectations and characteristics. According to Castriota (2006), the higher the educational level, the less relevant is the absolute level of income for self-declaration of satisfaction with life. This explains why the pattern of southern European countries is more in line with common evidence (Albert and Davia, 2005).

By way of illustration, one of the most used indicators to measure inequality is the Gini index. Figure 4 shows this coefficient for some EU countries:



Source: Own elaboration from Wold Bank Data

It can be seen from the graph that the countries of the South reach values well above the average, so it can be said that there is greater inequality in these countries compared to the European average. On the other hand, Germany and France show values slightly below the European average, although they are very close.

2.3 Level of education and productivity

A higher level of human capital provides a greater capacity to absorb new technologies and business techniques. In other words, the level of human capital, approximated as the educational level of the active population, can have an impact on productivity levels (what is known in the literature as "*level-level effect*") and/or on the growth rates of this ("*level-growth effect*"). Specifically, the first effect is due to school returns, while the second is through innovation. Just as the accumulation of human capital produces income growth, so do the corresponding social or national aggregates (Mincer, 1984). In fact, both Lucas (1988) and Barro (2001) pointed out that the educational level can also affect productivity through different ways such as improving the capacity for innovation and the quality of the workforce.

Numerous studies have highlighted the importance of education on labour productivity. Denison (1985) found that an increase in the average worker's schooling has significant effects on income. And authors like Benhabib and Spiegel (1994) found that productivity growth would be around 0.13% against a 1% increase in human capital. In this sense, Becker (2009) affirmed that the expansion of scientific and technical knowledge, which increases the productivity of labour and other inputs in production, is the reason for the persistent growth per capita in the United States, Japan, and European countries in the last hundred years. Consequently, there is a link between wage growth and education and training.

The growing number of skilled workers and the ability to absorb advanced innovations is related to productivity. Chansan (2010) showed the suitability of education as a key factor in labor productivity by analyzing 30 countries during the period 1981-2005.

In this sense, as Barro and Lee (2013) argue, the level and distribution of educational achievement also have an impact on social and welfare outcomes, such as infant mortality, fertility, child education and income distribution, in addition to social status, as Fershtman et al. (1996) had already pointed out. In addition, these authors stated that, in general, growth may be favoured by an increase in the number of workers investing in education. However, they found inefficiency in talent allocation. In this sense, and more recently, Vandenbussche et al. (2016) argued that an optimal composition of public spending on education is necessary, and this depends on the relative distance of the economy from the technological frontier. And in the same vein, stands out the analysis of Benos and Karagiannis (2016), in which they show that human capital presents a strong positive association with productivity through upper secondary and tertiary education for the case of Greece.

2.4 The efficiency of spending on education

When education succeeds in improving human capital endowment and thus productivity, it is concluded that education funding has been efficient. Education spending decisions are closely related to efficiency, which has been extensively studied. Authors such as Sutherland et al. (2007) found a weak relationship between educational achievement and increased availability of resources, which can be explained by international differences in efficiency levels in primary and secondary education. In this regard, these authors stressed that there is significant scope for improving efficiency by moving towards best practices. Hence, analyses on the efficiency of spending on education are abundant. Rajkumar and Swaroop (2008) noted that the efficiency of education spending depends on the governance of countries, measured by the degree of corruption and the quality of bureaucracy. Mandl et al. (2008) and St. Aubyn et al. (2009) studied the case of EU states and found that outcomes varied across countries, depending on the independence of institutions and educational policy decisions. Blankenau and Camera (2009) pointed out that an excess of subsidies increases the number of students but decreases the incentives of these to acquire skills. Annabi et al. (2011) showed that incentives for higher education can promote the accumulation of human capital and alleviate the negative effects of unemployment. But the final impact depends on how distortive alternative fiscal instruments are and on the degree of efficiency of education spending.

Hanushek and Woessman (2011) found that it is the institutional structure that determines the incentives, and that the differences in the structures of the educational systems are those that condition for the attainment achieved by the students. Sibiano and Agasisti (2013) and Agasisti (2014) found that differences in the economic development of the regions influence the acquisition of human capital, and that there is no linear relationship between increases in public spending on education and increases in educational attainment. Other factors related to the composition and distribution of expenditure should therefore be addressed.

On the other hand, Heckmann et al. (2014), noted that schooling at all stages has a positive impact on health and wages, analysing a model with multiple schooling options that recognizes the fundamentally non-linear effect of schooling on a variety of outcomes. It is a powerful reason for governments to increase investment in education. However, the effectiveness of education is necessary and may be reduced when spending decisions are not adequate (Kingdon et al., 2014).

Wolff (2015) analysed the relationship between public spending on education and the result of students. He found that it responds to an unbalanced growth model, given that the productivity and cost of components of the educational service (use of technological advances and teacher activity, for example) do not grow at the same pace. Dissou et al. (2016) concluded that different ways of financing education led to long-term growth, but that there are differences which can be observed in the short term and the transition to the long term. More recently, Canton et al. (2018)

measured the efficiency of public spending on education in the EU and find different results depending on the functioning of the institutions.

3. Methodology and data

As indicated before, and in the light of the issues covered in the literature, we intend to analyse how public expenditure on education affects productivity, wages, and growth at EU level. We are trying to find out to what extent education expenditures and human capital contribute to improving productivity, achieving higher wages, and improving the standard of living of the population, as measured by per capita growth. To complete our objectives, we will estimate in a first approximation the following equations.

$$PRO_{it} = f\,(GPE_{ijt}, GID_{it}, EST_{it}) \qquad (1)$$
$$WEM_{it} = f\,(PRO_{it}, EDU_{iht}, EPL_{it}) \qquad (2)$$
$$CREpc_{it} = f\,(PRO_{it}, EDU_{iht}) \qquad (3)$$

Where t is the time reference (year), i the member state, h the level of education and j the level of government funding education. In the first equation, *PRO* represents the productivity of work per person to which, presumably contributes, public spending on education *GPE,* public spending on *R&D* in the education sector, *GID*, and employment in high-tech intensive sectors *EST*, variable that collects those workers with the highest expected level of human capital.

On the other hand, in the second equation, average wage earnings, *WEM*, are related with productivity, *PRO*, with the educational level of the population, *EDU*, which approximates the level of human capital acquired, and the work experience measured by the years worked, *EPL*, which is supposed to be an alternative to training and allowing to acquire human capital. Finally, the third equation considers that both productivity and educational attainment can contribute to improving the standard of living of the population, measured by GDP growth in per capita terms, *CREpc*.

To perform the quantitative analysis, we will use the panel data estimation methodology. In this paper, data on the variables of interest have been obtained from Eurostat. And the sampling period extends from 2009 to 2020, years for which we find data on the relevant variables. The implementation of panel data econometry allows us to combine the power of averaging cross-section with all the advantages of time dependence (see Baltagi, 2008). Some of the strengths and limitations of using panel datasets are listed in Hsiao (2003). Among the advantages with respect to a single cross-section or time series are the following: (i) more precise inference of the parameters of the model, (ii) greater ability to capture the complexity of economic relations, (iii) more informative results, (iv) allows control of unobserved individual heterogeneity, and (v) simplifies calculation and statistical inference.

In this paper, specifically, as a first approximation to analyze the effects of public spending on education on productivity, wages, and growth, we will apply the methodology of cointegrated panel estimates Dynamic Ordinary Least Squares (DOLS) and Fully Modified Ordinary Least Squares (FMOLS). For what previously, we will check the existence of unitary roots and cointegration relations, to identify the presence of long-term characteristics in each variable, as well as detect if there are long-term relationships between them.

Estimates of cointegration equations following the DOLS and FMOLS approaches were proposed by Stock and Watson (1993), Kao and Chiang (2000) and Pedroni (2001); and Phillips and Moon (1999) and Pedroni (2000b), respectively. These approaches allow quantifying the long-term relationship between the variables. Specifically, DOLS estimates solve the endogeneity problem, starting from one equation models with leads and lags of explanatory variables I (1) in first differences. They also eliminate the serial correlation present in standard ordinary least squares (OLS), which results in inconsistent estimates for cointegrated panel data (Dreger and Reimers, 2005). DOLS and FMOLS estimates have the advantage of correcting serial autocorrelation, as well as the possible endogeneity of the relationship between the variables.

Both the DOLS and FMOLS approaches solve the problem of endogeneity and eliminate small sample bias. And, in addition to being an alternative to other methods of estimating the cointegration relationship, DOLS prevents the lack of stationarity of the series (Phillips and Hansen, 1990; Stock and Watson, 1993). This is an additional advantage, given our sampling period, due to the lack of power of the unit root tests in small samples and the presence of structural changes that may raise doubts about the order of integration of the series. But the application of FMOLS requires that all variables must have the same order of integration and that regressors must not appear as cointegrated. In this sense, following Kao and Chiang (2000), DOLS provides better results than FMOLS estimators in terms of average biases. Although in this paper, as a first approximation to our study, we will perform both estimation methods.

3.1 Variables and data set

As we have already stated, in our first empirical analysis we have used time series of annual data taken from Eurostat, for the years 2009 to 2020 of the 27 EU member states, for the following variables:

PRO: Work productivity per person. Real labour productivity per person, as a percentage of change over the previous year.

GPE: Public expenditure on education. Total central government expenditure on education as a percentage of GDP.

GID: Public expenditure on R&D in the education sector. Total central government expenditure on research and development in the higher education sector as a percentage of GDP.

EST: Employment in technology intensive sectors. Employment in high technology and knowledge intensive sectors as a percentage of total employment.

WEM: Average wage gains. Average individual annual net earnings expressed in purchasing power parity units (PPS, Purchasing Power Standard)

WRM: Average wage income. Income from wages and salaries as a percentage of GDP.

EDS: Educational level of the population, secondary level. Percentage of population with secondary and post-secondary education.

EDT: Educational level of the population, tertiary level. Percentage of population with tertiary education.

EPL: Work experience measured by the years worked. Average years worked, duration of working life.

CRP: GDP growth. Chained volumes of GDP at market prices, as a percentage change over the previous year.

CPC: Per capita GDP growth. Chained volumes of GDP at market prices, as a percentage change over the previous year, per capita.

Table 1 shows the main statistics of the series.

Table 1. Statistics of the series. EU-27, 2009-2020

	PRO	GPE	GID	EST	WEM	WRM
Mean	0.617593	5.090741	0.410093	4.152469	18603.93	36.43148
Median	0.700000	5.100000	0.350000	4.000000	19045.50	37.30000
Maximum	20.20000	7.100000	1.040000	9.200000	33707.00	50.40000
Minimum	-10.80000	2.800000	0.040000	1.800000	5490.000	22.80000
Std. Dev.	3.014778	0.961346	0.226678	1.335961	6943.532	5.115253
Skewness	0.334693	0.006011	0.652333	0.907195	0.083136	-0.130610
Kurtosis	9.001382	2.368010	2.864333	4.227235	1.875975	2.909036
Jarque-Bera	492.2730	5.394010	23.22758	64.77462	17.42957	1.032884
Probability	0.000000	0.067407	0.000009	0.000000	0.000164	0.596640
Sum	200.1000	1649.400	132.8700	1345.400	6027674.	11803.80
Sum Sq. Dev.	2935.710	298.5122	16.59670	576.4880	1.56E+10	8451.559
Observ.	324	324	324	324	324	324
Cross sect.	27	27	27	27	27	27

Table 1. Statistics of the series. EU-27, 2009-2020 (cont.)

	EDS	EDT	EPL	CRP	CPC
Mean	47.39599	26.51420	35.06265	0.823148	0.809259
Median	45.90000	27.20000	34.80000	1.400000	1.300000
Maximum	71.40000	42.80000	42.00000	23.20000	23.20000
Minimum	17.70000	11.20000	28.80000	-14.60000	-14.60000
Std. Dev.	11.78746	7.479370	2.792226	4.008612	4.020317
Skewness	-0.225080	-0.065601	0.297563	-0.432937	-0.416070
Kurtosis	2.395395	2.030446	2.445790	7.015156	6.941733
Jarque-Bera	7.670581	12.92287	8.927891	227.7614	219.1012
Probability	0.021595	0.001563	0.011517	0.000000	0.000000
Sum	15356.30	8590.600	11360.30	266.7000	262.2000
Sum Sq. Dev.	44878.98	18068.93	2518.278	5190.276	5220.632
Observ.	324	324	324	324	324
Cross sect.	27	27	27	27	27

3.2 Some preliminary results

Before making the estimates, we will explore the cointegration relationships of the variables that are analysed for the group of individuals in the set (EU member states). To this end, as a preliminary study, we will check the order of integration of the series. For this we will apply the tests of Levin et al. (2002), Im et al. (2003), Maddala and Wu (1999) or Fisher type ADF and Choi (2001) or Fisher type PP, whose null hypothesis is the existence of unitary root. These unit root tests for panel data are based on those developed for time series, but by also taking into account cross-sectional data they increase degrees of freedom, improve estimator properties and correct unobserved heterogeneity. The analysis is completed with the Hadri test (2000), based on the LM estimator proposed by Kwiatkowski et al. (1992), which considers the cross-dependence between individuals (EU states), and whose null hypothesis is that the series is stationary.

The results of unit root tests are presented in the Appendix. The results of Table A.1 indicate that, except for the PRO, CRP and CPC series, the null hypothesis of the presence of a unit root in the first four tests cannot be rejected, and the hypothesis of seasonality when the Hadri test is applied. Table A.2 shows the cointegration tests for variables that presented a unit root, but this time expressed in first differences. In this case the results show that the variables in first differences no longer present a unitary root.

The results of the cointegration tests for the equations to be estimated given by (1), (2) and (3) described in section 3 are shown in the Appendix. The results indicate that the null hypothesis of no cointegration may be rejected.

Once the cointegration relationship has been verified, we will proceed to estimate the long-term parameters in the next section.

4. Discussion of the results

After detecting the cointegration relationship, we proceed to estimate the equations (1), (2) and (3) for the variables considered. For some of them we have used two alternative measures, as described in subsection 3.1. Namely, for wage earnings, for education and for growth.

The basic estimates for both DOLS and FMOLS are showed below. The leads and lags of the DOLS estimates have been obtained using the

Schwartz criterion and the correction of heteroscedasticity and autocorrelation of residues of Newey-West. For the FMOLS estimates no leads and lags have been applied, and for the estimation of covariances in the long term Barlett and Newey-West corrections have been used.

Columns (1), (2) and (3) of the tables indicate the three possible estimation options: (i) grouped estimates (pooled), after eliminating the deterministic components of the variables; (ii) weighted grouped estimates (pooled weighted), which makes use of the information given by the residues of estimates of cross-sections; and (iii) average grouped estimates (grouped), which calculates the average of the individual cross-section.

In table 2, we see how, regardless of the chosen method (DOLS or FMOLS), the results are mixed. The variable public education expenditure has a positive sign and is significant for the grouped estimation of DOLS and FMOLS and the weighted DOLS. While it has a negative and significant effect on the average estimate of DOLS and weighted FMOLS. The variable R&D expenditure in the education sector shows only a positive and significant influence on the average estimate of DOLS and the weighted and average of FMOLS. Finally, the variable representing employment in sectors with a high technological content always has a positive effect (except for the average estimate) and is significant in the weighted estimate in both options.

Table 2. Estimates equation (1)

Dependent variable: PRO						
	DOLS			**FMOLS**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
GPE	0.57*** (2.35)	0.68*** (3.83)	-1.71*** (-2.26)	0.34* (1.57)	-0.27*** (-14.87)	-0.09 (-0.16)
GID	-7.31*** (-2.91)	-6.14*** (-4.38)	5.93*** (3.66)	-3.12 (-1.23)	0.46*** (14.08)	11.27* (1.61)
EST	0.45 (1.04)	0.40* (1.36)	-0.81 (-0.59)	0.67* (1.71)	0.34*** (8.93)	-1.15* (-1.48)

Note: t statistics in parentheses. The stars ***, ** y *, indicate 1%, 5% y 10% significance levels, respectively. Columns (1), (2) y (3) correspond to pooled, pooled weighted and grouped estimates, respectively.

Given the signs and the observed significance, the result that may be more consistent is that offered by the weighted estimate (column 2) of FMOLS. Public expenditure on education shows a negative (though very low) and significant coefficient. This could be explained by the fact that in the period considered (2009-2020) it has not yet been possible to recover the return of expenditure on education. However, R & D spending in the education sector and employment in sectors with a high technological content (highest expected level of human capital) contribute to explaining productivity over the period considered. Those results are in line with the reviewed literature, in the basis that education affects productivity boosting innovation and quality of the workforce.

When we measure average wage gains in (logarithms of) units of PPS (Tables 3.1.1 and 3.1.2), work experience is the variable that explains, with the expected sign and significantly, the evolution of these gains regardless of the estimate made.

Table 3.1.1 Estimates equation (2)

Dependent variable: log (WEM)						
	DOLS					
	(1)		(2)		(3)	
PRO	0.01 (0.01)	-0.01 (-1.03)	0.01 (1.13)	-0.01* (-1.57)	0.01 (0.30)	-0.01 (-0.31)
EDS	-0.01*** (-3.58)		-0.01*** (-7.61)		-0.01 (-0.92)	
EDT		0.01* (1.58)		0.01*** (4.51)		0.02*** (3.44)
EPL	0.07*** (10.73)	0.07*** (6.41)	0.07*** (22.23)	0.06*** (10.78)	0.07*** (5.88)	0.04*** (4.83)

Note: see note table 2.

Table 3.1.2 Estimates equation (2) (cont.)

Dependent variable: log (WEM)						
	FMOLS					
	(1)		(2)		(3)	
PRO	-0.01 (-0.32)	-0.01 (-0.11)	-0.33*** (-3.55)	-0.32*** (-3.41)	0.01 (1.09)	-0.01 (-0.78)
EDS	-0.01*** (-3.33)		0.01 (0.49)		-0.01 (-1.25)	
EDT		0.01 (1.40)		-0.08*** (-8.55)		0.02*** (12.26)
EPL	0.07*** (10.90)	0.07*** (6.23)	-0.01 (-0.75)	0.06*** (3.96)	0.08*** (14.66)	0.03*** (6.08)

Note: see note table 2.

The population with higher education contributes positively and significantly to explain wage gains, when estimated by DOLS. The opposite is true for the population with secondary education, which in no case contributes positively and significantly. Also, productivity is not significant, except in the weighted estimate of FMOLS in which it appears negative. But the main result, given by DOLS estimation, show that tertiary education and work experience (that can be seen as a way of acquiring human capital) are the main drivers of wage gains. Being this result consistent with the literature.

When choosing average wage incomes to measure wage gains (Tables 3.2.1 and 3.2.2), productivity is always significant and shows a negative sign, in any case. The educational level of the population (both secondary and higher) does not contribute positively to wage gains. While work experience maintains the expected sign (positive) and proves also to be significant.

Table 3.2.1 Estimates equation (2) (cont.)

Dependent variable: WRM						
	DOLS					
	(1)		(2)		(3)	
PRO	-0.33*** (-2.72)	-0.46*** (-3.64)	-0.16*** (-3.96)	-0.33*** (-6.57)	-0.21*** (-2.54)	-0.26*** (-3.05)
EDS	-0.30*** (-2.93)		-0.31*** (-7.97)		-0.38 (-1.17)	
EDT		-0.09 (-0.88)		-0.15*** (-4.29)		-0.11 (-0.46)
EPL	0.54*** (2.65)	0.95*** (2.93)	0.41*** (5.81)	1.05*** (8.10)	0.18 (0.55)	0.65 (1.21)

Note: see note table 2.

Table 3.2.1 Estimates equation (2) (cont.)

Dependent variable: WRM						
	FMOLS					
	(1)		(2)		(3)	
PRO	-0.28*** (-4.47)	-0.28*** (-4.22)	-0.44*** (-4.75)	-0.47*** (-5.07)	-0.22*** (-7.33)	-0.25*** (-8.35)
EDS	-0.25*** (-2.94)		-0.21*** (-16.58)		-0.25*** (-2.31)	
EDT		-0.13* (-1.49)		-0.11*** (-11.54)		-0.04 (-0.49)
EPL	0.43*** (2.42)	0.86*** (3.06)	0.47*** (33.99)	0.78*** (48.55)	0.02 (0.16)	0.59*** (2.35)

Note: see note table 2.

To try to explain the evolution of economic growth, measured as GDP growth (Tables 4.1.1 and 4.1.2), the variables that capture productivity and the population with higher education are that contribute positively and significantly to growth, whatever the method of estimation.

Table 4.1.1 Estimates equation (3)

Dependent variable: CRP						
	DOLS					
	(1)		**(2)**		**(3)**	
PRO	1.39*** (13.85)	1.31*** (13.05)	1.46*** (24.50)	1.39*** (20.70)	1.53*** (14.00)	1.68*** (14.13)
EDS	0.03 (0.34)		0.01 (0.18)		0.09 (0.35)	
EDT		0.16*** (3.04)		0.10*** (2.91)		0.22*** (3.39)

Note: see note table 2.

Table 4.1.2 Estimates equation (3) (cont.)

Dependent variable: CRP						
	FMOLS					
	(1)		**(2)**		**(3)**	
PRO	1.21*** (20.14)	1.23*** (21.11)	1.29*** (14.34)	1.09*** (11.16)	1.28*** (22.52)	1.33*** (25.07)
EDS	0.08 (1.03)		-0.13*** (-10.21)		0.30** (1.84)	
EDT		0.23*** (4.73)		0.23*** (23.11)		0.36*** (7.74)

Note: see note table 2.

And the results are equivalent (tables 4.2.1 and 4.2.2), when we choose GDP growth in per capita terms as a dependent variable.

Table 4.2.1 Estimates equation (3) (cont.)

Dependent variable: CPC						
	DOLS					
	(1)		**(2)**		**(3)**	
PRO	1.37*** (13.86)	1.28*** (13.20)	1.43*** (23.98)	1.37*** (20.52)	1.50*** (14.13)	1.66*** (14.43)
EDS	0.03 (0.33)		0.02 (0.73)		0.09 (0.36)	
EDT		0.15*** (2.98)		0.10*** (3.06)		0.21*** (3.48)

Note: see note table 2.

Table 4.2.2 Estimates equation (3) (cont.)

Dependent variable: CPC						
	FMOLS					
	(1)		(2)		(3)	
PRO	1.19*** (20.42)	1.22*** (21.46)	1.29*** (14.82)	1.07*** (11.31)	1.26*** (22.84)	1.31*** (26.34)
EDS	0.07 (0.97)		-0.12*** (-9.39)		0.28 (1.81)	
EDT		0.23*** (4.81)		0.22*** (24.89)		0.36*** (7.92)

Note: see note table 2.

Regarding the effects of education and productivity on economic growth, our findings seem to be robust. Showing that productivity is the engine of growth, and that human capital development (proxied by population with tertiary education level and presumably leading to highly skilled workers) led to increases in output. Results that are in line with those of the literature on economic growth.

5. Some conclusions.

In this paper we have presented a first approximation to the study of the effects of public expenditure on education on productivity, wages, and growth at the level of the European Union (EU). For this purpose, we have used the methodology of estimating DOLS and FMOLS cointegrated panel data, that solve the endogeneity problem and eliminate small sample bias.

Our first exploratory empirical analysis provides us with some basic results.

When we try to explain to what extent contribute to productivity, public spending on education, R&D spending on education and employment in high-tech sectors, the results are mixed. However, the variable that contributes positively and significantly in most cases is employment in sectors with high technological content.

When analysing the factors that may explain the evolution of average wage earnings (measured both in PPS units and using wage incomes as a percentage of GDP) work experience is the variable that best explains, with the expected sign and significantly, the evolution of such gains whatever the estimate made.

And finally, when trying to explain the evolution of economic growth (measured as growth of GDP or GDP per capita) productivity and population with higher education level are the variables that contribute positively and significantly, whatever the method of estimation.

Summarizing, and with the exception that this is an exploratory analysis, our results show that: (i) employment in sectors with high technological content is the variable that best explains productivity, (ii) work experience is the variable that best explains wage gains, and (iii) productivity and the population with higher education level are the variables that best explain economic growth.

From these results, it could be inferred that high skills favour employment in sectors with a high technological content, and this sector is that contributes most to productivity. While work experience, which can be interpreted as a means of acquiring human capital, is relevant when explaining the evolution of wage earnings. Our results do not show a clear and direct relationship between public expenditure on education and productivity, but it could be inferred that there is an indirect relationship; to the extent that public expenditure on education facilitates access to higher education and the acquisition of a higher level of human capital and technological skills.

From these findings, we must bear in mind the limitations of the present work, such as the sample size and the type of the variables used. The natural extension would be to explore other databases and consider the inclusion of different explanatory variables. Further research on this issue, will allow us to explore the extent to which public expenditure on education, as an instrument of fiscal policy, can fulfill the distributive function reducing inequality. And to what extent public spending on education contributes to the acquisition of human capital, thus guiding possible future public policies on education and spending.

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Appendix
Unit root tests

Table A.1. Unit root tests. Levels

test	PRO		GPE		GID		EST	
	statistic	prob	statistic	prob	statistic	prob	statistic	prob
Levin, Lin & Chu t*	-13.5494	0.0000	-4.93589	0.0000	-1.49851	0.0670	-2.3435	0.9904
Im. Pesaran and Shin W-stat	-10.5468	0.0000	-2.19468	0.0141	0.15316	0.5609	4.74961	1.0000
ADF - Fisher Chi-square	204.418	0.0000	76.6515	0.0230	63.8583	0.1687	26.3016	0.9995
PP - Fisher Chi-square	224.014	0.0000	67.0539	0.1093	61.2117	0.2331	26.4352	0.9994
Hadri Z-stat	3.97974	0.0000	7.65014	0.0000	5.49039	0.0000	10.3576	0.0000

Table A.1. Unit root tests. Levels

test	WEM		WRM		EDS		EDT	
	statistic	prob	statistic	prob	statistic	prob	statistic	prob
Levin. Lin & Chu t*	5.11650	1.0000	-1.05408	0.1436	-1.65501	0.0490	-2.78564	0.0027
Im. Pesaran and Shin W-stat	7.75660	1.0000	2.22340	0.9869	2.66472	0.9961	4.82473	1.0000
ADF - Fisher Chi-square	21.8757	1.0000	52.8348	0.5194	42.9783	0.8593	35.9883	0.9719
PP - Fisher Chi-square	39.1371	0.9360	47.1257	0.7346	37.6235	0.9559	71.3714	0.0568
Hadri Z-stat	11.6580	0.0000	8.12657	0.0000	10.8930	0.0000	11.7148	0.0000

Table A.1. Unit root tests. Levels

test	EPL		CRP		CPC	
	statistic	prob	statistic	prob	statistic	prob
Levin. Lin & Chu t*	-3.57285	0.0002	-7.12497	0.0000	-7.20265	0.0000
Im. Pesaran and Shin W-stat	2.56852	0.9949	-7.73311	0.0000	-7.84784	0.0000
ADF - Fisher Chi-square	50.2488	0.9963	154.963	0.0000	156.154	0.0000
PP - Fisher Chi-square	37.1690	0.9609	190.745	0.0000	192.119	0.0000
Hadri Z-stat	10.9594	0.0000	2.83170	0.0023	2.86898	0.0021

Table A.2. Unit root tests. First differences.

test	GPE		GID		EST		WEM	
	statistic	prob	statistic	prob	statistic	prob	statistic	prob
Levin. Lin & Chu t*	-5.19980	0.0000	-12.8953	0.0000	-10.4036	0.0000	-8.57854	0.0000
Im. Pesaran and Shin W-stat	-3.55540	0.0002	-8.26144	0.0000	-6.71611	0.0000	-5.822572	0.0000
ADF - Fisher Chi-square	99.0849	0.0002	106.447	0.0000	149.276	0.0000	125.721	0.0000
PP - Fisher Chi-square	101.784	0.0001	204.503	0.0000	180.780	0.0000	137.571	0.0000
Hadri Z-stat	4.32058	0.0000	1.75775	0.03494	3.33616	0.0004	3.24449	0.0006

Table A.2. Test de raíces unitarias. Unit root tests. First differences.

test	WRM		EDS		EDT		EPL	
	statistic	prob	statistic	prob	statistic	prob	statistic	prob
Levin. Lin & Chu t*	-7.47987	0.0000	-11.1223	0.0000	-8.62199	0.0000	-9.61989	0.0000
Im. Pesaran and Shin W-stat	-3.98628	0.0000	-6.79076	0.0000	-5.57190	0.0000	-6.45665	0.0000
ADF - Fisher Chi-square	114.778	0.0000	140.005	0.0000	129.272	0.0000	135.999	0.0000
PP - Fisher Chi-square	131.199	0.0000	181.759	0.0000	128.205	0.0000	149.902	0.0000
Hadri Z-stat	7.54657	0.000	3.39857	0.0003	-0.47853	0.6839	2.2378	0.0126

Cointegration tests

FIRST EQUATION

Cointegration tests. Equation (1)

Pedroni	statistic	probability
Panel v-Statistic	3.131368	0.0009
Panel rho-Statistic	0.871316	0.8082
Panel PP-Statistic	-6.490570	0.0000
Panel ADF-Statistic	-1.808749	0.0352
Group rho-Statistic	3.160868	0.9992
Group PP-Statistic	-8.673286	0.0000
Group ADF-Statistic	-1.537623	0.0621
Kao	**statistic**	**probability**
ADF	-2.867762	0.0021

SECOND EQUATION

Cointegration tests. Equation (2). WE and EDS

Pedroni	statistic	probability
Panel v-Statistic	-2.396966	0.9917
Panel rho-Statistic	3.668544	0.9999
Panel PP-Statistic	0.073952	0.5295
Panel ADF-Statistic	2.214258	0.9866
Group rho-Statistic	4.800013	1.0000
Group PP-Statistic	-5.899732	0.0000
Group ADF-Statistic	0.225995	0.5894
Kao	**statistic**	**probability**
ADF	-2.996990	0.0014

Cointegration tests. Equation (2). WE and EDT

Pedroni	statistic	probability
Panel v-Statistic	-0.761583	0.7768
Panel rho-Statistic	2.843756	0.9978
Panel PP-Statistic	-0.886397	0.1877
Panel ADF-Statistic	-0.317722	0.3753
Group rho-Statistic	5.090050	1.0000
Group PP-Statistic	-5.247920	0.0000
Group ADF-Statistic	-1.509324	0.0656
Kao	**statistic**	**probability**
ADF	-1.602389	0.0545

Cointegration tests. Equation (2). WR and EDS

Pedroni	statistic	probability
Panel v-Statistic	-0.210344	0.5833
Panel rho-Statistic	2.671524	0.9962
Panel PP-Statistic	-1.308203	0.0954
Panel ADF-Statistic	3.646410	0.9999
Group rho-Statistic	5.506665	1.0000
Group PP-Statistic	-3.404236	0.0003
Group ADF-Statistic	-2.013258	0.0220
Kao	**statistic**	**probability**
ADF	1.005218	0.1574

Cointegration tests. Equation (2). WR and EDT

Pedroni	statistic	probability
Panel v-Statistic	1.285316	0.0993
Panel rho-Statistic	2.230989	0.9872
Panel PP-Statistic	0.089112	0.5355
Panel ADF-Statistic	2.099559	0.9821
Group rho-Statistic	5.666022	1.0000
Group PP-Statistic	-1.686493	0.0459
Group ADF-Statistic	-2.194800	0.0141
Kao	**statistic**	**probability**
ADF	1.281603	0.1000

THIRD EQUATION

Cointegration tests. Equation (3). CR and EDS

Pedroni	statistic	probability
Panel v-Statistic	0.630916	0.2640
Panel rho-Statistic	0.649648	0.7420
Panel PP-Statistic	-3.644789	0.0001
Panel ADF-Statistic	-0.396568	0.3458
Group rho-Statistic	2.687258	0.9964
Group PP-Statistic	-3.879998	0.0001
Group ADF-Statistic	-1.911703	0.0280
Kao	**statistic**	**probability**
ADF	-5.283646	0.0000

Cointegration tests. Equation (3). CR and EDT

Pedroni	statistic	probability
Panel v-Statistic	2.047229	0.0203
Panel rho-Statistic	-0.400620	0.3443
Panel PP-Statistic	-4.940357	0.0000
Panel ADF-Statistic	-1.415315	0.0785
Group rho-Statistic	2.788729	0.9974
Group PP-Statistic	-3.610698	0.0002
Group ADF-Statistic	-1.955540	0.0253
Kao	**statistic**	**probability**
ADF	-4.966559	0.0000

Cointegration tests. Equation (3). CPC and EDS

Pedroni	statistic	probability
Panel v-Statistic	0.593191	0.2765
Panel rho-Statistic	0.565516	0.7141
Panel PP-Statistic	-3.825929	0.0001
Panel ADF-Statistic	-0.371375	0.3552
Group rho-Statistic	2.701800	0.9966
Group PP-Statistic	-3.546909	0.0002
Group ADF-Statistic	-1.550191	0.0605
Kao	**statistic**	**probability**
ADF	-5.182386	0.0000

Cointegration tests. Equation (3). CPC and EDT

Pedroni	statistic	probability
Panel v-Statistic	2.250644	0.0122
Panel rho-Statistic	-0.512476	0.3042
Panel PP-Statistic	-5.176772	0.0000
Panel ADF-Statistic	-1.417918	0.0781
Group rho-Statistic	2.647017	0.9959
Group PP-Statistic	-3.539758	0.0002
Group ADF-Statistic	-1.457869	0.0724
Kao	**statistic**	**probability**
ADF	-4.897017	0.0000