THE TWO FACES OF HUMAN CAPITAL AND THEIR EFFECT ON TECHNOLOGICAL PROGRESS[1].

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Summary:
The aim of the paper is to investigate the effect of a new international estimate of human capital on the process of innovation and technology catch-up in developed countries. The new human capital variable is a measure of average human capital efficiency per hour worked that considers the role of both the quantity and quality of education. Our methodology is based on the framework proposed by Benhabib and Spiegel (2005) that uses a logistic function of technology diffusion. The analysis employs panel econometrics and tackles the endogeneity bias. Empirical results show robust evidence of the significance of this human capital variable as a driver of innovation and diffusion. The effects of cognitive skills on technological progress are higher the closer the economies are to the technology frontier. Furthermore, as technological progress has been measured using the improved TFP variables built in PWT 8.0, we confirm the existence of social returns to human capital.
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A central idea in the critique of early human capital ideas was that human capital was inherently an elusive concept that lacked any satisfactory measurement. Hanushek (2013, 205)

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1.-INTRODUCTION

The purpose of this paper is to validate the usefulness of new human capital data to explore the relationship between human capital and technical change. Two kinds of human capital data are used: the new variable supplied by recent PWT 8.0 (*khpwt*) and a new variable (*khgls*) previously designed in Gregorio Gimenez, Carmen Lopez-Pueyo, and Jaime Sanau (2015). The theoretical relationship between human capital and technical change is based on Jess Benhabib and Mark Spiegel (2005). They consider that human capital has two faces: it drives domestic innovation as was firstly recognized at a theoretical level in the endogenous growth model of Paul Romer (1990), and it promotes a country's capabilities to imitate taking advantage of its backwardness as was recognized in the seminal paper of Nelson and Phelps (1966).

Our contribution differs from the previous work in the following dimensions. First, we use a new human capital variable that incorporates education quality into the labor force and is measured per hour worked. Second, the impact of this variable on technological progress is tested using the recent PWT8.0 which incorporates two "sophisticated" TFP measures and a variable of human capital. This allows us to distinguish between private and social returns to education. Third, the estimation of the relationship is carried out with adequate econometric techniques (system GMM).

The results obtained allow us to ensure the existence of social returns to human capital. They also reveal a higher social return to innovation than to diffusion when human capital is measured by combining qualitative and quantitative components, as it is done in the *khgls* variable. Furthermore, from a given initial proximity to the technology frontier, the human capital variable that includes cognitive skills seems to have a greater net effect on technological progress than the variable that does not incorporate them.

The remainder of the paper is organized as follows. In Section 2, we review recent developments in the literature. In Section 3, we address the difficulties of measuring human capital. In Section 4, we propose the theoretical framework. In Section 5, we describe the data and endogeneity problems and estimate the proposed model. In Section 6, an analysis of the results is carried out. Finally, the conclusions of the work are presented in the last section.

2. THE EFFECT OF HUMAN CAPITAL ON ECONOMIC GROWTH: RECENT DEVELOPMENTS

Modern economic theories consider human capital as a key driver of endogenous economic growth. One strand of the literature– the *accumulationist* follows the proposal of Robert Lucas (1988) to recognize the role of human capital as a direct factor of production whose accumulation enhances output growth. On the other hand, the Schumpeterian or *assimilationist* tradition emphasizes the role of human capital as a key element in the generation of technological progress (or TFP growth) which, in the long term, drives equilibrium growth rates of the economy. The first class of models emphasizes the accumulation of human capital as a source of growth. On the contrary, the second approach considers growth as being promoted by the stock of human capital which is measured by school attainment or, alternatively, by the flow of education spending.

Following these two theoretical proposals, the empirical literature on human capital and economic growth has adopted a double perspective. In the accumulationist tradition, a huge strand of research follows the influential paper of Gregory Mankiw, David Romer, and David Weil (1992) which studies the effect of the growth of human capital on per capita output growth. The results of this literature- reviewed in the work of Alan Krueger and Mikael Lindhal (2001) and recently in Michael Delgado et al. (2014)- are somewhat puzzling: education is positively and significantly associated with growth only in countries with the lowest level of education.

One of the possible explanations of this counterintuitive result is the existence of an indirect effect of education on growth which operates through its impact on TFP growth, an idea also validated by the assimilationist tradition. Within this line of research, the work of Benhabib and Spiegel (2005) is the most influential.

As in their well-known paper of 1994 (Jess Benhabib and Spiegel, 1994), these authors follow the proposal of Romer (1990) and model the effect of human capital in boosting innovation by introducing it as a direct explanatory factor in the knowledge production function. Additionally, as in Richard Nelson and Edmund Phelps (1966), Benhabib and Spiegel (2005) consider the stock of human capital as a catalyst of technological diffusion. This "imitation effect" is incorporated into the knowledge production function interacted with the distance to the frontier. Benhabib and Spiegel (2005) introduce three important novelties: the superiority of the logistic (vs the exponential) diffusion function to model TFP growth, the possibility of economic divergence across nations and the existence of a threshold value below which countries fall into the poverty trap.

The authors test this specification for 84 countries from 1960 to 1995 and obtain robust evidence only of the imitation effect of human capital. This result is also corroborated in, among many others, the work of Jakob Madsen, Md. Rabiul Islam, and James Ang (2010) who obtain insignificant coefficients for the innovation effect of educational attainment on TFP growth whereas the imitation (interaction effect) is positive for the overall sample of 55 developing and developed countries over the period 1970-2004 but not for each of the subgroups when the sample is split into developed and developing countries. The authors attribute this result to the existence of a small sample bias. Also, for 159 European regions in 1992-2005, Johanna Vogel (2013) obtains evidence of an innovation effect of human capital on TFP growth only when the interaction term is excluded to resolve multicollinearity problems.

The works of Philippe Aghion et al (2005) and Jerome Vandenbussche, Philippe Aghion, and Costas Meghir (2006) introduce an important novelty in this line of research by considering that imitation and innovation require skilled and unskilled workers in different proportions. If this is so, different countries will require different compositions of human capital in order to grow, depending on their distance from the frontier. Papers like that of Md. Rabiul Islam (2010) and James Ang,. Jakob Madsen, and Md. Rabiul Islam. (2011) provide support for this proposal while others, like

Fabio Manca (2011) and Marianna Papakonstantinou (2014), offer evidence of the positive effect of skilled workers on productivity growth whatever the distance to the frontier.

Most of the studies cited above measure human capital and its composition by average years of education, by far the most commonly used proxy of the stock of human capital. This choice is justified by the availability of large databases like that of Robert Barro and Jong-Wha Lee (2013). Nevertheless, recently, a second strand of analysis has emphasized variables that represent the *quality* of human capital because the use of average years of schooling assigns the same return of an additional year of education to countries whose education systems are extremely different.

The multiple works of Eric Hanhusek (see, for example, Eric Hanushek and Ludger Wößmann (2012)] emphasize cognitive skills to explain the importance of human capital and conclude that human capital causes economic growth and when it is incorporated into growth regressions, school attainment loses its significance

Manca (2011) reexamine Benhabib and Spiegel (2005) covering 88 countries (both developed and developing) for the period 1960-2000. First, he elaborates a composite indicator, which adjusts Daniel Cohen and Marcelo Soto's (2007) number of years of schooling data for the differences in the quality of each country's educational system, based on internationally comparable test scores. Then, he regresses TFP growth on this indicator and its interaction with the TFP gap and finds that education plays a fundamental role in the explanation of economic growth at all stages of development; but the magnitude of the effect is very heterogeneous, being much larger in developing countries. George Messinis and Abdullahi Ahmed (2013) delve into this line of research with a new latent indicator of cognitive skills for seventy nations in 1970-2003. They demonstrate that, when this indicator —that accounts for years of schooling, cognitive skills used in scientific research, life expectancy, and the use of modern IT equipment for educational purposes— is used, human capital drives both domestic innovation and technology diffusion. Similarly, Garett Jones (2012) obtains evidence of the relevance of the quality of human capital for different samples of developed and developing countries in 1960-1995. Using the national average IQ (Intellectual Quotient) of Richard Lynn and Tatu Vanhanen (2002, 2006) -who take into account data from hundreds of published intelligence studies performed in 113 countries over the last century- Jones (2012), demonstrates that IQ and its interaction term are much more statistically significant than the quantity of education term. Md. Rabiul Islam, James Ang, and Jakob Madsen (2014) try to capture the quality of human capital through two schooling inputs—the teacher-pupil ratio and the real public educational expenditure per student/real per capita GDP— and five schooling output variables —the number of universities per million workers listed in the top 500 Academic Ranking of World Universities published by the Shanghai Jiao Tong University, the rates of non-repetition and the results of international test scores in mathematics, science and reading—. In their study, for a panel of 60 countries in 1970-2010, they find a robust relationship between the direct and the indirect effects of a quality-adjusted human capital variable on TFP growth.

So, recent evidence is conclusive. It is possible to assert as Jones (2012: 452) does that "*the horse-race results of most papers provide no support for the hypothesis that the quantity of education is more important that the quality of education in producing and adopting TFP growth*". Our work is framed in this strand of analysis in which quantity human capital variables are adjusted for by some measure of quality of education. The next section presents the novelties in detail.

3.- THE DIFFICULTIES OF MEASURING HUMAN CAPITAL AND NEW CONTRIBUTIONS

In spite of the huge number of theoretical and empirical studies published in recent decades, measuring human capital remains a challenging task. The indicators that are usually employed by growth researchers are strongly conditioned by the availability of the data. As schooling indicators have been traditionally the most easily available variables, and because schooling is a key determinant of earnings many empirical studies use these variables as a measure of human capital. However, the traditional indicators of formal education, such as the enrolment rates of the school-age population or the average years of schooling, fail to collect the complex nuances of the concept of human capital, which goes far beyond mere formal education. As Gregorio Gimenez (2005) stresses, the concept includes many elements apart from formal education, including innate capacities, non-formal education, on-the-job training, experience and health. Furthermore, many empirical studies that use these traditional indicators take into account the human capital of the school-age population or the whole population, when the relevant variable should be the human capital of the workforce.

Due to these conceptual limitations of the variables that are used as proxies of the concept and also to the poor quality of the data available for international comparisons, measurement errors in human capital are very common. These limitations may be behind the fact that many empirical research works struggle to find a clear link between human capital and economic growth, as authors such as Krueger and Lindahl (2001), Ludger Wößmann (2003), Angel De la Fuente and Rafael Domenech (2006), Cohen and Soto (2007), Yousif Al-Yousif (2008) and Eric Hanushek (2013) have pointed out. This problem is of particular importance when we work with growth models based on innovation, because human capital is a cornerstone to understand research processes and technology adoption.

Despite the recognized limitations of the traditional indicators, essays that use conceptually richer indicators, which take into account a greater number of elements in the concept of human capital, are few. In recent years, some researchers have made valuable efforts to build more elaborate and accurate indicators. As we have seen in the previous section, the new indicators are used in the hope of modelling the relationship between human capital and technological progress more precisely.

Notable among these new attempts is the index of human capital included in version 8.0 of the Penn World Table (PWT), see Robert Feenstra, Robert Inklaar, and Marcel Timmer. (2013) and Robert Inklaar and Marcel Timmer (2013). This index is based on a Mincerian transformation of the average years of schooling calculated by Barro and Lee (2013). The indicator has the important advantage of being comparable across countries and over time, and estimates the human capital hc of country i at time t as a function of the average years of schooling s:

$$hc_{it} = e^{\phi(s_{it})} \qquad [1]$$

where $\phi(s)$ are the Mincerian rates of return to education defined by Psacharopoulos (1994).

Another recent attempt to build a more accurate international indicator of human capital is that of Gimenez, Lopez-Pueyo and Sanau (2015) (GLS indicator, from now on). These authors make a methodological proposal to calculate international stocks of human capital by taking into account a double dimension: quantitative and qualitative. The indicator proposed reflects three factors: 1) educational levels achieved; 2) differences in productivity and wages, based on the education possessed; and 3) differences in educational quality and knowledge. The information corresponding to hours worked and salaries comes from the EU KLEMS Growth and Productivity Accounts database, financially supported by the European Commission (see Marcel Timmer, Mary O'Mahony, and Bart van Ark, 2008) and the results on cognitive skills from Hanushek and Wößmann (2012), who use all available international tests datasets between 1964 and 2003 and put performance on a common scale in order to facilitate comparisons.

With this data, the authors estimate differences in productivity among workers, calculated from the differences in remuneration according to their levels of education. The differences in productivity are used to weight the total hours worked in the economy. Finally, the stock of human capital, in terms of numeraire hours of work according to the basic educational level, is corrected by internationally comparable test scores.

The PWT and GLS indicators provide more accurate ways to measure human capital. However, they differ in key aspects. The PWT indicator, available for a wide set of economies from 1950 to 2011, is based on the average years of schooling transformed according to Mincerian rates of return that are common to all countries. The GLS indicator is constructed in terms of the stock of numeraire hours, based on differences in levels of education and productivity that are calculated for each economy and weighted by the quality of education. Thus, unlike other indicators, it allows to take into account the existence of differences in productivity among workers, countries and years, regardless of whether the workers have the same level of education. Moreover, using numeraire workers allows to exclude differences in productivity between countries resulting from factors that are not strictly human capital, such as differences in the stock of physical capital or in technology. Nevertheless, as it needs much more information to be constructed, it is only available for 15 OECD economics between 1980 and 2005.

Table 1: Country rankings in terms of human capital (1995-2005)*							
khpwt				**khgls**			
	1995		**2005**		**1995**		**2005**
United States	3.508	United States	3.575	United States	1.733	United States	2.058
Australia	3.289	Czech Rep.	3.536	Czech Rep.	1.637	Hungary	1.767
Czech Rep.	3.231	Australia	3.333	U. Kingdom	1.608	U. Kingdom	1.716
Slovenia	3.148	Germany	3.325	Germany	1.567	Netherlands	1.705
Japan	3.049	Korea Rep.	3.255	Netherlands	1.553	Czech Rep.	1.693
Korea Rep.	3.048	Hungary	3.245	Hungary	1.538	Japan	1.600
Netherlands	3.029	Slovenia	3.244	Austria	1.520	Slovenia	1.572
Hungary	3.023	Japan	3.198	Japan	1.509	Germany	1.570
Belgium	2.910	Netherlands	3.099	Slovenia	1.479	Austria	1.542
Denmark	2.869	Belgium	3.029	Korea Rep.	1.400	Belgium	1.498
Germany	2.770	Denmark	2.907	Belgium	1.376	Finland	1.480
Finland	2.753	Finland	2.887	Denmark	1.353	Spain	1.443
Austria	2.663	Spain	2.878	Finland	1.336	Denmark	1.404
U.Kingdom	2.636	Austria	2.792	Australia	1.291	Australia	1.348
Spain	2.597	U.Kingdom	2.759	Spain	1.290	Korea Rep.	1.296
Media	2.968		3.137		1.479		1.579
St.deviation	0.261		0.257		0.134		0.191
Coef. Variation	0.088		0.082		0.090		0.121
*The ranking has been calculated for 1995 because Hungary, Slovenia and Czech Rep.only have khgls data from 1995.							

Table 1 shows the ranking change of the countries in terms of the two human capital variables*:* *khpwt* and *khgls*. Furthermore, it offers the traditional measures of dispersion, showing greater dispersion in *khpwt* and lower dispersion in *khgls* between the beginning and the end of the period. All the countries, with the exception of the Republic of Korea in *khgls*, have experienced a growth in their human capital. First, we present the results in which the two variables show similar behaviour. The United States occupies the leader position in both variables with a great increase in *khgls* during the period and Hungary reaches a better position in both cases, occupying second place in *khgls* in 2005. Below, we discuss the results in which the two variables show different results (the Republic of Korea, Germany and the United Kingdom). The six countries with less *khgls* are, both in the initial and final year: Spain, Australia, Finland, Denmark, Belgium and the Republic of Korea. The latter occupies the last position in 2005 while it rises from the sixth to the fifth position when using the *khpwt* indicator. Germany goes down to eighth position in *khgls* while it experiences a great growth in *khpwt* in the same period. Finally, while the United Kingdom occupies the third position in *khgls*, it falls to bottom place in *khpwt* at the end of the period analyzed.

These differences in the rankings and in the evolution of the endowments are logical, given that the two indicators measure human capital in different ways. While *khpwt* is based on a quantitative dimension of the concept and is constructed using average years of schooling and fixed rates of returns of education, *khgls* is based on differences in productivity and in the quality of education. The stock of human capital in the first case would increase if we increase the duration of formal education. In the second case, increases in the stock may be the result of I) increases in the proportion of workers who have received higher education; II) improvements in the quality of education; and III) improvements in the productivity of workers with higher educational levels, in comparison with unskilled workers. In sum, the two indicators could evolve in different ways; for example, an increase in the number of average years of schooling is not necessarily accompanied by better educational outcomes or increases in the labour productivity gap between workers with higher and lower educational levels.

Innovation and imitation processes have become increasingly complex. As the PWT and GLS indicators measure the stock of human capital more completely, they offer new possibilities of establishing, with more empirical precision, the ties between human capital, innovation and imitation. In the following sections, we test the capacity of these novel human capital indicators to explain innovation and technology diffusion. We also present our results and those obtained by other research papers that use the same theoretical framework but different indicators of human capital.

4.- EMPIRICAL MODEL

The purpose of this section is to establish the equation to estimate the impact of human capital on technological progress. Technological progress in a country is the result of two components: the domestic innovation driven by human capital and the technology diffusion from the leader country. Following Benhabib and Spiegel (2005), the specification of a logistic functional form of technology diffusion is used. In this functional form, technology diffusion depends on the human capital of the recipient country and on the distance to the frontier interacted with an extra term. This extra term seeks to capture the idea introduced by Susanto Basu and David Weil (1998) that the frontier technology may not be immediately "appropriated" by the follower when the differences in the factor proportions between leader and follower are large. Likewise, this extra term could also capture all other impediments to assimilating foreign technology such as intellectual property rights, social values and incompatibilities with domestic technology. In contrast to the exponential case of technology diffusion that does not incorporate this extra term, the logistic diffusion function implies a faster catch-up process when the country is in the middle distance and slower when it is too near or too far from the frontier.

Another feature of the logistic model is that convergence in productivity growth rates depends on the relationship between the relative magnitude of the difference in the growth rate due to innovation and the growth rate due to diffusion. Growth rates will converge when, due to the human capital of a follower, the diffusion rate exceeds the differential innovation growth rate between the leader and the follower. Growth rates will diverge when the human capital of a follower is too low and, consequently, the catch-up rate is smaller than the differential innovation growth rate between the leader and the follower. For this reason, investing in human capital is one way of overcoming the difficulties of adopting distant technologies for the follower countries and of diminishing the distance to the leader.

Equation (5) captures these two faces of human capital. In this equation, ΔTFP is the technological progress, H the human capital, TFP the total factor productivity, and subscripts *i*, *max* and *t* denote country, country leader and year, respectively:

$$\Delta \log \mathrm{TFP}_{it} = \mathrm{g} \log H_{it} + \mathrm{c} \log H_{it} \left(\frac{TFP_{max\,t} - TFP_{it}}{TFP_{it}}\right)\left(\frac{TFP_{it}}{TFPmax\,t}\right) \qquad [5]$$

$$\Delta \log \mathrm{TFP}_{it} = (\mathrm{g+c}) \log H_{it} - \mathrm{c} \log H_{it} \left(\frac{TFP_{it}}{TFPmax\,t}\right) \qquad [6]$$

.

As in Benhabib and Spiegel (2005), human capital is a measure of an economy's capacity for domestic innovation and technology adoption from abroad. These two roles of human capital are captured, respectively, by the first and the second term of equation [5]. Rearranging this equation, we obtain equation [6], which will now be estimated. The coefficients to be estimated are (g+c) and –c. In this equation, the net effect of human capital on technological progress depends on how far a country is from the frontier and corresponds to the expression [(g+c) - c $\frac{TFP_i}{TFP_{max}}$]. Consequently, the net effect of human capital on TFP for the leader is only the domestic innovation effect (g).

5.- ESTIMATION AND RESULTS

The sample is made up of a panel of data from fifteen countries for the years 1979-2005. The selection of the countries has been conditioned by the availability of data about the *khgls* human capital indicator. The countries included are Australia, Austria, Belgium, Czech Republic, Denmark, Finland, Japan, Germany, Hungary, Netherlands, Korea Republic, Slovenia, Spain, United Kingdom, and United States. The variables of TFP level and TFP growth are taken from Penn World Tables (PWT version 8.0). Human capital is measured by two alternatives variables: the first (*khpwt*) comes from PWT 8.0 and the second (*khgls*) is that proposed by Gimenez, López-Pueyo, and Sanaú (2015), in terms of human capital per hour worked.

For the first time, the PWT 8.0 offers data on TFP that can be used for comparing TFP levels across countries and for comparing TFP growth over time. The new TFP measures in PWT are a great improvement on the standard approach used by previous versions. Asset composition in capital input and labour income of the self-employed are taken into account; purchasing power parities are used to compare capital levels across countries; and, labour input is adjusted by an index of human capital based on the average years of schooling of the population aged 15 and over and the assumed rate of return (Barro and Lee, 2013). See Inklaar and Timmer (2013) for a detailed and technical document about these improvements and Fenestra, Inklaar, and Timmer (2013) for the underlying theory.As a result of these improvements, PWT 8.0 offers two sets of productivity measures: one suitable for cross-country comparison at a point in time to measure a country's proximity to the frontier, and the other suitable for comparisons over time. Furthermore, as these new sophisticated measures of productivity take into account differences in the educational attainment of the labour force and, thus, private returns to education, it is possible to estimate the social returns or externalities to human capital in the framework of Benhabib and Spiegel's (2005) model.

Our model is a dynamic panel data model in which there are arbitrary distributed fixed effects and current realizations of the dependent variable are influenced by past ones, generating the "dynamic panel bias". This means that at least one regressor —the lagged endogenous variable— is correlated with the error, violating an assumption necessary for the consistency of OLS. It inflates the coefficient estimated for the lagged endogenous variable, by attributing predictive power to it that actually belongs to the country´s fixed effect. Additionally, the relationship between human capital and TFP growth is likely to be simultaneous and affected by reverse causality, so endogeneity is a question that needs to be addressed in this context. As David Roodman (2009) states, there are two ways to tackle this endogeneity. One, at the heart of difference GMM, is by transforming all the regressors by differencing to remove fixed effects. The other, the system Generalized Method of Moments (GMM), developed by Manuel Arellano and Olympia Bover (1995) and Richard Blundell and Stephen Bond (1998), is to instrument endogenous regressors by variables thought to be uncorrelated with the fixed effect. In our study, we take this second alternative because it allows the introduction of more instruments (the first difference of instrument variables) and dramatically improves on the efficiency of the GMM estimator. The two-step system GMM estimation has been applied using the STATA statistical software package developed by Roodman (2009). Specifically, we use the xtabond2 STATA routine. As technological progress is conditioned by innovation in previous periods, regressors are considered as predetermined but not strictly exogenous and lags 1 to 3 of them are used as instruments; the *collapse* option is implemented, so only one instrument for each variable and lag is created. All significance levels of the variables are based on the t-statistic using Windmeijer's finite-sample correction for the two-step covariance matrix.

The coefficients to be estimated in equation [6] are $(g+c)$ and $(-c)$. Table 2 presents the system GMM panel estimation using the two alternative variables of human capital. Column (1) presents the results of using *khpwt* and column (2) shows those of *khgls*. In both columns, the coefficient $(g+c)$ of human capital is positive at the 5 per cent confidence level. As predicted, the coefficient of the catch-up term $(-c)$ shows a negative sign at the 5 per cent confidence level in both columns. Therefore, the results support the existence of two faces of human capital in the promotion of economic growth: human capital promotes domestic innovation and also acts as a catalyst of technological diffusion from the leader.

Table 2: System GMM estimation results		
	[1]	[2]
	H = khpwt	**H = khgls**
Log H	0.087** (0.019)	0.080* (0.034)
$\log H_i\ (\frac{TFP_i}{TFPmax})$	-0.086* (0.022)	-0.077* (0.036)
Sample size	368	332
Number of countries	15	15
Number of instruments	5	6
AR(1)	-2.02 (0.043)	-1.99 (0.046)
AR(2)	-0.35 (0.728)	-1.08 (0.279)
Sargan test	2.70 (0.259)	2.64 (0.450)
Hansen-J test	1.16 (0.561)	2.65 (0.449)
Note: In parentheses are the corrected standard errors of the coefficients where ** and *denote the 1 and 5 % respectively level of significance by the t-statistic. The parentheses of the other tests show the probability of their null hypothesis		

The estimations are accompanied by the Arellano and Bond test to detect the first and second-order autocorrelation in first differences. As Table 2 shows, the test AR(1) on the residuals in first differences do not allow us to accept the hypothesis of no first-order serial correlation and confirms the expected AR(1) in first differences. Nevertheless, the hypothesis of no second-order serial correlation in the perturbations tested with AR(2) is accepted. Furthermore, the Sargan and Hansen tests for the joint validity of the instruments allow the acceptance of the joint exogeneity of the instruments and support the estimations. The Sargan test is based on the observation that the residuals must be correlated with the set of exogenous variables if all the instruments are truly exogenous. The Sargan test under the null hypothesis that all the instruments are exogenous, is distributed as a chi-square of *m-r* degrees of liberty, where *m-r* is the difference between the number of instruments and the number of endogenous variables employed. Although the Sargan test is not robust to heteroskedasticity or autocorrelation, it is calculated because the Hansen J test, though robust, can be weakened by instrument proliferation.

These results support the existence of productivity externalities from human capital, whether we use the human capital variable *khgls* or *khpwt*. These externalities mean that, human capital leads to productivity gains at the macroeconomic level through different channels: part of an individual's education can be captured by other workers or by the owners of other factors of production. As Serge Coulombe and Jean-Francois Tremblay (2009) state, individual human capital can increase the productivity of co-workers or can have a positive impact on technological progress. This result has implications in terms of economic policy: from an efficiency perspective, large public investment in education may be easier to defend if macroeconomic returns to education exist and are large.

6.- ANALYSIS OF RESULTS

In this section we offer a threefold analysis of the results obtained: an analysis of our coefficients and those obtained in previous studies, a calculation of the threshold value of human capital to catch-up, and an analysis of individual countries' behaviour.

Based on the estimation results in Table 2, we have calculated the more relevant economic magnitudes in Table 3. First, the effect on the growth of productivity of one more unit of human capital for the leader is 0.003 or 0.001, depending on whether we measure human capital with *khpwt* or *khgls*. Second, comparing our results with the point estimates obtained in similar studies we can conclude that, given a country's proximity to the frontier, human capital measured with *khgls* has a higher relative productivity in innovation vs diffusion (g/c = 0.003/0.077) than if it is measured with *khpwt* (g/c= 0.001/0.086). As these two variables have been built in different ways, the estimates may be underlining that an additional unit of human capital, measured considering both qualitative and quantitative items, has a greater relative innovation vs diffusion effect than an additional unit of only "quantitative human capital". Approximating human capital without taking the quality of education into account could result in an under-estimation of the impact of human capital on innovation and an over-estimation of its impact on imitation.

Table 3 also offers a comparison between the estimated values obtained in this work and those of previous papers, and gives additional information about their respective samples. First, we have to consider the different human capital and total factor productivity variables, periods, number and kinds of countries, and estimation methods they use. Benhabib and Spiegel (2005) used the PWT 6.1 to calculate TFP and the updated Barro and Lee human capital variable (both the initial and the average period of the years of schooling in the population over 25 years of age). On the other hand, Messinis and Ahmed (2013) used PWT 6.2 to calculate TFP and estimated a composite index of the cognitive skills employed by the adult population. They also used Robert Barro and Jong-Wha Lee (2010) human capital variable, but they do not obtained significative values of the estimator. We observe larger coefficients in absolute value for the more recent estimations.

Table 3: Innovation and imitation coefficients in logistic diffusion models						
	g+c	**c**	**g+c-c leader**	**Period**	**n**	**Estimation**
Khpwt	0.087	0.086	0.001	1979-2005	15	System GMM panel
Khgls	0.080	0.077	0.003	1979-2005	15	System GMM panel
Messinis and Ahmed (2013) with skills	0.084	0.075	0.009	1970-2003	70	System GMM panel
Manca (2011) with cognitive skills	0.018	0.015	0.003	1960-2000	88	System GMM panel
Benhabib and Spiegel (2005) with years of education (period average)	0.016	0.012	0.004	1960-1995	84	Maximum likelihood cross-section
Benhabib and Spiegel(2005) with years of education (initial values)	0.013	0.007	0.006	1960-1995	84	Maximum likelihood cross-section

Based on these results and the predictions of the theoretical model, we now try to find out if there are any countries that, as a consequence of their low level of human capital, will experience no catch-up with the technology frontier. As Benhabib and Spiegel (2005) underline, the logistic diffusion model implies that the steady state growth relationship will depend on the relative magnitude of the difference in the growth rate due to innovation between the leader and the follower and the catch-up rate. If this relative magnitude is only the consequence of human capital differences between the leader and the follower, then the TFP growth rate of the follower will converge to the growth rate of the leader when the catch-up rate exceeds the differential growth in innovation. This condition of convergence can be expressed in terms of a human capital threshold value below which a country will fall farther and farther behind the leader nation over time. This critical value is:

$$\log H_t^* = \frac{g \ \log H_{leader,t}}{g + c}$$

Comparing the human capital coefficient estimated (g+c) with that of the interaction term (-c) in Table 2, we can appreciate that the estimate for g is positive in both columns. This positive value allows us to calculate a positive critical human capital value below which catch-up in TFP is not possible. The threshold value H* in the initial year for variable *khpwt* is 1.0081 while it is 1.0099 for variable *khgls* (see Table 4). Because all the countries in our sample are developed countries, they all surpass this critical value and could converge to the leader under the conditions previously explained. In 2005, the countries also have their human capital values greater than the critical value, as Table 4 shows: 1.0085 for *khpwt* and 1.0232 for *khgls*. These values are greater than those of the initial year because the human capital of the leader has grown during the period and, consequently, as there will be innovation at a higher rate, followers will need to growth at a higher rate to experience higher total factor productivity growth than the leader.

Table 4: Critical values of human capital

	khpwt	**khgls**
g	0.0006	0.0025
g+c	0.0865	0.0797
h*1981	**1.0081**	**1.0099**
h*2005	**1.0085**	**1.0232**

With these results, if the ranking of the countries in terms of human capital did not change, all the countries would exhibit faster growth in total factor productivity in the future than the leader. Another way to predict the same is to calculate the total annual effect of human capital on technological progress. Table 5 shows the ranking of countries according to their estimated net effect of human capital on technological progress, considering the initial distance to the leader *[(g+c) - c* $\frac{TFP_{io}}{TFP_{max0}}$]. Due to the specification chosen, the country position is the same as that derived from its initial proximity to the frontier country. Logically, then, the ranking is the same but the values are different when they have been estimated using the alternative variables of human capital *khpwt* and *khgls*, respectively. As we can see in Table 5, all the countries have a greater net effect than the leader and, consequently, if the ranking of their respective human capital does not change over the period, the follower countries will have faster total factor productivity growths than the leader.

Table 5: Total annual effect of human capital on technological progress				
	calculated with *khpwt*			**calculated with *khgls***
United States	0.0006		United States	0.0025
Austria	0.0011		Austria	0.0030
Spain	0.0011		Spain	0.0030
Germany	0.0025		Germany	0.0043
United Kingdom	0.0026		United Kingdom	0.0044
Belgium	0.0033		Belgium	0.0050
Netherlands	0.0060		Netherlands	0.0074
Australia	0.0101		Australia	0.0111
Japan	0.0162		Japan	0.0166
Denmark	0.0185		Denmark	0.0186
Czech Rep.	0.0202		Czech Rep.	0.0201
Finland	0.0221		Finland	0.0219
Slovenia	0.0278		Slovenia	0.0269
Hungary	0.0394		Hungary	0.0374
Korea Rep.	0.0407		Korea Rep.	0.0386

Table 5 shows that, in countries with a proximity to the frontier in the initial year of less than 0.78 (Czech Rep., Finland, Slovenia, Hungary and Korea Rep.), one more unit of *khgls* leads to less technological progress than an additional unit of *khpwt*. In other words, in countries near the frontier, one more unit of *khgls* results in greater technological progress than an additional unit of *khpwt*. This is consistent with our previous analysis of Table 2 and could be a sign of the higher effect of cognitive skills on technological progress for a certain level of proximity to the technology frontier.

From these results, it can be inferred that an innovation-effective education policy should thus focus not only on increasing school attainment, but also on enhancing skills. This goal is especially important for countries that have reached high levels of development and have little scope for increasing their average years of schooling. However, it is not an easy goal to achieve because raising spending on education has little consistent impact on improving cognitive skills if it is not accompanied by other instruments. The policies that appear most effective in the long run take an integrated approach that comprises all levels of education, from preschool to college. These policies focus on a) ensuring access to quality preschool education as a way to encourage early cognitive and social skills; b) expanding the autonomy of the educational centers; c) promoting grant programs that ensure that the best students have access to the highest educational levels; d) developing systems to evaluate the performance of students and institutions; and e) encouraging competition among the latter. And above all, the evidence suggests that the most effective way to increase educational quality is by improving teacher quality. This requires an effective designin the way teachers are hired, trained, motivated and paid. Finally, it should be noted that the efforts to equip the workforce with the necessary skills should not focus only on the years of formal education, that is, before entering the labour market. Investment in education is a lifelong process, and on-the-job training has become crucial. Surveys such as the OECD Programme for the International Assessment of Adult Competencies (PIAAC) have pointed out the big differences that exist in labour force skills in developed countries. It is critical to underscore that, as advanced skills play a central role in innovation processes, improving workforce skills is the only way to excel in an increasingly competitive global environment.

7.- CONCLUSIONS

This paper presents a new variable of human capital and applies it to explain technological progress, using the new total factor productivity variables from PWT 8.0. This new variable *(khgls)* is a measure of human capital efficiency per hour worked that considers the role of both education quantity and quality. Moreover, the improved total factor productivity variables already discount the private returns to education. So, using the logistic model of technology diffusion proposed by Benhabib and Spiegel (2005) and applying dynamic panel estimations, the results capture the social returns of education. Furthermore, our results have shown the two faces of human capital, that is, its role in the innovation process and, above a threshold value, its role in the imitation process for countries far from the technology frontier.

In our attempt to contribute to the debate on the measurement of the externalities of education, these findings encourage us to future extensions. First, with the aim of providing a more solid basis for policy initiatives, the disaggregation of this human capital variable by levels of education, or a differentiation between its quantity and quality components, would be necessary. Second, it would be desirable to expand the sample to detect possible differences between developed and developing countries. Finally, the addition of institutional variables which have a direct relationship in the appearance of education externalities would enable a better understanding of the catch-up process.

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Appendix A: **Variables, definitions and data**	
ΔTFP	TFP at constant national prices are used to implement system GMM panel estimation. Variable rtfpna in PWT 8.0 (2005=1)
TFP	TFP level at current PPPs(USA=1) Variable ctfp in PWT 8.0
khpwt	PWT 8.0. index of human capital per person, based on years of schooling (Barro/Lee, 2013) and returns to education (Psacharopoulos, 1994). See Inklaar and Timmer (2013).
khgls	Gimenez et al. (2015) index of human capital.