Human Capital Measurement in OECD Countries and Its Relation to GDP Growth and Innovation

Medición del capital humano en los países OCDE y su relación con el crecimiento del PIB y la innovación

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Abstract

Empirical literature finds difficulties specifying and selecting proxies for human capital. These difficulties may explain why the indicators used in several international empirical studies are not closely linked to economic growth and its sources.

This study offers an innovative perspective with an international indicator of human capital that takes into account the quantitative and the qualitative dimension of the concept, through the calculation of working hours corrected by productivity on the basis of differences in educational attainment and differences in skills and knowledge which exist between countries.

The study also applies Granger's test to analyse, in a sample of 15 OECD countries, the causality between the new indicator of human capital and GDP and the new indicator and innovation, concluding that the multidimensional indicator possesses a relation of causality that does not appear when tests are carried out with traditional measures of human capital (gross enrolment rate in secondary and average schooling years).

Keywords: Human Capital; Economic Growth; Technology; OECD; Causality Test.

Resumen

La literatura empírica encuentra dificultades a la hora de definir el capital humano y seleccionar *proxies* para su medición. Estas dificultades podrían explicar por qué diversos trabajos empíricos internacionales no encuentran una relación estrecha entre los indicadores utilizados y el crecimiento económico y sus fuentes.

Este trabajo ofrece una perspectiva innovadora, aportando un indicador de capital humano que tiene en cuenta las dimensiones cuantitativa y cualitativa del concepto, a través del cálculo de las horas trabajadas corregidas por las diferencias en productividad, en base a las diferencias en niveles educativos alcanzados, y a las diferencias en habilidades y conocimientos existentes entre países.

El trabajo aplica, a su vez, test de Granger para analizar, para una muestra de 15 países OCDE, la causalidad entre el indicador propuesto y el PIB y el nuevo indicador y la innovación, concluyendo que el indicador multidimensional posee una relación de causalidad que no aparece cuando se trabaja con las medidas tradicionales de capital humano (tasas brutas de matriculación en secundaria y años medios de estudio)

Palabras clave: Capital humano; Crecimiento económico; Tecnología; OCDE; Test de causalidad.

JEL codes: I25, O20, O31.

1. Introduction

In neo-classical growth models, the rate of growth is exogenously determined by either the savings rate or the rate of technical progress (Solow model). However, during the last decades of the 20th century many growth theorists, increasingly dissatisfied with the previous models, developed new theoretical proposals able to identify the causes of economic growth. The new models give special importance to the investment in human capital and its link with innovation.

In this sense, two principal lines of thought have been developed regarding the role of human capital in economic growth. On the one hand, Lucas (1988) and Mankiw *et al.* (1992) consider human capital as a factor of the production function, and hold that the accumulation of human capital is the principal determinant of productivity growth and, consequently, that the rate of economic growth depends directly on the rate of accumulation of human capital, not on the human capital stock.

On the other hand, authors such as Nelson and Phelps (1966), Benhabib and Spiegel (1994, 2005), Barro (1999) and Barro and Sala-i-Martin (2003), consider that an increase in human capital stock indirectly boosts economic growth, by expanding the ability of a country to develop its own innovations and increase its capacity to adopt technologies developed in other countries.

In spite of the importance that the specialists concede to human capital, no generally accepted definition exists. Furthermore, diverse studies (such as those by Krueger and Lindahl, 2001, De la Fuente and Domenech, 2006, Cohen and Soto, 2007 or Al-Yousif, 2008) have underlined the difficulties of measuring human capital, and, since the empirical evidence for the link between human capital and growth depends on the selection, the specification and the choice of proxy for human capital, these difficulties may explain why the indicators used in several empirical studies are not closely linked to GDP growth. Limitations are still greater in the international context, where it is difficult to find measurements of human capital that are comparable and have a time perspective. The difficulties in measuring and even defining the variables used and the heterogeneity of the data available then become evident.

According to Wößmann (2003), two errors may be produced in the measurement of human capital: errors due to the use of inadequate proxies (since the majority of studies select them for the availability of the data and not for their suitability) and measurement errors in the true sense of the word. As a result,

the question of the proxy of human capital is shown to be fundamental when evaluating its true importance.

The main objective of the present study is to make a methodological proposal to elaborate an indicator of human capital which provides more nuances and information than traditional indicators and facilitates the comparison of endowments between economies. The indicator takes into account the quantitative dimension of human capital, correcting working hours by productivity, on the basis of educational attainment, for each group of workers with similar characteristics of gender and age.

Furthermore, it considers the qualitative dimension of the concept and corrects the hours worked for the differences in abilities and knowledge which exist between countries. The new indicator, explained in the second section of the paper, permits, therefore, the measurement of the stock of human capital in a richer way, and offers new possibilities of establishing, with more empirical precision, the ties between human capital, innovation and GDP. To test its properties, the third section provides a Granger causality tests analysis in a sample of OECD countries. Our work shows that when human capital is measured by the indicator proposed, it Granger-causes GDP (the basic measure of a country's overall economic output). However, when human capital is measured by traditional indicators it does not maintain a relation of causality with GDP. Moreover, a Granger causality test has been performed, to check whether innovation can be explained by human capital. We find that when human capital is measured with the indicator proposed, it maintains a relation of causality with the technological variable. In this case, causality is bidirectional: human capital causes innovation and innovation causes human capital (in the sense of Granger). However, this relation is not observed with traditional human capital indicators. The fourth section presents the principal conclusions of the study. The research is accompanied by two annexes which contain the description of the variables employed, the descriptive statistics and the elaborated data.

2. Human capital measurement

2.1. Human capital indicators

The majority of studies which measure human capital can be classified according to two broad approaches: the quantitative perspective and the qualitative perspective. The former includes studies based on measuring the formal education received, the cost of investment in human capital and the wage differences originating from distinct educational levels. The indicators constructed on the basis of measurements of formal education have been those most commonly used in the literature, for at least three reasons: due to considering that formal education is the fundamental source of human capital acquisition; due to observing a strong correlation between this and other acquisition paths; and due to the existence of comparable international data.

With regard to the cost of investment in training, it is understood that this offers an approximation of the value of human capital possessed. It is assumed that the greater the cost of acquisition the greater will be the training it provides. Finally, indicators based on wage differentials quantify productivity divergences originating in the different levels of education completed, according to the remuneration received by a representative or numeraire worker.

In turn, the qualitative perspective emphasises the differences in the quality of the training received, which will be reflected in qualifications. To proxy the qualifications really possessed, this perspective employs indicators of educational inputs and, principally, the results from international tests of knowledge.

Table 1 synthesizes the principal studies, methodological contributions and sources surrounding the measurement of human capital.

Table 1. Human capital measurement

Perspective	Indicator type	Studies	Field of application
Quantitative	Indicators based on formal education received	Psacharopoulos and Arriagada (1986, 1992)	Field: 99 countries. Period: 1960 to 1983.
		Kyriacu (1991)	Field: 113 countries. Period: 1965 to 1985.
		Lau et al. (1991)	Field: 58 countries. Period: 1965 to 1985.
		Nehru et al. (1995)	Field: 85 countries. Period: 1960 to 1987.
		Barro and Lee (1993, 1996 y 2001)	Field: 126 countries. Period: 1960 to 2000.
		De la Fuente and Domenech (2006)	Field: 21 OECD countries. Period: 1960 to 1995.
		Cohen and Soto (2007)	Field: 95 countries. Period: 1960 a 2000.
		Lutz et al. (2007)	Field: 120 countries. Period: 1970 to 2000.
	Cost-based approach	Shultz (1961)	Field: United States. Period: 1900 to 1956.
		Kendrick (1976)	Field: United States. Period: 1929 to 1969.
		Eisner (1985)	Field: United States. Period: 1945 to 1981.
	Income-based approach	Jorgenson and Fraumeni (1989, 1992)	Field: United States. Period: 1949 to 1984
		Mulligan and Sala-i-Martin (1997)	Field: United States. Period: 1940 to 1990.
		Jorgenson et al. (1987)	Field: United States. Period: 1948-1979
		Bureau of Labor Statistics (1993)	Field: United Staes Period: 1948-1990
		Timmer et al. (2007)	Field: United States and EU27 Period: 1970-2004

		Scarpetta and Tressel (2002)	Field: 18 OECD countries Period: 1995.
Qualitative	Indicators based on academic results	International Adult Literacy Survey	Field: 29 OECD countries. Period: 1994 a 1998.
		International Association for the Evaluation of Educational Achievement (IEA) - International Mathematics Study - International Science Study - International Reading Study - Progress in International Reading Literacy (PIRLS) - Trends in International Mathematics and Science Study (TIMSS)	Field: between 11 and 45 countries. Period: distinct years between 1964 and 2011
		Programme for International Student Assessment (PISA)	Field: distinct countries, up to a total of 65 countries Period: 2000 to 2012
		Hanushek and Kimko (2000)	Field: 87 countries. Period: 1 average observation between 1964 and 1991.
		Hanushek and Wößmann (2012)	Field: 77 countries. Period: 1 average observation between 1964 and 2003.

2.2. Proposal for a new human capital indicator

In recent years new international databases have appeared, containing varia-bles to elaborate more sophisticated indicators. An appropriate strategy for the construction of new indicators, richer and more solvent than their antecedents, is based on the use of techniques which combine the two principal approaches to human capital measurement. This is the objective of the present study, which makes a methodological proposal in order to construct a human capital indica-tor which facilitates international comparisons, supplies more nuances and pro-vides more information than traditional indicators. The methodological proposal for the construction of the indicator reflects three factors:

i. Educational levels achieved.
ii. Differences in educational quality and knowledge.
iii. Differences in productivity and wages, based on the education possessed and discounting other individual questions except for educational factors, which condition wages, specifically gender and age.[1]

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[1] Denison (1967) signalled that the heterogeneity of the labour force becomes clear in the wage differences which may result from hours worked, gender and age, and weighted the labour force on the basis of existing wage differences, in accordance with the characteristics mentioned. The present study takes into account the hours worked at each educational level and subtracts the effects on the remuneration of the gender and age variables. These factors condition, at all educational levels, the remuneration received. See, on this question, Fitzenberger and Wunderlich (2002) or OECD (2010, indicator A10). In the majority of countries, women continue to earn, on average, less than men. In turn, the level of remuneration is conditioned by age, since this determines both accumulated experience, the bargaining power of workers and the wage entitlements acquired within companies.

Thus, S will denote the human capital stock of each country, calculated formally as:

$$S = \sum_i \sum_g \frac{w_{i,g}}{w_{1,g}} l_{i,g} Q \qquad (1)$$

Country and time subscripts are excluded for simplicity in (1):

$W_{i,g}$ is the average hourly compensation received by a worker with a specific level of qualification i, with $i = 1,...,N$, and for a group g of workers, of similar gender and age characteristics, with $g = 1,...,M$.

$W_{1,g}$ is the average hourly compensation received by a numeraire worker, with a basic educational level within each group g of workers of similar characteristics of gender and age.

$i_{i,g}$ is the total number of hours worked by workers who have reached each educational level i for each group g of workers, with similar gender and age characteristics.

Q is the level of knowledge possessed by numeraire workers; this is the basic or representative educational level, measured by the scores obtained in international tests of knowledge.

Consequently, the indicator proposed uses the divergences in remuneration among workers with different levels of education but identical gender and age, to quantify their differences in productivity. These productivity differences are used to weight the total hours worked in each economy, on the basis of the number of hours completed by workers at each level of training. Thus, the human capital stock is obtained in numeraire hours of work, according to the basic educational level, which is corrected by the differences in educational quality, at that level, among the distinct countries.

The triple approach for human capital stock measurement in the international context requires adopting a more complete methodology than that of other proposals. Thus, increases in this stock may be the result of:

• Increases in the number of hours worked by the labour force belonging to each educational level.
• Increases in the proportion of workers who have received higher education.
• Improvements in the productivity of workers with higher educational levels, in comparison with workers with a basic educational level.
• Improvements in the quality of education, captured through the results of international tests of knowledge.

In addition to providing greater information, the indicator has other advantages compared with traditional measures. The latter, being based exclusively on the quantification of the academic education received, adopt somewhat unrealistic hypotheses, as underlined by Mulligan and Sala-i-Martin (2000). Thus, it is difficult to believe that each year of schooling has exactly the same value

and affects a worker's productivity in the same way, independently of his or her educational level.[2] It is also difficult to accept that workers are perfectly substitutive, either if different educational levels are contemplated or if international comparisons are made. In response to this, the indicator proposed presents an initial advantage, since as it takes wage differences into account, it permits productivity divergences to be recognised (on the basis of the particularities of each economy) among individuals with the same educational level, among countries and among years.

Secondly, the use of the indicator proposed avoids the use of an arbitrary depreciation rate, since this rate can be explicitly observed through the development, for each educational level, of earnings throughout working life.

Thirdly, the correction made by the numeraire or representative worker permits the exclusion of productivity differences among countries, caused by the different endowments of physical capital and technology, since these factors are common to all workers. Furthermore, it incorporates wage correction by groups of workers with similar characteristics which are not education-related.

Fourthly, the methodology proposed also incorporates innovations compared to other studies which use wage differences (the income-based approach) to estimate human capital. Jorgenson *et al.* (1987) build an index of labour services in the United States assuming that aggregate labour services are a translog function of the services of individual types based on gender, age, education, employment status and occupation of workers. It is assumed that the flow of labour services for each labour type is proportional to hours worked and workers are paid according to their marginal productivities measured by labour compensation.[3] From 1993, the US Bureau of Labor Statistics uses a small number of differentiating characteristics chosen in order to minimize the correlation between them.[4] A Törnqvist index is also used to combine the growth rates of the hours of each type of worker into a composite growth rate of labour input. The hours of each group of workers classified by education, work experience and gender are weighted by their share of labour compensation. Hourly earnings for each type of worker are based on econometrically estimated hourly earnings functions based on the work of Mincer (1974). Recently, the EU KLEMS database, following Jorgenson *et al.* (1987)[5] has calculated an index of labour services for European countries. Unlike this methodo-

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[2] As Aghion and Howitt (2009) state, the number of education years variable includes an extra year of primary education in the same way as an extra year in a doctoral program and, consequently, this variable cannot reliably report on the effect of human capital stock on innovation and imitation processes and, indirectly, on the growth of PTF.

[3] Jorgenson (1995: 23-27), offers a comparison of his methodology and that of the previous approaches of the Bureau of Labor Statistics (1983), Denison (1985) and Kendrick (1983). He also quantifies the biases that arise from using un weighted measures of labour inputs and the exaggerated role of productivity change that is obtained as consequence.

[4] Using different characteristics correlated, the resulting labour composition measure reflects both the direct contributions of these characteristics to output growth and the interaction effects between them.

[5] Updated and summarized in Jorgenson (1995).

logy and that proposed by Mulligan and Sala-i-Martin (1997), which quantify wage differences for the United States by assuming that numeraire workers are perfectly replaceable, whatever their place of residence, the human capital indicator that we propose recognises the existence of differences among numeraire workers, based on the differences in the educational quality of each country. Furthermore, the proposed indicator is not an index but a new measure of international homogeneous labour hours that has taken two kinds of heterogeneity into account: differences in wages based on education, age and gender (as in the EU KLEMS database) and differences in skills and knowledge. To our knowledge, there has not been any proposal combining these two sources of heterogeneity in labour input to estimate a human capital variable. In addition, the methodology used by Mulligan and Sala-i-Martin (1997), based on wage differentials, is circumscribed to the United States and has no international perspective.

Fifthly, the indicator proposed considers that educational levels among countries are not homogeneous. Thus, divergences in the quality of educational systems become differences in knowledge and abilities and, consequently, productivity.

Sixthly, the calculation of human capital stock on the basis of the total hours worked in the economy demands greater quantitative precision compared with other indicators based on a unipersonal perspective, or which, from aggregate data, use the population as a whole, potentially active workers or the number of persons in work.

Seventhly, it implies that there are no limits to human capital stock increases. Thus, there exists a limit to the total number of hours worked an economy can assume, and also a limit to the maximum number of years which citizens can be educated, given the logical restrictions of an economic or strictly natural type. All in all, and as Wößmann (2003) states, the proposed indicator considers that improvements in the quality of education guarantee that the stock of human capital can increase indefinitely.

Finally, the proposed indicator groups different measures of human capital, quantitative and qualitative, in a single easy to interpret indicator: homogeneous hours worked. This indicator is more intuitive than other indicators, provides more information and permits more precise international comparisons. Condensing all the information in a single indicator represents an advantage when capturing the different nuances of the concept of human capital, interpreting it and using it to test the theories of growth.

Nevertheless, the methodology proposed presents certain limitations, currently insoluble due to the non-availability of data. Firstly, it must be underlined that, despite correction for gender and age, there exist other elements, apart from educational levels, which determine wage differences. Among these are to be found, for example, negotiating power, trade union organisation or the sectoral structure of the economy.

Furthermore, indexation based on workers with lower educational levels does not permit the capture of improvements in the productivity of numeraire

workers, but instead only the differences in productivity between them and those with greater qualifications.

Lastly, it must be emphasised that the design itself of international knowledge tests (the results obtained in each year in which the tests are performed are standardised around a common average) and the shortage of comparable data hinder the use of the indicator in historical perspective.

The measurement error (ME) in human capital variables may come from the use of partial and inaccurate proxies to the concept and from data recording errors. The proposed indicator might reduce the potential ME because it uses more elements than the mere quantity of education and because the EU KLEMS database ensures access to rich, precise and homogenous international data. The proxies used in empirical work, often schooling variables, enrolment ratios and years of schooling, are frequently employed for availability reasons and not for their conceptual adequacy according to the theory of human capital. Hence, many observations are often missing and data quality is questionable, largely due to the presence of repetition and dropout rates. Furthermore, to assume that education levels are analogous, regardless of the country where they were acquired, is unrealistic. As a result of all this, differences in country rankings across data sets are very significant, which shows that such indicators are poor proxies for human capital.

Although a omitted variables bias might be lower with the proposed indicator, the ME still exists since no composite indicator can capture the entire concept. On the one hand, the correspondence between academic success and productivity in the labour market is questionable. On the other hand, it must be borne in mind that the human capital really used in each economy depends on various factors like the structure of labour markets (e.g. access of women), leisure preferences, family behaviour or the stock of technology. With the proposed indicator, we account not for the human capital available in each country, but for its use in the labour market, which depends on the above factors. Therefore, the information derived from it and the relationships established with other indicators should be interpreted properly and take into account the fact that the indicator refers to the productive human capital.

In addition, there is a time gap between the moment at which the school tests were carried out and the incorporation of the students into the labour market. The fact that the test scores cover a long period, from the 1960s to the 2000s, suggests that, on average, the scores were achieved by numeraire workers who were working in the years for which the indicator was calculated. However, this remains a mere approximation since the years in which the tests were carried out vary from country to country, as does the age structure of their labour markets. It is also difficult to accept that the data about the tests constitute an accurate indicator of human capital. The problem is the difficulty involved in implementing this type of test internationally and in designing questions that are uniform, understandable and relevant to students of a large number of countries. It also has to be pointed out that the test scores may vary

depending on specific conditions and circumstances that affect the students' performance. Consequently, the same students may get different scores depending on when the test is done or on the structure of the questions. Moreover, there are skills and values that the tests may not show but that determine their productivity in the labour market; e.g. other formal subjects being taught in schools, cognitive skills learned at higher education levels such as university, team working skills or fellowship and honesty, among others.

Finally, we have to point out that our indicator might present the same ME data as the original data sources. Despite the aggregation and calibration effort in constructing the data about cognitive skills that we use, and even though the different international test scores show a high correlation, the fact that the data come from various sources, countries and years can lead to problems of homogeneity.

Likewise, the EU KLEMS primary variables used in our proposed human capital variable have been carefully elaborated, as EU KLEMS (2009) and O'Mahony and Timmer (2009) explain. Nevertheless, some biases could be related to the following issues:

• National Accounts are the major starting point for constructing the series of employment and hours, using other complementary country sources, such as national labour force surveys, given in the EU KLEMS Sources document. Care has been taken to create series which are time consistent, as most employment surveys are not designed to track developments over time and breaks in methodology or coverage frequently occur.

• Labour compensation data include wages and salaries but also all other costs of employing labour which are paid by the employer. These employers' social contributions must be included to correctly measure marginal products. Furthermore, data on earnings of self-employed workers are included assuming that the compensation per hour of the self-employed equals the compensation per hour of the employees.

• The definitions of high, medium and low education are consistent over time for each country, but might differ across countries. Some sub-categories with relatively high wages may be classified as high skill in one country and medium skill in another.

Therefore, comparisons of skill shares across countries should be interpreted with caution; in addition, labour composition measures tend to be somewhat volatile over time since the underlying surveys are not designed to generate time series (O'Mahony and Timmer, 2009).

The proposed methodology has been used to calculate the human capital stock in 15 developed countries between 1980 and 2005. The formal description of the variables employed, their sources, the descriptive statistics and a comparison between several proxies of human capital stock and the indicator

proposed are provided in Annex 1. Annex 2 contains the values of the human capital indicator proposed.

3. Causality between the human capital indicator proposed and GDP growth and innovation

3.1. Data

The sample comprises 15 OECD countries: Australia, Austria, Belgium, Czech Rep., Denmark, Finland, Germany, Hungary, Japan, the Netherlands, the Republic of Korea, Slovenia, Spain, the United Kingdom and the United States. An unbalanced panel is used (since data were not available for all the variables, years and economies) covering the period 1980-2005[6].

3.2. Methodology

Once the human capital indicator is proposed, our objective is to test if this indicator has better empirical properties than traditional indicators. If this is the case, we expect that this indicator will be able to demonstrate a greater explanatory power in economic growth models. In these models, two are the main variables with which human capital is related and that human capital should be able to explain: GDP and innovation. Therefore, to check the explanatory power of the human capital indicator with respect to the traditional ones, we are going to implement a series of Granger causality tests that will prove the relationship between human capital and GDP as well as human capital and innovation.

Cheng and Hsu (1997), In and Doucouliagos (1997), Asteriou and Agiomirgianakis (2001), Al-Yosif (2008), Ljungberg and Nilsson (2009) and Omojimite (2010), among many others, have examined the relationship between human capital and GDP, applying the Granger causality tests.

The basic idea of the methodology proposed by Granger (1969) is to test whether lagged values of one variable significantly affect the contemporary values of another. It should be noted that the initial formulation by Granger used the levels of variables rather than the differences. Following the development of unit root testing and cointegration for non-stationary variables, the differences will be used to avoid problems of spurious regression[7]. More specifically, in order to test whether GDP Granger causes human capital the following equation is estimated:

$$\Delta hc_t = \sum_{i=1}^{m} \beta_i \Delta hc_{t-i} + \sum_{i=1}^{n} \lambda_i \Delta pat_{t-i} + v_t \qquad (2)$$

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[6] Although Granger causality was initially examined using time series data, for several years it has also been evaluated with samples which provide information on various individuals over time (panel data).
[7] See Chontanawat *et al.* (2008).

where $hc_t = ln(HC_t)$; $gdp_t = ln(GDP_t)$; HC_t is the human capital indicator; GPD_t the gross domestic product; i is the lag length and Δ is the first difference operator. The presence of Granger causality depends on the significance of the Δgdp_t term in Equation (2); *GDP* Granger causes human capital if the current value of human capital is predicted better including the past values of *GDP* than excluding them.

Alternatively, to test whether human capital Granger causes GDP the following equation can be estimated:

$$\Delta gdp_t = \sum_{i=1}^{m} \alpha_i \, \Delta gdp_{t-i} + \sum_{i=1}^{n} \varphi_i \Delta hc_{t-i} + v_t \tag{3}$$

The hypotheses tested are that the coefficients of the regression of GDP on human capital and human capital on GDP are null for the support variable; in other words, GDP does not provide information to explain human capital and human capital does not provide information to explain GDP[8]. If the value of the reference statistic *F* exceeds the tabulated value the null hypothesis is rejected and, therefore, it is accepted that GDP causes human capital or vice versa.

Granger and Newbold (1974) concluded that the Granger causality test initially proposed by Granger (1969) led to spurious results if the time series data set is non-stationary. Therefore, before applying the Granger causality test it is necessary to check if the variables are non-stationary[9].

3.3. Causality between the human capital indicator proposed and economic growth

The results of the panel unit root test for human capital indicators and GDP, using the Augment Dickey-Fuller test (ADF test) and the Phillips-Perron test (PP test) are reported in Table 2. Both tests indicate that the null hypothesis can be rejected and that, consequently, variation of the human capital indicators and GDP growth are not I(1). Since cross-sectional dependence may be present in the sample, Pesaran (2007) CIPS tests were also applied, using the STATA *multipurt* command developed by Eberhardt (2011). The results are also

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[8] Lütkepohl (1993: 41) states the term "causality" suggests a cause and effect relationship between two sets of variables. Such an interpretation is problematic with respect to instantaneous causality. The direction of causation must be obtained from further knowledge on the relationship between the variables. Such knowledge may exist in the form of an economic theory. The lack of a Granger-causal relationship from one group of variables to the remaining variables cannot necessarily be interpreted as lack of a cause and effect of relationship. For this reason, some authors suggest using "precedence" instead of "Granger causality", since we are testing whether a variable X precedes a variable Y.

[9] If both variables were I(1), it would be necessary to test for the cointegration and if cointegration was accepted, then a long run relationship would exist and there should be causality for at least one direction. In this case, an error correction model approach could be applied to the Granger causality test.

included in Table 2. Note that the null hypothesis that the series are I(1) can be rejected. Then, and according to Chontanawat *et al.* (2008), the Granger causality test can be performed using these variables.

Table 2. Panel unit root test.

Variable	ADF. Exogenous variables: Individual effects	ADF. Exogenous variables: Individual effects, individual linear trends	PP. Exogenous variables: Individual effects	PP. Exogenous variables: Individual effects, individual linear trends	CIPS. Without trend*	CIPS. with trend*
Δ Human capital indicator proposed	110.843	81.055	109.036	87.000	-4.341	-2.000
Δ Average schooling years in the total population	457.166	253.229	2704.87	3298.34	-9.293	-7.145
Δ Gross enrolment rate, secondary, total	82.378	62.137	74.971	65.774	-8.850	-6.875
Δ GDP	97.061	84.735	101.062	89.183	-2.595	-4.135
Δ patents granted	320.580	542.943	387.468	1889.85	-10.707	-9.370

Notes: Δ means annual growth of the variable. Automatic lag length selection based on AIC and Bartlett kernel for ADF test and PP test. *Zt-bar values for CIPS test.

The results, listed in Table 3, show firstly that GDP Granger causes the human capital indicator proposed (with one, two or three lags)[10]. Secondly, the human capital indicator proposed Granger causes GDP[11]. However, GDP does not Granger cause the "average schooling years in the total population" varia-

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[10] According to Chontanawat *et al.* (2008) the maximum lag is set at about 20% of the total observations, so that for countries with data covering the 1995-2005 period, the maximum lag is 2. As the result of causality could be sensitive to the lag length adopted in models, Table 3 and 4 contain the results with one, two and three lags. Dietrich (2012) also presents results for one, two and three lags.

[11] These results, for instance, are similar to those obtained by Cheng and Hsu (1997) for Japan and by In and Doucouliagos (1997) for the United States.

ble or the "gross enrolment rate, secondary total" variable. "Average schooling years in total population" and "gross enrolment rate, secondary total" do not Granger cause GDP.

In sum, it can be stressed that when human capital is quantified using an indicator as the one suggested, it is caused by GDP; in turn, GDP causes human capital. By contrast, when human capital is measured by other indicators causality relationships with GDP are not always found.

Table 3. Granger causality test. Human capital indicators and GDP growth.

Null hypothesis	Number of lags	Observations	F-statistic	Conclusion
Δ Human capital indicator proposed does not Granger causes GDP growth	1	302	7.982	Can be rejected
GDP growth does not Granger causes Δ human capital indicator proposed	1	302	129.860	Can be rejected
Δ Human capital indicator proposed does not Granger causes GDP growth	2	287	8.074	Can be rejected
GDP growth does not Granger causes Δ human capital indicator proposed	2	287	76.565	Can be rejected
Δ Human capital indicator proposed does not Granger causes GDP growth	3	272	8.941	Can be rejected
GDP growth does not Granger causes Δ human capital indicator proposed	3	272	63.744	Can be rejected
Δ Average schooling years in the total population does not Granger causes GDP growth	1	314	0.117	Cannot be rejected
GDP growth does not Granger causes Δ average schooling years in the total population	1	314	1.412	Cannot be rejected
Δ Average schooling years in the total population does not Granger causes GDP growth	2	299	0.211	Cannot be rejected

GDP growth does not Granger causes Δ average schooling years in the total population	2	299	0.956	Cannot be rejected
Δ Average schooling years in the total population does not Granger causes GDP growth	3	284	0.671	Cannot be rejected
GDP growth does not Granger causes Δ average schooling years in the total population	3	284	0.293	Cannot be rejected
Δ Gross enrolment rate, secondary, total does not Granger causes GDP growth	1	196	0.120	Cannot be rejected
GDP growth does not Granger causes Δ gross enrolment rate, secondary, total	1	196	0.441	Cannot be rejected
Δ Gross enrolment rate, secondary, total does not Granger causes GDP growth	2	170	0.204	Cannot be rejected
GDP growth does not Granger causes Δ gross enrolment rate, secondary, total	2	170	0.088	Cannot be rejected
Δ Gross enrolment rate, secondary, total does not Granger causes GDP growth	3	145	0.317	Cannot be rejected
GDP growth does not Granger causes Δ gross enrolment rate, secondary, total	3	145	0.063	Cannot be rejected

Notes: Δ means annual growth of the variable.

In this context, it can be mentioned that many papers concluded than causality only ran in one sense using non suitable measures of human capital. For instance, according to Asterius (2001) in Greece causality ran from human capital (measured by formal education) to GDP, with the exception of higher education for which there was a reverse causation. Al-Yousif (2008) concluded that in the six Middle East Gulf Cooperation Council economies causality between human capital (proxied by education spending) and GDP varied by countries and human capital measures. Ljungberg and Nilsson (2009), with data based on enrolment in different forms of education, concluded that human capital was a causal factor in economic growth in Sweden after industrialization. However, after 1975, the growth of human capital has not been able to match the demands of the Third Industrial Revolution. Lastly, Omojimite (2010) concluded that public expenditures on education Granger caused economic growth in Nigeria during the 1980-2005 period, but there was no reverse causality.

3.4. Causality between the human indicator proposed and innovation

As indicated above, Nelson and Phelps (1966) propose that a more qualified labour force facilitates the adoption of new technologies by companies. The theories of second generation endogenous growth —advanced by Romer (1990), Aghion and Howitt (1992, 1998) and Acemoglu (1996, 1998)— agree with this perspective, and consider that human capital directly raises the growth of total factor productivity (TFP) through the generation of innovation.

More recent studies —such as those by Vandenbussche *et al*. (2006), Aghion *et al*. (2006) and Aghion and Durlauf (2009)— consider that the closer countries are to the technological frontier, the more important innovation processes will be for their economic growth and, consequently, investment efforts will be more significant at higher education levels, strongly linked to the development of domestic innovations. In turn, the further countries are from the technological frontier, the more important imitation processes will be for them and, as a consequence, it will be more advisable to invest in more basic education levels, linked to the capture and use of foreign technologies.

Suying *et al*. (1997), Feng and Chen (2010) and Han and Meng (2010), among others, have examined the relationship between human capital and innovation, applying the Granger causality tests.

In this paper, the relation between human capital indicators and innovation, measured by the number of patents granted[12], has been tested estimating the following Granger equations:

$$\Delta hc_t = \sum_{i=1}^{m} \beta_i \Delta hc_{t-i} + \sum_{i=1}^{n} \lambda_i \Delta pat_{t-i} + \nu_t \tag{4}$$

$$\Delta pat_t = \sum_{i=1}^{m} \alpha_i \Delta pat_{t-i} + \sum_{i=1}^{n} \varphi_i \Delta hc_{t-i} + \nu_t \tag{5}$$

where $hc_t = ln(HC_t)$; $pat_t = ln(pat_t)$; HC_t is the human capital indicator; pat_t the number of patents granted; *i* is the lag length and Δ is the first difference operator.

Table 4 reflects that when human capital is measured with the indicator proposed, it maintains a relation of causality with the technological variable. In this case, causality is bidirectional: human capital causes innovation and innovation causes human capital (in the sense of Granger). By contrast, when

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[12] As more valuable ideas get to be patented, patents are considered a leading indicator of innovation. See, for that purpose, Jones (2005). However, they are imperfect approximations to a variable as complex as innovation.

human capital is measured by average schooling years in the total population or by gross enrolment rate in secondary education does not cause, in the sense of Granger, innovation, as measured by patents granted. At the same time, the innovation variable does not Granger cause human capital when this variable is proxied with these two traditional indicators.

In this context, it can be mentioned that Suying *et al.* (2011) concluded that human capital (measured as years of education law) played a significant role in promoting China's scientific and technological innovation (proxied by domestic patent applications) during the 1996-2008 period. The reverse causality is not found. Feng and Chen (2010) obtained a similar result: human capital (proxied by the number of college students) Granger caused patents (a measure of national innovation capacity) in China from 1986 to 2008. However, patents did not Granger cause human capital.

Table 4. Granger causality test. Human capital indicators and patents granted.

Null hypothesis	Number of lags	Observations	F -statistic	Conclusion
Δ Human capital indicator proposed does not Granger cause Δ patents	1	302	2.091	Cannot be rejected
Δ Patents does not Granger cause Δ human capital indicator proposed	1	302	9.782	Can be rejected
Δ Human capital indicator proposed does not Granger cause Δ patents	2	287	3.296	Can be rejected
Δ Patents does not Granger cause Δ human capital indicator proposed	2	287	5.974	Can be rejected
Δ Human capital indicator proposed does not Granger cause Δ patents	3	272	2.125	Can be rejected
Δ Patents does not Granger cause Δ human capital indicator proposed	3	272	24.689	Can be rejected
Δ Average schooling years in the total population does not Granger cause Δ patents	1	307	0.019	Cannot be rejected
Δ Patents does not Granger cause Δ average schooling years in the total population	1	307	0.132	Cannot be rejected

Δ Average schooling years in the total population does not Granger cause Δ patents	2	292	0.062	Cannot be rejected
Δ Patents does not Granger cause Δ average schooling years in the total population	2	292	0.060	Cannot be rejected
Δ Average schooling years in the total population does not Granger cause Δ patents	3	277	0.158	Cannot be rejected
Δ Patents does not Granger cause Δ average schooling years in the total population	3	277	0.085	Cannot be rejected
Δ Gross enrolment rate, secondary, total does not Granger cause Δ patents	1	189	0.068	Cannot be rejected
Δ Patents does not Granger cause Δ gross enrolment rate, secondary, total	1	189	0.043	Cannot be rejected
Δ Gross enrolment rate, secondary, total does not Granger cause Δ patents	2	163	0.021	Cannot be rejected
Δ Patents does not Granger cause Δ gross enrolment rate, secondary, total	2	163	0.016	Cannot be rejected
Δ Gross enrolment rate, secondary, total does not Granger cause Δ patents	3	138	0.014	Cannot be rejected
Δ Patents does not Granger cause Δ gross enrolment rate, secondary, total	3	138	0.026	Cannot be rejected

Notes: Δ means annual growth of the variable.

As to why traditional indicators, enrolment rates and schooling years do not seem to capture the relationship between human capital and innovation, the measurement errors that they incorporate are a determining factor. The enrolment rates are mere flow variables, used as a proxy for the stock variable human capital. Moreover, empirical studies often use gross enrolment rates rather than net, because of their availability. This leads to problems of interpretation due to mismatches in the age at which students begin the courses and because of the presence of dropout and repetition rates. Furthermore, although, in principle, the enrolment rates can refer to any academic level, there are difficulties in using this indicator for college students. Some examples are the difficulties in choosing an appropriate

age group or the differences in the duration of the curricula in this type of education.

The use of schooling years represents a different problem: assuming that each year of college is just as productive as each year at lower educational levels is not realistic. Besides, both the indicators of schooling have a time lag with respect to technology production processes because they measure investment decisions that took place in many cases more than a decade ago. Additionally, they only take into account the potential skills acquired throughout schooling, ignoring the student´s innate skills and other ways of acquiring human capital, like the instruction that individuals receive in their family and their closest social environment and all types of knowledge gained through self-teaching. Finally, these indicators provide information about the quantity of education across the population spectrum, not about the employed population. Therefore, this is *potential* (and not really employed) human capital.

Dealing with these issues, the new indicator provides a perspective oriented to the real productive capacity of the stock of human capital embodied in the labour force: working hours corrected for differences in knowledge and productivity among individuals, countries and years. This brings the indicator closer to the concept of human capital, which assumes that the skills must be economically productive (OECD 1996, 1999). The increased accuracy of the indicator and the presumed reduction in the measurement error, explained in Section 2.2, means that the indicator better captures the relationship between the input and output technology variables.

Although the sample used is limited to OECD countries, the results suggest, on the one hand, that, in order to explain GDP growth, it is convenient to improve the measurement of human capital by introducing its qualitative dimensions, the abilities and the knowledge of workers, as these better capture the relations between human capital and economic growth on the other hand, this relation must be taken into account when proposing and estimating models of economic growth.

4. Conclusions

Empirical studies which attempt to evaluate the importance of human capital for growth use increasingly complex models and techniques. Recently, interest has centred on analysing the connection existing between human capital and the development of innovation, as researchers consider that innovation is one of the most important effects of human capital on productivity and growth. There exist serious limitations to empirical research, due to the deficiencies and limited information of traditional human capital indicators, such as average years of education or enrolment.

In this sense, the human capital indicator presented here has been calculated taking into account, on the one hand, the quantitative dimension of human capital, by calculating hours worked corrected by productivity, on the basis

of educational levels; on the other, it assesses the qualitative aspect, namely hours worked corrected by the differences in existing abilities and knowledge among the OECD countries. Thus, the new indicator provides more information, permits human capital stock to be measured more deeply and facilitates the observation of differences in the training of the labour force among OECD countries; it also permits analysis of the causes of these differences.

This piece of research has demonstrated, using Granger tests of statistical causality that, when human capital is proxied by the human capital indicator proposed, it Granger causes GDP growth. At the same time, GDP Granger causes the human capital indicator proposed. However, when the variables *gross enrolment rate in secondary* and *average schooling years in the total population* are used there is not a causality running from human capital to GDP. Last, when human capital is proxied by the traditional indicators causality from GDP to these variables is not found.

Analysing the relationship between the human capital indicators and innovation, only the human capital indicator proposed Granger causes patents and vice versa. The other two human capital indicators do not maintain relationships of causality with patents. In summary, and in accordance with the Granger test, the innovation capacity appears to be compatible with the new theories of endogenous growth, which argue that human capital causes the growth of TFP.

The results of the present study show, on the one hand, that to understand the processes of innovation and economic growth more precisely, it is necessary to elaborate more sophisticated indicators that can estimate human capital in an unbiased manner and reduce the potential omitted variables bias; on the other hand, it has been made evident that human and technological capital can show a relationship of complementarity. Therefore, the development of accurate indicators, which quantify the skills and productivity differences that exist in the labour market, should constitute a key objective of economic policy. Indicators based on a multidimensional perspective, such as the one presented in this paper, have proved to be more effective in explaining how educational outcomes relate to economic outcomes.

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Annex 1. Variables and sources employed

The sample comprises the following OECD countries: Australia, Austria, Belgium, Czech Republic, Denmark, Finland, Germany, Hungary, Japan, the Netherlands, the Republic of Korea, Slovenia, Spain, the United Kingdom and the United States. The data correspond to the period 1980-2005, although it is an unbalanced panel, since there is no information for all the variables and years of the 15 countries.

Variables proxying human capital

The data for the "average schooling years in the total population" variable were taken from Barro and Lee (2001, 2011) and interpolated for the years that are not calculated. Those for the "Gross enrolment rate (%), secondary, total" variable are extracted from the *World Bank Development Indicators Online*.

To calculate the human capital indicator proposed, the information corresponding to hours worked and salaries comes from the EU KLEMS Growth and Productivity Accounts database, financially supported by the European Commission[13]. The database distinguishes between three educational levels (low-skilled, medium-skilled and high-skilled)[14] and provides information concerning salaries and hours worked, on the basis of these qualifications, for men and women in three age groups: 15 to 29, 30 to 49 and over 50. Consequently, examination has been made of six categories or groups with similar characteristics of gender and age, for each of the three levels of education. Formally, in accordance with the EU KLEMS variables, the calculation of the human capital indicator described above takes the following expression, in which country and time subscripts are eliminated for simplicity:

(A.1)

$$S = \sum_{i} \sum_{g} \frac{w_{i,g}}{w_{1,g}} l_{i,g} Q = \sum_{i} \sum_{g} \frac{LAB_{i,g}/H_{i,g}}{LAB_{1,g}/H_{1,g}} H_{i,g} Q$$

In this expression:

$LAB_{i,g}$ is labour compensation for persons engaged with skill level i, with $i = 1,...,N$, and for a group g of workers with similar characteristics of gender and age, with $g = 1,...,M$.

$LAB_{l,g}$ is the labour compensation for low-skilled persons engaged within each group g of workers with similar characteristics of gender and age.

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[13] See Timmer *et al.* (2008) and EU KLEMS (2009).

[14] A detailed description of the academic years completed within each educational level and for each country can be consulted in Table 5.3. of Timmer *et al.* (2007) In general terms, the basic level *(low-skilled)* corresponds to primary and basic secondary education, the intermediate level (*medium-skilled*) to upper secondary and non-university post-secondary education, and the upper level (*high-skilled*) to university studies.

$H_{i,g}$ are the hours worked by engaged persons within each group g of workers with similar characteristics of gender and age.

$H_{i,g}$ are the hours worked by low-skilled persons engaged within each group g of workers with similar characteristics of gender and age.

Q is the level of knowledge possessed by workers with a basic or numeraire education, measured by the results obtained in international tests of knowledge. The data employed come from Hanushek and Wöβmann (2012). These data use the information of all available international tests between 1964 and 2003 and put performance on a common scale in order to facilitate comparisons. Thus, the information used for the indicator covers all that part of the population that made the test in primary and secondary levels between 1964 and 2003, which constitutes a large proportion of the employed population. Q is obtained by relating the average test score achieved in the international tests by students in each country with the results obtained by the country with the students who get the minimum score, through the expression[15]: $Q = \frac{Q_{country}}{\min(Q)}$, which permits the calculation of the variable, with

Hanushek and Wöβmann (2012) data.

Variable proxying GDP

GDP, PPP (constant 2005 international USA dollar). The source is the *World Development Indicators* of the World Bank.

Variable proxying innovation

The number of patents granted as distributed by year of patent grant were taken from the U.S. Patent and Trademark Office (elaborated by Patent Technology Monitoring Team).

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[15] This is one of the most common normalisation procedures to apply. For a full analysis and an example of its application to human capital indicators see OECD (2008a, c.5). Normalizing with the minimum value in the tests implies a methodological correspondence with the adoption of somebody with lower qualifications as a numeraire worker. Being OECD countries, variations in academic performance among the sample was not large per se, and this normalization involves increasing the range of variation, giving greater weight to countries that get better scores. As robustness test, we carried out our empirical estimations with other common normalisation procedures, specifically the mean and maximum ratios, and we did not find any relevant variation in our results.

Table A1: Descriptive statistics

Variable	Minimum	Maximum	Average	Number of obser- vations
Human capital indicator pro- posed	2,477.60	520,603.80	66,775.57	332
Average schoo- ling years in the total population	5.93	12.91	9.88	360
Gross enrolment rate, secondary, total	62	162	104.87	276
GDP, PPP (constant 2005 international $)	28,316,290,529	13,144,400,000,000	1,352,141,202,296	400
Patents granted	1	89,823	4,160.14	393

Figures A1 to A3 show the relationship between three proxies of the stock of human capital (average years of schooling, tertiary attainment for age group 25-64 and the number of researchers per thousand employed, full-time equivalent) and the human capital indicator proposed.

Figure a1. Relationship between average years of schooling and the human capital indicator proposed

$$y = 8E\text{-}06x + 8.5406$$
$$R^2 = 0.33$$
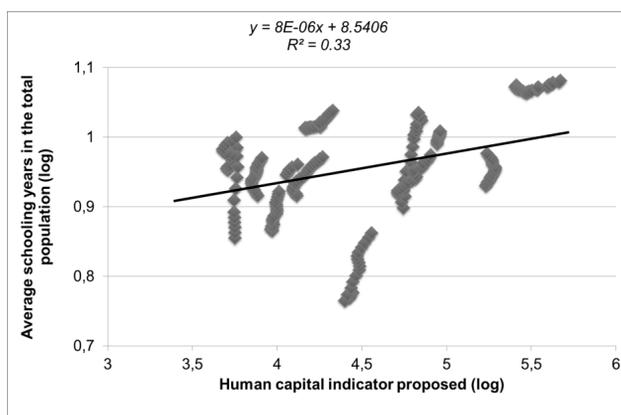
Being the explaining variable significant at a level of 1%, with a t-ratio of 10.55.
Source: Own elaboration data and Barro and Lee (2001, 2011).

Figure a2. Relationship between tertiary attainment for age group 25-64 and the human capital indicator proposed
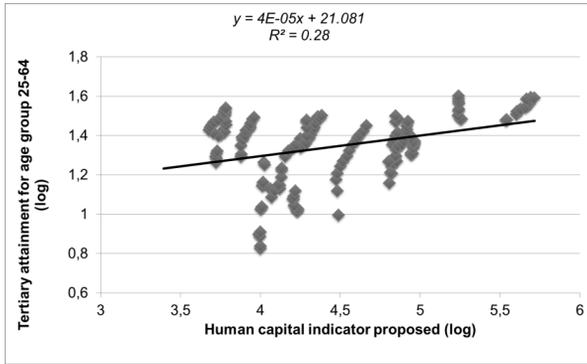
Being the explaining variable significant at a level of 1%, with a t-ratio of 14.49.
Source: Own elaboration data and OECD (2008b).

Figure a3. Relationship between number of researchers per thousand employed, full-time equivalent and the human capital indicator proposed

Being the explaining variable significant at a level of 1%, with a t-ratio of 9.17.
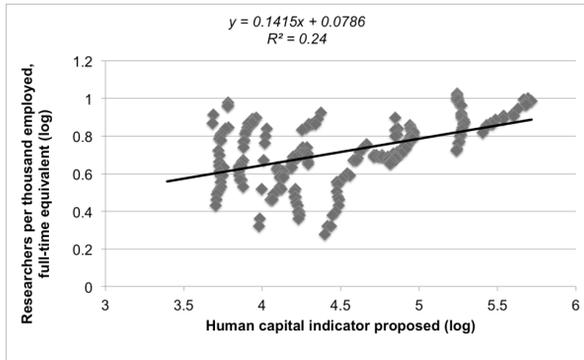Source: Own elaboration data and OECD (2008b).

Annex 2. Values of the human capital indicator proposed

	Australia	Austria	Belgium	Czech Rep.	Denmark	Finland	Germany	Hungary	Japan	Korea Rep.	Netherlands	Slovenia	Spain	United Kingdom	United States
1980		9,395.8	7,723.9		5,174.9	5,642.9			171,077.1	55,611.2	13,090.8		28,001.9	52,177.5	258,134.3
1981		9,225.5	7,555.4		5,054.3	5,659.3			172,401.9	54,584.1	12,961.9		27,196.6	51,430.7	254,737.9
1982	14,816.5	9,358.9	7,382.9		5,119.0	5,641.0			174,885.7	56,955.4	12,645.2		27,114.1	51,669.6	259,388.5
1983	14,665.3	9,316.1	7,217.5		5,129.7	5,604.2			177,736.2	56,124.4	12,407.0		26,989.3	53,370.2	268,581.6
1984	15,062.6	9,414.2	7,158.1		5,225.4	5,604.8			180,966.4	55,689.5	12,461.3		25,640.8	55,113.4	284,542.6
1985	15,475.0	9,541.8	7,107.0		5,340.3	5,602.6			181,892.0	56,640.8	12,519.1		25,067.5	57,410.8	295,532.3
1986	15,819.0	9,471.3	7,090.8		5,483.0	5,599.6			184,621.1	57,970.7	12,822.2		26,083.1	58,211.7	299,123.4
1987	16,457.8	9,393.6	7,138.4		5,442.7	5,702.8			186,629.3	62,183.3	12,781.4		27,447.7	59,235.0	306,716.9
1988	17,101.4	9,504.8	7,341.5		5,392.8	5,820.6			189,497.3	61,983.6	13,067.0		28,042.4	63,414.4	318,594.8
1989	18,072.6	9,630.6	7,451.7		5,340.2	5,880.4			191,276.5	63,288.5	13,492.3		29,348.1	65,453.6	343,195.7
1990	18,092.3	9,933.6	7,553.6		5,324.8	5,819.6			193,590.9	64,470.0	14,011.2		30,700.7	66,542.4	343,077.0
1991	17,905.8	10,023.0	7,562.1		5,303.3	5,456.8	88,039.1		194,798.1	64,309.9	14,374.0		30,835.4	65,483.5	345,462.2
1992	17,900.3	10,021.8	7,612.4		5,331.8	5,086.8	88,083.7		193,014.3	66,589.5	15,012.9		30,400.7	63,729.2	348,329.2
1993	18,597.5	9,955.1	7,598.4		5,268.2	4,820.5	88,375.2		187,398.9	65,541.8	15,287.4		29,919.3	64,228.2	392,388.0
1994	19,107.0	9,943.8	7,588.4		5,263.5	4,794.8	89,862.4		186,078.9	66,973.1	15,700.6		29,847.4	71,042.3	401,529.0
1995	19,697.1	9,813.0	7,693.5	16,995.8	5,319.4	4,869.6	90,328.9	11,344.0	186,510.5	71,666.1	16,171.4	2,512.8	30,338.3	72,613.3	403,273.3
1996	19,850.0	9,999.0	7,768.5	17,176.4	5,371.7	4,972.5	91,073.4	11,611.9	185,829.8	70,363.6	16,777.7	2,482.1	31,716.4	72,896.1	419,809.5
1997	20,248.1	10,090.1	7,904.9	17,279.2	5,482.3	5,112.2	91,499.7	11,789.5	182,577.8	70,475.9	17,446.7	2,505.9	32,946.4	77,186.4	426,174.2
1998	20,742.1	10,223.7	8,039.5	16,970.1	5,689.1	5,438.2	91,997.4	12,293.8	177,831.7	67,081.0	17,861.5	2,477.6	34,831.2	79,467.7	459,059.3
1999	21,323.1	10,257.3	8,140.1	16,820.6	5,820.0	5,739.8	92,001.3	13,243.0	173,758.7	68,378.8	18,586.3	2,579.9	36,213.4	80,811.0	471,086.4
2000	21,804.9	10,302.0	8,537.0	16,497.0	5,974.5	5,908.5	92,612.3	13,231.9	174,490.7	68,607.2	18,863.5	2,725.1	38,089.2	82,148.0	483,211.4
2001	22,094.0	10,487.8	8,660.8	16,334.0	6,104.1	5,914.6	91,617.9	12,934.3	174,924.7	70,328.6	19,310.5	2,739.6	39,628.5	83,427.0	485,678.6
2002	22,568.2	10,418.0	8,593.2	16,113.1	6,070.0	5,991.6	90,068.4	13,128.7	175,447.5	72,402.7	19,582.4	2,575.8	40,613.0	82,618.4	484,043.2
2003	22,990.1	10,414.1	8,725.4	16,009.9	6,008.4	5,985.4	88,218.9	13,566.1	173,814.8	70,302.8	19,620.1	2,684.5	41,862.9	82,913.3	464,333.4
2004	23,722.0	10,506.8	8,980.6	16,229.7	6,044.6	6,066.5	88,245.8	13,635.4	174,593.6	73,318.6	19,517.6	2,686.7	44,146.7	83,906.1	495,276.5
2005	24,303.0	10,677.0	9,157.4	16,599.9	5,978.1	6,093.9	87,497.0	13,665.1	174,589.6	70,288.6	19,536.9	2,579.5	46,281.1	84,090.2	520,603.8