STATISTICS SHOWS THAT ECONOMIC PROSPERITY NEEDS BOTH HIGH SCIENTIFIC PRODUCTIVITY AND COMPLEX TECHNOLOGICAL KNOWLEDGE, BUT IN DIFFERENT WAYS

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SUMMARY

Statistical analyses, focused on the difference in the contribution of scientific knowledge and technical expertise in promoting the wealth of nations, showed that both types of knowledge are tightly related to the wealth of nations, but in distinct ways. Scientific productivity correlates stronger with Gross National Income than technological sophistication; science is important for economic growth among developed economies, whereas technical complexity is more important for the economic development of poorer countries; and per capita scientific productivity seems to reach an upper limit in the most developed countries, suggesting that future growth in world science will come from developing countries. The analysis shows trends that are not visible with classical regression analysis, suggesting the need of alternative ways to explore economic data.

Introduction

Knowledge and wealth have been recognized to be related since ancient times. Yet how this relationship works in the modern world is still a sensitive political issue (Salter and Martin, 2001; Nelson, 1959; King, 2004; Royal Society, 2011). A significant recent contribution to the debate was made by Hidalgo *et al*. (Hidalgo *et al*., 2007; Hidalgo and Hausmann, 2009; Hausmann *et al*., 2011) proposing a novel Economic Complexity Index (ECI) to account for knowledge embedded in society that produces wealth. In their words, "Modern societies can amass large amounts of productive knowledge because they distribute bits and pieces of it among its many members. But to make use of it, this knowledge has to be put back together through organizations and markets. Thus, individual specialization begets diversity at the national and global level. Our most prosperous modern societies are wiser, not because their citizens are individually brilliant, but because these societies hold a diversity of knowhow and because they are able to recombine it to create a larger variety of smarter and better products." The ECI is built based on the relative amount of exports of different products for each country and on an index of the complexity or difficulty in producing each product. Although ECI reflects many different features of an economy, the authors (Hausmann *et al*., 2011) maintain that it mainly reflects the composition of a country's productive output and its structure, which in turn is a strong reflection of the country combined productive knowledge.

On the other hand, scientific development and the wealth of nations have been postulated to be closely linked. Scientific productivity showed to be a much better predictor of economic wealth of a nation than all educational variables tracked by the United Nations Development Program and the World Bank

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ESTADÍSTICAS MUESTRAN QUE LA PROSPERIDAD ECONÓMICA NECESITA TANTO DE ALTA PRODUCTIVIDAD CIENTÍFICA COMO DEL CONOCIMIENTO TECNOLÓGICO COMPLEJO, PERO DE DIFERENTES MANERAS

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RESUMEN

Un análisis estadístico centrado en estudiar las diferencias en la contribución del conocimiento científico y la experiencia técnica en la promoción de la riqueza de las naciones, mostró que ambos tipos de conocimiento están estrechamente relacionados con la riqueza de las naciones, aunque de maneras diferentes. La productividad científica se correlaciona más fuertemente con la Renta Nacional Bruta que con un índice de sofisticación tecnológica; la ciencia es más importante para el crecimiento económico entre las economías desarrolladas, mientras que la complejidad técnica es más importante para el desarrollo económico de los países más pobres; y la productividad científica per capita parece tener un límite superior en la mayoría de los países desarrollados, lo que sugiere que el crecimiento futuro de la ciencia mundial vendrá de países en desarrollo. Este análisis muestra tendencias no visibles con un análisis de regresión clásico, lo que sugiere la necesidad de formas alternativas para explorar los datos económicos complejos.

ESTATÍSTICAS MOSTRAM QUE A PROSPERIDADE ECONÔMICA NECESSITA TANTO DE ALTA PRODUCTIVIDADE CIENTÍFICA COMO DO CONHECIMENTO TECNOLÓGICO COMPLEXO, MAS EM DIFERENTES MANEIRAS

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RESUMO

Uma análise estatística centrada no estudo das diferênças na contribuição do conhecimento científico e a experiência técnica na promoção da riqueza das nações, mostrou que ambos os tipos de conhecimento estão estreitamente relacionados com a riqueza das nações, todavia de formas diferentes. A produtividade científica se correlaciona mais fortemente com a Renda Bruta Nacional que com um índice de sofisticação tecnológica; a ciência é mais importante para o crescimento econômico entre as economias desenvolvidas, enquanto que a complexidade técnica é mais importante para o desenvolvimento econômico dos países mais pobres; e la produtividade científica per capita parece ter um limite superior na maioria dos países desenvolvidos, o que sugere que o crescimento futuro da ciência mundial virá de países em desenvolvimento. O resultado de uma análise de regressão clássica mostra tendências não visíveis, o que sugere a necessidade de formas alternativas para explorar os dados econômicos complexos.

(Jaffe, 2005). Scientific development was shown to correlate with tolerance and openness of a society, reflecting the fact that attitudes favoring science are related to valuation of empirical facts over personal convictions, which lay at the base of modern scientific progress (Jaffe, 2009).

Scientific knowledge reflected through indices of scientific productivity, and knowledge related to industrial production and technologies, quantified with the ECI, have many aspects in common. Both seem to affect economic development. Hausmann *et al*. (2011) compared ECI to indicators of education showing that ECI is a much better predictor of economic growth than any of the other indices they tested. However, they only used r-squared values of regressions in their comparisons, and did not test indices for scientific productivity which were found to be linked much stronger to economic developments than other indices related to education (Jaffe, 2005). Thus, a more extensive analysis including all three factors: economic development, economic complexity and scientific development, is required.

Linear General Models

When the analysis of the data used by Hausmann *et al.* (2011) was repeated, we obtained similar results to those published in the Atlas of Economic Complexity, but found that scientific productivity is a much better predictor of economic wealth than technological knowledge reflected in the Economic Complexity Index (ECI). For example, in order to estimate the power of ECI and SPSc, assessed in a given year, in predicting economic growth during the following 10 years, we compared two different general linear models, using the variables defined in Box 1. In Model 1, build to estimate the effect of ECI on future economic growth, the percent change increase in GNIc (%ΔGNIc) during 1998-2008 is regressed against logGNIc and ECI, both assessed in 1998. In Model 2, built to estimate the effect of SPSc on future economic growth, %ΔGNIc during 1998-2008 is regressed against logGNIc in 1998 and logSPSc in 1998. Results (Table Ia) show that both models predict future economic growth with high probability, but Model 2 was better than Model 1 in rejecting the null hypothesis, that no correlation between economic growth and the selected variables exists.

In Model 3 we included logSPSc, ECI and logGNIc assessed in 1998 in the general regression to predict %ΔGNIc during 1998-2008. The effect sizes and power of the variables is given in Table Ib. The results in Table I suggest that adding ECI to log SPSc does not increase the predictive value of Model 2, but rather decreases it slightly.

Using the Akaike information criterion (AIC) to compare model 1, 2 and 3 we obtained lower AIC values for Model 2 compared to Model 1, and very similar AIC values for Models 2 and 3. These results indicate that Model 1 was 0.36 times as likely as Model 2 to minimize information loss, and that Model 2 was 0.7 times as likely as Model 3 to minimize information loss (Akaike, 1974). Thus, ECI estimated for 1998 carried much less information com-

BOX 1 - DEFINITION OF THE VARIABLES ANALYZED

Economic wealth

GDPc: Gross Domestic Product *per capita* at constant US$ 2000 (World Bank)

GNIc: Gross National Income *per capita* (World Bank Atlas method)

Growth

Δ: difference in the respective variable between 1998 and 2008

%: difference expressed in percent between 1998 and 2008

Knowledge

ECI: Economic Complexity Index (Hausmann et al. 2011)

SP: Scientific productivity irrespective of its measure as SPW or SPS

SPc: Scientific productivity *per capita*

SPWc: Scientific Productivity measured as the number of publications in scientific and engineering journals published in physics, biology, chemistry, mathematics, clinical medicine, biomedical research, engineering and technology and earth and space sciences, *per capita*. (World Bank)

SPSc: Scientific Productivity measured as the number of academic documents *per capita* published, compiled by Scopus (SCImago. 2007)

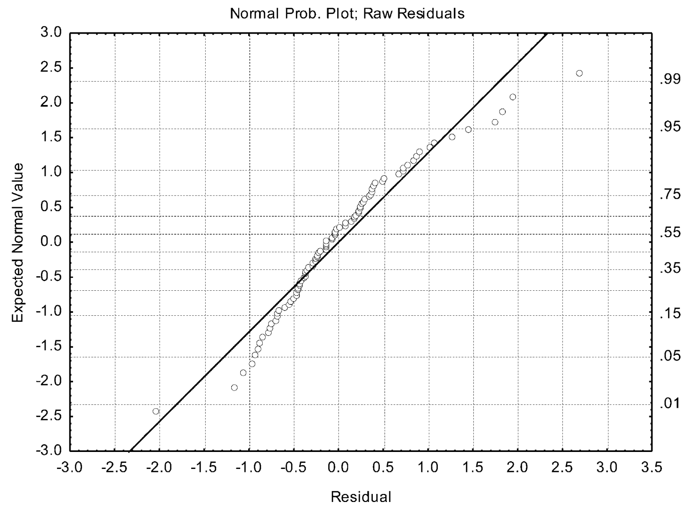

Figure 1. Residual analysis: Normal probability plot of the raw residuals of general Model 3.

pared to SPSc in predicting economic growth in the decade 1998-2008.

A series of similar tests, using the AIC to compare models built to regress ECI growth or SPSc growth with %ΔGNIc, produced the same outcome; ECI estimates carried much less information compared to SPSc in predicting economic growth. Hausmann *et al*. (2011) calculated the correlation between ECI and the countries level of income, and used the deviations from this relationship to predict future growth. We compared these deviations in ECI with %ΔGNIc, and the equivalent deviations in SPSc with %ΔGNIc. Again, ECI estimates carried much less information compared to SPSc in predicting economic growth.

We believe however that multiple or general regression analysis is not the best method to understand the complex non-linear relationships between different kinds of knowledge and wealth accumulation of nations. This kind of analysis presupposes that data are normally distributed or that when appropriately transformed, they become normally distributed. This is not the case with the present data. For example, a plot of the residuals of the linear regression Model 3 is given in Figure 1. The expected normal behavior was unsatisfactory for a sound linear statistical analysis. We believe that non-parametric statistics seems to be more appropriate to handle this data.

Non-Parametric Analysis

Here we analyze data for economic growth, ECI and scientific productivity, with tools that do not require normally distributed data. Regressions are only used as a visual reference to classical economic thinking, when deemed useful. The variables used in this analysis are presented in Box 1.

Comparing the correlation between economic wealth, assessed through GDP or GNI, with ECI, as a proxy of the embedded knowledge underlying the industrial complexity of a nation, and scientific productivity (SPc), measured by the number of academic papers published by researchers of a given country per year and *per capita*, revealed that SPc is a much better predictor of economic wealth than ECI (Table II).

The correlations show that both, the World Bank data on scientific publications (SPWc) and that of Scopus (SPSc), are highly correlated with GDPc and GNIc. The addition of more journals in the Scopus database in relation to that of the World Bank, do not seem to render SPSc less reliable. On the contrary, SPSc scores in Table II are in most cases slightly higher

TABLE I

A: AKAIKE INFORMATION CRITERION (AIC) AND REGRESSION COEFFICIENTS OF THE THREE MODELS

%ΔGNIc 1998-2008	AIC	Multiple R^2	Adjusted R^2	SS Model	df Model	MS Model	SS Residual	df Residual	MS Residual	F	p
Model 1	210.88	0.146	0.126	8.824	2	4.412	51.77	85	0.609	7.245	0.00120
Model 2	206.89	0.183	0.164	11.10	2	5.55	49.49	85	0.582	9.529	0.00018
Model 3	206.17	0.208	0.180	12.60	3	4.20	47.99	84	0.571	7.36	0.00020

B: EFFECT SIZES AND POWER OF THE VARIABLES OF MODEL 3

	SS	Degrees of freedom	MS	F	p	Observed power (alpha=0.05)
Intercept	16.08	1	16.08	28.14	0.000001	0.999
Log GNI 1998	12.00	1	12.00	21.00	0.000016	0.995
ECI 1998	1.51	1	1.51	2.64	0.107938	0.362
Log SPSc 1998	3.78	1	3.78	6.62	0.011855	0.720
Error	47.99	84	0.57			

TABLE II
SPEARMAN RANK ORDER CORRELATIONS ALL CORRELATIONS ARE SIGNIFICANT AT p<0.001*

	GNIc 1988	GNIc 1998	GNIc 2008	GDPc 1988	GDPc 1998	GDPc 2008	ECI 1988	ECI 1998	ECI 2008	SPWc 1987	SPWc 1997	SPWc 2007	SPSc 1998	SPSc 2008
GNIc 1988		0.94*	0.94*	0.96*	0.95*	0.94*	0.77	0.75	0.62	0.81	0.81	0.87	0.89	0.88
GNIc 1998	0.94*		0.97*	0.98*	0.99*	0.98*	0.80	0.81	0.71	0.79	0.80	0.87	0.89	0.87
GNIc 2008	0.94*	0.97*		0.97*	0.98*	0.98*	0.83	0.83	0.73	0.80	0.81	0.88	0.89	0.90
GDPc 1988	0.96*	0.98*	0.97*		0.99*	0.98*	0.79	0.81	0.71	0.81	0.81	0.87	0.90	0.87
GDPc 1998	0.95*	0.99*	0.98*	0.99*		0.99*	0.80	0.81	0.70	0.80	0.81	0.88	0.89	0.88
GDPc 2008	0.94*	0.98*	0.98*	0.98*	0.99*		0.82	0.84	0.74	0.80	0.80	0.88	0.89	0.89
ECI 1988	0.77	0.89	0.83	0.79	0.80	0.82		0.93*	0.85	0.77	0.77	0.85	0.83	0.84
ECI 1998	0.75	0.81	0.83	0.81	0.81	0.84	0.93*		0.90	0.76	0.77	0.84	0.82	0.83
ECI 2008	0.62	0.71	0.73	0.71	0.70	0.74	0.85	0.90		0.68	0.68	0.75	0.72	0.74
SPWc 1988	0.81	0.79	0.80	0.81	0.80	0.80	0.77	0.76	0.68		1.00*	0.88	0.92*	0.88
SPWc 1998	0.81	0.80	0.81	0.81	0.81	0.80	0.77	0.77	0.68	1.00*		0.89	0.92*	0.88
SPWc 2007	0.87	0.87	0.88	0.87	0.88	0.88	0.85	0.84	0.75	0.88	0.89		0.97*	0.99*
SPSc 1998	0.89	0.89	0.89	0.90	0.89	0.89	0.83	0.82	0.72	0.92*	0.92*	0.97*		0.97*
SPSc 2008	0.88	0.87	0.90	0.87	0.88	0.89	0.84	0.83	0.74	0.88	0.88	0.99*	0.97*	

* Correlations above 0.9 are marked*.

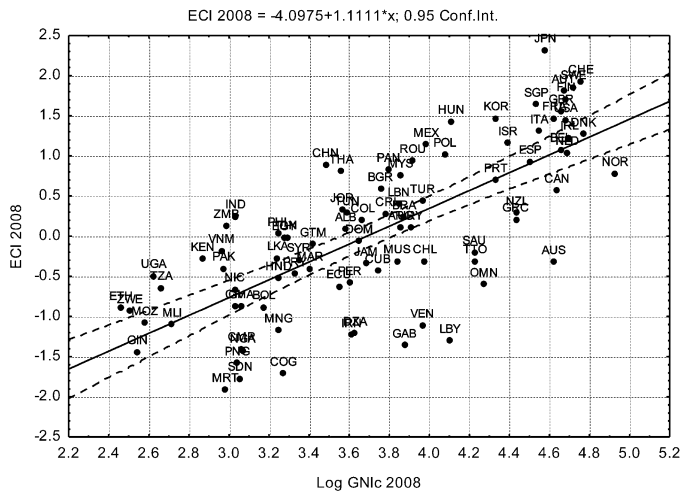

Figure 2. Relation between GNI *per capita* and ECI for 2008. Countries are indicated using their ISO abbreviations.

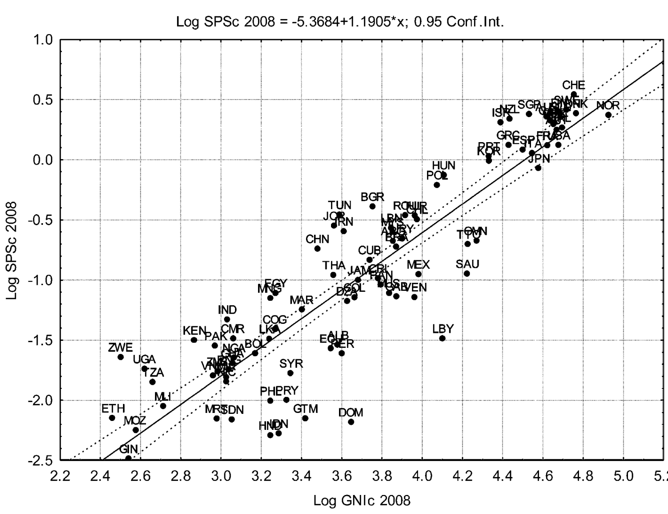

Figure 3. Relation between indices of GNI *per capita* and scientific productivity for 2008.

than the equivalent scores of SPWc. Data for SPWc are only available until 1997 and data for SPSc are not available prior to 1996.

The refining of the assessment of national wealth done by the World Bank when calculating GNIc compared to GDPc does not seem to affect the measure of the relationship between scientific knowledge and economic wealth. Surprisingly, measures of SPc are very resilient and hold over long time periods. That is, correlating SPc with GNPc data for the same year or from data with a 10 or even 20 years gap produced very similar results. The knowledge measured as ECI also correlate with GDPc but less than SPc, and ECI is slightly more susceptible to shifts in time in comparisons with GDPc or GNIc. GNIc correlated slightly better than GDPc, with SPc and partly also with ECI, in 2008. Thus, for further analysis we used SPSc and GNIc.

Scatter plots visualizing the relationship between these variables are presented in Figures 2 to 7. Both indices of knowledge correlate with GNIc but in different ways (Figures 2 and 3). The relation between ECI and SPSc is presented in Figures 4 and 5; whereas correlations between ECI and SPSc with parameters related to economic growth are shown in Figures 6 and 7. For country identification, see Box 2.

Clearly, SPSc and ECI are closely correlated, but their differences reveal the countries peculiar mix of knowledge (Figure 4). Countries with a higher score for ECI than what the mean correlation would suggest, such as Japan, Germany (not shown in the figure), Mexico, China and India are countries with important non-scholar knowledge acquisition systems in place that complement scholar knowledge acquisition practiced in universities. Countries with a higher score for SPSc than the corresponding mean, such as Switzerland, Denmark and Chile, are countries with a strong long term investment

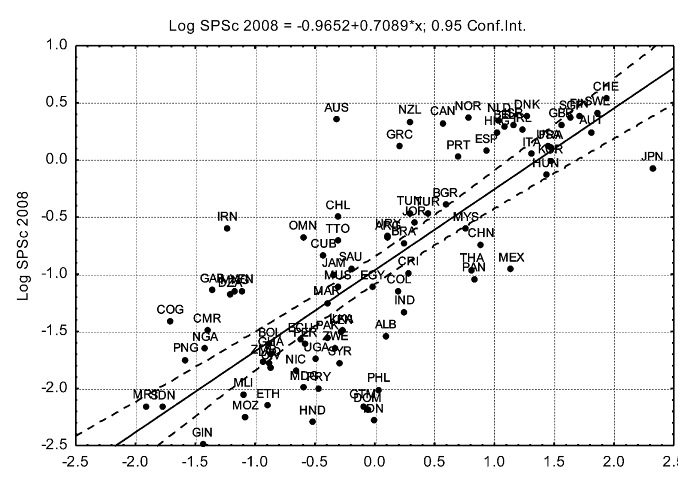

Figure 4. Relation between ECIc and SPSc.

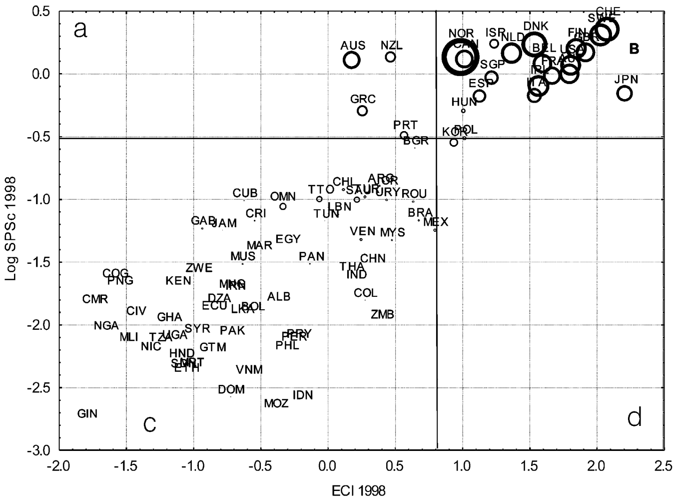

Figure 5. Relationship between ECI, SPSc in 1998 and economic wealth expressed as GNIc for 2008. The size of the bubbles is proportional to GNIc in 2008.

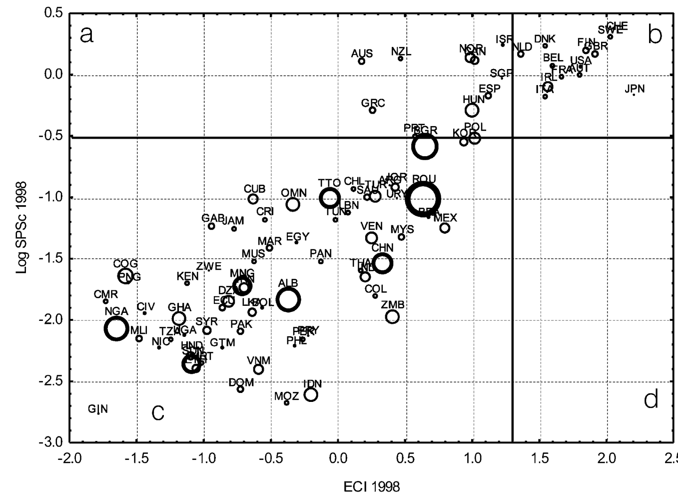

Figure 6. Relationship between ECI, SPSc in 1998 and economic growth expressed as the % change in GNIc for 1998-2008. Bubbles with negative data are revalued to 0. The size of the bubbles is proportional to %ΔGNIc for 1998-2008.

in formal education. Countries such as Australia, Kuwait and Congo whose national wealth is based mainly on the exploitation of natural resources with a low dependence on industry, also show a relative higher SPSc compared to ECI at their corresponding level of economic development.

The strong relationship between wealth (GNIc), scientific knowledge (SPSc), and to a lesser degree, technical knowledge (ECI), is evidenced in Figures 5 and 6. Figure 5 shows a cluster of countries with high scores in these indices (quadrant B). No country with low scores in two of these indices scored high in the other (quadrants A and C). The outlier data points for high GNIc, such as Australia (quadrant A), reflect the fact that high commodity prices affect the wealth of a nations exploiting natural resources adding to that created by science and technology (Hausmann *et al.* 2011). Development of economic wealth and/or economic complexity without a simultaneous development of science was achieved by no country (quadrant D). Thus, a tightly knit ensemble of technical knowledge, scientific knowledge and wealth seems to exist in our economies.

The relationship between the growth in ECI, SPSc and economic growth is more subtle. Correlations of ΔECI and ΔSPSc with ΔGNI during a 10 year period (1998-2008) are presented in Table III. A striking result is that ΔECI is correlated negatively with ΔGNI in the decade 1998-2008, whereas ΔSPSc correlates very strongly in a positive direction with ΔGNI in that period. None of the knowledge indicators; ECI or SPSc correlated with economic growth expressed as % increase in GNIc (%ΔGNIc). These results suggest non-uniform distributions between countries, of the relationships between these variables, which cancel their effects when aggregated.

Figure 6 shows the relationship between the knowledge indicators ECI and SPSc in 1998 with percent economic growth in the following decade (1998-2008). All fast growing countries were found in quadrant C, where countries with low SPSc and ECI in 1998 are grouped. Transforming economic growth data in percentages normalizes for the absolute amounts of ΔGNIc between countries. Many poor countries with low ECI and/or SPc showed high % growth in GNIc (quadrant C) and many rich counties showed low %ΔGNIc (quadrant B). That is, caching up in economic development seems to require less knowledge than expanding the economic frontier of humanity. Poorer countries have much more space to grow than richer ones, so that growth expressed as % favors poorer countries over richer ones. This may explain why no rich country with high scientific output (quadrant B) showed high %ΔGNIc in Figure 6.

BOX 2 - ISO ABBREVIATIONS FOR THE 90 COUNTRIES WITH COMPLETE DATA SETS

ALB	Albania	GIN	Guinea	NLD	Netherlands
ARG	Argentina	GRC	Greece	NOR	Norway
AUS	Australia	GTM	Guatemala	NZL	New Zealand
AUT	Austria	HND	Honduras	OMN	Oman
BEL	Belgium	HUN	Hungary	PAK	Pakistan
BGR	Bulgaria	IDN	Indonesia	PAN	Panama
BOL	Bolivia	IND	India	PER	Peru
BRA	Brazil	IRL	Ireland	PHL	Philippines
CAN	Canada	IRN	Iran	PNG	Papua New Guinea
CHE	Switzerland	ISR	Israel	POL	Poland
CHL	Chile	ITA	Italy	PRT	Portugal
CHN	China	JAM	Jamaica	PRY	Paraguay
CIV	Cote d'Ivoire	JOR	Jordan	ROU	Romania
CMR	Cameroon	JPN	Japan	SAU	Saudi Arabia
COG	Congo, Rep.	KEN	Kenya	SDN	Sudan
COL	Colombia	KOR	Korea, Rep.	SGP	Singapore
CRI	Costa Rica	KWT	Kuwait	SWE	Sweden
CUB	Cuba	LBN	Lebanon	SYR	Syria
DNK	Denmark	LBY	Libya	THA	Thailand
DOM	Dominican Rep.	LKA	Sri Lanka	TTO	Trinidad and Tobago
DZA	Algeria	MAR	Morocco	TUN	Tunisia
ECU	Ecuador	MEX	Mexico	TUR	Turkey
EGY	Egypt	MLI	Mali	TZA	Tanzania
ESP	Spain	MNG	Mongolia	UGA	Uganda
ETH	Ethiopia	MOZ	Mozambique	URY	Uruguay
FIN	Finland	MRT	Mauritania	USA	United States
FRA	France	MUS	Mauritius	VEN	Venezuela
GAB	Gabon	MYS	Malaysia	VNM	Vietnam
GBR	United Kingdom	NGA	Nigeria	ZMB	Zambia
GHA	Ghana	NIC	Nicaragua	ZWE	Zimbabwe

TABLE III
SPEARMAN RANK ORDER CORRELATIONS*

	%ΔGNIc 1998-2008	ΔGNIc 1988-1998	ΔGNIc 1998-2008	ΔECI 1988-1998	ΔECI 1998-2008	ΔSPSc 1998-2008
%ΔGNIc 1998-2008		-0.32**	0.21*	-0.15	-0.01	0.03
ΔGNIc 1988-1998	-0.32**		0.68***	0.16	-0.18	0.74***
ΔGNIc 1998-2008	0.21*	0.68***		0.14	-0.30**	0.84***
ΔECI 1988-1998	-0.15	0.16	0.14		-0.21	0.16
ΔECI 1898-2008	-0.01	-0.18	-0.30**	-0.21		-0.27*
ΔSPSc 1998-2008	0.03	0.74***	0.84***	0.16	-0.27*	

Correlations are significant at; *** p <.001, ** p<0.01, * p<0.05.

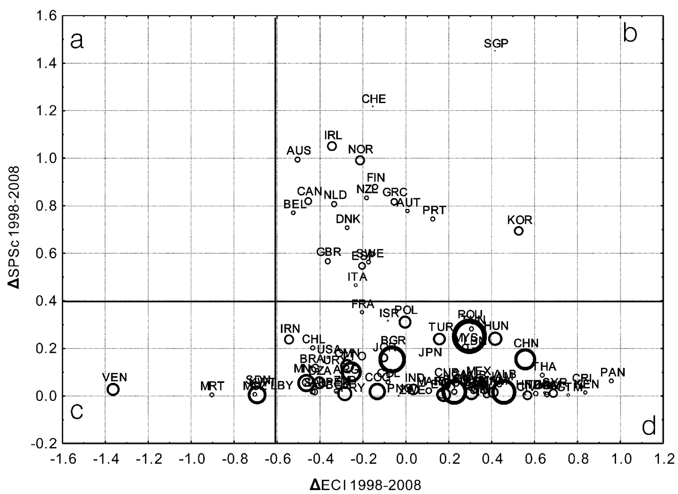

Figure 7. Correlation between growth in ECI and SPSc during 1998-2008 and economic development. The size of the bubbles indicates % Growth in GNIc during 1998-2008.

Figure 7 illustrates the divergence between ΔSPSc and ΔECI during 1998 to 2008. It shows that no country with a ΔECI score <-0.6 increased its scientific productivity during this period (quadrant A). All countries with large increases in scientific productivity showed ΔECI between -0.6 and 0.1 (quadrant B). That is, countries with large increases in scientific productivity also showed relative high ΔECI, and countries with a large %ΔGNIc were countries with low ΔSPSc and relative high levels of ΔECI during the last decade (quadrant D). The countries with the largest ΔECI score (Panama, Kenya and Costa Rica) had only a modest %ΔGNIc and low ΔSPSc.

The results in Figure 7 show those rich countries with high scientific productivity and high ECI that got somewhat richer in the decade 1998-2008 and also increased their scientific productivity in this period (quadrant B). The poorer countries that showed important % increase in GNIc in the last decade got richer while avoiding drastic decreases in diversification of their economic activity (ΔECI>-0.6) but maintaining low growth in SP (ΔSPSc) in this period (quadrant D). No country reached high scientific productivity with low technical development (quadrant A). Countries with high increases in SPSc and healthy ECI (quadrant B) showed intermediate values of %ΔGNI. In this group, the outlier country with the lowest %ΔGNI and highest ΔSPSc was Singapore, which showed high %ΔGNI in other periods. All fast growing countries were grouped in quadrant D. A few countries managed to achieve conspicuous industrial and scientific contraction simultaneously (quadrant C).

Many recent studies prefer to use citation impact instead of number of publications as a measure of the quality of scientific productivity (Royal Society, 2011). A Spearman correlation between GNIc 2008 and citations per documents for each country as calculated by SCImago (2007) gives a highly statistically significant value of 0.67, which however is much lower than that between SPSc and GNIc as used here (0.90 for 2008). Citation patterns reveal many interesting features, such as, that 'scientific humility' and citation impact are correlated (Jaffe 2011), but the economic implications of scientific productivity are better reflected by the number of publications as done here.

Conclusions

Many more factors than those analyzed here, including economic, physical, historical and cultural factors, affect economic growth and explain differences in the wealth of nations. Here we focused only on the difference in the contribution of scientific knowledge and technical expertise (industrial economic complexity) in powering the wealth of nations. Our results suggest a tight relationship between economic prosperity, scientific development and economic complexity. It is shown that technological knowledge required to power industrialization in an economy, measured with ECI, differs from that produced by science, measured with SPc. Both measures correlate with the wealth of nations, but SPc does so to a larger extent than ECI. Short term economic growth in economically less developed countries may not require autochthonous production of science or technology, but sustained economic wellbeing seems to be inseparable from both types of knowledge.

Repeating this analysis for other time periods with different macro-economic conditions would be desirable, but publication counts in the past were much more skewed to English language journal that they are today, distorting any rigorous historical analysis. Thus we used other methods for a historical analysis, such as comparing the changes in the relative importance of the different scientific disciplines in each country with its economic growth. These studies showed that the development of the natural sciences correlates with future economic growth in most historical periods examined (see Jaffe *et al.*, 2012).

An interesting finding is that the richest nations seem to slow their exponential growth in scientific productivity *per capita* as they seem to reach an upper limit in the intensity of scientific productivity. This trend presages that future worldwide scientific growth will relay more on the economic development of poorer countries.

Clearly, correlation is not causation. Even if some of the variables may be good in predicting future economic growth, this does not assure that there is a causal effect between them. Detailed case studies, not attempted in this work, are required for this. The relationship between economic wealth, scientific knowledge and economic prosperity seems to be multidirectional. Rich countries can afford more science and more technology, and more science and technology allows increasing and maintaining wealth. However, scientific knowledge affects the nation's economy only after a certain economic development has been achie*ve*d (Jaffe, 2005), whereas technical expertise may favor in some cases growth in poor countries. More technology allows for more and better science, and more science advances technology. This multi-mutual relationship allows proposing the existence of a Wealth-Science-Technology complex, whose fine workings are still open to more research.

Results from the analysis of the figures presented here suggest that:

-Science is more closely related to economic prosperity of nations than complex technological expertise.

-Science is essential for economic growth among developed economies, whereas technical complexity may be more important for the economic development of poorer countries.

-There might be an upper limit to the intensity of scientific activity a contemporary society is able to sustain, suggesting that future growth in world science will come from developing countries.

The analysis presented here showed trends that are not visible with classical regression analysis. This calls for reflection about the need to use alternative ways to explore economic data in order to gain a deeper insight into the complex relationship between multiple factors affecting economic growth.

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