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A cross-country empirical test of cognitive abilities and innovation nexus

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ABSTRACT

In this study we analyze the relationship between national cognitive abilities and innovational output using data from 124 countries of the world. By employing cross-country IQ scores traditionally used by psychological literature to represent national intelligence, and Economic Complexity Index as a novel measure of innovation, our study shows that there is a positive connection between them. We use a variety of tests to check the robustness of the nexus. Overall, our findings indicate that more intelligent nations export more sophisticated and diverse products to the world market and thus are more innovative. Therefore, developing countries should consider investing in human capital and related institutions if they are to boost innovative capabilities and move up the technology ladder in producing and exporting sophisticated and varied lines of products. This should bring them greater economic diversity which could be a right lever in mitigating negative external shocks.

1. Introduction

Recently there has been a growing body of development literature that has pointed out the importance of producing and exporting sophisticated goods in order to drive future economic growth (Lall et al., 2006; Hausmann et al., 2007; Hidalgo et al., 2007; Jarreau and Poncet, 2012; Berg et al., 2012). This strand of research has firmly established that it does not matter how much countries export, but what they export is more important for their growth and prosperity (Hausmann et al., 2007; Lederman and Maloney, 2012). Indeed, some products have greater complexity in a way that they are associated with higher productivity and those countries that lean on manufacturing and exporting such products will eventually perform better than others.

It is no invention that producing and exporting sophisticated goods certainly requires adequate level of human capital that spurs innovation. It is this capital, based on which innovation leads to greater productivity, competitiveness, and economic growth (Mincer, 1984; Barro, 2001). For example, Lynn and Vanhanen (2012) summarize 11 studies where national intelligence, a reliable indicator of human capital (Jones and Schneider, 2006), is treated as an important antecedent of various innovation metrics such as academic publications, patents, technology exports, Nobel Prize awards in literature, science and peace, etc. From among these cognitive outputs the correlation of IQ turns out to be high enough especially with academic publications (0.87), STEM, a measure of excellence in science and technology (0.74), and so called "intellectual autonomy", which refers to the independence of thought (Gelade, 2008, p. 717) (0.61). In line with these findings, there is a reason to believe that human capital is "a key requirement for the establishment and maintenance of effective institutions . . . [and] the ultimate requirement for innovation, efficient use of resources, and economic growth" (Meisenberg and Lynn, 2011, p. 421).

Indeed, as micro level research suggests cognitively able individuals show better performance in undertaking complex tasks and duties. "More intelligent persons can better cope with difficult cognitive demands, they make fewer errors, they are more innovative and generally more productive" (Rindermann, 2012, p. 110). This may then translate into a production of more diversified and sophisticated exports.

After all, extant literature suggests that intelligence brings about innovation through various channels.

First, innovation, the act of introducing a novel product (service) to the market (Acs and Audretsch, 1988), is often a result of a process whose success relies on both formal and informal

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interactions and exchanges of knowledge (knowledge spillover) among various economic agents (Doh and Acs, 2010). In light of this it can be claimed that social capital is an important causal element of innovation. For example, by analyzing the survey data administered to 440 manufacturing firms in one of the regions of Canada, Landry et al. (2002) show how diverse forms of social capital contribute to the increase of innovation within firms, and certain types of it (e.g. research networks) even determine the radicalness of innovation. A study by Doh and Acs (2010) supports the necessity of building strong social interrelationships in today's knowledge- and network-based economy. Indeed, the importance of social capital in inducing innovation can at least be characterized by lowered transaction costs (information costs, coordination costs, contract and law enforcement costs etc.) among firms and between them and other economic agents (Maskell, 2000). From this stance it can be argued that there is a higher intensity of innovation in countries with more intelligent populations who are more willing to collaborate in favor of long-term rewards (Shamosh and Gray, 2008; Salahodjaev, 2015).

Second, a slightly different approach could be the so called O-ring theory. Initially suggested by Kremer (1993), the theory states that positive assortative matching, according to which individual laborers (in our case scientists and other types of innovators) with similar levels of skills tend to team up with each other, brings about per capita productivity increases in countries. This channel can be best explained by examples. Firms with the most advanced technology are better off hiring highly skilled workers, but those employing an average class of technology should hire appropriately skilled laborers, not highly skilled ones. By the same token, in different areas it is more productive if high IQ agents interact with each other, and low IQ individuals would gain more if they cooperate with more experienced individuals of comparable IQ level. According to the O-ring theory, this type of same IQ level clustering increases collective intelligence and leads to greater productivity. In a cross-country scale, the O-ring theory explains why those countries that have small differences in IQ levels may have significantly higher differences in income: it is a collective impact of individual country's IQ level (because of positive assortative matching or clustering) that creates its productivity level (Jones, 2011, 2013). This is why the effect of IQ on overall productivity is higher across countries than across individuals (Burhan et al., 2015). Therefore, the O-ring theory should be regarded as an important channel through which intelligence influences innovation.

Third, another strand of literature assert that it is not mean intelligence, but the IQ level of the so called smart fractions – intellectual classes with the highest abilities in a country (e.g. top 1% or 5%) – that push ahead with innovation (e.g. see Coyle et al., 2016; Rindermann, 2012). For instance, using a cross-national data on more than 110 countries, Gelade (2008) pinpoints these cognitive elites with IQ levels greater than 140 as a primary driver of patent rates and GDP. They affirm that in those countries with a greater proportion of smart fractions more technological knowledge circulates and more innovation takes place than in other countries (Gelade, 2008, p. 711). This sort of literature further regards the abilities of smart fractions as "more important for country differences in wealth, nations' intellectual excellence and political attributes of societies than the average ability or the ability level of a non-smart fraction" (Rindermann et al., 2009, p. 20) because "highly able intellectual classes are necessary to manage growing complexity in technology, economy and everyday life" (Rindermann, 2012, p. 111).

Combining all three channels, we hereby argue that intellectual classes include not only smart individuals on their own (smart fractions theory), but their clusters around firms (O-ring theory) where they rely on social interactions (social capital channel) to innovate and be more productive. Since literature suggests that the probability of exporting is high among productive firms and those that are not productive usually work for the domestic market (Wagner, 2007; Pertl and o Polanec, 2007), the suggested theoretical blend can readily be justified by the empirical finding that positive link between firm productivity and exports is attributed to the firm's innovation decisions (Cassiman et al., 2010).

Whilst a recent study by Squalli and Wilson (2014) has first provided a test of the intelligence-innovation hypothesis using data on US states, our contribution in this paper is to investigate how persistent the hypothesis is in a cross-country scale based on the above discussed theoretical channels. We use different sets of variables and employ a variety of statistical methods to check the robustness of our results. The intelligence-innovation nexus is tested on a sample of 124 nations. The Economic Complexity Index is used as a measure of innovation since it represents materialized innovations and is a better measure of innovation given some problems inherent to traditional proxies of innovation such as patents rate and R&D expenditure (e.g. see Sweet and Maggio, 2015; for a detailed discussion). After controlling for endogeneity our findings show that one standard deviation unit increase in national IQ scores is associated with a 0.069 standard deviation units increase in the economic complexity, *ceteris paribus*.

The paper proceeds in the following way: Section 2 is on data and methodological issues; Section 3 provides econometric results. Robustness tests of findings are presented in Section 4; and Section 5 concludes.

2. Econometric model and data

2.1. The model

To get the quantitative impact of IQ on innovation, we estimate the following regression model:

$$ECI_i = \beta_o + \beta_1 IQ_i + \beta_x CV_i + e_i \tag{1}$$

where the dependent variable is Economic Complexity Index, ECI; IQ is an average national intelligence; and CV is a vector of control variables.

2.2. Data

2.2.1. Dependent variable

The Economic Complexity Index (ECI) ranks countries of the world according to the level of diversification and complexity of their export baskets. The idea is that the state of production of goods reflects the existing productive knowledge in a society. It is based on the realistic assumption that those countries that export more complex as well as a larger number of different goods are typically more economically developed and have higher potential for future growth. As such, the index features two dimensions of goods produced and exported:

a) The state of complexity: goods produced within chemical and machinery industries can be attributed to complex products whereas those that are raw and purely agricultural are considered to be less complex products.
b) The state of diversification: the number of goods the country can produce (how diversified the export is) and export refined by the number of countries able to make those goods (how ubiquitous the export is) can represent the level of diversification of the country.

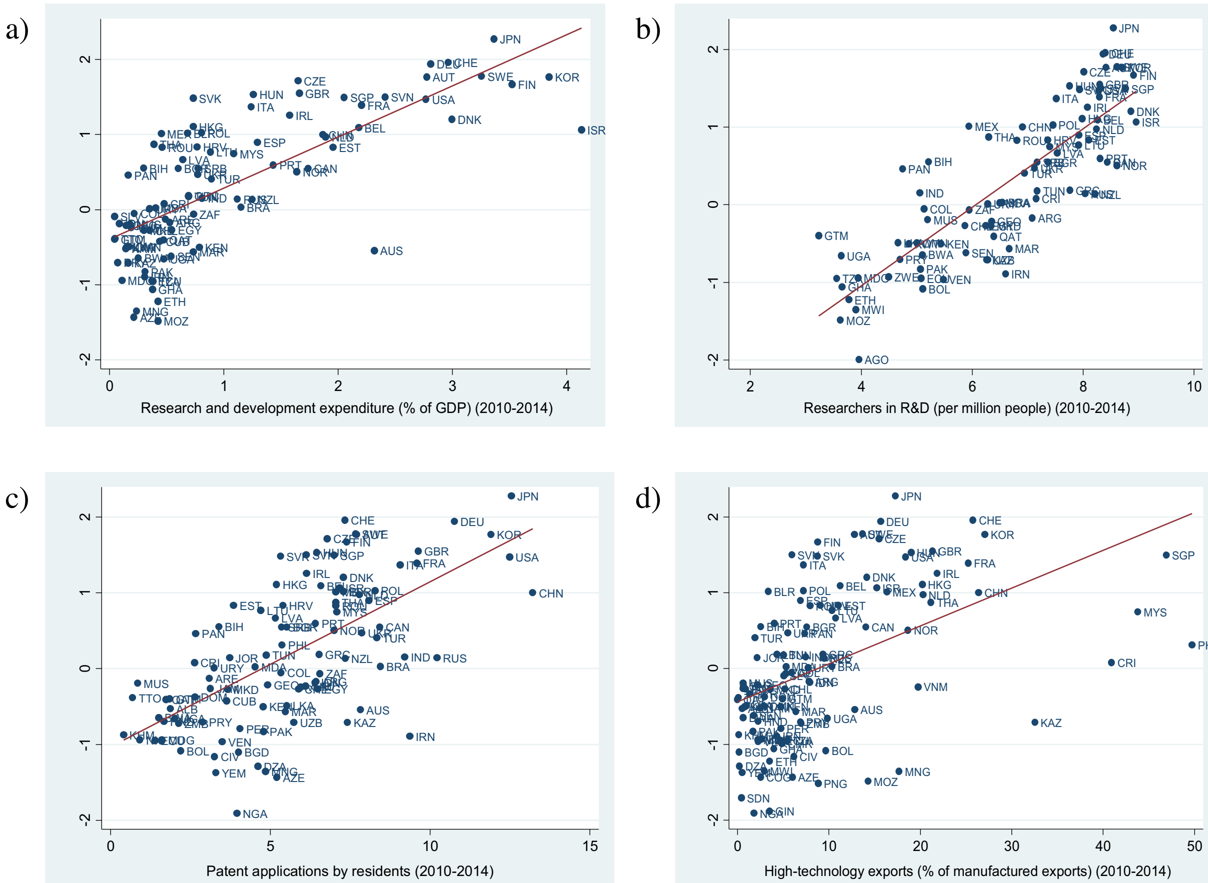

Fig. 1. ECI and traditional measures of innovation (a–d).
Source: author's calcualtions based on WDI and the Atlas of Economic Complexity data.

In sum, the ECI portrays how complex and diversified the country's export basket is. It can be a good proxy for the level of productive knowledge, i.e. innovation in a country.

However, due to the nature of the index which is based on UN COMTRADE database, one of its possible drawbacks is that it represents innovation across only goods exported whereas it may be a case that certain countries specialize in exports of innovative services. Another downside of the index rests upon the fact that it doesn't include information on non-tradable products that may be intrinsically innovative and representative of 'internal' productive knowledge. I.e. certain complex goods may be produced and consumed domestically which can't be observed through trade data. Despite these disadvantages, the ECI is a novel measure and well correlated with traditional metrics of innovation as might be observed from Fig. 1 and Table 1.

The index includes data for 124 economies for 1995–2014 and comes from the Atlas of Economic Complexity, a Harvard-MIT joint research project. The data ranges between −2.5 and 2.5. The higher the index is, the more complex products the country produces and exports.

For the purposes of present research we take the average value of the ECI for 2010–2014.

Table 1
Correlation matrix of ECI and traditional measures of innovation.

	eci	r&d	researchers (log)	patents (log)	ht exports
eci	1				
r&d	0.77	1			
researchers (log)	0.74	0.91	1		
patents (log)	0.59	0.61	0.49	1	
ht exports	0.47	0.40	0.43	0.38	1

2.2.2. Independent variable

The independent variable of our interest is a cross-national measure of IQ, intelligence. It is taken from Lynn (2012) (missing data is further updated from Lynn and Vanhanen, 2012) and represents average IQ scores for 190 nations of the world. These IQ scores are collected from a variety of sources that reflect the outcomes of different IQ tests carried out in many countries of the world. They are scaled so that their mean value is 100 and standard deviation equals to 15, with the mean based on the IQ level of the United Kingdom. National IQ data ranges between 61.2 (Niger) and 106.9 (Singapore).

We hypothesize that the measure of intelligence is positively associated with the dependent variable because more intelligent nations possess more productive knowledge and hence are more innovative.

Indeed, Fig. 2 graphically proves our hypothesis. The correlation coefficient between ECI and intelligence is equal to 0.76 (see Table 2). Countries with higher IQ and higher ECI mainly include some East Asian countries such as Japan, South Korea, and Singapore as well as some European countries such as Germany, Switzerland, Czech Republic, and Finland.

2.2.3. Control variables

The literature review shows that a number of control variables should be included into the model as antecedents of innovation.

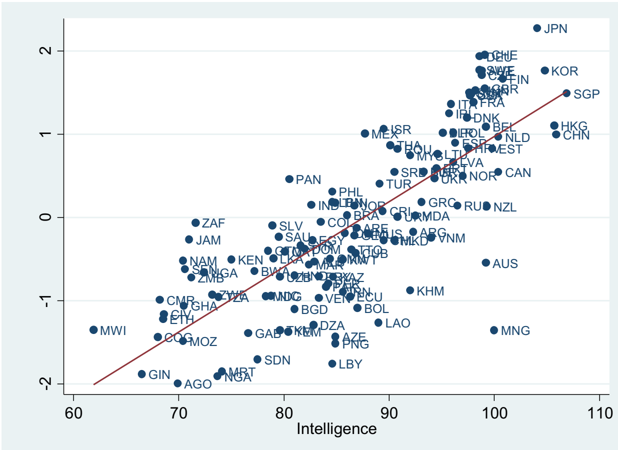

Fig. 2. ECI and intelligence.
Source: The Atlas of Economic Complexity, Lynn (2012) and Lynn and Vanhanen (2012).

We use average years of schooling to proxy for education as the latter may have an independent effect on innovation beyond what intelligence might exhibit.

Research and development activities are also considered to be a widely used contributor to innovation (e.g. see Landry et al., 2002; Doh and Acs, 2010; Squalli and Wilson, 2014).

To capture the level of economic development of countries we use GDP per capita in PPP terms (in logarithm).

We further incorporate a population density variable defined as a percentage of population per 1 sq. km of area to capture the effects of spatial clustering and agglomeration on the flow of ideas that bring about innovation (Carlino et al., 2007). It is essentially a representative of knowledge spillovers within countries (Squalli and Wilson, 2014).

We include trade openness measure into the model as openness to the outside world may be associated with greater innovation due to productivity increase and technological spillover effects throughout domestic economies because of greater market competition (e.g. see Xu and Chiang, 2005; Coyle et al., 2016).

Foreign direct investment can also be an important channel through which transfers of new technologies and related technological diffusion may take place and result in the production of more complex export products (e.g. see Xu and Wang, 2000; Cheung and Ping, 2004).

Lastly, the democracy (the average of civil liberties and political rights indicators) variable by Freedom House is also in our model to control for the institutional quality of the political system present in individual countries of the world. A number of studies indicate that institutional setting, or in more specific terms, “social technologies” provide low transaction cost ways of getting something done” (Nelson and Nelson, 2002, p. 268) and thus a strong predictor of innovative capacity. Indeed, innovation is sometimes associated with risk and uncertainty which raise transaction costs. Innovative capabilities flourish in those open societies where those costs are low enough and institutions play an important role in this regard (Van Waarden, 2001; Coyle et al., 2016).

We expect the coefficient estimates for all right-hand side variables to be positive and that for democracy to be negative as to the nature of construction of the variable (i.e. the lower values of the democracy index stands for the higher levels of democracy).

All control variables are average values for 2010–2014. Descriptive statistics of variables are presented in Table 2. Table 3 is a correlation matrix.

3. Empirical results

Stepwise regression results by using standard OLS method are presented in Table 4. One-to-one regression of ECI on IQ renders a positive and statistically significant coefficient estimate. The variance in intelligence quotient explains 60% of the variance in economic complexity in the restricted model.

Statistically, the inclusion of the education variable seems equally important in explaining variations in innovation. However, controlling for further macro-institutional factors turns the

Table 2
Descriptive statistics.

Variable	Source	Obs.	Mean	Std.dev.	Min	Max
ECI	The Atlas of Economic Complexity	124	−0.05	1.02	−1.99	2.27
IQ	Lynn (2012) and Lynn and Vanhanen (2012)	190	84.19	10.81	61.2	106.9
Education	UNDP Human Development Reports	186	7.88	3.06	1.3	12.9
R&D	WDI, World Bank	110	0.92	0.96	0.01	4.13
GDP per capita (log)	WDI	192	9.16	1.23	6.47	11.79
Density (log)	Author's calculations based on WDI	213	4.39	1.57	−1.98	9.83
Trade openness	WDI	185	95.08	53.22	24.36	444.9
FDI stock p/c (log)	UNCTAD	195	7.70	2.19	0.53	16.39
Democracy	Freedom House	193	3.33	1.96	1	7

Table 3
Correlation matrix.

	I	II	III	IV	V	VI	VII	VIII	IX
ECI	1.00								
IQ	0.76	1.00							
Education	0.66	0.73	1.00						
R&D	0.75	0.63	0.56	1.00					
GDP per capita (log)	0.62	0.69	0.74	0.52	1.00				
Density (log)	0.33	0.13	−0.02	0.18	0.06	1.00			
Trade openness	0.30	0.32	0.24	0.08	0.29	0.30	1.00		
FDI stock p/c (log)	0.62	0.68	0.73	0.53	0.86	−0.00	0.46	1.00	
Democracy	−0.52	−0.40	−0.52	−0.48	−0.36	0.05	−0.04	−0.54	1.00

Table 4
ECI and intelligence: OLS results.

	(1)	(2)	(3)	(4)	(5)
IQ	0.078*** (0.006)	0.054*** (0.008)	0.040*** (0.010)	0.030*** (0.011)	0.031*** (0.011)
Education		0.123*** (0.031)	0.042 (0.031)	0.058 (0.037)	0.033 (0.039)
R&D			0.388*** (0.072)	0.349*** (0.077)	0.312*** (0.073)
GDP p/c (log)				0.009 (0.096)	0.146 (0.090)
Density (log)				0.144** (0.059)	0.139** (0.061)
Trade openness				−0.000 (0.001)	0.002 (0.001)
FDI stock p/c (log)				0.037 (0.071)	−0.078 (0.070)
Democracy					−0.108** (0.044)
Constant	−6.858*** (0.496)	−5.791*** (0.540)	−4.081*** (0.688)	−4.327*** (0.712)	−4.401*** (0.683)
N	124	124	90	88	87
adj. R^2	0.604	0.654	0.690	0.727	0.747

Dependent variable: Economic Complexity Index.
Heteroskedasticity adjusted robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

coefficient of the education variable insignificant. Nevertheless, we still keep the latter in further steps as it is theoretically relevant to the model.

In the meantime, the R&D expenditures variable moderates the effect of intelligence on ECI, but doesn't change its significance (column 3). The model reveals that both intelligence and R&D variables are statistically important variables.

Although the introduction of economic variables such as GDP per capita, trade openness, and FDI stock per capita as well as the density variable are necessitated by the theory, empirically estimated individual coefficients of these variables, except for the density variable, happen to be statistically not significant even at 10% level.

Column 5 shows that when we include the democracy variable into the regression it is pertinent to the context: its coefficient is individually statistically significant at 5% and it further contributes to the explanatory power of the model (adjusted coefficient of determination goes up from 0.73 to 0.75).

Up to this point the coefficient estimate of R&D variable has remained its significance at 1% level. In the meantime, one should note that the variable of our interest, national intelligence, consistently keeps its statistical significance at 1% level. Testing the model as specified in column 5 for the omitted variable bias (Ramsey's RESET test) shows that it does not suffer from this problem ($p = 0.23$).

After all, in an OLS setting, one standard deviation unit increase in national IQ scores would be associated with 0.03 standard deviation units increase in ECI, *ceteris paribus*.

The coefficients of independent variables across all specifications match our a priori expectations given that they are statistically significant. For instance, those countries where

Table 5
ECI and intelligence: IV regression results.

Stage:	(1)		(2)	
Dep. variable:	IV – 1st stage IQ	IV – 2nd stage ECI	IV – 1st stage IQ	IV – 2nd stage ECI
IQ		0.069** (0.030)		0.069*** (0.026)
Education	0.677* (0.371)	−0.018 (0.050)	0.305 (0.401)	−0.017 (0.047)
R&D	2.207** (0.902)	0.207* (0.107)	2.114** (0.839)	0.208** (0.099)
GDP p/c (log)	2.237 (1.409)	0.076 (0.104)	2.842** (1.367)	0.077 (0.101)
Density (log)	0.716 (0.651)	0.130* (0.073)	0.632 (0.613)	0.130* (0.073)
Trade openness	0.025 (0.017)	0.001 (0.002)	0.024 (0.016)	0.001 (0.002)
FDI stock p/c (log)	−0.127 (0.793)	−0.086 (0.074)	−0.363 (0.776)	−0.085 (0.074)
Democracy	0.033 (0.607)	−0.113*** (0.044)	−0.064 (0.586)	−0.113*** (0.043)
Absolute latitude	0.173*** (0.046)			
UV damage			−0.049*** (0.012)	
Constant	49.43*** (9.522)	−6.358*** (1.636)	63.24*** (9.566)	−6.331*** (1.463)
N	87	87	87	87
adj. R^2	0.675	0.718	0.706	0.720
1st stage F-stat (p-value)	35.21 (0.00)	–	39.82 (0.00)	–
Wooldridge's robust score (p-value)	–	2.07 (0.15)	–	3.46 (0.07)

Heteroskedasticity adjusted robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

political rights and civil liberties (democracy) are relatively in good shape experience a higher level of innovative activities which translate into the production of more sophisticated export goods.

In the meantime, major criticism of our results may be the endogeneity problem. One possibility is that intelligence and innovation may be correlated with a third variable(s) which may be unobserved and thus not included into the model. Measurement errors in variables are another likely reason why we should apply a different econometric estimation method. The ignorance of the endogeneity problem in our context may result in biased and inconsistent OLS estimates (see e.g. Gujarati, 2014).

To solve the mentioned problem it is conventional to apply an instrumental variable (IV) approach. Following León (2015, 2016), Salahodjaev and Azam (2015) and Kanyama (2014) we use two different instruments that are individually related to intelligence, but are unrelated to ECI. They are absolute latitude of the geographical location of each country, and ultraviolet (UV) exposure of population.

The use of these instruments is justified by the relevant literature. León and León (2014, 2015) have recently proposed a new theory where IQ gains of recent generations of populations are the result of the following chain of effects: absolute latitude → UV_B

radiation → vitamin D_3 → parents' sexual hormones → family size → child's intellectual environment → IQ. By analyzing Peruvian children's math and reading abilities they conclude that intelligence increases with absolute latitude (León and León, 2014). Besides, Rindermann et al. (2015) show that absolute latitude has highest correlations with cognitive ability mean, and in the same country sample – with cognitive ability, top ability level and innovation. Further, by analyzing the impact of altitude above sea level on intelligence, León and Avilés (2016) note that "UV radiation, which is stronger at high altitude, is theorized to negatively affect intelligence".

By using data on absolute latitude and UV exposure from Ashraf and Galor (2013) as instruments, the regression results show that the coefficients of national intelligence are statistically significant across all specifications indicating the robustness of results (Table 5). This can be verified through the adjusted coefficient of determination (R^2) of the model which is equal to 72%, and first stage F-statistic which is greater than 35% and statistically significant. Wooldridge's robust score test of overidentifying restrictions indicates that we fail to reject the null of valid instruments at the same significance level ($p = 0.15$; 0.07). So, the variables are exogenous and the model is specified correctly.

One should note that our findings from IV regressions empirically, but indirectly support the UV Radiation Theory of Intelligence proposed by León, (2015, 2016), León and León (2014, 2015).

4. Robustness checks

In this paper we also try to check the robustness of our results in several ways.

First, we re-estimate the initial model with a quantile (QREG) and robust regression (RREG) options (Table 6). The QREG approach addresses the dissimilarity of nations, i.e. intelligence may have differential influence on countries with different levels of the ECI. This method generates more efficient coefficient estimates especially when OLS residuals are not normally distributed (Buchinsky, 1998). On the other hand, the robust regression option is usually used to control for heteroskedasticity and influential observations (outliers). The results of implementing both techniques clearly exhibit that the coefficients of national IQ scores remain intact at the 1% significance level and range between 0.031 and 0.038.

Second, we re-estimate our model with an alternative set of control variables. We keep IQ and GDP per capita variables in the model and further extend the dataset to include the number of researchers in R&D (per million people) and mean tariff rates from World Bank's World Development Indicators, intellectual property rights protection data from Park (2008), and information on British, French, Scandinavian and Socialist legal origins (German legal origin is a reference group) from La Porta et al., (1999). Relevant literature states that all of these variables theoretically belong to the model (see e.g. Qiu and Lai, 2004; Furukawa, 2010;

Table 6
ECI and intelligence: quantile and robust regression results.

	(1) Q 0.2	(2) Q 0.4	(3) Q 0.5	(4) Q 0.6	(5) Q 0.8	(6) RREG
IQ	0.032*	0.035**	0.035***	0.031***	0.031***	0.038***
	(0.017)	(0.016)	(0.013)	(0.008)	(0.009)	(0.009)
Education	0.021	0.019	0.042	0.033	0.084***	0.028
	(0.053)	(0.061)	(0.047)	(0.028)	(0.032)	(0.033)
R&D	0.372***	0.401***	0.360***	0.321***	0.260***	0.311***
	(0.125)	(0.140)	(0.099)	(0.060)	(0.077)	(0.068)
GDP p/c (log)	0.029	0.132	0.026	0.160	0.182	0.119
	(0.193)	(0.237)	(0.176)	(0.097)	(0.114)	(0.119)
Density (log)	0.057	0.053	0.143**	0.170***	0.123**	0.083*
	(0.081)	(0.083)	(0.062)	(0.035)	(0.047)	(0.042)
Trade openness	0.001	0.001	0.001	0.001	0.003**	0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
FDI stock p/c (log)	−0.008	−0.085	−0.009	−0.036	−0.091	−0.073
	(0.140)	(0.173)	(0.120)	(0.073)	(0.093)	(0.084)
Democracy	−0.043	−0.093	−0.098*	−0.108***	−0.072	−0.111***
	(0.056)	(0.074)	(0.054)	(0.036)	(0.044)	(0.040)
Constant	−3.957***	−4.148***	−4.144***	−4.701***	−4.773***	−4.406***
	(1.492)	(1.561)	(1.153)	(0.690)	(0.752)	(0.763)
N	87	87	87	87	87	87
adj. R^2						0.768

Dependent variable: Economic Complexity Index. Columns 1-5 exhibit the outcomes of quantile regression across different quantiles, column 6 displays the results of RREG approach.
Standard errors in parentheses. In column 6 heteroskedasticity adjusted robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 7
ECI and intelligence: OLS regressions with alternative set of control variables.

	(1)	(2)	(3)	(4)	(5)
IQ	0.052***	0.054***	0.041***	0.039***	0.027**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)
Education	0.109***	0.038	0.002	0.009	−0.072
	(0.031)	(0.029)	(0.034)	(0.039)	(0.050)
GDP p/c (log)	0.071	0.012	0.016	−0.010	0.202
	(0.070)	(0.062)	(0.103)	(0.111)	(0.142)
Researchers (log)		0.000***	0.000**	0.000**	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
IPR protection			0.437***	0.385***	0.470***
			(0.104)	(0.119)	(0.134)
Tariff rates				−0.020	−0.015
				(0.013)	(0.015)
British legal origin					−0.746***
					(0.159)
French legal origin					−0.957***
					(0.172)
Scandinavian legal origin					−0.746***
					(0.265)
Socialist legal origin					−0.471**
					(0.204)
Constant	−6.143***	−5.191***	−5.256***	−4.647***	−4.371***
	(0.570)	(0.506)	(0.524)	(0.662)	(0.731)
N	122	84	70	66	64
adj. R^2	0.656	0.761	0.800	0.799	0.845

Dependent variable: Economic Complexity Index.
Heteroskedasticity adjusted robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 8
ECI and intelligence: regressions with alternative dependent variables.

	R&D	Researchers	Patents	HT exports
IQ	0.043***	0.081***	0.177***	0.462***
	(0.012)	(0.017)	(0.047)	(0.105)
Education	0.023	0.075	0.080	−0.575
	(0.045)	(0.049)	(0.138)	(0.431)
R&D	–	0.503***	1.098***	2.505**
		(0.088)	(0.305)	(1.024)
GDP p/c (log)	0.093	0.134	0.726	−4.299**
	(0.122)	(0.159)	(0.547)	(1.728)
Density (log)	0.075	−0.113*	0.047	0.613
	(0.069)	(0.068)	(0.185)	(0.675)
Trade openness	−0.002	0.000	−0.013**	0.010
	(0.002)	(0.002)	(0.005)	(0.026)
FDI stock p/c (log)	−0.027	0.074	−0.572**	3.194**
	(0.092)	(0.112)	(0.263)	(1.282)
Democracy	−0.151***	−0.023	0.312*	1.006
	(0.039)	(0.080)	(0.178)	(0.801)
Constant	−3.446***	−3.239**	−14.252***	−18.911**
	(0.870)	(1.359)	(4.773)	(8.565)
N	104	89	88	99
adj. R^2	0.450	0.842	0.557	0.363

Dependent variables: R&D – research and development expenditure as% of GDP; Researchers – number of researchers in R&D per million people (in logarithm); Patents – number of patents filed by residents (in logarithm); HT exports – high-tech exports as% of manufactured exports.
Heteroskedasticity adjusted robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Qian, 2007). The results demonstrate that national intelligence is indeed quite robust to a different setting of the same issue (Table 7). In particular, national intelligence, IPR protection variables, and dummies for different legal origins display statistical significance and have expected signs (column 5). It turns out that all types of legal origins are associated with less innovation than German legal origin. Indeed, Germany and other countries with German-type legal origins have high rankings in ECI.

Third, in Table 8 we regress other traditional metrics of innovation that are described in Fig. 1 on the initial set of explanatory variables. All of the regressions confirm our earlier findings: intelligence is an important antecedent of innovation.

Fourth, Tobler's First Law of Geography states that "All places are related but nearby places are more related than distant places". Using cross-country IQ data to explain the health care expenditure of nations, Lv and Xu (2016) have shown that controlling for spatial dependence may be of high importance when neighboring countries share similar or close socio-economic characteristics with each other than non-neighboring ones. Indeed, when sample data has a locational component it is likely that spatial dependence may exist between the observations and/or spatial heterogeneity occurs in the relationships (Ward and Gleditsch, 2008). In line with these considerations, as a further check for robustness we employ spatial econometric techniques to see whether they make sense in exploring the relationship between ECI and cross-country intelligence. We consider geographical locations of countries as represented by their respective latitude and longitude values to construct the spatial weight (W) matrix. Results presented in Table 9 suggest that indeed spatial dependence is relevant to our model. Outcome indicator of spatial lag model rejects the null hypothesis of no spatial dependence in the data. One should note that the coefficient of intelligence in spatial lag model still keeps its sign and statistical significance.[1]

5. Conclusion

In this study we attempt to analyze the relationship between national intelligence and innovation using data from 124 countries of the world over the period from 2010 to 2014. The results indicate that there is a robustly positive association between intelligence and innovation. We can also conclude that more intelligent nations export more sophisticated and diverse products to the world market. This suggests that developing countries should consider investing in human capital and related institutions if they are to boost innovative capabilities and move up the technology ladder in producing and exporting sophisticated products. This should bring them greater economic diversity which could be a right lever in mitigating negative external shocks.

In the meantime, we admit that our study has its shortcomings. Due to cross-sectional structure of the intelligence data, we

[1] We have also tried to enlarge the dimensions of W matrix to 118x118 by dropping the R&D variable from the model which has many missing values. The signs and significance levels of intelligence and other independent variables still remain intact.

Table 9
ECI and intelligence: control for spatial dependence.

	Spatial error model	Spatial lag model
IQ	0.032*** (0.009)	0.024*** (0.009)
Education	0.029 (0.032)	0.029 (0.032)
R&D	0.313*** (0.068)	0.303*** (0.066)
GDP p/c (log)	0.158 (0.119)	0.165 (0.116)
Trade openness	0.001 (0.001)	0.002 (0.001)
FDI stock p/c (log)	−0.074 (0.083)	−0.081 (0.082)
Democracy	−0.080* (0.043)	−0.101*** (0.039)
Density (log)	0.137*** (0.042)	0.127*** (0.041)
Constant	−4.620*** (0.849)	−3.861*** (0.786)
Spatial error (lambda)	0.359 (0.218)	
Spatial lag (rho)		0.237** (0.116)
N	87	87

Dependent variable: Economic Complexity Index.
Heteroskedasticity adjusted robust standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

couldn't make use of more sophisticated econometric methods in our analysis, nor have we been able to shed light on dynamic relationship between intelligence and innovation. What's more, ECI variable that we use in this paper doesn't take into account the global value chains phenomenon and its characteristics. Also, it doesn't cover exports of (sophisticated) services, an important element of global trade. In spite of these limitations, we reckon that we have been able to effectively blend theoretical channels through which intelligence is associated with innovation to explain how exactly the link works. Moreover, spatial characteristics of the intelligence-innovation nexus are explored in the paper by employing spatial econometric techniques, a promising methodological construct of recent decades that is indispensable if one deals with geographical data such as ours. Besides that, a number of alternative research methods are exercised to authenticate the robustness of the relationship.

With regard to the future directions of research on the topic, we suggest that above-mentioned limitations should be properly addressed. Some interactions between intelligence and different antecedents of innovation could be tested. Alternative measures of cognitive abilities should be employed to see how they translate into innovative products and decisions during various business cycles. Survey level studies on the issue would give a flexibility to analyze different dimensions of innovative behavior (e.g. among migrants) and thus can also be a promising avenue for future research.

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