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Intelligence, creativity, and innovation

Jay Squalli [a,*], Kenneth Wilson [b]

[a] Department of Economics, American University of Sharjah, P.O. Box 26666, Sharjah, United Arab Emirates
[b] Office of the Provost, Zayed University, P.O. Box 19282, Dubai, United Arab Emirates

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ABSTRACT

This study provides the first test of the intelligence–innovation hypothesis, which contributes to the intelligence–creativity debate in the psychology literature and to the innovation–growth debate in the economics literature. Using U.S. state-level data the study finds that, net of other factors, high-IQ states are more innovative as measured by the important innovation outcome measure, utility patents registered. This study highlights the need for a better understanding of the relationship between intelligence, creative achievement, and innovation, a nascent and under-researched field of inquiry. Our research also begs the question of whether efforts to nurture intelligence are a necessary first step to increasing the capacity to realize innovation improvements.

1. Introduction

The relationship between intelligence, creativity, and innovation is little understood by economists and psychologists alike and is a fertile area for research, particularly interdisciplinary research, where questions abound in terms of the influence of intelligence on both creativity and innovation. Indeed, the major focus of this paper is the question: do more intelligent societies or communities innovate more? Although psychologists have not addressed the intelligence–innovation relationship explicitly, they have made attempts at understanding how intelligence contributes to creativity, a related trait, but mainly at the individual level. However, the absence of a unified definition of creativity has made this task not only challenging but controversial. In addition, related inquiries face further complications arising from the fact that intelligence and creativity are constructed differently and are subjected to varying theoretical and psychometric development (see e.g. Kaufman & Plucker, 2011).

Empirical studies have generally reported little to no correlation between intelligence and creativity. Two notable examples include Wallach and Kogan (1965) and Kim (2005) who report average correlation between intelligence and creativity of 0.09 and 0.17, respectively.[1] The low correlation between intelligence and creativity, to some extent, arises from the confusing array of definitions and measures that are used to represent creativity in empirical studies. Indeed, Nusbaum and Silvia (2011) emphasize that modern creativity research emphasizes the difference between intelligence and creativity and draw particular attention to the work of Kaufman (2009) and Sawyer (2006). However, Nusbaum and Silvia take a different view and assert that intelligence is more central to creative cognition than is more popularly believed.

Just like psychologists, economists have expressed keen interest in the role that innovation plays in stimulating economic growth. There are strong theoretical foundations in four different branches of economic thought: evolutionary (Nelson & Winter, 1982; Schumpeter, 1934); neo-classical (Solow, 1956, 1957); post-Keynesian (Kaldor, 1957); and

* Corresponding author. Tel.: +971 65152318.
E-mail addresses: jsqualli@aus.edu (J. Squalli), Kenneth.Wilson@mcycd.gov.ae, kenneth.wilson@zu.ac.ae (K. Wilson).

[1] Wallach and Kogan (1965) correlate five different measures of creativity with ten measures of intelligence, whereas Kim (2005) undertakes a meta-analysis of 21 studies.

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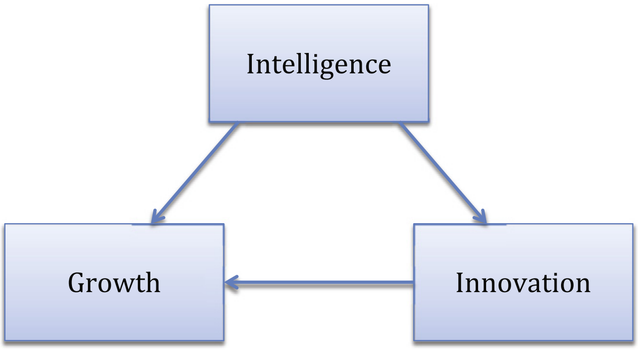

Fig. 1. The transmission of intelligence to growth via innovation.

endogenous growth (Romer, 1986, 1990). Although the transmission mechanism from innovation to economic growth varies depending upon the framework, the evidence consistently predict that more innovation leads to greater economic growth (Guellec & van Pottelsberghe de la Potterie, 2001; Lederman & Maloney, 2003). Innovation boosts productivity, improves an economy's competitiveness and contributes to building knowledge-based economies and societies. Intelligence is a key aspect of human capital in any society and human capital plays an important role in the theory of economic growth. For instance, Mankiw, Romer, and Weil (1992) include a human capital variable in their empirical test of the Solow (1957) model where human capital is measured by secondary school enrollments. Other human capital measures include primary school enrollments (Sala-i-Martin, 1997) and average years of schooling (Barro & Lee, 1993). More recently, Jones and Schneider (2006) use IQ as the human capital measure in their empirical test of the human capital-economic growth hypothesis. Similar to Weede and Kämpf (2002) they find that intelligence, measured by IQ, has a direct, positive effect on economic growth.

Given that intelligence is an important element of human capital, we propose that there is more innovation in societies that have high-IQ populations for three reasons. First, more intelligent people have longer time horizons, a consistent finding in psychology and economics (Potrafke, 2012; Shamosh & Gray, 2008) which enables them to better appreciate the increasing returns from innovation, entrepreneurship and risk-taking behavior. Second, in high-IQ population groups, knowledge spillovers from 'social technologies' (Nelson & Sampat, 2001) are likely to be greater.[2] Third, since a key part of innovation involves scientific and engineering discovery and applications that are embodied in intellectual property via patents, we propose that more intelligent people are more able to undertake the considerable intellectual challenges associated with knowledge creation and innovation. Indeed, there is compelling evidence that intelligence has a direct effect on job performance when a job is inherently less trainable; such as jobs that require creative problem solving, independent decision making and innovative adaptation (Gottfredson, 2004). These are the very skills needed for productive work in an innovation system. The transmission mechanism from intelligence to economic growth, illustrating support for the proposition that innovation has a direct, positive effect on economic growth, is represented in Fig. 1.

Building on scholarly work in the psychology and economics literature, the original contribution of this paper is to provide the first test of the intelligence–innovation hypothesis. This assessment would contribute to the current intelligence–creativity debate in the psychology literature and to the innovation–growth debate in the economics literature. To this end, the paper is organized as follows: Section 2 discusses creativity and innovation. Section 3 describes our empirical strategy. Section 4 summarizes the results. Section 5 summarizes robustness estimations. Section 6 discusses the results and concludes.

2. Creativity and innovation

Intelligence, creativity and innovation may be well understood in general terms but attract considerable controversy when attempts are made to define, measure and assess their inter-relationships. Consider the following basic definitions of intelligence and creativity. According to the Merriam-Webster dictionary, intelligence is "the ability to learn or understand things or to deal with new or difficult situations." By comparison, Mayer (1999) provides the following definition of creativity: "creation of new and useful products including ideas as well as concrete objects." Such definitions place the area of overlap between the constructs as quite small. This is consistent with the early findings of Wallach and Kogan (1965) noted above. By contrast, Silvia et al. (2008) undertake a latent variable reanalysis of Wallach and Kogan's findings and find a correlation of $r = 0.20$. Silvia (2008) continues this theme and argues that past work has tended to underestimate the relationship between intelligence and creativity. Silvia favors latent variable models which allow researchers "to estimate higher-order latent factors, such as a latent g composed of lower-order latent factors" (p. 1013). According to Silvia, testing the relationship between intelligence and creativity requires modeling intelligence as a higher-order, general factor composed of lower order cognitive skills. More recently, Nusbaum and Silvia (2011) use the latent variable approach to test the relationship between fluid intelligence and creativity and conclude that intelligence and creativity are more closely related than more popular research contends.

[2] Social technologies or social capital include the norms and social relations embedded in social networks and include the sum of the resources that accrue to an individual or group when individuals work and interact together.

Another more recent study by Jauk, Benedek, and Neubauer (2014) provides evidence of the relationship between intelligence and creativity, particularly creative achievement. These authors use an original creative inventory approach to capture creative achievements in a sample of 297 subjects. Their inventory "assesses creative activities and achievements in eight domains, including literature, music, arts and crafts, creative cooking, sports, visual arts, performing arts and science and engineering" (p. 98). Using a latent variable structural equation model of creativity and intelligence they find support for the proposition that intelligence is important for creative achievement; it takes intelligence to convert creative activities into creative achievements.

The discussion about intelligence and creativity highlights the challenges researchers investigating questions concerning the intelligence–creativity relationship face; as constructs they confound process and outcome and create special challenges when it comes to measuring each construct. Piffer (2012) emphasizes this point, particularly with respect to the measurement of creativity. Piffer shows that the three dimensions of creativity (novelty, appropriateness and impact) constitute a framework within which creativity can be defined and measured. Moreover, Piffer highlights that creativity is relevant to both products and people and requires careful definition in order to obtain accurate measures: "Should we measure the creativity of the person or the product? How do we measure them?" (p. 259). Piffer continues, "I regard a person's creativity as the total sum of the creativity of the products he/she has generated. Thus, I argue that the definition of creativity corresponds to that of creative achievement" (p. 259). That is, Piffer favors outcome based measures of creativity such as securing a patent or publishing a novel.

Innovation is the development and commercialization of products, services and processes that are new to a firm, the market or the world (Organisation for Economic Co-operation and Development, 1996). Schumpeter (1934) defines product innovation as "the introduction of a new good É or a new quality of a good," and process innovation as "the introduction of a new method of production … or a new way of handling a commodity commercially" (p. 66). The emergence of new forms of organization and the opening of new markets and of new source materials were additional types of innovation considered by Schumpeter. Schumpeter also stresses the role of individuals rather than organizations in the innovation process. Pavitt (2005) suggests that it is useful to divide innovation into three partially overlapping processes, namely the production of scientific and technological knowledge, the translation of knowledge into artifacts, and responding to and influencing market demand. In all three processes people play an essential role and within each process the intelligence of individuals is important. Key to innovation is the active engagement of people and organizations coupled with entrepreneurship and risk taking behavior.

Innovation emerges from an innovation system. An innovation system refers to the rules and governance structure that empower the network of universities, research labs and firms to generate, acquire and disseminate knowledge. Innovation is by definition, novelty. "It is the creation of something qualitatively new, via processes of learning and knowledge building. It involves changing competencies and capabilities, and producing qualitatively new performance outcomes" (Smith, 2006, p. 149). So how do we measure innovation? Since innovation is usually conceptualized in terms of ideas, learning and the creation of knowledge, or in terms of competencies and capabilities, then it may be measured in a range of different ways. Innovation measures include: research and development expenditure; bibliometric indicators such as publications and citations; and patent data. Utility patents are examples of outcomes of a vibrant innovation system.[3]

This discussion highlights the considerable overlap that exists between the outcome measures of creativity that fit comfortably inside the psychology literature and the outcome measures of innovation that fit comfortably in the economics literature. Therefore, if we test the intelligence–innovation hypothesis with an outcome measure like patents, we are also by implication able to test the intelligence–creativity hypothesis.

3. Empirical strategy

3.1. Data

To test the intelligence–innovation hypothesis we use a data set comprising indicators of intelligence and innovation for all U.S. states except the District of Columbia. We use the IQ estimates created by McDaniel (2006), which are derived using scores of the National Assessment of Educational Progress (NAEP) across multiple years.[4] The NAEP test is administered to students in grades 4 and 8 to measure academic achievement in reading, mathematics, science, writing, history, geography, and other subjects (Perie, Grigg, & Donahue, 2005). Due to the cross-sectional nature of our study and the fact that IQ data are limited to a single observation for each state, limiting our analysis to a single year could result in a potentially spurious attribution of innovation to intelligence. To introduce a certain degree of variability, we generate data for our dependent variable and most of our explanatory variables by averaging over the 2005–2010 period.

Each U.S. state possesses its own innovation system. Innovation generates knowledge embodied in technical progress. Much of this technical progress is captured in patents. We use the well-known innovation outcome measure of utility patents registered with the USPTO. We use population data from the Bureau of Economic Analysis to scale our utility patent data to the number of patents per million people. Our patent data are averaged over the 2005–2010 period.

We control for income using real GDP per capita, in 2005 chained dollars, from the Bureau of Economic Analysis and use observations averaged over the 2005–2010 period. We control for population density using land area per capita. This variable allows us to control for knowledge spillovers. Land area (per km^2) data are from the U.S. Census Bureau and are scaled using population data averaged over the 2005–2010 period. We control for research and

[3] According to the United States Patent and Trademark Office (USPTO), a utility patent is "issued for the invention of a new and useful process, machine, manufacture, or composition of matter, or a new and useful improvement thereof, it generally permits its owner to exclude others from making, using, or selling the invention for a period of up to twenty years from the date of patent application filing ++, subject to the payment of maintenance fees."

[4] Although these IQ estimates may vary over time, the rank order of states in the scores of NAEP exams (on which IQ estimates are based) is stable over time (McDaniel, 2006).

development (R&D) spending using data from the National Science Foundation. We use data for R&D spending as a percentage of gross domestic product by state averaged over the 2005–2008 period.[5] Finally, we control for the number of doctorates awarded in science and engineering using data from the National Science Foundation. The data are scaled to the number of doctorates per one million people. Observations are computed for each year between 2005 and 2010 before being averaged over this period. Table 1 provides summary statistics for the variables.

To illustrate the association between intelligence and innovation we present a scatter plot of utility patents per million people and IQ (both in log). As Fig. 2 shows, IQ appears to be positively correlated with utility patents registered. States with high-IQ populations and high utility patent registrations include Massachusetts, New Hampshire, Minnesota and Vermont, whereas those with low IQ and low utility patents include Mississippi, Louisiana, and Hawaii.

3.2. Specification and methodology

The following represents our empirical specification:

$$\begin{aligned}\ln \mathrm{PPM}_i = \alpha_0 + \alpha_1 \ln \mathrm{IQ}_i + \alpha_2 \ln Y_i + \alpha_3 \ln \mathrm{AREAPC}_i \\ + \alpha_4 \ln \mathrm{DOC}_i + \alpha_5 \mathrm{RD}_i + \epsilon_i\end{aligned} \quad (1)$$

where we estimate utility patents per million people (PPM) in state i with respect to IQ, income (Y), land area per capita (AREAPC), the number of awarded doctorates in science and engineering per million people (DOC), and R&D as a percentage of GDP (RD). We expect the coefficient estimates for IQ, DOC, and RD to be positive and that for AREAPC to be negative. However, we do not have any specific a-priori expectations with respect to the coefficient estimate for income.

To account for potential nonlinearity between income and PPM, we also introduce income in its quadratic form in our estimations. In addition, we control for state location and any ensuing spillover benefits by introducing, in two separate specifications, regional and divisional dummy variables, consistent with the U.S. census classification of U.S. regions and divisions.[6] We introduce three regional dummies for Northeast, South, Midwest, and omit West as a reference region. As for divisions, we introduce eight dummies for New England, Middle Atlantic, South Atlantic, East South Central, West South Central, East North Central, West North Central, Mountain, and omit Pacific as a reference division.[7]

We estimate our specification using three procedures: (a) least squares (OLS) with standard errors that are cluster-robust to arbitrary heteroskedasticity and arbitrary intragroup correlation; (b) robust regression (RREG); and (c) quantile regression (QREG). Robust regression is used to deal with potential heteroskedasticity and outliers as it represents a form of weighted least squares that reduces the weight of extreme values on estimation results. As for quantile regression, commonly referred to as median regression, it is known to yield more efficient estimates when OLS residuals are not normally distributed (Buchinsky, 1998). In addition, the fact that quantile regression estimates the median of the dependent variable makes it less sensitive to outliers and heteroskedastic residuals.

For robustness and to eliminate potentially implausible economic relationships, we also estimate a parsimonious version of our empirical specification by removing variables that are consistently statistically insignificant. Upon preliminary review, the DOC variable, representing the number of awarded doctorates in science and engineering per million people, is the only one that is consistently statistically insignificant across all estimations. Thus, we also estimate Eq. (1) after excluding the DOC variable.

4. Empirical results

Tables 2 through 4 summarize our OLS, RREG, and QREG estimation results respectively. Column (1) reports estimates of our full specification, whereas column (2) reports those of our parsimonious specification, which excludes the DOC variable. The most notable observation is that the coefficient estimates for IQ and area per capita hold their sign and are statistically significant across all estimations. Thus, higher IQ and lower area per capita are associated with more innovation. However, the coefficient estimates for IQ are significantly higher when using OLS especially after the introduction of regional and divisional dummies. This suggests that using robust and quantile regression may have properly accounted for potential outliers.

OLS estimates in Table 2 show the expected sign and statistical significance for IQ, area per capita, and R&D. We also observe a marginally significant ($p < 0.10$) bell-shaped relationship between income and innovation, suggesting that innovation increases with income up to an estimated turning point of $46,182 before decreasing. This income–innovation relationship, however, disappears with the introduction of regional and divisional dummies. Surprisingly, the DOC is consistently statistically insignificant. On the other hand, the R&D coefficient estimate is consistently positive and statistically significant at least at the 0.05 level. As for our second set of estimations, excluding the DOC variable has no noticeable effect on our results.

Robust regression estimates in Table 3 depict a similar picture to our OLS estimations and provide support for a bell-shaped relationship between income and innovation, with estimated turning points of $47,577 and $46,504 for the estimations without dummies and with regional dummies, respectively.[8] The coefficient estimates for R&D are also positive and statistically significant across these two procedures. However, when divisional dummies are introduced, both effects (income and R&D) disappear. We find support for the inclusion of divisional dummies with the rejection of the null hypotheses

[5] To the authors' knowledge, no data beyond 2008 are available.

[6] These variables also help allay concerns about the remoteness of Alaska and Hawaii on the grounds that there are minimal regional innovation spillover opportunities due to their isolation.

[7] The full list and breakdown of the U.S. census classification are available at www.bls.gov/lau/laurd.htm.

[8] The absence of a monotonic relationship between income and innovation may suggest the presence of an *Innovation Kuznets Curve*. More specifically, this may suggest that higher income, at least at the U.S. state level, is not a necessary condition for higher innovation. This is an important finding that undoubtedly deserves more attention in future research and especially from a cross-country perspective.

Table 1
Summary statistics ($n = 50$).

Variable	Mean	Std. dev.	Min	Max
Area (km^2) per capita	0.102	0.310	0.002	2.155
Awarded S&E doctorates per million people	95.758	42.208	27.379	280.888
IQ	100.344	2.707	94.2	104.3
Utility patents per million people	244.388	189.831	42.309	859.936
R&D (% of GDP)	2.223	1.566	0.415	7.782
Real GDP per capita	41,504.27	7,694.419	28,717.5	63,486.83

Notes: S&E represents Science and Engineering.

that their coefficient estimates are jointly equal to zero. In our second set of estimations, although excluding the DOC variable does not alter our results, we observe a slight increase in the statistical significance of R&D and income estimates in our estimation with regional dummies and an increase in the statistical significance of the R&D estimate in our estimation with divisional dummies.

Quantile regression estimates in Table 4 are consistent with those described above. There is support for a non-linear relationship between income and innovation after the introduction of regional and divisional dummies. On the other hand, the exclusion of the DOC variable has no effect on our overall conclusions although it results in a slight increase in the statistical significance of the R&D and income estimates in the estimation without dummies and reduces the statistical significance of the income variable in the estimations with dummies. Based on the Wald test, we find support only for the inclusion of regional dummies.

In sum, focusing on our key variable, irrespective of the estimation procedure and specification, we observe consistently a positive and statistically significant relationship between IQ and utility patents registered. Thus, we estimate that a one percent increase in IQ is associated with approximately 10 percent more innovation (as measured by utility patents).

5. Robustness of the results

In the presence of heteroskedasticity, which is inevitable in many cases, robust and quantile regression may yield understated standard errors (Rogers, 1992). Given our small sample size and the complex nature of the relationship between intelligence and innovation, we can address this concern and assess the robustness of our estimates by deriving bootstrapped standard errors (Buchinsky, 1995, 1998; Koenker & Hallock, 2001). The benefit of bootstrapping lies in its ability to derive estimates of standard errors and confidence intervals based on the underlying distribution of the sample (Efron, 1982) and to allay concerns about within-sample distortions.

We re-estimate our specifications (full and parsimonious) using least squares and quantile regression with bootstrapped standard errors and 500 replications. We report our estimated standard errors in Tables 5 and 6. We assess the reported values in the context that our coefficient estimates hold their sign and statistical significance.

Overall, we observe increases in the standard errors of our key variable across both OLS and quantile regression estimations. Nevertheless, as shown in Table 5, the coefficient estimate for IQ remains statistically significant at least at the 0.05 level when using OLS. On the other hand, when using quantile regression, as shown in Table 6, statistical significance holds only for the full specification without the DOC variable and with the introduction of regional dummies. In fact, upon close inspection of our estimation results, we find that the coefficient estimates for Northeast, South, and Midwest are statistically significant at the 0.05, 0.05, and 0.10 levels, respectively. This is further supported by the p value of the Wald test for the estimation without the DOC variable and with regional dummies which suggests, although marginally

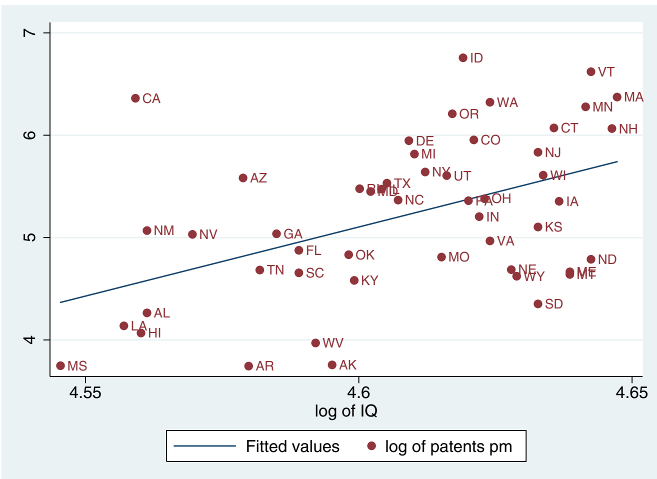

Fig. 2. Scatter plot of IQ and utility patents per million people.

Table 2
Least squares (OLS) estimation results.

Variables	OLS		OLS with regional dummies		OLS with divisional dummies	
	(1)	(2)	(1)	(2)	(1)	(2)
IQ	10.187***	10.07***	15.237***	15.231***	15.552***	15.474***
	(3.780)	(3.567)	(4.384)	(4.262)	(4.527)	(4.381)
Area per capita	−0.097*	−0.09	−0.268***	−0.268***	−0.302**	−0.294***
	(0.059)	(0.062)	(0.098)	(0.087)	(0.125)	(0.107)
Doctorates pm	−0.057		−0.002		−0.048	
	(0.275)		(0.244)		(0.294)	
R&D	0.218***	0.213***	0.138**	0.138**	0.137**	0.133**
	(0.066)	(0.059)	(0.062)	(0.058)	(0.069)	(0.061)
Income	71.041*	69.694*	49.195	49.180	44.985	44.740
	(37.816)	(37.159)	(41.236)	(40.689)	(46.991)	(46.441)
Income squared	−3.307*	−3.245*	−2.307	−2.306	−2.102	−2.092
	(1.77)	(1.742)	(1.933)	(1.908)	(2.206)	(2.178)
R^2	0.57	0.57	0.67	0.67	0.68	0.68
Income TP ($)	46,182	46,006				
Wald F statistic			2.48	2.46	1.17	1.19
p value			0.072	0.073	0.338	0.327

Notes: Coefficient estimates are reported with their corresponding cluster-robust standard errors between parentheses. Asterisks, *, **, and *** denote statistical significance respectively at the 0.10, 0.05, and 0.01 levels. The intercept is omitted from the results. The Wald test is for the null hypothesis that the coefficient estimates of the regional and divisional dummies are jointly equal to zero. TP stands for turning point.

($p = 0.053$), the rejection of the null hypothesis that the coefficient estimates for regional dummies are jointly equal to zero. In sum, based on our bootstrap estimations, our main conclusion that states with higher IQ are associated with more innovation (as measured by utility patents) still holds.

6. Discussion and conclusions

We provide the first empirical test of the intelligence–innovation hypothesis. We make use of U.S. state level data to assess the relationship between intelligence and innovation. Our results show that U.S. states with high-IQ populations are more innovative as measured by utility patents registered. The direct positive effect of innovation on economic growth (Guellec & van Pottelsberghe de la Potterie, 2001; Lederman & Maloney, 2003) and intelligence on economic growth (Jones & Schneider, 2006; Weede & Kämpf, 2002) is complemented by an indirect positive effect from intelligence to growth via innovation.

These results are also consistent with other research reported recently investigating economic aspects of intelligence. The economics of intelligence is an area deserving further investigation and international cross-comparisons, assuming away data challenges, should provide fertile new ground for suitable inquiry. An additional interesting conclusion is that our use of utility patents in the regression analysis enables us to provide support for the intelligence–creativity hypothesis. Since patents are favored by Piffer (2012) as one of several outcome measures of creativity in the psychology literature, then we find support for the argument that more intelligence leads to more creativity at the aggregate level.

Table 3
Robust regression (RREG) estimation results.

Variables	RREG		RREG with regional dummies		RREG with divisional dummies	
	(1)	(2)	(1)	(2)	(1)	(2)
IQ	8.092***	8.521***	9.252***	9.718***	9.737***	10.371***
	(2.810)	(2.731)	(2.771)	(2.674)	(3.152)	(3.101)
Area per capita	−0.116*	−0.130***	−0.350***	−0.367***	−0.368***	−0.399***
	(0.061)	(0.054)	(0.066)	(0.058)	(0.083)	(0.073)
Doctorates pm	0.162		0.124		0.162	
	(0.250)		(0.201)		(0.219)	
R&D	0.173***	0.188***	0.076*	0.090**	0.067	0.085*
	(0.054)	(0.049)	(0.045)	(0.040)	(0.048)	(0.044)
Income	74.548**	79.598**	59.071*	59.662**	54.709	52.363
	(37.019)	(36.122)	(30.080)	(29.295)	(33.885)	(33.528)
Income squared	−3.460**	−3.693**	−2.748*	−2.771**	−2.549	−2.433
	(1.735)	(1.694)	(1.410)	(1.373)	(1.587)	(1.57)
R^2	0.56	0.56	0.64	0.64	0.66	0.66
Income TP ($)	47,577	47,786	46,504	47,202		
Wald F statistic			9.61	10.15	3.55	3.64
p value			0.000	0.000	0.004	0.003

Notes: Coefficient estimates are reported with their corresponding standard errors between parentheses. Asterisks, *, **, and *** denote statistical significance respectively at the 0.10, 0.05, and 0.01 levels. The intercept is omitted from the results. The Wald test is for the null hypothesis that the coefficient estimates of the regional and divisional dummies are jointly equal to zero. TP stands for turning point.

Table 4
Quantile regression (QREG) estimation results.

Variables	QREG		QREG with regional dummies		QREG with divisional dummies	
	(1)	(2)	(1)	(2)	(1)	(2)
IQ	8.597**	11.521***	11.563***	11.644***	10.247**	10.038**
	(3.496)	(3.457)	(4.034)	(3.683)	(4.770)	(4.862)
Area per capita	−0.155**	−0.152***	−0.323***	−0.324***	−0.313**	−0.385***
	(0.076)	(0.069)	(0.097)	(0.081)	(0.125)	(0.115)
Doctorates pm	0.250		0.150		0.306	
	(0.311)		(0.292)		(0.331)	
R&D	0.131*	0.158**	0.085	0.079	0.055	0.073
	(0.067)	(0.062)	(0.065)	(0.055)	(0.073)	(0.069)
Income	58.315	83.860*	89.559**	64.217	96.233*	81.986
	(46.047)	(45.731)	(43.792)	(40.359)	(51.277)	(52.564)
Income squared	−2.712	−3.908*	−4.185**	−2.985	−4.507*	−3.822
	(2.159)	(2.145)	(2.053)	(1.892)	2.401	(2.462)
Pseudo-R^2	0.43	0.43	0.53	0.52	0.54	0.53
Income TP ($)		45,567	44,354		43,290	
Wald F Statistic			3.23	4.56	1.53	1.50
p value			0.032	0.007	0.181	0.193

Notes: Coefficient estimates are reported with their corresponding standard errors between parentheses. Asterisks, *, **, and *** denote statistical significance respectively at the 0.10, 0.05, and 0.01 levels. The intercept is omitted from the results. The Wald test is for the null hypothesis that the coefficient estimates of the regional and divisional dummies are jointly equal to zero. TP stands for turning point.

Table 5
OLS bootstrapped standard errors.

Variables	OLS		OLS with regional dummies		OLS with divisional dummies	
	(1)	(2)	(1)	(2)	(1)	(2)
IQ	4.138**	3.869***	4.867***	4.579***	5.735***	5.450***
Area per capita	0.084	0.087	0.115**	0.110**	0.165*	0.154*
Doctorates pm	0.296		0.304		0.385	
R&D	0.097**	0.089**	0.087	0.079*	0.109	0.106
Income	46.267	45.312	49.486	48.160	62.039	57.791
Income squared	2.176	2.128	2.325	2.264	2.918	2.716
Wald F statistic			7.56	7.03	7.93	7.46
p value			0.056	0.071	0.44	0.487

Notes: Bootstrap estimations are completed with 500 replications. Asterisks, *, **, and *** denote statistical significance respectively at the 0.10, 0.05, and 0.01 levels.

The policy implications of this research are interesting if not perplexing. Investment in research and development by governments and business enterprises may yield greater returns where the general level of intelligence, as measured by IQ, is higher. Given the fact that 40 to 70% of phenotypic variance in intelligence is of non-genetic origin (Plomin, DeFries, Knopik, & Neiderhiser, 2013), this begs the question of whether efforts to nurture intelligence are a necessary first step to increasing the capacity to realize innovation improvements. Investment in innovation may not realize a sufficient return without also investing in intelligence. That is, it makes sense to invest in education and other activities that raise the average IQ of a community in order to improve the pay back or return on an investment on innovation.

Table 6
QREG bootstrapped standard errors.

Variables	QREG		QREG with regional dummies		QREG with divisional dummies	
	(1)	(2)	(1)	(2)	(1)	(2)
IQ	5.458	5.078**	5.657**	5.696**	7.746	6.632
Area per capita	0.109	0.113	0.120***	0.122**	0.185*	0.173**
Doctorates pm	0.373		0.304		0.430	
R&D	0.107	0.101	0.103	0.098	0.147	0.125
Income	57.118	52.761	57.308	58.581	71.948	61.653
Income squared	2.682	2.483	2.694	2.753	3.38	2.902
Wald F statistic			1.86	2.77	0.87	0.83
p value			0.152	0.053	0.548	0.582

Notes: Bootstrap estimations are completed with 500 replications. Asterisks, *, **, and *** denote statistical significance respectively at the 0.10, 0.05, and 0.01 levels.

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