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On the Causal Relationship between IQ and GDP: An Instrumental Analysis

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Abstract

Although a substantial positive correlation between IQ and GDP per capita has been established at the national level over the past two decades (e.g. Lynn & Vanhanen, 2012), the causal direction of the observed association has been a subject of continuous debate. Here, we make use of a non-recursive path analysis involving two different instrumental variables in order to shed more light on the issue. The results of three analyses with two different instrumental measures strongly suggest that IQ is the cause of GDP and not the other way around. This conclusion is consistent with Lynn & Vanhanen's (2002) original conjecture as well as with several other studies employing different methodologies.

Keywords: IQ, GDP, Causal analysis, Instrumental variables

1 Introduction

Ever since the publication of Lynn & Vanhanen's seminal *IQ and the Wealth of Nations* in 2002, the precise causal nature of the strong positive correlation between nations' average IQs and GDPs per capita has been the subject of an intense debate. For example, Lynn & Vanhanen (2002) use both theoretical arguments and regression analyses while arguing that IQ influences national wealth rather than the other way around; Rindermann (2008) uses longitudinal path analyses (with educational achievement as a proxy for general intelligence) as well as structural equations modeling (Rindermann & Thompson, 2011) for making a similar claim. In the same vein, Weede and Kämpf (2002) argue for effects of IQ on economic growth. But their standard regression analyses and temporally static estimates of countries' IQ scores still prevent the interpretation of the results within an unequivocal causal framework. On the other hand, researchers such as Wicherts et al. (2010) and Volken (2003) have argued that the direction of causal influence between IQ and GDP has not been reasonably established due to lack of appropriate control measures and different potential confoundings between IQ and a plethora of measures related to general societal well-being.

In that sense, we have two competing accounts: The first one posits that high general intelligence leads to increased economic well-being within societies (e.g. by increasing levels of innovation and technological developments as well as by facilitating successful management of various economic and socio-political challenges). The other account argues that increased IQ levels are themselves the result of increased well-being. More precisely, it is hypothesized that better educational opportunities (e.g. Campbell & Ramey, 1994), improved nutrition (e.g. Stein et al., 2005), less frequent exposure to toxins (e.g. Grandjean & Landrigan, 2006), reduced levels of stress and trauma (e.g. Saltzman et al., 2006), better control of infectious diseases (e.g. MacKenzie, 2010), and generally more stimulating cognitive environments lead to higher measured cognitive abilities. Finally, it may well be the case that both mechanisms play a role (both IQ facilitates economic development and more developed countries manage to provide living and educational conditions which directly stimulate cognitive development). This argument has received some support from a partially longitudinal path analysis (Meisenberg & Lynn, 2012). This work is an attempt to investigate the causal connections between IQ and GDP directly and to quantify their respective strengths.

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Here, we make use of an instrumental approach within the non-recursive path analysis framework (e.g. Kline, 2010) in order to address this issue from a methodological perspective which, to our knowledge, has not yet been applied to the above mentioned problem. The instrumental approach makes use of a variable (the so-called Instrument) which can be assumed to be directly related only to one of the measures involved in the ambiguous causal relationship which is to be disentangled. The Instrument in question allows the non-recursive path model to allocate its weights along the different paths so as to reproduce the observed correlations in a manner which sheds light upon the precise causal nature of the relationship in question. In a similar fashion, as long as an Instrument is uncorrelated to other important predictors of the dependent variable which are inadvertently omitted from the analysis, the path coefficient from the independent to the dependent variable remains an unbiased estimate of the population parameter (e.g. Andrews et al., 2019).

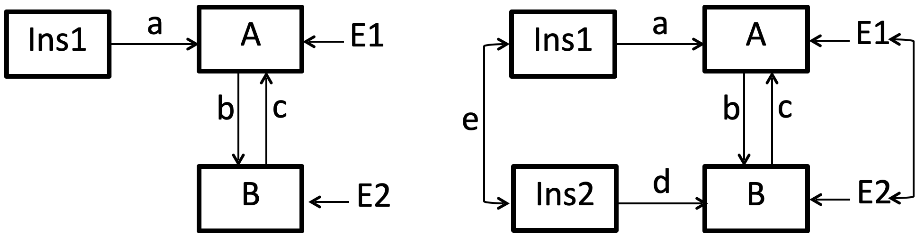

Figure 1: Non-recursive path models with an instrumental variable. For explanations, see text. Ins1, Ins2, Instruments, E1, E2, error terms..

Figure 1 and its caption provide a clear non-technical illustration of how the non-recursive path analysis investigates the causal structure between IQ and GDP. In the left panel, variables labeled A and B constitute the problematic pair of correlated measures, the causal relationship between which is to be disentangled; Ins1 denotes the Instrument which is supposed (on purely theoretical grounds) to be directly related only to one of the measures which we are interested in. In the figure this is variable A. Now, if Ins1 is really connected directly only to A, then its relationship with B depends on the empirically observed correlations. For example, if Ins1 does not correlate significantly with B, the path labeled b on the diagram is redundant, i.e. unnecessary in reproducing the observed correlations. This path can be thought of as representing the indirect effect of Ins1 on B through A. In other words, when there is no observed relationship between Ins1 and B, this path's estimate will tend towards zero and the relationship between A and B can be captured solely on the basis of path c. In this case, our model would indicate that B influences A but not vice versa.

Conversely, a significant observed correlation between Ins1 and B would indicate that the b path is important in reproducing this relationship. If the a and b paths reproduce all three observed relationships by themselves, the c path's estimate will tend towards zero and we will conclude that A influences B but not vice versa. Finally, if all three paths (a, b, c) are important for the model to reproduce the relationships observed between the three measures, then we will have an indication for a feedback loop. Within a feedback loop, in addition to the direct influence of one variable over another, we have both variables (A and B in Figure 1) influencing each other within a dynamic system whereby series of indirect effects accumulate over time. The crucial assumptions for the instrumental approach to give unbiased results are:

1. The Instrument is indeed related directly only to one of the measures in question and any other observed relationships are due only to indirect effects;

2. The system has settled to a stable state (attractor) before the measurement of the variables in question (i.e. the correlation between the measures no longer changes over time due to the system's internal dynamics).

Both assumptions are to be argued from a theoretical perspective because they cannot be demonstrated empirically within the non-recursive path model itself.

The right panel illustrates a similar non-recursive model where the same logic applies. Here, however, we have two different Instruments, each supposedly directly affecting only a single variable. This model has more degrees of freedom which allows us to specify a correlated error structure. Errors are denoted by E1 and E2 in the diagrams; double arrows indicate unanalyzed correlations between variables (i.e. correlations included in the model which are not explained by a causal path) in contrast to single arrows which indicate path coefficients with explicitly specified causal directions. This allows us to test for variables which are omitted from the model but which affect the measures in question thereby increasing the observed association between them. Such a correlated error structure cannot be specified with only a single Instrument (left panel) due to identification problems which occur when the number of parameters specified for a model (indicated by lower-case letters in Figure 1) exceeds the number of observed associations. Both models displayed above are just-identified (degrees of freedom = 0), and the statistical significance of the individual path coefficients can be tested via the standard maximum likelihood methods described in the structural equations modeling literature.

2 Variables

Because we were interested in the causal relationship between IQ and GDP, we tried to procure measures which were instrumental in that context, i.e. we were looking for variables which were related directly either to *per capita* GDP or to general intelligence but not both. We selected two Instruments which, we believe, fulfill the requirements listed above, i.e. Instruments which can be plausibly presumed to be directly related to only one of the two target measures (IQ or GDP).

First, we selected countries' oil production (OIL) as an Instrument with respect to GDP. We can easily see how OIL is directly related to countries' access to economic resources; at the same time, it is highly implausible to assume any kind of direct relationship between the amounts of oil at the disposal of a particular nation and its aggregate IQ.

Second, we elected to make use of the average skin color within different countries as an Instrument with respect to IQ. Being a measure simultaneously related to both different groups' evolutionary histories[1] and various contemporary environmental factors, skin colour (SC) can reasonably be supposed to be related to IQ (e.g. Kanazawa, 2004, 2008; Lynn, 1991; Rushton, 2000; Templer, 2008; Templer & Arikawa, 2006). It makes little theoretical sense to expect that SC by itself exerts direct causal influence on economic development, hence our claim that SC can serve as a meaningful Instrument with respect to IQ in the context of its relationship to GDP. We provide a description of each of the measures used in the current study in the following paragraphs.

Our first analysis is simply a reanalysis of the data provided by Templer (2008) in the context of a non-recursive path model with SC as an Instrument which supposedly directly relates only to IQ. In that sense, we used Templer's data which the reader can easily find in the respective reference. Templer provides SC data for 129 countries. SC was obtained from Biasutti (1967) and was measured on a quasi-continuous scale ranging from 1 (very light) to 8 (very dark). Overall, the SC measure contains 20 distinct values and is hence treated as an interval scale in the analyses below which is consistent with Templer's (2008) original approach. In addition to SC, Templer used national average IQs and GDPs *per capita* obtained from Lynn & Vanhanen (2002, 2006).

Our second and third analyses involved OIL as an Instrument with respect to GDP. OIL was conceptualized by the number of barrels obtained per year by a given country divided by the country's population, a measure we can call "Oil *per capita*". The number of barrels produced yearly was taken from

[1] The two main theories referenced above regard high IQs as a specific evolutionary adaptation. Lynn (1991) puts forward the "Cold Winter Hypothesis", which regards higher cognitive capacities as an adaptation to the challenges (finding food and shelter, etc.) presented by colder climates (see also Rushton, 2000). Kanazawa (2004), on the other hand, argues that higher aggregate IQs arise as an adaptation to evolutionary novelty. His theory predicts that groups which had settled away from *homo sapiens*' evolutionary origin in Africa and had faced challenges adapting to their novel environments should demonstrate higher average cognitive capacities. Attempts at demonstrating the validity of these evolutionary accounts have included correlating national IQ averages with countries' average annual temperatures and with countries' geographic distance from humankind's evolutionary origin in Africa (e.g. Kanazawa, 2008).

the Worldometer database[2]; the same source was used for the estimates of each country's population. The most recent data concerning OIL was available for 2016.

Our national aggregate IQ measures used in analyses 2 and 3 were taken from Lynn & Vanhanen (2012) — more recent aggregate estimates incorporating newer studies than the ones employed by Templer (2008). The estimates for *per capita* GDP were also taken for 2016. This preserves the cross-sectional nature of the non-recursive path analysis as best as possible and reduces the risk of violating its second assumption listed in the introduction. These data were obtained from the World Bank's database[3]

We see that we have two different waves of GDP measurements: the one used by Templer (2008), and the 2016 measurement wave used in analyses 2 and 3. Similarly, we have two estimates of national IQs provided by different editions of Lynn & Vanhanen's aggregation efforts. This diversity of measurements, sources and samples (see the Appendix) should serve to increase the validity of our results should these prove to be consistent across the different analyses.

Finally, we should point out that all of the analyses provided below were based on the logarithms of the data pertaining to GDP and OIL production *per capita*. These transformations produced distributions with lower skewness which brought them closer to the Gaussian family. We should stress, however, that all results reported below remained virtually identical when we repeated the analyses on the raw untransformed measures of GDP and OIL which provides us with a helpful "robustness check".

The tables containing the data for our second and third analyses are available in the Appendix. All reported analyses were conducted via the open source lavaan module within the R environment (Rosseel, 2012).

3 Analyses and Results

Our first analysis uses Templer's (2008) data which includes IQ, (log-transformed) GDP, and SC as an Instrument. The correlations between the three measures were as follows: r(IQ, GDP) = .73, $p < .001$; r(IQ, SC) = -.91, $p < .001$; r(SC, GDP) = -.71, $p < .001$. Based on 129 countries, the results can be seen in Figure 2. The analysis suggests that IQ is the cause rather than the effect of economic development.

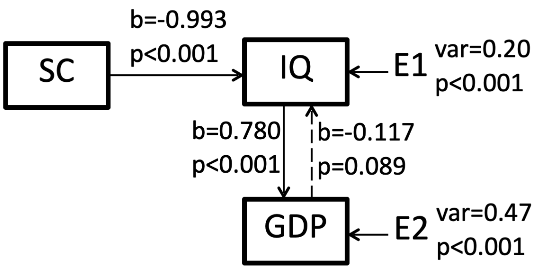

Figure 2: Standardized path coefficients, error variances, and significance levels. The statistically non-significant ($p > .05$) paths are shown as dashed arrows.

Our second analysis makes use of OIL as an Instrument with respect to GDP, i.e. we investigated the same relationship by making use of a different Instrument (OIL) acting upon our second target measure (GDP). We obtained data from 98 countries (see the Appendix) with complete data records for OIL and GDP (for 2016) and for IQ (2012). The results are shown in Figure 3 and are based on the following correlations: r(GDP, OIL) = .23, p = .022; r(GDP, IQ) = .74, $p < .001$; r(OIL, IQ) = -.03, p = .758.[4] We see that the exact same conclusions with respect to the direction of causal influence of IQ on GDP are implied by our second analysis as well.

The third analysis we conducted used both OIL and SC as Instruments within a model analogous to the one shown in Figure 1 (right). As briefly mentioned in the introduction, the approach involving two

[2] https://www.worldometers.info/oil/oil-reserves-by-country/

[3] https://data.worldbank.org/indicator/NY.GDP.PCAP.CD

[4] Note that the lack of correlation between IQ and OIL supports OIL's validity as an Instrument.

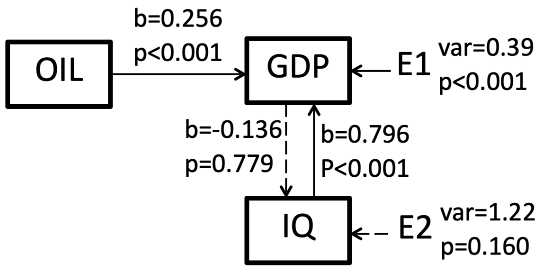

Figure 3: Standardized path coefficients, error variances and significance levels for the second analysis. The statistically non-significant ($p > .05$) paths are shown as dashed arrows.

Instruments provides additional information regarding the plausible values of the paths connecting our target variables (IQ and GDP in this case); it also allows for the estimation of the correlation between the errors (E1 and E2), which accounts for common causes for the target measures which may have been omitted from the analysis. This analysis used the same data as Analysis 2 in addition to SC taken from Templer's (2008) data. 76 countries with complete data records with respect to the four variables in question (see the Appendix) were entered into the non-recursive path model. The correlations between the four variables (IQ, GDP, OIL, and SC) are shown in Table 1; the results are reported in Figure 4.

Table 1: Correlations between GDP and OIL per capita, IQ and Skin Color (SC) for our third analysis. * $p < .05$, ** $p < .001$.

	GDP	OIL	IQ
OIL	0.230*		
IQ	0.739**	-0.073	
SC	-0.616**	0.094	-0.838**

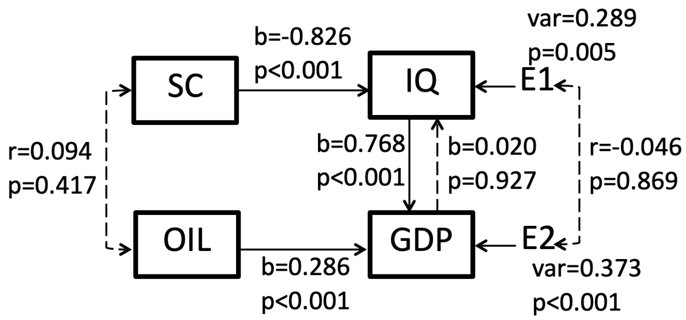

Figure 4: Standardized path coefficients, error variances, correlations (r) and significance levels for the third analysis. The statistically non-significant ($p > .05$) paths and correlations are shown as dashed arrows.

Again, we see the same pattern of results whereby IQ influences GDP but not vice versa. Interestingly, it appears that the correlation between the two error terms is negligible and far from significant which indicates that important predictors which influence both IQ and GDP were unlikely to have been omitted from the analyses. In that sense, the coefficients from the first two analyses seem unlikely to be subject to bias resulting from omitted common causes. Similarly, the lack of correlation between the error terms strongly suggests that the relationship between IQ and GDP is the result of a direct causal connection between the two target measures rather than resulting from the influence of variables not included in the model.

4 Discussion

The analyses presented above strongly suggest that IQ might be a stronger predictor of economic development than the reverse. The results from our analyses are strikingly consistent — all standardized path coefficients from IQ to GDP indicate a large effect (e.g. Cohen, 1992) and vary only between .768 and .796. These results are consistent with several other studies (e.g. Rindermann, 2008; Rindermann & Thompson, 2011) which employ different datasets and analytical techniques (for example, these studies make no use of instrumental variables) but arrive at the same general conclusions. This remarkable degree of consistency supports the validity of the reported findings.

Similarly, all three analyses indicate that the causal paths from GDP to IQ are entirely redundant. These paths seem unnecessary with respect to reproducing the observed correlations, their magnitudes are negligible, and they consistently fail to reach statistical significance.[5] This result may appear counterintuitive as it is well-known that the lack of educational opportunities and a cognitively stimulating environment as well as certain extreme conditions can hinder cognitive development as we discussed in the introduction. In the same vein, the observed results can be seen as being at odds with the Flynn effect (e.g. Flynn, 2012), which establishes a global increase in IQ during the 20th century. Today the rate of said increase is especially pronounced in developing countries. This was originally attributed to rapidly improving living conditions.

In order to reaffirm the relationship between IQ and environmental effects on living conditions within the proposed analytical framework, we conducted another non-recursive analysis. We used Templer's dataset and modeled the relationship between IQ (with SC as an Instrument) and infant mortality (IM) as a proxy for quality of life during crucial stages of cognitive development. We used the same model as the one depicted in Figure 2, but with infant mortality instead of GDP as the third variable depicted at the bottom. This time the results clearly indicated the presence of a significant feedback loop between IQ and IM. The standardized path from SC to IQ was equal to -0.787 ($p < .001$) and the path from IQ to IM was equal to -0.780 ($p < 0.001$), i.e. higher aggregate national IQs were associated with lower IM; importantly, the path from IM to IQ was also significant ($p = .001$) and in the predicted direction ($b = -0.173$). Still, the effect of IQ on IM was significantly stronger than the effect of IM on IQ. The difference between the two estimates was equal to -0.607 which was significantly different from zero ($p < .001$). These tentative results[6] are consistent with previous observations establishing environmental effects on IQ in the context of the Flynn effect; also, they show that nothing in our instrumental approach necessarily precludes IQ from emerging as an effect within a causal loop which should lend further credence to the results discussed above.

One plausible way to reconcile the results reported here with the Flynn effect and the environmental factors underlying it is to speculate that improvement in living conditions in developing countries (for which the Flynn effect is the most pronounced) is not overly correlated with their *per capita* GDPs. This may indeed be the case if a large portion of the improvement in living conditions in such regions is due to foreign aid and investment. Foreign aid/investment (direct material and financial aid and technological know-how as well as the general increase in availability of different medical, information and agricultural technologies) is not always directly included in the calculation of GDP, but it is probably partially responsible for developing nations' rapid increase in well-being. In that sense, foreign aid/investment presumably affects developing countries' living conditions to a much larger extent than their relative standing on the GDP continuum thereby diminishing the observed correlation between GDP and general well-being[7]. Although

5 Indeed, as Figures 2 and 3 show, two of our analyses indicate that GDP has a small (insignificant) negative effect on IQ once the other path coefficients have explained the observed correlations away. This appears to be a case of "negative suppression" whereby high positive correlations between two measures reverse in sign when other important variables have been taken into account (e.g. Maassen & Bakker, 2001).

6 This result should be regarded as preliminary because the Instrument used here (Skin Colour) may be connected to Infant Mortality through means other than IQ; actually, a direct biological link between the two may be suggested on the basis of the *r–K* selection theory (e.g. Templer, 2008; Rushton, 2004).

7 Another reason for the higher rate of increase of IQ and living conditions in developing countries might have to do with the so-called advantage of backwardness effect whereby underdeveloped countries tend to show higher economic growth rates (e.g. Weede & Kämpf, 2002), for example by implementing new technologies developed by more advanced countries while sparing themselves the costs of research and development. Indeed, it has been shown that countries with high IQs and low initial prosperity exhibit the highest rates of economic growth (e.g. Meisenberg & Lynn, 2012). The extent to which this

this speculation can readily explain the unidirectional influence of IQ on GDP described above while still acknowledging that environmental effects play an important role in cognitive development, further studies would be needed in order to ascertain its veracity or lack thereof.

5 Conclusion

The presented findings can be taken to indicate that societies with higher aggregate cognitive capacities tend to manage to create intra-societal environments which more or less adequately provide the necessary and sufficient conditions for their citizens to experience unhindered cognitive development. Such environments seem not to be directly dependent on GDP, but rather ensure suitable living conditions coupled with intellectually challenging surroundings. This makes it likely that citizens reach their full cognitive potential and hence provide the human capital which is essential for sustained economic growth (see Hafer, 2017 and Meisenberg & Lynn, 2011, 2012 for similar arguments).

Naturally, no single study should be taken as conclusive, especially on a topic as complex as this. For example, it may be argued that our samples are less than adequate in terms of size and representativeness, that the chosen Instruments don't fulfil the prerequisites needed in order to obtain unbiased results, and so on. Similarly, despite the remarkable degrees of both intra- and inter-study consistency mentioned above, the possibility of biased results due to model misspecification and various confounding factors should be kept in mind. We do, however, hope that future critiques of the proposed conclusions present sound theoretical counterarguments coupled with rigorous empirical support.

Future studies employing a similar methodology can make use of various different instrumental measures. For example, aggregate indices of access to natural resources (i.e. indices reflecting not only oil but also precious metals and minerals), which embody broader economic relevance, may be employed as potentially more reliable Instruments with respect to economic development; similarly, geographic measures such as distance from humankind's evolutionary origin (Kanazawa, 2008) and average temperature (e.g. Lynn, 1991; Rushton, 2000) can be employed as Instruments with respect to IQ.

The data for aggregate IQ levels across different countries has never come in pre-specified time waves designed to facilitate testing of various hypotheses regarding the causal interplay between IQ and other measures such as GDP, living conditions, education, etc. Previous research has concentrated mainly on using variables which do come in such waves (e.g. the PISA assessments) as proxies for IQ (e.g. Rindermann, 2008; but see also Rindermann, 2007 for an argument claiming that IQ tests and international scholastic achievement reflect the same general cognitive construct). The main strength of the approach proposed here is that it attempts to investigate the causal structure between IQ and economic development by means of a cross-sectional design which requires no proxy variables and uses Instruments in order to compensate for the lack of a structured longitudinal dataset with respect to IQ. That being said, it would make sound theoretical sense to establish the proposed results further in the context of a temporally dynamic framework. For example, using data on economic growth (instead of static measures such as GDP) and temporal differentials in international scholastic achievement within models such as longitudinal path analysis and/or growth regression (Rindermann, 2008; Meisenberg & Lynn, 2012) would allow researchers to gain insights into the causal structure of the variables in question from a different perspective. If the results from different research strategies and analytical approaches converge, a more sound theoretical understanding of IQ in terms of its causal antecedents and consequents could be achieved.

Based on the discussed observations, we would venture to speculate that results of future studies will be similar to the ones reported here. This conjecture is not only consistent with a plethora of empirical observations but also makes sound theoretical sense within the paradigm regarding high general intelligence as a biological adaptation (e.g. Kanazawa, 2008; Lynn, 1991; Rushton, 2000), described as an abstract cognitive ability aimed at general problem solving. The problems which contemporary societies face include various technological, institutional, socio-political, economic, ecological and environmental challenges which, being evolutionarily and even historically novel, require precisely such an abstract cognitive competence in

phenomenon affects the correlations between IQ (including the Flynn effect), GDP, and general well-being remains to be investigated further.

order to be adequately addressed (e.g. Rindermann, 2008; Rindermann & Thompson, 2011; Meisenberg & Lynn, 2011, 2012; Weede & Kämpf, 2002). This makes different strands of intelligence research all the more relevant.

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Conflicts of Interest

None

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References

Andrews, I., Stock, J., & Sun, L. (2019). Weak instruments in instrumental variables regression: Theory and practice. *Annual Review of Economics*, *11*, 727–753.

Biasutti, R. (1967). *Le razze e i popoli della terra*. Torino, Italy: Unione pipografiza-Editrice Torinese.

Campbell, F. A., & Ramey, C. T. (1994). Effects of early intervention on intellectual and academic achievement: A follow-up study of children from low-income families. *Child Development*, *65*(2), 684–698.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155–159.

Flynn, J. (2012). *Are We Getting Smarter? Rising IQ in the Twenty-First Century* (1st ed.). Cambridge Univ. Press.

Grandjean, P., & Landrigan, P. (2006). Developmental neurotoxicity of industrial chemicals. *Lancet*, *368*(9553), 2167–2178.

Hafer, R. (2017). New estimates on the relationship between IQ, economic growth and welfare. *Intelligence*, *61*, 92–101.

Kanazawa, S. (2004). General intelligence is a domain-specific adaptation. *Psychological Review*, *111*, 512–523.

Kanazawa, S. (2008). Temperature and evolutionary novelty as forces behind the evolution of general intelligence. *Intelligence*, *36*, 99–108.

Kline, R. (2010). *Principles and Practice of Structural Equation Modelling* (3rd ed.). Guilford Press.

Lynn, R. (1991). The evolution of racial differences in intelligence. *Mankind Quarterly*, *32*, 99–173.

Lynn, R., & Vanhanen, T. (2002). *IQ and the Wealth of Nations* (1st ed.). Westport, CT: Praeger.

Lynn, R., & Vanhanen, T. (2006). *IQ and Global Inequality* (1st ed.). Augusta, GA: Washington Summit.

Lynn, R., & Vanhanen, T. (2012). *Intelligence. A Unifying Construct for the Social Sciences* (1st ed.). Ulster Institute for Social Research.

Maassen, G., & Bakker, A. (2001). Suppressor variables in path models: Definitions and interpretations. *Sociological Methods & Research*, *30*(2), 241–270.

MacKenzie, D. (2010). Link found between infectious disease and IQ. *New Scientist*, *207*(2767), 12.

Meisenberg, G., & Lynn, R. (2011). Intelligence: A measure of human capital in nations. *Journal of Social, Political, and Economic Studies*, *36*(4), 421–454.

Meisenberg, G., & Lynn, R. (2012). Cognitive human capital and economic growth: Defining the causal paths. *Journal of Social, Political, and Economic Studies*, *37*(4), 141–179.

Rindermann, H. (2007). The g-factor of international cognitive ability comparisons: The homogeneity of results in PISA, TIMSS, PIRLS and IQ-tests across nations. *European Journal of Personality*, *21*(5), 667–706.

Rindermann, H. (2008). Relevance of education and intelligence for the political development of nations: Democracy, rule of law and political liberty. *Intelligence*, *36*(4), 306–322.

Rindermann, H., & Thompson, J. (2011). Cognitive capitalism: The effect of cognitive ability on wealth, as mediated through scientific achievement and economic freedom. *Psychological Science*, *22*(6), 754–763.

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, *48*(2), 1–36.

Rushton, P. (2000). *Race, Evolution, and Behavior: A Life History Perspective* (abridged 2nd ed.). Charles Darwin Research Institute.

Rushton, P. (2004). Placing intelligence into an evolutionary framework or how g fits into the r–K matrix of life history traits including longevity. *Intelligence*, *32*(4), 321–328.

Saltzman, K., Weems, C., & Carrion, V. (2006). IQ and posttraumatic stress symptoms in children exposed to interpersonal violence. *Child Psychiatry and Human Development*, *36*(3), 261–272.

Stein, A., Behrman, J., DiGirolamo, A., et al. (2005). Schooling, educational achievement, and cognitive functioning among young Guatemalan adults. *Food and Nutrition Bulletin*, *26*(2), 46–54.

Templer, D. (2008). Correlational and factor analytic support for Rushton's differential K life history theory. *Personality and Individual Differences*, *45*, 440–444.

Templer, D., & Arikawa, H. (2006). Temperature, skin color, per capita income, and IQ: An international perspective. *Intelligence*, *34*(2), 121–139.

Volken, T. (2003). IQ and the Wealth of Nations. A critique of Richard Lynn and Tatu Vanhanen's recent book. *European Sociological Review*, *19*(4), 411–412.

Weede, E., & Kämpf, S. (2002). The impact of intelligence and institutional improvements on economic growth. *Kyklos*, *55*(3), 361–380.

Wicherts, J., Borsboom, D., & Dolan, C. (2010). Why national IQs do not support evolutionary theories of intelligence. *Personality and Individual Differences*, *48*(2), 91–96.

Appendix

Table A1: Data used for Analysis 2. Per capita GDP and Oil production per capita (OIL) are log-transformed.

Country	GDP	OIL	IQ	Country	GDP	OIL	IQ	Country	GDP	OIL	IQ
Albania	8.32	4.08	82	Ethiopia	6.56	-5.69	68.5	Pakistan	7.29	0.39	84
Algeria	8.29	5.59	84.2	France	10.52	0.19	98.1	Papua NG	7.75	2.86	83.4
Angola	7.50	5.44	71	Gabon	8.81	6.71	69	Peru	8.73	2.99	84.2
Argentina	9.46	3.95	92.8	Georgia	8.31	2.24	86.7	Philippines	8.02	0.17	86.1
Australia	10.82	3.81	99.2	Germany	10.65	0.46	98.8	Poland	9.42	1.21	96.1
Austria	10.72	1.62	99	Ghana	7.55	2.96	69.7	Qatar	10.98	9.14	90.1
Azerbaijan	8.26	6.51	84.9	Greece	9.79	-0.03	93.2	Romania	9.15	3.41	91
Bahrain	10.04	4.43	85.9	Guatemala	8.34	1.52	79	Russia	9.07	6.32	96.6
Bangladesh	7.41	-1.82	81	Hungary	9.48	1.04	98.1	Saudi Arabia	9.90	8.88	79.6
Barbados	9.76	2.11	80	India	7.45	1.20	82.2	Serbia	8.66	2.38	90.3
Belarus	8.53	3.04	95	Indonesia	8.18	2.59	85.8	Slovakia	9.71	0.44	98
Belize	8.72	2.79	76.8	Iran	8.61	7.48	85.6	South Africa	8.65	-1.39	71.6
Benin	6.96	-0.54	71	Iraq	8.37	8.05	87	Spain	10.19	1.15	96.6
Bolivia	8.01	2.84	87	Israel	10.54	0.42	94.6	Sudan	7.87	4.64	77.5
Brazil	9.07	4.31	85.6	Italy	10.34	2.29	96.1	Suriname	8.65	5.08	89
Brunei	10.19	7.80	89	Japan	10.58	-1.03	104.2	Syria	6.50	4.68	82
Bulgaria	8.93	0.81	93.3	Jordan	8.29	-2.43	86.7	Taiwan	10.05	-2.31	104.6
Cameroon	7.26	1.94	64	Kazakhstan	8.95	7.33	85	Tajikistan	6.69	0.17	80
Canada	10.65	8.39	100.4	Kuwait	10.20	10.07	85.6	Thailand	8.67	1.73	89.9
Chad	6.54	4.41	66	Kyrgyzstan	7.02	1.78	74.8	Trinidad & T.	9.69	6.16	86.4
Chile	9.53	2.03	89.8	Libya	8.98	8.86	85	Tunisia	8.24	3.53	85.4
China	9.00	2.87	105.8	Lithuania	9.62	1.48	94.3	Turkey	9.30	1.29	89.4
Colombia	8.69	3.79	83.1	Malaysia	9.16	4.65	91.7	Turkmenistan	8.73	4.52	80
Congo	7.65	5.57	73	Mauritania	7.36	1.41	74	Uganda	6.62	3.94	71.7
Croatia	9.44	2.87	97.8	Mexico	9.12	4.33	88	Ukraine	7.69	2.37	94.3
Cuba	8.99	2.40	85	Morocco	8.05	-4.01	82.4	UAE	10.62	9.24	87.1
Czechia	9.83	0.36	98.9	Myanmar	7.11	-0.09	85	United Kingdom	10.62	3.71	99.1
Côte d'Ivoire	7.60	1.24	71	Netherlands	10.74	2.08	100.4	United States	10.97	4.64	97.5
Denmark	10.91	4.53	97.2	New Zealand	10.60	2.51	98.9	Uzbekistan	7.90	2.83	80
DR Congo	6.12	0.57	68	Niger	6.21	1.71	70	Venezuela	8.21	9.25	83.5
Ecuador	8.71	6.12	88	Nigeria	7.67	5.11	71.2	Vietnam	7.92	3.80	94
Egypt	8.11	3.66	82.7	Norway	11.17	6.84	97.2	Yemen	6.98	4.47	80.5
Equ. Guinea	8.99	6.46	69	Oman	9.75	7.04	84.5				

Table A2: Data used for Analysis 3. Per capita GDP and Oil production per capita (OIL) are log-transformed.

Country	GDP	OIL	IQ	Skin color	Country	GDP	OIL	IQ	Skin color
Albania	8.32	4.08	82.0	1.7	Kuwait	10.20	10.07	85.6	4.0
Algeria	8.29	5.59	84.2	4.3	Kyrgyzstan	7.02	1.78	74.8	2.0
Angola	7.50	5.44	71.0	7.0	Libya	8.98	8.86	85.0	4.3
Austria	10.72	1.62	99.0	1.0	Lithuania	9.62	1.48	94.3	1.3
Azerbaijan	8.26	6.51	84.9	2.0	Malaysia	9.16	4.65	91.7	4.7
Bahrain	10.04	4.43	85.9	4.0	Mauritania	7.36	1.41	74.0	5.0
Bangladesh	7.41	-1.82	81.0	4.3	Morocco	8.05	-4.01	82.4	2.7
Belarus	8.53	3.04	95.0	1.3	Netherlands	10.74	2.08	100.4	1.0
Benin	6.96	-0.54	71.0	7.0	Niger	6.21	1.71	70.0	7.0
Brunei	10.19	7.80	89.0	4.0	Nigeria	7.67	5.11	71.2	7.0
Bulgaria	8.93	0.81	93.3	1.7	Norway	11.17	6.84	97.2	1.0
Cameroon	7.26	1.94	64.0	7.0	Oman	9.75	7.04	84.5	5.0
Chad	6.54	4.41	66.0	7.0	Pakistan	7.29	0.39	84.0	3.7
China	9.00	2.87	105.8	2.0	Philippines	8.02	0.17	86.1	4.0
Congo	7.65	5.57	73.0	6.7	Poland	9.42	1.21	96.1	1.0
Croatia	9.44	2.87	97.8	2.0	Qatar	10.98	9.14	90.1	4.0
Czechia	9.83	0.36	98.9	1.3	Romania	9.15	3.41	91.0	2.0
Côte d'Ivoire	7.60	1.24	71.0	6.3	Russia	9.07	6.32	96.6	2.0
Denmark	10.91	4.53	97.2	1.0	Saudi Arabia	9.90	8.88	79.6	4.0
DR Congo	6.12	0.57	68.0	7.0	Serbia	8.66	2.38	90.3	2.0
Egypt	8.11	3.66	82.7	4.0	Slovakia	9.71	0.44	98.0	1.3
Equ. Guinea	8.99	6.46	69.0	6.0	South Africa	8.65	-1.39	71.6	6.7
Ethiopia	6.56	-5.69	68.5	6.7	Spain	10.19	1.15	96.6	2.0
France	10.52	0.19	98.1	1.0	Sudan	7.87	4.64	77.5	6.7
Gabon	8.81	6.71	69.0	7.0	Syria	6.50	4.68	82.0	3.3
Georgia	8.31	2.24	86.7	2.0	Taiwan	10.05	-2.31	104.6	3.0
Germany	10.65	0.46	98.8	1.0	Tajikistan	6.69	0.17	80.0	2.7
Ghana	7.55	2.96	69.7	7.0	Thailand	8.67	1.73	89.9	3.7
Greece	9.79	-0.03	93.2	2.0	Tunisia	8.24	3.53	85.4	3.0
Hungary	9.48	1.04	98.1	1.0	Turkey	9.30	1.29	89.4	2.0
India	7.45	1.20	82.2	6.3	Turkmenistan	8.73	4.52	80.0	2.3
Indonesia	8.18	2.59	85.8	4.7	Uganda	6.62	3.94	71.7	7.7
Iran	8.61	7.48	85.6	3.0	Ukraine	7.69	2.37	94.3	1.7
Iraq	8.37	8.05	87.0	3.3	UAE	10.62	9.24	87.1	4.0
Italy	10.34	2.29	96.1	1.7	United Kingdom	10.62	3.71	99.1	1.0
Japan	10.58	-1.03	104.2	2.0	Uzbekistan	7.90	2.83	80.0	2.0
Jordan	8.29	-2.43	86.7	3.0	Vietnam	7.92	3.80	94.0	4.0
Kazakhstan	8.95	7.33	85.0	2.0	Yemen	6.98	4.47	80.5	6.0