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Religious belief and intelligence: Worldwide evidence

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ABSTRACT

Is there a positive impact of intelligence on religious disbelief after we account for the fact that both average intelligence and religious disbelief tend to be higher in more developed countries? We carry out four beta regression analyses and conclude that the answer is *yes*. We also compute impact curves that show how the effect of intelligence on atheism changes with average intelligence quotients. The impact is stronger at lower intelligence levels, peaks somewhere between 100 and 110, and then weakens. Bootstrap standard errors for our point estimates and bootstrap confidence intervals are also computed.

Contents

1. Introduction

Is there a statistically significant relationship between the lack of religious belief and intelligence? Howells (1928) showed that there is a negative correlation between intelligence and religious belief among college students using different measures of religious belief. Argyle (1958) concluded that intelligent students are less inclined to hold religious beliefs. Lynn, Harvey, and Neyborg (2009) used data on 137 countries and showed that the correlation between intelligence and religious disbelief is positive and statistically significant: 0.60. There is thus evidence of a positive relationship between atheism and intelligence. Additionally, Reeve (2009) examined the degree to which IQ, belief rate and health form a meaningful nexus of relations. He showed that IQ is positively associated with health and negatively related to the nation belief rate (i.e., the percentage of population that believe in a god).

It has also been established that religious disbelief tends to increase with economic development. That is, religious beliefs loose strength, on average, as a country becomes richer; see, for instance, Barber (2011, 2013). The prevalence of atheists is typically higher in economically developed countries in contrast to what is observed in low income economies. For instance, in most African countries the

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percentage of nonbelievers does not exceed 1% (Zuckerman, 2007) whereas in Sweden it reaches 64%. In other developed countries the percentage of population that does not hold religious beliefs is also high: 48% in Denmark, 44% in France and 42% in Germany. It is true that proportion of the population in the United States that are religious is large, but it is also true that it has been decreasing over time. For example, polls have shown that 95.5% of the U.S. population believed in God in 1948 (Argyle, 1958) and that such a figure dropped to 89.5% in 2004 (Zuckerman, 2007).

Pesta, McDaniel, and Bertsch (2010), using data on the fifty U.S. states, created a well-being index and showed that it tends to be higher for states located on the East Coast, where people are more liberal, more educated, wealthier, and more intelligent than average and at the same time are less religious than average. Lynn (2010) claims that regional differences in intelligence are the major factor for regional discrepancies in Italy when it comes to per capita income and also to stature, infant mortality, and education. One of the hypotheses presented by Lynn (2010) is that the North–South gradient of IQs in Italy may explain much of the economic development discrepancy between the North and the South of the country. The correlation coefficient between regional IQ and per capita income is 0.94. The substantial regional IQ variations in Italy can, to a large extent, explain the large differences in regional per capita income. The author claims that the strong positive correlation between population IQ and per capita income follows from a feedback loop in which higher population IQ leads to higher per capita income, and higher per capita income in turn leads to higher IQs. Thus, higher population IQ is both a cause and a result of higher per capita income. Higher IQ leads to higher per capita income because high IQ individuals are able to work more efficiently and consequently to command higher incomes. On the other hand, higher income is associated with better nutrition, health care and education and thus leads to higher intelligence levels. Reeve and Basalik (2010), using data on the U.S., examined the degree to which differences in average IQ across the 50 states are related to differences in health indicators. Their results show that, even after controlling for differences in state wealth and health care expenditures, average IQ is positively associated with a wide range of positive health indicators and negatively associated with many state health problems.

Kanazawa (2009) carried out a macro level analysis that shows that nations with higher average intelligence tend to be more liberal (higher marginal individual tax rate and, as a result, lower income inequality), less religious and more monogamous. The author also modeled the proportions of religious people in different countries using control variables that include national IQ and per capita GDP. After estimating a linear regression, he concluded that, net of the controls, national IQ negatively impacts the proportion of the population who believes in God. In particular, "each point in national IQ decreases the proportion of the population who believes in God by more than a percentage point" (p. 548). As we shall explain in Section 4, however, the linear regression model is not the best tool to analyze data that assume values in (0,1) since it can yield predictions (fitted values) that go beyond the interval limits. The model also implies that the impact of a given covariate on the mean response is constant, i.e., it is the same regardless of the values of all covariates. Notice that the author concludes that each unit increase in national IQ is associated with a decrease of over 1% in the proportion of religious people, the conclusion holding for all levels of national IQ and also for all values of all other covariates (including per capita GDP). Our empirical analysis is based on a model tailored for dealing with proportions and our estimated impacts are not constant. Indeed, we show that the impact of intelligence on religious disbelief is stronger in countries where national IQ lies between 100 and 110.

Nyborg (2009) examined whether IQ systematically relates to denomination and income within the *g*-nexus framework using representative data from the National Longitudinal Study of Youth. The *g*-nexus is a network of intercorrelated variables with general mental ability at the center; see Jensen (1998). It has both horizontal and vertical components. The horizontal component includes real world variables which co-vary and interact with general mental ability whereas the vertical component includes presumed causes of individual differences in *g*, with special focus on biological and neuropsychological variables. High IQ people are able to curb magical, supernatural thinking and tend to deal with the uncertainties of life on a more rational/critical/empirical basis whereas low IQ people tend to become trapped in religious/magical thinking.

There is thus evidence that religious disbelief is positively correlated with both intelligence and economic development. As a consequence, in order to determine whether there is a statistically significant positive relationship between intelligence and religious disbelief using a cross-country dataset it is important to account for the impact of economic development on atheism. In particular, the question we pose can be stated as follows: Is there a statistically significant relationship between intelligence and religious disbelief *after accounting for the impact of economic development on atheism*? If such a relationship does exist it is then important to measure it. This is our chief goal. In what follows, we shall use regression analysis to model the impact of intelligence on religious disbelief. In particular, we shall use the class beta regression models introduced by Ferrari and Cribari-Neto (2004) to model the prevalence of atheists in 124 countries. Our results suggest that the positive impact of intelligence on religious disbelief is statistically significant even when we account for the positive impact of economic growth on atheism. Similar results are found when we model the proportion of the population in 84 countries that do not consider religion important in their daily lives.

The paper unfolds as follows. Section 2 describes the data. In Section 3 we briefly present the class of beta regression models, which are useful for modeling data that assume values in the standard unit interval. Section 4 contains the empirical analyses. We model two different dependent variables, determine whether there is a positive relationship between intelligence and religious disbelief when the effect of economic development is accounted for and construct impact curves that describe how intelligence impacts religious disbelief. Bootstrap-based inference is also carried out. Section 5 offers some concluding remarks.

2. The data

Lynn et al. (2009) provide data on the percentages of atheists in 137 countries (which account for over 95% of world population) extracted from Zuckerman (2007). The data were collected from various published articles, mostly in 2004. They also present data on the average intelligence quotients for the same 137 nations. Since our interest lies in estimating the net impact of intelligence on religious disbelief, we have also collected data on other conditioning variables, such as purchasing power parity adjusted per capita income (in 2008), economic openness (in 2008) and prevalence of Muslims (in 2004).

Atheists are heavily concentrated in economically developed countries. In poor and developing countries, the prevalence of atheists is typically low. A possible explanation lies in the fact that as a country grows and becomes richer and more developed, the institutions become more reliable, the average family size decreases, health care improves, and more people have access to the benefits of science and technology. Thus, most people's daily lives are less subject to fear and uncertainty, thus reducing the appeal of many religious discourses. In order to account for such a trend we shall include the variable *INCOME* as a regressor in our analysis. The gross domestic income adjusted for purchasing power parity is constructed from a unique international basket of goods and services that is regularly referred from pricing researches and cost spreadsheets in different countries that belong to the United Nations International Comparison Program.

Another important covariate is the ratio between the sum of imports and exports and GDP (Gross Domestic Product) in each country (*OPEN*). It is included in our regression analysis to account for the fact that some communist countries have high prevalences of atheists not as a result of personal choice, but because people are not, for the most part, exposed to the different religious discourses. *OPEN* is thus a proxy for the degree of exposure to different ideas and cultures. Recall that we are mainly interested in the relationship between religious disbelief and intelligence. It is thus important that religious disbelief be the result of informed choice and reasoning.

We have also considered variates that account for the prevalence of Muslims in the general population. In countries with high prevalence of Muslims there is typically little separation between state and religion. Quite often religion is taught at public schools and the scope for religious disbelief as the result of informed choice is thus reduced. Another distinctive feature of such countries is that the Quran is typically taken in literal fashion, i.e., as the inerrant word of God. In most Western countries, in contrast, the Bible is taken less literally. It can thus be expected that the higher the prevalence of Muslims in a country the smaller the scope for informed choice that leads to religious disbelief. It is also noteworthy that in these countries there is more social (family and peer) pressure on people for not leaving the mainstream religion.

We also note that Lewis, Ritchie, and Bates (2011) showed that lower intelligence is most strongly associated with higher levels of religious fundamentalism. They also show openness negatively correlates with religious fundamentalism.

The variables used in our regression analysis are: proportion of atheists in 124 nations (*ATH*), proportion of people who did not consider religion important in their daily lives in 2009 (*RELIG*), average intelligence quotient of the population (*IQ*), Gross National Income adjusted for purchasing power parity in 2008, in thousands of dollars (*INCOME*), sum of total imports and exports divided by the Gross Domestic Product in 2008 (*OPEN*), a dummy variable that equals 1 if the percentage of Muslims exceeds 50%, and 0 otherwise (*MUSL*) and life expectancy in 2007 in years (*EXPEC*). The data sources are Lynn et al. (2009), The World Bank, http://www.gallup.com and http://www.qran.org/a/a-world.htm. We obtained data for 124 countries, except for *RELIG*, for which data corresponding to 84 nations were collected.

In 75% of the countries the proportion of atheists does not exceed 0.15. The largest prevalence of atheists is 0.81. In half of the countries the average IQ does not exceed 87. The largest value of the ratio between the sum and exports and imports and GDP is 361.60, which is nearly fifteen times larger than the smallest value. The average proportion of people who do not consider religion important in their daily lives is 0.25, the largest value being 0.82.

Vietnam has the largest proportion of atheists and it is also one of the countries with the largest proportion of people who do not consider religion important in their daily lives. Other countries with large prevalences of atheists are Japan, Sweden and the Czech Republic. We also note that in 29 out of the 124 countries more than 50% of the population is Muslim. The countries with the largest average intelligence quotient are Singapore and South Korea. The country with the most open economy is Singapore, which has also the fifth largest per capita GDP.

The nations with the largest proportions of people who do not value religion are Switzerland, Denmark and Estonia. Their proportions of atheists are also high: 0.64, 0.48 and 0.49, respectively. The average intelligence quotients in these nations are high as well. Finally, we note that although the average IQ in the United States is large (98), the proportion of people who do not consider religion important there is low (0.34) relative to countries with similar average intelligence quotients.

Table 1 contains the sample correlations between all pairs of continuous variates used in our empirical analysis. Notice that *ATH* and *RELIG* are positively correlated with all variables except for *MUSL*. The responses *ATH* and *RELIG* strongly correlate with *INCOME* and *IQ*. The latter two variables are also positively correlated. It is also noteworthy that the correlation between the proportion of atheists and the proportion of people who do not consider religion important in their daily lives is 0.86, i.e., our two dependent variables are highly correlated.

3. Beta regression

Our two dependent variables assume values in the standard unit interval. It is thus not appropriate to base an empirical analysis on the linear regression model. The linear regression model can be written as $\mu_t = \beta_1 + \beta_2 x_{t2} + \cdots + \beta_k x_{tk}$, $t = 1, \ldots, n$. Here, n is the sample size, μ_t is the mean of the tth response (i.e., $\mu_t = \mathrm{IE}(y_t)$), the β's are regression coefficients and the x's are explanatory variables (regressors). Notice that the left hand side assumes values in (0,1) whereas the right

Table 1
Sample correlations.

	ATH	*IQ*	*INCOME*	*OPEN*	*EXPEC*	*MUSL*
ATH	–	–	–	–	–	–
IQ	0.61	–	–	–	–	–
INCOME	0.61	0.71	–	–	–	–
OPEN	0.26	0.29	0.21	–	–	–
EXPEC	0.49	0.86	0.70	0.18	–	–
MUSL	−0.35	−0.34	−0.38	−0.05	−0.27	–
RELIG	0.86	0.73	0.72	0.16	0.58	−0.36

hand side assumes values in the real line (IR). It then follows that the fitted model can yield predicted response values outside (0,1), which would not make sense. For instance, one may obtain negative predicted atheism rates. One can transform the dependent variable so that the transformed responses (say, y_t^*) assume values in (0,1) and use them in the linear regression analysis. This has, nonetheless, a shortcoming: the regression coefficients (i.e., the β's) are to be interpreted in terms of the mean of the artificial, transformed responses (say, μ_t^*), and not in terms of the original mean responses (μ_t). Additionally, in linear regression analyses, interval estimation and hypothesis testing inference are usually based on the assumption that the response distribution is symmetric (usually, normal), and yet responses that assume values in the standard unit interval are typically asymmetrically distributed. A final shortcoming of the linear regression model is that the marginal effects are constant, which is usually not appropriate for data in (0,1). That is, in the classic linear model the mean impact that follows from varying a covariate value whereas holding all other covariate values fixed is constant; it does not depend on the covariate values. With responses limited to the standard unit interval, however, marginal effects typically depend upon covariate values. We note that we did estimate a linear regression model using *ATH* as dependent variable and the estimated model yielded 22 negative predictions for the response.

A regression model specifically designed for such variates was introduced by Ferrari and Cribari-Neto (2004) and further generalized by Simas, Barreto-Souza, and Rocha (2010). The main underlying idea is that the response (y) follows the beta law, i.e., is beta-distributed. The beta density parameterization introduced by Ferrari and Cribari-Neto (2004) is

$$f(y;\mu,\phi)=\frac{\Gamma(\phi)}{\Gamma(\mu\phi)\Gamma((1-\mu)\phi)}y^{\mu\phi-1}(1-y)^{(1-\mu)\phi-1},0<y<1, \quad (1)$$

where $0<\mu<1$, $\phi>0$ and $\Gamma(\cdot)$ is the gamma function. Here, $\mathrm{IE}(y)=\mu$ (i.e., μ denotes the mean response) and $\mathrm{var}(y)=V(\mu)/(1+\phi)$, where $V(\mu)=\mu(1-\mu)$ is a variance function. Notice that ϕ can be interpreted as a precision parameter in the sense that, for fixed μ, the response variance decreases as ϕ increases.

Let $y_1, \ldots, y_n$ be independent random variables, each y_t, $t=1, \ldots, n$, having density (1) with mean μ_t and precision parameter ϕ_t.[1] The mean response is related to a set covariates (independent variables) as follows:

$$g(\mu_t)=\sum_{i=1}^{k}x_{ti}\beta_i=\eta_t,$$

where $\beta=(\beta_1, \ldots, \beta_k)^\top$ is a vector unknown parameters ($\beta\in\mathrm{IR}^k$) and $x_{t1}, \ldots, x_{tk}$ are observations on k covariates. Also, $g:(0,1)\to\mathrm{IR}$ is a strictly monotonic and twice differentiable link function. Therefore, $\mu_t=g^{-1}(\eta_t)$ and $\mathrm{var}(y_t)=\mu_t(1-\mu_t)/(1+\phi)$. The precision parameter ϕ_t is also related to a set of covariates through a link function:

$$h(\phi_t)=\sum_{i=1}^{q}z_{ti}\gamma_i=\nu_t,$$

[1] Note that we allow the precision parameter to vary across observations.

where $\gamma=(\gamma_1, \ldots,\gamma_q)^\top$ is a vector of unknown parameters, $z_{t1}, \ldots, z_{tq}$ are observations on q covariates ($k+q<n$) and $h:(0,\infty)\to\mathrm{IR}$ is a strictly monotone and twice differentiable link function.

Notice that the regression structure is defined as $g(\mu_t)=\sum_{i=1}^{k}x_{ti}\beta_i$, where g (the link function) maps the standard unit interval onto the real line, IR. Thus, both the left and the right hand sides assume values in IR. As a consequence, the model will never yield predicted values outside (0,1). Several different link functions can be used when modeling data using the class of beta regressions. It is also noteworthy that the model allows for nonconstant responses variances; recall that $\mathrm{var}(y_t)=\mu_t(1-\mu_t)/(1+\phi_t)$. Additionally, the response distribution, which is beta, can be symmetric or asymmetric (to the left or to the right). There is thus no symmetry assumption. Finally, all regression parameters can be interpreted in terms of the mean response, μ_t.

Parameter estimation can be carried out using the maximum likelihood (ML) method. The ML estimators cannot be expressed in closed form and it is necessary to use a nonlinear optimization algorithm (e.g., a Newton or quasi-Newton algorithm) to numerically maximize the log-likelihood function. When the sample size is not small, the ML estimators are approximately normally distributed and such approximate normality can be used to construct confidence intervals and perform hypothesis tests. For more details on beta regression, including its implementation into the R computing environment (http://www.R-project.org), see Cribari-Neto and Zeileis (2010).

4. Religious disbelief and intelligence: empirical evidence

In what follows we shall model religious disbelief in different countries as a function of average intelligence and other conditioning variates. Recall that both religious disbelief and average population intelligence are positively correlated with economic prosperity. Our chief goal, as noted earlier, is to answer the following question: Is there a statistically significant relationship between intelligence and religious disbelief *after accounting for the impact of economic development on atheism*? In what follows we use the class of beta regressions. All estimations were carried out using the betareg package of the R statistical computing environment (Cribari-Neto & Zeileis, 2010). Model selection was performed using sequential testing and the Akaike information criterion (AIC); see Akaike (1974).

In our fist analysis, we use as dependent variable (response) the proportions of atheists in 124 countries. At the outset, we tested the null hypothesis of fixed precision, i.e., $H_0:\phi_1=\phi=\phi_n=\phi$, which was rejected at the usual nominal levels. We thus conclude that precision is variable, i.e., that the precision parameter varies across observations.

After an exhaustive process of model selection, we arrived at the following beta regression model:

$$\mathrm{loglog}(\mu_t)=\beta_0+\beta_1 IQ_t+\beta_2 IQ_t^2+\beta_3 MUSL_t+\beta_4 INCOME_t+\beta_5 \log OPEN_t$$

$$\log(\phi_t)=\gamma_0+\gamma_1 IQ_t,$$

$t=1, \ldots, 124$. Parameter estimates along with the corresponding p-values of z-tests for testing the exclusion of the different covariates are presented in Table 2. The covariates

Table 2
Parameter estimates and p-values; response: proportion of atheists in 124 nations.

	$\hat{\beta}$	p-Value	$\hat{\gamma}$	p-Value
Intercept	6.042	$<1 \times 10^{-4}$	13.446	$<1 \times 10^{-4}$
IQ	−0.222	$<1 \times 10^{-4}$	−0.118	$<1 \times 10^{-4}$
IQ^2	0.002	$<1 \times 10^{-4}$	–	–
MUSL	−0.097	0.0165	–	–
INCOME	0.007	0.0493	–	–
log *OPEN*	0.101	0.0169	–	–

INCOME and *OPEN* positively influence the mean proportion of atheists, unlike *MUSL*. We also note that precision is inversely related to intelligence, i.e., dispersion increases with *IQ*. The ratio between the largest and smallest precisions (λ) equals 180.97 and the pseudo-R^2, which is an overall measure of goodness-of-fit, equals 0.64. Our model thus explains nearly 2/3 of the variation in the prevalences of atheists across different nations.

Fig. 1 shows the normal probability plot with simulated envelopes (left panel) and the plot of observed versus predicted responses (i.e., y_t versus $\hat{\mu}_t = g^{-1}(\hat{\eta}_t)$; right panel). There is no indication that the regression model is misspecified and, except for a few observations, there is good agreement between the observed prevalences of atheists and the corresponding model predictions. In Fig. 2 we plot the Cook distances against the predicted values. There are only three atypical points, namely: Singapore, Vietnam and Mozambique. Singapore has the largest average intelligence and is the most open country. Vietnam has the largest prevalence of atheists, but it does not have a large average IQ. Finally, the prevalence of atheists in Mozambique is large relative to countries with similar average intelligence quotients.

It is important to comment on the fact that in the U.S. the prevalence of atheists (0.105 — i.e., approximately 10%) is low relative to other high average IQ countries (the average IQ in the U.S. is 98). It is well known that the U.S. received a large influx of immigrants from Catholic countries, such as Mexico and Italy, which most likely had a negative impact on its prevalence of atheists. Additionally, the U.S. Constitution explicitly commands the separation between state and religion. As a consequence, the different religious denominations must interact with believers in a market-oriented fashion: they must compete with other denominations for followers, and that competion causes them to adapt more quickly. Competition, as it is usually the case, leads to prosperity. It is thus not all that surprising that religion has prospered more in the U.S. than in countries in which there is a prevalent religious denomination that enjoys a privileged position.

We shall now construct an estimate for the impact of intelligence on religious disbelief. The impact is defined as

$$\frac{\partial \mathrm{IE}(y_t)}{\partial IQ_t} = \frac{\partial \mu_t}{\partial IQ_t}, \tag{2}$$

where

$$\mu_t = g^{-1}\left(\beta_0 + \beta_1 IQ_t + \beta_2 IQ_t^2 + \beta_3 MUSL_t + \beta_4 INCOME_t + \beta_5 \log OPEN_t\right).$$

Notice that we measure how much, on average, the prevalence of atheists changes with *IQ* when other conditioning variables are held constant. Using the log–log link function, Eq. (2) can be expressed as

$$\begin{aligned}\frac{\partial \mathrm{IE}(\delta y_t)}{\partial IQ_t} &= \exp\left(-\exp\left(-\begin{pmatrix}\beta_0 + \beta_1 IQ_t + \beta_2 IQ_t^2 + \beta_3 MUSL_t + \beta_4 INCOME_t \\ +\beta_5 \log OPEN_t\end{pmatrix}\right)\right) \\ &\quad \times\left(-\exp\left(-\begin{pmatrix}\beta_0 + \beta_1 IQ_t + \beta_2 IQ_t^2 + \beta_3 MUSL_t \\ +\beta_4 INCOME_t + \beta_5 \log OPEN_t\end{pmatrix}\right)\right) \\ &\quad \times(-(\beta_1 + 2\beta_2 IQ_t)).\end{aligned}$$

Fig. 3 shows the estimated impact of intelligence on the mean prevalence of atheists for a non-Muslim country with per capita income fixed at its first, second and third quartiles and *OPEN* fixed at its median. Notice that the impact varies with *IQ*, i.e., it is not constant. The estimated impact is always positive and becomes stronger up until the average intelligence quotient reaches 107. For all *IQ* levels, the larger the average intelligence the larger the mean proportion of atheists. The impact of intelligence on religious disbelief is strongest when *IQ* is close to 110. It is positive but rather weak when average IQ is low.

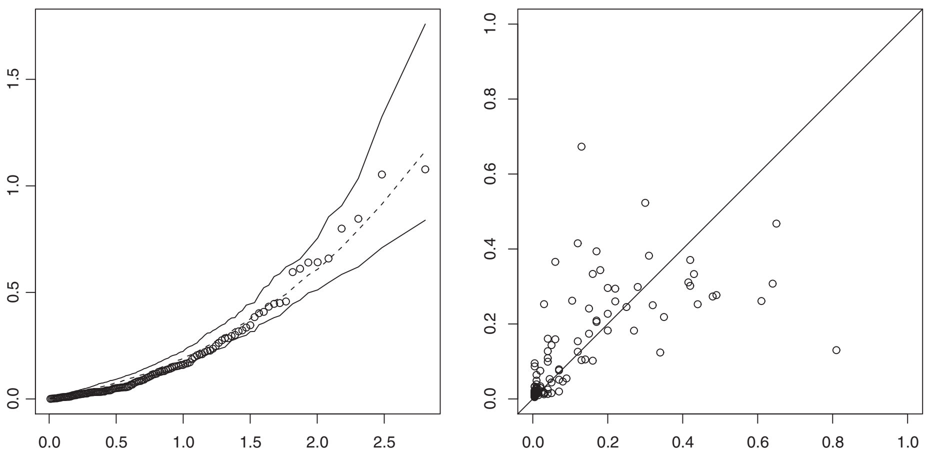

Fig. 1. Normal probability plot with simulated envelopes (left) and observed versus predicted responses (right); the response variable is the proportion of atheists in 124 nations.

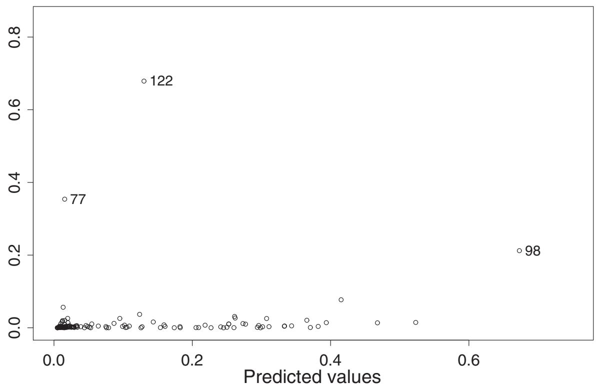

Fig. 2. Cook's distance versus predicted values; the response variable is the proportion of atheists in 124 nations.

We shall now perform two alternative empirical analyses in order to check whether our main findings still hold when different responses are used. At the outset, we shall only use data for countries in which the prevalence of atheists equals 1% or more. The selected model uses the logit and log link functions for the mean and precision submodels, respectively, and the following covariates are used: *IQ*, *INCOME* and *OPEN* (mean) and *IQ* (precision). We shall call it 'scenario 2'; 'scenario 1' shall be used to refer to the previous regression analysis. In the third analysis ('scenario 3'), we restrict attention to the fifty countries with the largest prevalences of atheists. The selected model uses the logit and square root links (for the mean and precision, respectively). The covariate *EXPEC* and the interaction between *INCOME* and log *OPEN* enter the mean submodel (in addition to the regressors previous used) and the precision submodel includes the following regressors: *IQ*, *INCOME* and *EXPEC*.

Table 3 contains the estimated impacts of intelligence on the average proportion of atheists. These impacts were computed by considering the three beta regression models described above. The value of *IQ* is fixed at 85, 95 and 110. The values of the remaining covariates are fixed at their median values, except for *MUSL* which equals zero (i.e., we consider non-Muslim countries). We notice that the estimated impacts are similar in all three modeling strategies, being slightly more pronounced in 'scenario 1' when *IQ* is set at 85 or at 95.

We carried out bootstrap resampling (Efron, 1979) in order to obtain standard errors for the estimated impacts of intelligence on religious disbelief. The main idea is to obtain a large number of artificial datasets, compute the impact measure for each of them and finally compute the standard deviation of the impacts. The number of bootstrap replications was 1000, i.e., we generated 1000 artificial data sets. The bootstrapping scheme we used can be outlined as follows:

1. For each $t = 1, \ldots, n$, we generated y_t^* from the beta law indexed by $\hat{\mu}_t$ and $\hat{\phi}_t$.
2. We estimated the beta regression using $y^* = (y_1^*, \ldots, y_n^*)^\top$.
3. After obtaining the parameter estimates, we computed the impact of intelligence on atheism:

$$\frac{\partial \mathrm{IE}\left(y_{t,b}\right)}{\partial IQ_t} = \frac{\partial \mu_{t,b}}{\partial IQ_t}.$$

4. Steps (1) to (3) were executed 1000 times.
5. The impact standard error was obtained as the standard deviation of the 1000 computed impacts, i.e., as the standard deviation of all impacts computed using artificial data.

We have also used the parametric bootstrap procedure to construct 95% confidence intervals for the impact of intelligence on religious disbelief. To that and, we used the

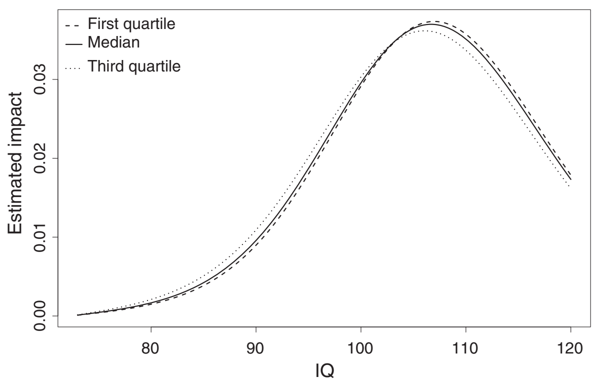

Fig. 3. Impact of intelligence on the prevalence of atheists with *INCOME* fixed at the first, second and third quartiles; the response is the proportion of atheists in 124 nations.

Table 3
Estimated impacts of intelligence on atheism.

IQ	Scenario 1	Scenario 2	Scenario 3
85	0.0043	0.0040	0.0008
95	0.0192	0.0180	0.0140
110	0.0349	0.0448	0.0423

Table 5
Bootstrap confidence intervals.

IQ	Scenario 1	Scenario 2	Scenario 3
85	(0.0031;0.0054)	(0.0029;0.0050)	(−0.0074;0.0044)
95	(0.0130;0.0256)	(0.0114;0.0258)	(0.0052;0.0216)
110	(0.0313;0.0368)	(0.0307;0.0503)	(0.0089;0.0384)

percentile method, i.e., the lower and upper confidence interval limits are the 0.025 and 0.975 quantiles of the bootstrap impacts.

Table 4 displays the bootstrap standard errors. Notice that they are all small relative to the corresponding impacts, which is evidence that the latter are accurate. The different 95% level confidence intervals are presented in Table 5. Zero is only covered by one of the intervals, namely: $IQ = 85$, 'scenario 3'. Therefore, in all but one situation the impact of intelligence on atheism is statistically significant at the 5% nominal level.

Fig. 4 shows estimated impacts of intelligence on religious disbelief in the three scenarios. It noteworthy that they are similar in shape and they all peak at approximately the same intelligence level, the estimated impact from the second scenario being stronger than in the first scenario (all countries in the data) around the peak.

We shall now consider a different response variable. The variable of interest in the previous analyses was the proportion of atheists (i.e., people who do not believe in God or gods) across different countries. We shall now model the proportion of people who do not consider religion important in their daily lives. The link functions used were log–log (mean) and log (precision) and the following covariates entered the mean submodel: *IQ*, IQ^2, *INCOME*, *OPEN* and *MUSL*; the covariates used in the precision submodel were *IQ* and *INCOME*. All estimations were carried out using data on 84 countries, 19 of which had more than 50% of Muslims. The model pseudo-R^2 was 0.64, i.e., our model explains nearly 2/3 of the total variation in the response. We computed the impact of intelligence on the mean response in the same fashion as in the previous analyses. The estimated impact curve is very similar to the ones in Fig. 4; it peaks at approximately 109. Our main findings are thus robust to different responses, i.e., they hold regardless of whether we model the proportion of atheists or the proportion of people who do not value religion in their daily lives.

Finally, we shall address the following question: are the results reported above driven by religious fundamentalism? Using the proportion of atheists as the response, we estimated the impacts of average intelligence on religious disbelief using three samples, namely: (i) all 124 countries, (ii) subsample 1 — we removed from the data countries where there is considerable religious fundamentalism (Algeria, Azerbaijan, Bangladesh, Egypt, Jordan, Lebanon, Morocco, Libya, Nigeria, Pakistan, Senegal, Uzbekistan, and Yemen), and (iii) subsample 2 — we removed from the data all countries for which the proportion of Muslims exceeds 50%. The three impact curves are displayed in Fig. 5. They are remarkably similar. This indicates that our results are not driven by fundamentalist religious belief.

The main findings from our analyses are that intelligence positively impacts religious disbelief even after we account for the positive impact of economic and social development on atheism, and also that the impact is weaker at lower levels of average intelligence.

Table 4
Bootstrap standard errors.

IQ	Scenario 1	Scenario 2	Scenario 3
85	0.0006	0.0005	0.0031
95	0.0031	0.0037	0.0042
110	0.0014	0.0051	0.0064

5. Conclusions and further discussion

An important issue is whether there is an association between intelligence and religious belief. It has been argued that higher levels of intelligence, which are closely related to logical reasoning, are associated with lower levels of religious belief. Lynn et al. (2009) reported the results of a correlation analysis. Using data on over one hundred countries they showed that intelligence positively correlates with religious disbelief. It is well known, however, that both intelligence and religious disbelief are positively correlated economic development. Hence, an important question is: Is there a statistically significant relationship between intelligence and religious disbelief *after we account for the negative impact of economic development on religious belief*?

In this paper we used the class of varying dispersion beta regressions, which is tailored for modeling data that assume values in the standard unit interval. We used two different responses, namely: the proportions of atheists and of people who do not consider religion important in their daily lives. We also considered different samples of countries. The

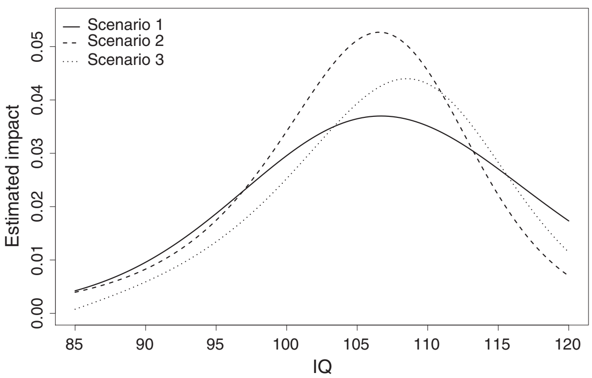

Fig. 4. Impact of intelligence on atheism: three scenarios.

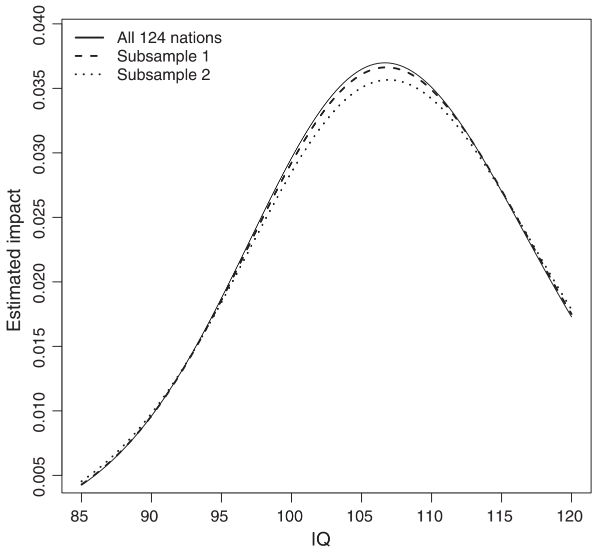

Fig. 5. Impact of intelligence on atheism: all 124 countries and two subsamples.

estimated regression models explain nearly 2/3 of the total variation in the dependent variable. We defined a measure for the impact of intelligence on religious disbelief, which was computed for all estimated models. The results show that such an impact is always positive, being weaker at low intelligence levels and much stronger at a peak that takes place when the average intelligence quotient is close to 105. We have used bootstrap resampling to obtain standard errors for the computed impacts. The standard errors were all small, thus indicating that the impact estimates are accurate.

It is only natural for the impact of intelligence on religious disbelief to vary with national IQ. When the latter is small the impact is also likely to be small since it relies on critical reasoning. Additionally, when national IQ is, on average, quite large the effects on intelligence on religious disbelief have, for the most part, already taken place and further increases in IQ are likely to have more modest impacts. It is thus in the intermediate region that variations in the average IQ should impact religious disbelief in stronger measure. This is exactly what our model predicts. More specifically, the impact is strongest when national IQ is around 105.

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