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Are greenhouse gas emissions and cognitive skills related? Cross-country evidence

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ABSTRACT

Are greenhouse gas emissions (GHG) and cognitive skills (CS) related? We attempt to answer this question by exploring this relationship, using cross-country data for 150 countries, for the period 1997–2012. After controlling for the level of economic development, quality of political regimes, population size and a number of other controls, we document that CS robustly predict GHG. In particular, when CS at a national level increase by one standard deviation, the average annual rate of air pollution changes by nearly 1.7% (slightly less than one half of a standard deviation). This significance holds for a number of robustness checks.

1. Introduction

The last several years have witnessed rising interest in the consequences of cross-national differences in cognitive skill (CS). Although scholars debate on how they specify cognitive abilities (or intelligence), there is general consensus that cognitive capital represents the capacity to reason, solve problems, think abstractly, and acquire knowledge (Snyderman and Rothman, 1988, p. 56). Moreover, Gottfredson (1997, p. 13) suggests that '[cognitive capital] reflects a broader and deeper capability for comprehending our surroundings – "catching on", "making sense" of things, or "figuring out" what to do. Indeed, while cognitive skills is a multidimensional concept which may encompass social intelligence, emotional intelligence and general intelligence (Freeman et al., 2016), in this paper we focus on one aspect of this concept, namely general intelligence.[1] At a macro-societal level CS is measured by different psychometric tests such as Raven's Standard Progressive Matrices (SPM) and its derivatives.

Research on this subject can generally be broken down into three major streams. The first thoroughly explores the economic correlates of CS in cross-national literature. The key findings of this research positively associate CS with economic growth (Jones and Schneider, 2006), per capita wealth (Whetzel and McDaniel, 2006), financial development (Salahodjaev, 2015a, 2015b, 2015c) and welfare (Hafer, 2017).

The second line of study investigates the link between CS and quality of life. In most of these studies, CS is shown to predict life expectancy (Lv and Xu, 2016), tolerance (Souza and Cribari-Neto, 2015), life satisfaction (Veenhoven, 1996) and happiness inequality (Nikolaev and Salahodjaev, 2016).

The third research stream studies the consequences CS has on environmental quality. There is evidence that CS at a national level predicts the quality of environmental institutions, such as the ratification of environmental agreements (Obydenkova and Salahodjaev, 2016) and the stringency of climate change policies (Obydenkova and Salahodjaev, 2017). However, the evidence regarding the 'hard measures' of environmental sustainability is still mixed and debated. For example, Squalli (2014), using US-state level data, failed to establish that CS significantly affects greenhouse gas emissions. While CS seemed to be positively related to N2O emissions in that study, CS had no significant link with CH4 and CO2. The study concluded by stating that future 'scholarly work should consider assessing the intelligence–environment relationship using alternative measures of intelligence'. Salahodjaev (2016), meanwhile, using data from 186 nations from 1990 to 2010, found new evidence indicating that human psychology, proxied by CS, inversely relates to forest cover loss. In a different study, Salahodjaev (2016) further provides evidence that environmental sustainability, measured by the Environmental Performance Index is significantly predicted by CS at a national level.

While extant studies focus on such aspects of environment as deforestation, climate change policies or sustainability, it is crucially important to accumulate new evidence about the relationship between CS and greenhouse gas emissions using cross-country data for a number of reasons. First, the World Health Organisation (WHO) reports that approximately 7 million people died in 2012—one-eighth of the total number of global deaths that year—as a result of air pollution exposure.

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[1] In this study we use intelligence and cognitive skills interchangeably.

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This more than doubles previous estimates and confirms air pollution as the world's largest single environmental health risk today.[2] In addition, worldwide ambient air pollution contributes to 5.4% of all deaths each year. What's more, related studies have revealed that air pollution significantly relates to life satisfaction (Ferreira et al., 2013), suicide rates (Lin et al., 2016) and intention to migrate (Qin and Zhu, 2015).

Overall, the current literature offers ambiguous predictions regarding the link between CS and greenhouse gas emissions. On the one hand, considering that CS positively affects economic development and gross domestic product (GDP) growth, it can be detrimental for the environment. On the other hand, while some studies seem to find that air pollution and deforestation increases with economic development, growing evidence suggests that the trend between GDP per capita and environmental degradation reverses once nations reach a certain threshold level (Van Alstine and Neumayer, 2010).[3] Moreover, in their influential study, Grossman and Krueger (1995, p. 370) found 'no evidence that economic growth [causes greater pollution]. Instead [they] find that while increases in GDP may be associated with worsening environmental conditions in very poor countries, air and water quality appear to benefit from economic growth once some critical level of income has been reached'.

On top of this, a possible mechanism by which CS can affect air pollution is delay discounting—a '"commitment-choice" procedure typically present[ing] choices between larger delayed and smaller but more immediate reinforcers' (Reynolds and Schiffbauer, 2005). Research in the field of intelligence suggests that high-IQ individuals tend to reject the smaller-sooner rewards despite its close temporal proximity in favour of delayed environmental benefits (Squalli, 2014). In this vein, Shamosh and Gray (2008, p. 296) argue that 'more intelligent people demonstrate less of a preference for smaller, immediate rewards versus larger, delayed rewards'. Moreover, at the national levels, scholars have found that citizens in more intelligent societies tend to have longer time horizons (Potrafke, 2012), build more efficient institutions (Kanyama, 2014) and avoid informal activities (Salahodjaev, 2015a, 2015b, 2015c), which in turn have been linked to environmental degradation.

Another important aspect is that even if cognitive capital fosters economic development, it does so by affecting the economy's structure. For example, cognitive abilities positively relate to innovation (Azam, 2017) and economic diversification (Kodila-Tedika and Asongu, 2016). For example, Burhan et al. (2015, p. 152) argues that 'it is possible to increase per capita national income by raising the impact of IQ on productivity through the O-ring effect of skill complementarities. Accordingly, with diverse levels of IQ distributed within a country, when individual laborers with equivalent levels of cognitive skills work in groups, they are inclined to cooperate through positive assortative matching, resulting in magnified per capita productivity'. In fact, these factors have also been linked with environmental improvements, meaning that CS could indirectly decrease air pollution by firms adopting more efficient technologies.

Moreover, Obydenkova and Salahodjaev (2017, p. 183) argue that 'socio-intellectual capital is paramount for environmental policies at both a micro- and macro-social level. Cognitive abilities are necessary for institutionalised environmental commitment, protecting the environmental resource base, environmental stringency and government effectiveness'. Indeed, cognitive capital is instrumental to competence of policymakers in overseeing the quality of environmental resources. In a similar vein, intelligence is associated with greater liberties and freedom such as minority equality, freedom of media and speech. As a result, societies with liberal and free media are described their of external influences in terms of democracy promotion and cross-border diffusion of values like the bureaucrats' accountability to society (Lankina et al., 2016; Libman and Obydenkova, 2014a; Obydenkova and Libman, 2012; Obydenkova, 2012).

This study explores the relationship between CS at a national level and easily quantifiable indicators of environmental degradation: greenhouse gas emissions. We investigate this conjectured link between CS and air pollution through a sample of 150 nations for the years 1997–2012. This study is the first to explore whether CS are important predictors of greenhouse gas emissions in the era of Kyoto protocol, which was adopted in Kyoto, Japan on 11 December 1997. The Kyoto Protocol is an international agreement linked to the United Nations Framework Convention on Climate Change, which commits its Parties by setting internationally binding emission reduction targets. The main aim of the Kyoto Protocol is to contain emissions of the main greenhouse gases in ways that can reflect underlying national differences in emissions, wealth, and capacity, following the main principles agreed in the 1992 United Nations Framework Convention on Climate Change (Grubb, 2004, p. 15).

Our results suggest a negative relationship between cognitive skills and air pollution. More specifically, when CS skills at a national level increase by one standard deviation, we found the average annual rate of air pollution to change by nearly 1.7% (slightly less than one half of a standard deviation). The results remain robust when we control for the level of economic development, democratisation rate, population size and a number of other control variables.

2. Method and data

2.1. Method

For our empirical exercise, we used an ordinary least squares (OLS) estimator in Stata 11.2 with a dependent variable of the average annual greenhouse gas emission change from 1997 to 2012. We included a variety of control variables measured in 1997. We also conducted a number of robustness tests in order to confirm that our estimates are not driven sample size of the choice of main estimation method.

2.2. Sample

Our sample contains all countries grouped as low-, middle- and high-income according to the World Bank. After discarding missing observations, our sample comprises 150 countries.

2.3. Dependent variable

The dependent variable in our study is the average annual percentage change in greenhouse gas emissions from 1997 to 2012. Greenhouse gas emissions are measured by total greenhouse gas emissions in kt of CO2 equivalent. This variable is composed of CO2 totals, excluding short-cycle biomass burning (such as agricultural waste burning and Savannah burning) but including other biomass burning (such as forest fires, post-burn decay, peat fires and decay of drained peat lands), all of which are anthropogenic CH4 sources, N2O sources and F-gases (HFCs, PFCs and SF6). In our sample, the average annual percentage change in greenhouse gas emissions ranges from − 17.1% in Papua New Guinea to 16.8% in Mozambique. The data came from the World Bank.

2.4. Independent variables

2.4.1. Cognitive skills

We rely on national IQs compiled by Lynn and Vanhanen (2012) as our proxy for CS. In their pioneering work, Lynn and Vanhanen (2002) reviewed studies in which cognitive abilities tests where administered. The authors were able to collect reliable data for 81 countries. For each of these countries they have calculated average national cognitive skill (national IQ) level by setting the IQ in Britain at 100 (standard

[2] www.who.int/mediacentre/news/releases/2014/air-pollution/en/.

[3] These findings hold even for sub-national data (Roca et al., 2001; Shaw et al., 2010).

deviation = 15), and rescaling all other scores to this scale. In their follow up study, Lynn and Vanhanen (2012), they updated their dataset by estimating national IQs for 192 countries and showed validity of their results by correlating their national IQs to international school assessment test results.

However, some studies attempted to criticize the validity of national IQs in cross-country research. For example, Barnett and Williams (2004) have argued that Lynn and Vanhanen (2002) datum are "virtually meaningless", and Hunt and Sternberg (2006, pp. 133, 136) have described them as "technically inadequate… and meaningless". On the other hand, a ballooning research evidence have shown the importance of cognitive skills by correlating them to shadow economy (Salahodjaev, 2015b), gender inequality (Salahodjaev and Azam, 2015), life satisfaction (Nikolaev and Salahodjaev, 2016), economic growth (Ram, 2007) and economic outcomes (Meisenberg, 2012).

2.5. Initial level of greenhouse gas emissions

It is important to include a measure that accounts for the potential biasing effects of the relative intensity of greenhouse gas emissions at the onset of the Kyoto protocol. Therefore, we include greenhouse gas emissions from 1997. We log transformed this variable to account for its skewed distribution.

2.6. Economic development

We include GDP per capita for 1997 as an indicator of economic development. Past studies suggest that economic development nonlinearly relates to air pollution (Environmental Kuznets curve). For example, Llorca and Meunie (2009), using data from a panel of 28 Chinese provinces, documented that GDP per capita has an inverted U-shaped link with sulphur dioxide (SO_2) emissions with a turning point of 4500 yuans. Similarly, an environmental Kuznets curve (EKC) type relationship has been documented for Finland (Kunnas & Mylyntaus), Africa (Sulemana et al., 2016) and global data (Lee et al., 2009). Explanations for this phenomenon usually revolve around the argument that, 'In the beginning of economic development, little weight is given to environmental concerns, raising pollution along with industrialization. After a threshold, when basic physical needs are met, interest in a clean environment rises, reversing the trend. Now society has the funds, as well as willingness, to spend to reduce pollution' (Farzin and Bond, 2006, p. 213).

On the other hand, empirical literature has also argued that the EKC relationship is weak or ambiguous. While supporters for the EKC theory argue that 'at higher levels of development, structural change towards information-intensive industries and services, coupled with increased environmental awareness, enforcement of environmental regulations, better technology and higher environmental expenditures, result in leveling off and gradual decline of environmental degradation (Panayotou, 1993, p. 1).' – opponents argue that inverted U-shaped relationship may be driven by serial dependence, stochastic trends in time-series or omitted variable bias (Stern, 2004).

On the other hand, emissions may decline with increase in income due to implementation of pollution control techniques, change in output mix, substitution of more environmentally damaging inputs for less damaging inputs, advancement of technological level, or outsourcing polluting industries to low income countries.

Therefore, we also include the GDP per capita squared term. In addition, we control for GDP growth as a proxy for the successfulness of economic policies. The data for GDP per capita and GDP growth came from the World Bank.

2.7. Democracy

We also include the democracy index from the Fraser House, as measured by the mean of civil rights and political liberties indices. Despite the generally acknowledged importance of democracy for environmental sustainability, 'The relationship between democracy and environmental protection has been subject to fierce, yet inconclusive, academic debates in, among others, political sciences, natural resource management studies and social geography' (Buitenzorgy and Mol, 2011, p. 59). While some studies claim that democracy reduces air pollution (Bernauer and Koubi, 2009), others studies report that democracy is insignificantly linked to greenhouse gas emissions (Li and Reuveny, 2006).

However, it is crucial to control for democracy as there is evidence that intelligence is causal to democracy (Vanhanen, 2003) and cognitive skills are linked to political preferences (Ganzach, 2017). Indeed, it is crucially important to take into account the role of democracy in the context of cognitive skills – pollution nexus as some studies explain how democracy may both increase and decrease the quality of environmental policies of the state Libman and Obydenkova (2014a, 2014b). Moreover, Obydenkova and Salahodjaev (2017) further show that democracy is an important antecedent of climate change policies even after taking into account the role of intelligence. Li and Reuveny (2006), using data from more than 100 countries, tests the hypothesis that democracy has negative effect on environmental degradation. The authors show that level of democracy has negative effect on per capita CO_2 emissions. Mak Arvin and Lew (2011) investigates the effect of democracy on environmental conditions using data from developing countries for the period 1976–2003. Their results show that overall the effect of democracy on CO_2 is significant but is different across different regions and income groups.

2.8. Other controls

We also control for population size as a proxy for demographic pressure, trade as a share of GDP as a proxy for relative trade openness (Managi et al., 2009; Libman and Obydenkova, 2014a, 2014b), and an OECD dummy to capture unobserved country-specific differences between developed and developing countries. For example, Managi et al. (2009), using data for 60 emerging and developing economies, documents that trade openness leads to higher CO_2 emissions. The data for this came from the World Bank.

Finally, we include the share of services in GDP and its squared term to capture the effects of structural transformation on air pollution. Research suggests that as GDP per capita increases and average wages rise, employment is driven in the services sector and the share of polluting industries decreases, such sectoral changes can favour less-polluting economic activities (Jänicke et al., 1997). This data came from the World Bank as well.

To estimate the link between CS and greenhouse gas emissions, we specify the regression equation as follows:

$$Y_i = \alpha + \beta CS_i + X\delta + \varepsilon_i, \tag{1}$$

wherein Y_i is the dependent variable of the average annual percentage change in greenhouse gas emissions from 1997 to 2012 in country i; CS is Lynn and Vanhanen (2012) datum; X is the vector of remaining independent variables; α, β and δ are parameters to be estimated; and ε is an error term satisfying normality assumptions. The descriptive statistics are presented in Table 1. The correlation matrix is presented in Table A1.

3. Regression results

Fig. 1 plots the data from Lynn and Vanhanen (2012) against greenhouse gas emissions. Visual changes in the figure suggest an inverse relationship between CS and air pollution. The correlation is − 0.40 and is statistically significant at the 1% level. The fitted trend in Fig. 1 suggests that air pollution tends to decrease over time in societies with higher average cognitive ability.

We next report our main results from estimating Eq. (1) in Table 2.

Table 1
Descriptive statistics.[a]

Variable	Description	Mean	Std. Dev.	Min	Max
GHG	Average annual percentage change in greenhouse gas emissions from 1997 to 2012. Source: World Bank	2.12	4.20	− 17.06	16.84
CS	Cognitive abilities averaged at a national level. Source: Lynn and Vanhanen (2012)	84.10	10.85	60.1	107.1
Initial emissions	Per capita GHG emissions in 1997, logged Source: World Bank	10.07	2.57	1.56	15.72
GDP per capita	GDP per capita, at purchasing power parities in 1997, ‘000$ Source: World Bank	13.12	16.41	0.49	110.14
GDP growth	Average annual GDP growth from 1997 to 2012 Source: World Bank	3.96	3.11	− 10.05	26.08
Democracy	Democracy index measured as average of civil rights and political freedoms Source: Freedom house	3.58	2.04	1	7
Population	Total population in 1997, logged. Source: World Bank	15.01	2.34	9.14	20.93
Trade	Trade as % of GDP from 1997 to 2012, logged. Source: World Bank	4.38	0.56	0.74	6.21
OECD	=1 if OECD country, 0 otherwise Source: Authors’ calculations	0.16	0.37	0	1
Services	Services as % of GDP from 1997 to 2012. Source: World Bank	56.59	15.35	10.66	91.15

[a] We average trade, economic growth and services variables to reduce the effects of short run macroeconomic business cycles.

Our first model displays a bivariate association between CS and the dependent variable. The estimate in Model 1 suggests that when CS at a national level increase by one standard deviation, the average annual rate of air pollution changes by nearly 1.7% (slightly less than one half of a standard deviation). This bivariate regression provides us with a sense of the overall relationship (both direct and indirect) between CS and air pollution. However, as reported in extant literature, CS correlates with numerous social and economic variables that also relate to air pollution. Thus, this estimate can also indicate a spurious association. Therefore, we included control variables in Models 2 and 3.

In Model 2, we include logged emission levels from 1997. As mentioned earlier, it is important to control for this variable as it accounts for the potential biasing effects of the relative intensity of greenhouse gas emissions at the onset of the Kyoto protocol. While the initial emission levels have an insignificant effect on air pollution change for the period of 1997–2012, the estimates for CS remain unaffected both quantitative and qualitatively.

Next we include the remaining control variables in Model 3. The positive and significant estimate for economic growth suggests that GDP growth led to higher air pollution levels in our sample. In particular, countries with an average GDP growth of 5% were associated with nearly 2% annual growth in air pollution. This is considerable, taking into account that the average global growth in greenhouse gas emissions was nearly 2%. We may conjecture that countries growing at around or above 5% level are likely to be still in the industrialization phase, or are investing heavily in manufacturing, further, they could have “benefitted” from the “pollution export” of heavy manufacturing. Our regression estimates also show that population pressure, as measured by the logged population size, is associated with higher air pollution.

In addition, sectoral changes also influence air pollution. We found that the share of services in GDP has a Kuznets curve type of relationship with the average annual percentage change in greenhouse gas emissions. The turning point of this relationship is 52.9%, which in our data equals the levels of Romania. This also implies that when services generate more than half of country's output, air pollutions starts to decrease.

However, we also found that democracy, the dummy variable for OECD countries, economic development and trade openness are insignificantly related to air pollution.

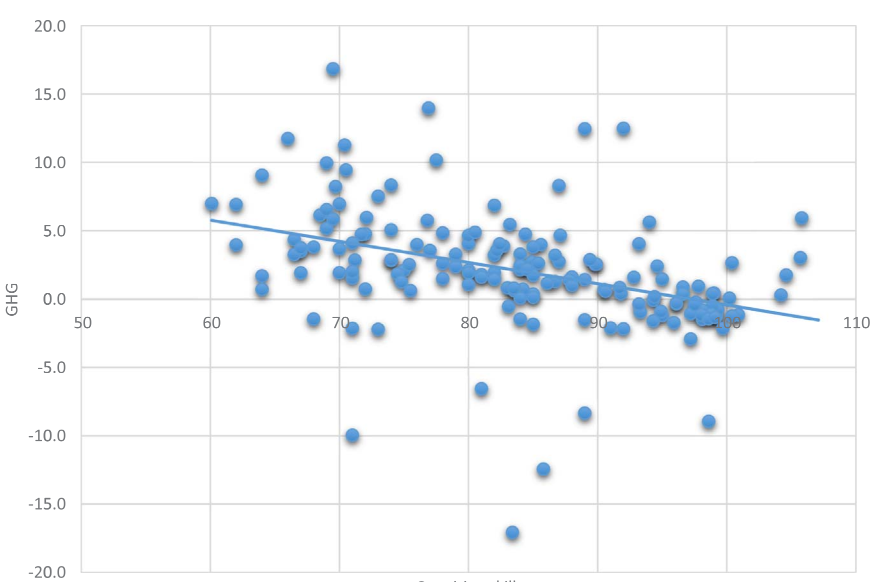

Fig. 1. Plot of CS against air pollution.
Source: World Bank, Lynn and Vanhanen (2012)

Table 2
Estimates of GHG (1997–2012) and cognitive skills OLS regression.

	(1)	(2)	(3)	(4)	(5)
CS	− 0.155***	− 0.136***	− 0.165***	0.421***	− 0.164**
	(0.028)	(0.032)	(0.047)		(0.069)
Initial emissions		− 0.194	− 1.535***	0.761***	− 1.535***
		(0.163)	(0.410)		(0.599)
GDP per capita			0.150	0.478	0.150
			(0.102)		(0.131)
(GDP per capita)^2			− 0.001	0.196	− 0.001
			(0.001)		(0.002)
Economic growth			0.408***	0.270***	0.408**
			(0.134)		(0.203)
Democracy			− 0.133	0.059	− 0.133
			(0.245)		(0.290)
Population			1.585***	0.688***	1.585***
			(0.439)		(0.619)
Trade			− 0.019	0.002	− 0.019
			(0.665)		(0.804)
OECD			− 0.367	0.035	− 0.367
			(1.246)		(0.864)
Services			0.415**	1.371**	0.415
			(0.186)		(0.307)
(Services)2			− 0.004**	1.269**	− 0.004
			(0.002)		(0.003)
Constant	15.067***	15.517***	− 7.766	–	− 7.766
	(2.336)	(2.364)	(6.888)		(11.000)
N	163	163	150	150	150
adj. R^2	0.158	0.160	0.317		0.317

Note: Standard errors in parentheses; Absolute values of standardized betas are reported in Model 4; *p < 0.1.
** p < 0.05.
*** p < 0.01.

Regarding our main variable of interest, we found that even after controlling for a rich set of the potential antecedents of greenhouse gas emissions, the coefficient for CS is negative and significant at the 1% level.

One other hand, the main results may be affected by issues such as heteroskedasticity. This may occur when there are outlier observations present in data, or there is a wide disparity between the largest and smallest. Indeed, heteroskedasticy commonly is a problem for cross-country studies leading to non-constant variance of error term. Therefore, we re-estimate our main results with bootstrap sampling estimator performing 1000 replications in column 5. Intelligence is negative and significant, albeit at a 5% level.

Overall, the results reported in Table 2 highlight CS as an essential and independent antecedent that enables researchers and policymakers to explain cross-national variations in greenhouse gas emissions.

4. Checks on robustness

For our first robustness check, we re-estimated Eq. (1) using quantile regression (QReg) in Table 3. Quantile regression, developed by Koenker and Bassett (1978), is an alternative method for disentangling the link between CS and greenhouse gas emissions and for investigating the effects across the distribution greenhouse gas emissions data for our sample of 150 countries. Chen (2005, p. 1) argues that 'quantile regression models the relationship between X and the conditional quantiles of Y … is especially useful in applications where extremes are important, such as environmental studies where upper quantiles of pollution levels are critical from a public health perspective'. For example, the correlation between CS and air pollution change is only − 0.09 for countries with air pollution below global averages while it is − 0.26 for countries above global average levels. As a result, the estimates reported in Table 2, which are grounded on the traditional mean regression estimator, may offer an 'incomplete' picture. Therefore, Qreg is the most convenient approach for understanding the differential effects of CS on greenhouse gas emissions conditional on their air pollution growth rates.

Table 3
Estimates of GHG (1997–2012) and cognitive skills Quintile regression.

	(1) Q 0.2	(2) Q 0.4	(3) Q 0.6	(4) Q 0.8
CS	− 0.111**	− 0.142***	− 0.160***	− 0.155
	(0.049)	(0.026)	(0.047)	(0.129)
Initial emissions	− 1.377***	− 1.295***	− 0.852**	− 0.217
	(0.497)	(0.239)	(0.390)	(0.901)
GDP per capita	0.147	0.168***	0.141	− 0.141
	(0.097)	(0.053)	(0.087)	(0.235)
(GDP per capita)^2	− 0.001	− 0.001**	− 0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.003)
Economic growth	0.249*	0.297***	0.316**	0.132
	(0.136)	(0.063)	(0.124)	(0.265)
Democracy	− 0.284	− 0.294**	− 0.141	0.151
	(0.310)	(0.144)	(0.225)	(0.506)
Population	1.425**	1.339***	0.915**	0.176
	(0.561)	(0.267)	(0.409)	(0.939)
Trade	0.346	− 0.405	− 0.153	− 0.822
	(0.610)	(0.411)	(0.597)	(1.204)
OECD	− 0.428	− 0.433	− 0.707	− 0.115
	(1.089)	(0.641)	(1.152)	(2.021)
Services	0.166	0.361***	0.268	0.044
	(0.259)	(0.109)	(0.174)	(0.388)
(Services)2	− 0.001	− 0.003***	− 0.002	− 0.001
	(0.002)	(0.001)	(0.002)	(0.003)
Constant	− 9.094	− 6.974*	0.592	20.625
	(7.063)	(3.975)	(6.638)	(17.754)
N	150	150	150	150
adj. R^2				

Standard errors in parentheses.
* p < 0.1.
** p < 0.05.
*** p < 0.01.

In Table 3, Eq. (1) is estimated at the 20th, 40th, 60th and 80th quantiles. The estimates in Models 1–4 suggest some differences in the estimated coefficients and corresponding significance levels across the distribution of dependent variables. With respect to the control variables, economic growth has a stronger positive effect on greenhouse gas emissions on the right hand side of the distribution, while estimates for logged population size increase moving towards the left side of the distribution. Another interesting observation is that economic development has a significant nonlinear effect on air pollution and the estimate for democracy is negative and significant at the 40th quantile. This implies that so-called Environmental Kuznets Curve hold for countries within this quantile of distribution.

Regarding our main variable of interest, the quantitative importance of CS rises with the increase in the average annual change in air pollution levels, although this effect is insignificant at the 80th quantile. However, we also found none of the independent variables to be significant in Model 4. One reason may be that in high-polluting countries, there is economic distortion or other phenomena as a result air pollution there is driven by other factors.

In Table 4, we report the next set of robustness tests. In Model 1, we checked whether our results were driven by abnormal observations in our data. Influential observations, outliers or high-leverage points (extremes) can lead to biased or insignificant estimates. For example, Fig. 2, which plots normalized residuals against leverage, enables us to visually detect abnormal observations in our sample. The scatterplot suggests that observations like Brunei (BRN), Equatorial Guinea and Myanmar (MMR) could have an influential effect on the regression estimates, while observations coded as PNG (Papua New Guinea), LAO (Lao PDR), IDN (Indonesia) significantly affect the residual (significance levels) of the regression parameters. To address this issue, we rely on robust regression (RREG), which first performs an initial

Table 4
Estimates of GHG (1997–2012) and cognitive skills Robust regression (RREG).

	(1)	(2)
CS	− 0.124***	− 0.139***
	(0.030)	(0.038)
Initial emissions	− 1.253***	− 1.344***
	(0.261)	(0.266)
GDP per capita	0.149**	0.076**
	(0.065)	(0.031)
(GDP per capita)^2	− 0.001*	
	(0.001)	
Economic growth	0.216**	0.203**
	(0.085)	(0.088)
Democracy	− 0.164	− 0.093
	(0.155)	(0.159)
Population	1.382***	1.587***
	(0.279)	(0.291)
Trade	0.285	0.320
	(0.422)	(0.437)
OECD	− 0.737	0.202
	(0.792)	(0.890)
Services	0.183	0.100
	(0.118)	(0.119)
(Services)^2	− 0.001	− 0.001
	(0.001)	(0.001)
GDP per capita* CS		− 0.004
		(0.003)
Constant	− 5.686	− 4.192
	(4.377)	(4.768)
N	150	150
adj. R^2	0.404	0.402

Note: Standard errors in parentheses.
* p < 0.1.
** p < 0.05.
*** p < 0.01.

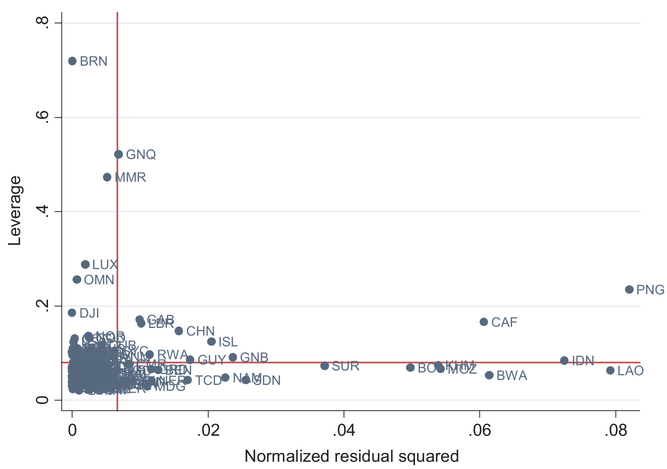

Fig. 2. Plot of normalized residuals against leverage.
Source: Authors' estimates based no Table 3 output

screening based on Cook's distance > 1 to eliminate gross outliers before calculating starting values, after which it performs Huber iterations followed by biweight iterations, as suggested by Li (1985). It begins by fitting the regression, calculating Cook's D and excluding any observation for which D > 1. Thereafter, RREG works iteratively, performing a regression, calculating case weights from absolute residuals and regressing again using those weights. The results reported in Model 1 suggest that the CS estimate is again negative and significant at the 1% level, although quantitatively slightly below its estimate in Table 2. Against this background, when CS increases by 10 points, the dependent variable decreases by slightly less than one half of a standard deviation. Moreover, after accounting for the effect of influential data points, we again found that GDP per capita has an inverted U-shaped

Table 5
Estimates of air pollution (1997–2012) and cognitive skills Sub-samples.

	(1)	(2)	(3)	(4)
CS	− 0.149**	− 0.165***	− 0.197***	− 0.132**
	(0.063)	(0.048)	(0.052)	(0.058)
Initial emissions	− 1.761***	− 1.560***	− 1.339***	− 1.137**
	(0.515)	(0.423)	(0.446)	(0.475)
GDP per capita	0.169	0.167	0.148	0.032
	(0.104)	(0.141)	(0.107)	(0.182)
(GDP per capita)^2	− 0.001	− 0.001	− 0.001	0.000
	(0.001)	(0.003)	(0.001)	(0.003)
Economic growth	0.401***	0.407***	0.380***	0.693***
	(0.144)	(0.136)	(0.141)	(0.214)
Democracy	0.065	− 0.127	− 0.075	− 0.172
	(0.287)	(0.247)	(0.269)	(0.288)
Population	1.831***	1.583***	1.528***	1.127**
	(0.522)	(0.457)	(0.516)	(0.539)
Trade	− 0.333	− 0.108	0.164	0.180
	(0.889)	(0.685)	(0.728)	(0.739)
OECD	− 0.847	− 0.444	− 0.404	1.308
	(1.160)	(1.279)	(1.421)	(1.596)
Services	0.277	0.445**	0.411**	0.499**
	(0.214)	(0.192)	(0.206)	(0.249)
(Services)2	− 0.002	− 0.004**	− 0.004*	− 0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	− 5.083	− 7.776	− 6.447	− 11.429
	(9.131)	(6.960)	(7.765)	(8.958)
N	101	147	128	112
adj. R^2	0.317	0.313	0.308	0.293
Restriction	GDP per capita above 3 thousand USD	GDP per capita below 53 thousand USD	Population size above 3 million	Population size below 50 million

Note: Standard errors in parentheses.
* p < 0.1.
** p < 0.05.
*** p < 0.01.

association with air pollution. The turning point for GDP per capita is 53,000 USD, approximately equal to the levels of Norway.

Next, we examined whether the association between CS and greenhouse gas emissions is conditional on the level of per capita income. To do so, we included interaction terms between CS and GDP per capita in our model. As seen in Model 2, the estimate for the interaction term is negative, albeit insignificant, implying that economic development does not moderate the link between CS and air pollution.

Next, we replicated our main results by breaking our data into subsamples. The estimates reported in Table 5 suggest that the link between CS and greenhouse gas emissions remains negative and significant when excluding the least (Model 1) and most (Model 2) developed countries, as well as the least (Model 3) and most (Model 4) inhabited countries.

As an additional robustness test, we have replicated our main results with alternative versions of CS data. For example, Wicherts et al. (2010, p. 1) 'systematically review published empirical data on the performance of Africans on the following IQ tests: Draw-A-Man (DAM) test, Kaufman-Assessment Battery for Children (K-ABC), the Wechsler scales (WAIS & WISC), and several other IQ tests (but not the Raven's tests)' and provide alternative estimates for national IQs for countries located in African continent. The results reported in Model 1 of Table 6 suggest our baseline results remain robust. In Model 2, we further replicate our baseline with the scores presented in Meisenberg and Lynn (2011). Again, the results are robust.

One may argue that a number of possible important control variables must be included into theoretical discussion or in the section on

Table 6
Estimates of air pollution (1997–2012) and cognitive skills Alternative measures.

	(1)	(2)
CS	− 0.155***	− 0.164***
	(0.047)	(0.047)
Initial emissions	− 1.552***	− 1.482***
	(0.413)	(0.417)
GDP per capita	0.121	0.168
	(0.100)	(0.105)
(GDP per capita)^2	− 0.001	− 0.001
	(0.001)	(0.001)
Economic growth	0.361***	0.416***
	(0.133)	(0.136)
Democracy	0.148	0.178
	(0.246)	(0.253)
Population	1.595***	1.528***
	(0.441)	(0.448)
Trade	− 0.115	− 0.041
	(0.663)	(0.669)
OECD	− 0.182	− 0.500
	(1.261)	(1.263)
Services	0.338*	0.432**
	(0.181)	(0.190)
(Services)2	− 0.003*	− 0.004**
	(0.002)	(0.002)
Constant	− 5.526	− 8.064
	(6.993)	(7.134)
N	150	145
adj. R^2	0.311	0.314
Source of CS data	Wicherts et al. (2010)	Meisenberg and Lynn (2011)

Note: Standard errors in parentheses.
* p < 0.1.
** p < 0.05.
*** p < 0.01.

Table 7
Estimates of air pollution (1997–2012) and cognitive skills Additional controls.

	(1)	(2)
CS	− 0.161***	− 0.116*
	(0.047)	(0.061)
Initial emissions	− 1.520***	− 1.305***
	(0.412)	(0.488)
GDP per capita	0.167	0.278**
	(0.103)	(0.130)
(GDP per capita)^2	− 0.001	− 0.003
	(0.001)	(0.002)
Economic growth	0.363**	0.436**
	(0.148)	(0.174)
Democracy	0.213	0.291
	(0.256)	(0.299)
Population	1.562***	1.192**
	(0.441)	(0.542)
Trade	− 0.302	− 0.130
	(0.733)	(0.841)
OECD	− 0.503	− 0.320
	(1.256)	(1.548)
Services	0.462**	0.787***
	(0.194)	(0.268)
(Services)2	− 0.004**	− 0.007***
	(0.002)	(0.003)
FDI	0.059	0.098
	(0.076)	(0.112)
Literacy		− 0.049*
		(0.028)
Constant	− 8.232	− 14.705*
	(6.920)	(8.728)
N	149	118
adj. R^2	0.317	0.269

Standard errors in parentheses.
* p < 0.1.
** p < 0.05.
*** p < 0.01.

Table 8
Estimates of air pollution (1997–2012) and cognitive skills Interactive effects.

	(1)	(2)
IQ	− 0.152**	− 0.194***
	(0.063)	(0.048)
Schooling	− 0.086	
	(0.218)	
IQ* Schooling	0.007	
	(0.014)	
Democracy		− 0.256
		(0.246)
IQ* Democracy		− 0.041**
		(0.017)
N	119	150
adj. R^2	0.293	0.339

Standard errors in parentheses; the baseline control variables and constant term are included but not reported.
* p < 0.1.
** p < 0.05.
*** p < 0.01.

"limitations". For example, one of the main control variables, democracy, can itself be a product of a number of external factors, foreign aid, and even can be influenced by the membership in international regional organizations that can positively impact democracy and society (Obydenkova, 2008, 2012; Lankina et al., 2016) as well as other external factors may have a negative impact on democracy (Obydenkova and Libman, 2012). Moreover, studies have shown that air quality is directly related to the connectedness to global economy and political system (Abdouli and Hammami, 2017; Kirkulak et al., 2011). Therefore, we include FDI net inflows as a share of GDP as an additional control variable from World Bank. Moreover, cognitive skills (intelligence) may be a function of the level of literacy rates. Therefore, we include literacy rates from World Bank to test the robustness of our main results. In addition research also suggests that education is an important antecedent of environmental quality and sustainable development (Drucker, 2016)

The results reported in Table 7 suggest that FDI does not influence our baseline findings with respect to cognitive capital (Model 1). However, the significance level of CS has decreased once we included literacy rates in our model. One reason is high correlation (r = 0.69) between cognitive skills and adult literacy rates. Therefore, literacy rates may be partially mediating the relationship between cognitive capital and air pollution.

Finally, in Table 8 we test the interactive effects between cognitive skills and education, and between cognitive skills and democracy. In column 1, we regress GHG on IQ, average years of total schooling from Barro-Lee dataset, their product and baseline control variables. The results show that intelligence is negative significant while schooling and interaction terms are insignificantly linked to GHG. In column 2, we again regress GHG on IQ, democracy, their product and baseline controls. In this specification we find that intelligence and democracy are compliments in reducing GHG.

5. Conclusion

There is a growing body of research evidence indicating that air pollution does not depend exclusively on economic development, but rather on a wide range of aspects. Among these potential factors, one variable that has been overlooked in the empirical literature is the role played by CS. This paper further extends the literature on the consequences of CS at a national level, pioneered by Lynn and Vanhanen (2002). Pulling from Lynn and Vanhanen's (2012) dataset, we specifically examine the relationship between average CS scores for the majority of countries and the average annual percentage change in greenhouse gas emissions. Our results robustly suggest that CS negatively relates to growth in air pollution across the world in the Kyoto protocol era. While overall the global emissions have been constantly growing, the country-by-country picture is more complex and suggests that the growth rates in GHG across developed and developing countries have been very heterogeneous. Thus, our results shed some light whether significant variations in air pollution across the world can be explained by cross-country differences in cognitive capital levels.

Our results remain robust even after controlling for potential interdependency between CS, economic development and democratisation. Additionally, we tested whether the effects of CS differ across the distribution of air pollution data. We found that the quantitative importance of CS rises with increases in the average annual change in air pollution levels, although this effect is insignificant at the 80th quantile.

In sum, cognitive skills may decrease the greenhouse gas emissions via their impact on quality of political regimes (institutions), social capital and preventing behavior aimed at exploitation of natural resource base. For example, Rindermann and Thompson (2011), using data from 90 nations, show that cognitive abilities are causal to quality of market reforms which in turn increase economic wealth and reduce air pollution. In a different study, Salahodjaev (2015b, p. 133) shows, “if a government implements policies designed to reduce underground economy [which is linked to greater environmental degradation], intelligence offers a reasonable estimate of the level of acceptance of these policies.”

Moreover, cognitive skills are an important predictor of social capital. For example, experimental data in Frederick (2005) provides evidence that intelligence is an important antecedent of risk and time preferences. Indeed, intelligent individuals are more patient and have longer time horizons (Potrafke, 2012). Furthermore, Benjamin et al. (2013) provide experimental evidence that cognitively able individuals tend to exhibit risk averse behavior and avoid uncertain outcomes. Other studies also linked intelligence to generalized interpersonal trust (Sturgis et al., 2010).

Prospective studies should examine CS in relation to a variety of other environmental indicators, such as the ratification of environmental agreements, environmental awareness of population and perceptions of climate change, in order to assess whether CS at a national level is associated with greater environmental sustainability. Moreover, prospective research should also consider other proxies for air pollution and economic impact of air pollution such as genuine savings. In addition, future studies should explore the role of social intelligence in the environmental sustainability. Indeed, a recent paper by Freeman et al. (2016) also highlights importance of social intelligence, at least for government effectiveness. In their study, authors using sub-national US data conclude that ‘[social intelligence] allows individuals to better diffuse perceived slights and resolve conflicts, which provides incentives for groups to engage in prosocial behavior and work toward common rather than narrowly defined goals’ (p. 53). Other studies measuring social capital (a proxy for social intelligence) have shown the importance of social capital for environmental sustainability (Wakefield et al., 2007; Grafton and Knowles, 2004). In a similar vein, Das and DiRienzo (2010) use cross-country data to test the effect of social capacity (ethnic diversity) on environmental performance. This research reports that ‘countries with moderate levels of ethnic diversity experience the greatest environmental performance as they reap the benefits of a civically engaged society with creative, innovative, and efficient human talent pool and do not bear the negative effects of a highly fractionalized society that typically suffers from poor communication and social cohesion, among other societal ills’ (p. 91).

Among of the other limitations is that the study deals with macro-level variables and cross-country analysis. While this approach is traditional, the recent literature specifically indicate that even the country level, the variations across subnational regions can be significant. If we consider, for example, the case of province Catalonia in Spain or the differences across the states of the USA. The States of the USA have its own regulations with regard to a number of environmental issues, differences across social cognitive capital and a number of control variables mentioned in the paper. While in this study, it is impossible to account for the possible cross sub-national heterogeneity in empirical analysis, the link between intelligence and air pollution at sub-national level is the agenda for future studies.

Moreover, intellectual (cognitive, social) capital may be the product of a number of historical legacies (Lankina et al. 2016; Libman and Obydenkova, 2015, 2013b; Obydenkova and Libman, 2015) – these studies demonstrate how historical legacies matter for the formation of human intellectual capital and for the quality of political regimes (democracy) and even for modern corruption which in turn matter for air quality. Therefore, future studies may also explore the interrelation between historical legacies, political regimes and cognitive skills, and their link to environmental degradation.

Appendix A1

see: Table A1

Table A1
Correlation matrix.

	I	II	III	IV	V	VI	VII	VIII	IX	X
GHG	1									
CS	− 0.45	1								
Initial emissions	− 0.28	0.50	1							
GDP per capita	− 0.33	0.60	0.24	1						
Economic growth	0.28	− 0.23	− 0.05	− 0.36	1					
Democracy	0.27	− 0.46	− 0.02	− 0.48	0.48	1				
Population	− 0.04	0.27	0.88	− 0.06	0.08	0.17	1			
Trade	− 0.07	0.08	− 0.39	0.15	0.04	− 0.18	− 0.50	1		
OECD	− 0.33	0.66	0.39	0.68	− 0.30	− 0.56	0.17	0.04	1	
Services	− 0.18	0.46	− 0.06	0.44	− 0.51	− 0.70	− 0.18	0.09	0.48	1

Das and DiRienzo (2010).

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