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Analysis

Plastic pollution and economic growth: The influence of corruption and lack of education

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ABSTRACT

Green economic growth led by technological solutions is often mentioned as a solution for mitigating plastic pollution. However, economic growth appears to be in contradiction to planetary boundaries. By developing two worldwide socio-economic models, for forecasting inadequately managed plastic waste up to the year 2050 across 217 countries and territories, we demonstrate the adverse ecological impacts of the lack of regulatory processes and educational environmental programs. We used country-by-country data from the World Bank for the model estimates. The global cumulative stock of plastic waste that is inadequately managed is predicted to increase from 61–72 million metric tons (MT) in 1990 to 5109–5678 MT by 2050. Four scenario analyses told different stories: The business-as-usual (BAU) scenario, mitigation scenario 1: Capping GDP, mitigation scenario 2: Extending education, and mitigation scenario 3: Fighting corruption. In "capping GDP," the annual amount of inadequately managed plastic waste slightly increases and reaches 64–119 million MT/year in 2050 instead of 61–110 million MT/year in the BAU scenario. In the "extending education" scenario, the amount decreases by 34% compared to the BAU scenario in 2050. In the "fighting corruption" scenario, the amount decreases by 60%. We provide further details in the country-by-country predictions

1. Introduction

The increase in plastic marine litter is evident, as are its harmful effects on marine ecosystems (inter alia, Ostle et al., 2019; Baztan et al., 2018). A growing number of studies provide estimates of the global annual amount of plastic entering the ocean from land-based sources (Jambeck et al., 2015; Lebreton et al., 2017; Schmidt et al., 2017; Cordier and Uehara, 2019). For example, Jambeck et al. (2015) estimate that in 2010, between 4.8 and 12.7 million metric tons (MT) of plastic entered the ocean. This relatively wide range shows further studies are needed to improve its accuracy.

One step in that direction is improving understanding of key factors determining plastic production, waste generation, and mismanagement. Barnes (2019) modeled the relationship between mismanaged plastic waste and income per capita for 151 countries. His results suggest that as income per capita increases in a country, environmental pollution such as mismanaged plastic waste per capita also increases up to a certain level of individual income. After this tipping point, mismanaged plastic waste per capita will decrease due to an increase in environmental improvement efforts, while average inhabitant income continues increasing (Barnes, 2019). Such a relationship is known in environmental economics as the environmental Kuznets curve (EKC) (Mazzanti et al., 2009; Stern, 2004). Additionally, Barnes (2019) argues that growing economies have more financial means for technological innovations to reduce pollution (Dinda, 2004), for reducing materials used in production (Lindmark, 2002) and for reducing the amount of polluting inputs per outputs (Stern, 2004).

Our study uses a recent database from the World Bank (2018) providing data observed in 2011–2017 to design two models demonstrating that inadequately managed plastic waste is not exclusively a

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function of GDP per capita; it also depends on factors such as geographic location, policy measures (e.g., corruption control policies), market regulations favoring the private sector, and education levels (e.g., the average number of years of schooling) (Hidalgo-Ruz et al., 2018). The two models have different focuses: corruption control policies and education levels. While a similar study by Barnes (2019) included only the number of scientific and engineering journal articles published (a proxy for investment in scientific and technological research) in addition to gross national income per capita and another study by Jambeck et al. (2015) included only geographical dummies in addition to income per capita, we include and test various predictors drawn from a literature review.

The remainder of the paper is organized as follows. The next section presents the models with empirical strategies and scenarios for forecasts. The third section reports and discusses the estimated models and forecasts using the models, followed by the limitations of our study. The last section concludes.

2. Method

2.1. Model structure

We developed two models to calculate how global economic growth, corruption control policies, market regulations in favor of the private sector, geographic location, urbanization, demography, and education influence inadequately managed plastic waste generated annually in all 217 countries and territories in the world. Model 1 focuses on the influence of corruption control policies and consists of Eqs. 1, 2, and 3. Model 2 focuses on the influence of education policies and consists of Eqs. 1, 2, and 3bis (see equations below).

Eq. 1 Inadequately managed plastic waste:

$$\begin{aligned} &\textit{Inadequately managed plastic waste} = \textit{Plastic waste per capita} \\ &\quad \times \textit{Inadequately managed waste\%} \times \textit{population} \end{aligned} \tag{1}$$

where *Plastic waste per capita* is computed in Eq. 2 and represents the amount of plastic waste individuals generate in one year (in kg/person/year), *Inadequately managed waste*% is computed in Eq. 3 and 3_{bis} and represents the percentage of municipal solid waste that is inadequately managed either because the waste treatment consists in disposing of it in open dumps or discarding it in waterways or marine areas, and *population* is the number of people living in the country. We adopted *Inadequately managed waste*%, not *Inadequately managed plastic waste*%, because the raw data for the latter does not exist in the World Bank Database. We separated inadequately managed plastic waste into the product of plastic waste per capita and inadequately managed waste % (and population) for two reasons. First, they could be explained by different predictors or some common predictors but in a different way. Second, we are interested in how each behaves over time as they may not be perfectly correlated.

We adopted the EKC that is a hypothesized relationship between environmental degradation and income per capita and there seems to be no consensus on its functional form (Mazzanti et al., 2009; Stern, 2004). We tested the hypothesis by specifying a form often used in the EKC studies and applied to mismanaged plastic waste (Barnes, 2019; Gui et al., 2019; Stern, 2004).

Eq. 2 Plastic waste per capita:

$$ln(\textit{Plastic waste per capita}_i) = \alpha + \beta ln(Q_i) + \gamma ln(Q_i)^2 + \delta X_i + \varepsilon_i \tag{2}$$

where the subscript i denotes countries, α is an intercept, Q_i is income per capita, X_i is a vector of exogenous variables explaining *Plastic waste per capita*, and ε_i are the disturbance terms. To achieve an inverted U-shaped curve, we expect β to be positive and γ to be negative at statistically significant levels. X_i and their justifications are discussed below.

There are two functional forms for inadequately managed waste percentages: one focusing on corruption control (Eq. 3) and the other focusing on education (Eq. 3bis). Biswas et al. (2012) and Damania et al. (2003) demonstrated that controlling corruption reduces polluting emissions generated by illegal economic activities or by lobbies intending to lower ecological targets in environmental legislation. Biswas et al. (2012) observed that corruption can increase pollution by affecting the stringency of environmental regulation and enforcement, but it can also reduce polluting emissions by lowering economic activity. Cole (2007) evaluated the magnitude of these two countervailing effects of corruption on pollution and showed that, for the majority of countries, the reduction effect of corruption outweighs the increasing impact on pollution. However, the statistical model designed by Biswas et al. (2012) shows it is more complex; the final net effect of corruption on pollution depends on the size of the shadow economy. The shadow economy comprises production activities – from legal or illegal firms – that avoid government regulation or taxation and as such are not following environmental standards and norms. Estimations from Biswas et al. (2012) show the marginal impact of an increase in corruption on polluting emissions is significantly positive when the size of the shadow economy is above the sample average. At the mean and maximum size of the shadow economy, a 1% increase in the corruption index increases polluting emissions per capita by 0.10% and 0.50%, respectively (Biswas et al., 2012).

Education is another critical factor. Making informed pro-environmental choices is difficult if one has no knowledge (Gifford and Nilsson, 2014). A minimum level of education is required to develop the ability to manage contrasting information, a skill that is central to ecological behaviors (Otto and Pensini, 2017). Hidalgo-Ruz et al. (2018) show that in countries with a lower education index, marine waste is increasing. Vicente-Molina et al. (2013) also found education is one of the most important variables identified by researchers to explain high levels of environmental behavior. However, as highlighted by Vicente-Molina et al. (2013), although education and environmental knowledge seem to be significantly and directly related, it is not clear how they affect actual pro-environmental behavior (Zsóka et al., 2012). Vicente-Molina et al. (2013) estimated for Spain and the United States (USA) that a 1% increase in objective environmental knowledge increases pro-environmental behaviors by 0.40%, suggesting that environmental education in plastic issues might be a promising solution to plastic waste. However, they found the opposite for Brazil and Mexico where a 1% increase in objective environmental knowledge decreased pro-environmental behaviors by 0.40%. Actually, correct knowledge has been shown to predict pro-environmental behaviors, recognizing knowledge is a necessary but not sufficient condition for decision-making (Gifford and Nilsson, 2014). Beyond the minimum knowledge required, which might be defined by the threshold of 12 schooling years, additional factors influence pro-environmental behavior as identified, inter alia, by Vicente-Molina et al. (2013): the type of information contained in environmental content, the type of studies/degree (social sciences, science, engineering), and the number of subjects taken that address environmental issues, among others. The number of schooling years is not the only influencing factor. Otto and Pensini (2017) evaluated the effect of nature-based environmental education on students from 9 to 11-years-old. They found increased participation in nature-based environmental education was related to greater ecological behavior, mediated by increases in environmental knowledge and connectedness to nature. Connectedness to nature explained 69% and environmental knowledge 2% of the variance in ecological behavior. It is essential to identify the types of knowledge and experiences that effectively encourage environmental behavior in school educational programs (Vicente-Molina et al., 2013). Following Jambeck et al. (2015), both equations (Eq. 3 and Eq. 3bis) assume the logistic function, which restricts *Inadequately managed waste*% to between zero and one.

Eq. 3 Inadequately managed waste % with a focus on corruption control policies:

$$Inadequately\ managed\ waste\% = \frac{e^{\rho_1+\sigma_1 ln(Q_i)+\tau_1 C_i+\varphi_1 Z_{1i}}}{1+e^{\rho_1+\sigma_1 ln(Q_i)+\tau_1 C_i+\varphi_1 Z_{1i}}} \quad (3)$$

where ρ_1 is the constant term, C_i is the degree of corruption control, and Z_{1i} is a vector of the exogenous variable explaining *Inadequately managed waste*%.

Eq. 3bis Inadequately managed waste % with a focus on education policies:

$$Inadequately\ managed\ waste\% = \frac{e^{\rho_2+\sigma_2 ln(Q_i)+\tau_2 E_i+\varphi_2 Z_{2i}}}{1+e^{\rho_2+\sigma_2 ln(Q_i)+\tau_2 E_i+\varphi_2 Z_{2i}}} \quad (3bis)$$

where ρ_2 is the constant term, E_i is the educational level, and Z_{2i} is a vector of the exogenous variable explaining *Inadequately managed waste* %.

2.2. Empirical strategy

2.2.1. Data

To make as many countries comparable as possible, we used only data provided by the World Bank (Hoornweg and Bhada-Tata, 2012; Kaufmann et al., 2010; Kaza et al., 2018; World Bank, 2018; World Bank, 2018a; World Bank, 2019a; World Bank, 2019a) except for the small island dummy created by the authors based on geographical information. All data used in this study are listed in Table 1 and are available in the supplementary material.

Inadequately managed plastic waste is measured by the annual generation of plastic waste for which waste treatment consists of landfilling in open dumps or collective discarding in waterways and marine areas. Inadequately managed plastic waste is a useful variable to study because it includes plastic waste that could eventually enter the ocean via inland waterways, wastewater outflows, storm drains, and transport by wind or tides. Plastic waste is sometimes also directly discarded at sea by fishing, aquaculture, and shipping activities but our models do not take that into account. Data is difficult to find since direct littering at sea is forbidden by international legislation. Plastic waste is also sometimes directly littered on the ground by individuals. Therefore, the variable studied by Barnes (2019) is mismanaged plastic waste: it includes plastic waste directly littered by individuals in addition to inadequately managed plastic waste. However, direct individual littering is difficult to estimate due to the lack of data. Barnes (2019) applied to all countries a constant coefficient from Jambeck et al. (2015) who estimated littered plastic waste is 2% of total municipal solid waste, based on USA national data for the year 2008, which is not representative of all countries. In several countries, a substantial portion of plastic waste is not categorized by any kind of waste treatment; the World Bank (2018) database categorizes these cases as “unaccounted for” or “others.” Our models consider that a proportion of these wastes are likely inadequately managed. However, since the content of the data in these categories are unclear (Jambeck et al., 2015; Kaza et al., 2018), we excluded countries with a high proportion of these categories. We estimated the equations for inadequately managed plastic waste (i.e., Eq. 3 and 3bis) based on a subset of data from 122 countries. We selected these countries because they reported percentages lower than 25% (less than 5% for most of them) of total municipal solid waste listed in both categories (i.e., “others” and “unaccounted for”), assuming that such countries reported on their waste management more rigorously.

2.2.2. Hypotheses

We conducted a literature review to identify potential predictors explaining *Plastic waste per capita* and *Inadequately managed waste*%. Variables can be categorized into economic, social, geographical, regulation and governance, and education (they are listed in Table 1).

Increase in GDP per capita improves standard of living, income levels, and existing infrastructure. It results in more plastic waste per capita up to a certain level and then is typically followed by a decline. Although there may be a better predictor (e.g., absolute poverty), we adopted GDP per capita to test the EKC hypothesis to determine whether inadequately managed waste percentages could improve proportional to GDP per capita.

Environmental awareness is another key factor explaining plastic waste generation. For example, a choice experiment conducted on a major Greek island revealed that the different degrees of environmental awareness explained individual preferences for reducing plastic waste pollution (Latinopoulos et al., 2018). Since data measuring environmental awareness are not available at the World Bank database, population density (which is higher in urban areas) and the percentage of urban population in the total population are used as proxies for environmental awareness (Table 1). We made that choice based on Otto and Pensini (2017) and Kiessling et al. (2017) who show that personal experience and interactions with natural areas influence environmental awareness and the resulting pro-environmental behaviors. The opportunities to develop such a connection with nature are reduced in urban areas, which is likely to decrease environmental awareness of urban populations and to generate a lack of interest in ecosystem preservation (Kiessling et al., 2017; Miller, 2005; Salhofer et al., 2008).

Geography is captured in Table 1 by geographical dummies. Geography combines demographics with contextual influences that vary across countries: e.g., styles of housing, living conditions, and political and historical context (Peattie, 2010). Lifestyles, consumption patterns, production systems, and available waste management infrastructures are influenced by geographical location. Tanner et al. (2004) found that living circumstances (e.g., size of household), time pressures (higher in urban areas compared to rural areas), and the characteristics of locally available retailers were more important than socioeconomic factors in influencing green consumption (e.g., plastic-free product consumption). The geographical variable “small islands” is also influential since places with large tourism flows compared to the limited sizes of local population, as is the case for small islands, generate massive amounts of plastic waste per capita (Eckelman et al., 2014). However, Kiessling et al. (2017) have observed that on small islands, the isolated geographic location, the unique cultural identity and biodiversity, the small size of the local community, and international tourism exert internal and external pressures that favor environmental awareness and engagement on the coastal litter problem by local populations and promote pro-environmental behaviors in the context of waste management (Kiessling et al., 2017).

The influence of cultural differences across regions of the world is also captured by geographical dummies in Table 1. Consumption behavior – and pro-environmental consumption behaviors – is a social process that is shaped, among others, by cultural conventions, cultural traditions, and cultural representations that govern what is considered to be appropriate behavior in different social contexts. Much of our consumption behavior does not simply reflect ourselves and our circumstances; it also reflects our social relationships and obligations so that we behave not just as individuals but as members of a household, a community, a country, a region of the world, and so on (Peattie, 2010).

In Table 1, market regulatory quality is a regulation and governance variable capturing perceptions of the ability of governments to formulate and implement sound policies and regulations permitting and promoting private sector development (World Bank, 2018a; Kaufmann et al., 2010). Consistent with the practice in the literature (see Kraipornsak, 2020; Law et al., 2013; Morrissey and Udomkerdmongkol, 2012; Nagaraj and Zhang, 2019; Nguyen and Jaramillo, 2014), we use percentile rank, which ranges from 0 to 100, with higher values corresponding to better governance outcomes.[1] Governance indicators are one of the most important factors enabling effective environmental

[1] We use the percentile rank in the estimation since we recognize that one should be careful in interpreting coefficients given the ordinal measure of market regulatory quality ranging from −2.5 to +2.5 (Morrissey and Udomkerdmongkol, 2012).

Table 1
Variables and reasons for including**

Category	Variable	Unit	Mean	Std. Dev.	Min	Max	Reasons for including: Plastic waste per capita	Reasons for including: Inadequately managed waste %	Data source
Economic	GDP per capita	PPP* in constant 2011 international $ per person	17,141.03	20,774.95	432.39	110,967.00	a) Standard of living (Bandara et al., 2007; Karak et al., 2012) b) Income levels (Bandara et al., 2007; Kolekar et al., 2016; Wilson et al., 2012) c) Existing infrastructure (Karak et al., 2012)	a) Standard of living (Bandara et al., 2007; Karak et al., 2012) b) Income levels (Barnes, 2019; Uehara and Cordier, 2019; Jambeck et al., 2015) c) Existing infrastructure (Karak et al., 2012)	World Bank (2018)
	LN(GDP per capita)	PPP in constant 2011 international $ per person	9.00	1.32	6.07	11.62			OECD (2020)
	[LN(GDP per capita)]^2	PPP in constant 2011 international $ per person	82.76	23.63	36.84	134.95			
	OECD countries***	dummy [0,1]	0.23	0.43	0	1			
	Tourism	annual number of tourists/number of inhabitants	1.22	3.63	0.00	34.13	d) Tourism in small islands (Eckelman et al., 2014; Mateu-Sbert et al., 2013)	d) Tourism in small islands (Kiessling et al., 2017)	World Bank (2019a)
Social	Population density	number of inhabitants per km^2	401.57	1819.96	0.14	19,767.83	a) Urbanization (Kiessling et al., 2017; Kolekar et al., 2016; Karak et al., 2012; Kaza et al., 2018; pp. 23–24; Salhofer et al., 2008; Hoornweg et al., 2013; Hoornweg and Bhada-Tata, 2012) b) Environmental awareness (Kiessling et al., 2017; Hidalgo-Ruz et al., 2018; Karak et al., 2012; Peattie, 2010) c) Demography (Kolekar et al., 2016; Peattie, 2010)	a) Urbanization (Kiessling et al., 2017; Heinen, 1995) b) Environmental awareness (Kiessling et al., 2017; Hidalgo-Ruz et al., 2018; Karak et al., 2012; Peattie, 2010) c) Demography (Peattie, 2010)	World Bank (2019a)
	Urban population	% of the country total population living in urban areas	61.80	23.54	13.01	100			
	Small islands	dummy [0, 1]	0.20	0.40	0.00	1.00			World Population Review (2020).
Geographical	Middle East and African countries	dummy [0, 1]	0.13	0.33	0	1	a) Cultural patterns (Bandara et al., 2007; Vicente-Molina et al., 2013) b) Geography (Peattie, 2010)	a) Cultural patterns (Vicente-Molina et al., 2013) b) Values, norms, and habits (Peattie, 2010) c) Geography (Peattie, 2010)	World Bank (2019)
	Latin American countries	dummy [0, 1]	0.20	0.40	0	1			
	Sub-Saharan Africa	dummy [0, 1]	0.13	0.33	0	1			
	Former communist states of Europe & Central Asia	dummy [0, 1]	0.14	0.35	0	1			
	East Asia and Pacific	dummy [0, 1]	0.20	0.40	0	1			
	Europe & Central Asia	dummy [0, 1]	0.14	0.35	0	1			
	North America	dummy [0, 1]	0.01	0.12	0	1			
Regulation and governance	Market regulatory quality	estimate from −2.5 to +2.5	0.17	0.97	−2.09	2.19	a) Governance (Karak et al., 2012; Milfont and Markowitz, 2016)	a) Governance (Karak et al., 2012; Milfont and Markowitz, 2016; Biswas et al., 2012; Cole, 2007; Damania et al., 2003)	World Bank (2018a)
		percentile rank from 0 to 100	54.79	28.10	1.01	99.76			
	Corruption control policies	estimate from −2.5 to +2.5	0.24	1.00	−1.41	2.28			
		percentile rank from 0 to 100	57.06	27.33	2.84	100.00			
Education	Years of school	average number of years of schooling in a country for people ≥25 years old	9.05	2.82	1.24	13.42		a) Education and knowledge (Hidalgo-Ruz et al., 2018; Morren and Grinstein, 2016; Karak et al., 2012; Peattie, 2010; Vicente-Molina et al. (2013); Gifford	World Bank (2019a)
	Years of tertiary school		0.56	0.42	0.00	1.76			

(continued on next page)

Table 1 (*continued*)

Category	Variable	Unit	Mean	Std. Dev.	Min	Max	Reasons for including: Plastic waste per capita	Reasons for including: Inadequately managed waste %	Data source
		average number of years of tertiary schooling in a country for people ≥25 years old						and Nilsson, 2014; Otto and Pensini, 2017; Zsóka et al., 2012)	
	Adult literacy rate	% of people ≥15 years old who can both read and write with understanding a short simple statement about their everyday life	83.29	20.97	25.31	99.99			
	Education funding	Initial government funding in education (from pre-primary to tertiary schooling) per student, constant PPP $ (in 2010, or closest year available)	3. E+10	8. E+10	3. E+07	8. E+11			World Bank (2020)

* PPP: purchasing power parity.
** Because not all models used the same countries, the resulting descriptive statistics differ for each model. The number of observations for each variable ranges from 100 to 149.
*** OECD: Organization for Economic Co-operation and Development.

management (Bennett and Satterfield, 2018). We include this variable in the model assuming market regulation enhances consumption of products and thus increases plastic waste generation per capita. The market consists of a set of rules, institutions, and economic agents that interact mutually to achieve resource efficiency and perfect competition as well as to avoid market failures and anti-competitive behaviors (Arnone and Borlini, 2014). A well-regulated market is likely to generate a more formal and structured market with greater industrial production and consumption of plastic products (e.g., products in plastic packaging and single-use plastic products).

2.2.3. Model selection algorithm

We adopted hierarchical regression analysis to select the best estimates (Hartley et al., 2018; Lewis, 2007). Unlike stepwise regression, the process of adding or removing variables from regression models is decided by researchers based on theory, hypothesis, or past research, and the subsequent change to the model fitness (e.g., adjusted R^2) is compared. Namely, the order of variable entry and what variables to retain are determined by researchers. This approach is more appropriate than stepwise regression as we have some variables we wanted to manually retain. We set several criteria to select the model estimates for prediction (i.e., Eq. 2, Eq. 3, and Eq. 3bis). First, we retained income per capita for all equations. Second, we retained a variable for corruption control policies for Eq.3 and education policies for Eq.3bis because we have key interest in them. Third, since the purpose of estimate was to predict the future, we selected other explanatory variables, shown in Table 1, to pursue the highest fitness measured by the Akaike information criterion (AIC) by following Jambeck et al. (2015). We also added some robustness checks by directly estimating the determinants of inadequately managed plastic waste so as to show if the estimated coefficients for the variables of primary interest (i.e., income per capita, corruption control policies, and education) were robust across different model specifications.[3] As for the linear equation (Eq. 2), we performed the Breusch-Pagan test for linear heteroskedasticity and corrected the model when necessary. We performed the estimates by using STATA 16.1 (https://www.stata.com). All data used in the model selection and for drawing figures in the paper are available in the supplementary material.

2.3. Scenario analysis

We developed four scenarios to forecast inadequately managed plastic waste up to the year 2050: namely, business-as-usual (BAU), Mitigation scenario 1 (capping GDP), Mitigation scenario 2 (extending education), and Mitigation scenario 3 (fighting corruption). Each scenario was chosen to see how each of the three key factor influences the future of inadequately managed plastic waste. Mitigation scenario 1 was chosen because our study tests the EKC hypothesis and several authors propose an economic slowdown policy as an intervention to reduce global environmental issues (Victor, 2019; Krausmann et al., 2009). As already discussed, education and corruption control are also critical and are two of our main focuses. The business-as-usual scenario (BAU) forecasts explanatory variables based on past trends observed from 1996 to 2017. The forecast relies on a linear regression calculated country by country. Regarding GDP per capita, we used forecasts from The Organization for Economic Co-operation and Development (OECD) (2019) and Hawksworth et al. (2017), which provide long-term forecasts of GDP per capita for 55 countries. In all mitigation scenarios, we only modify the explanatory variable under analysis (e.g., GDP per capita for Mitigation scenario 1). All other variables follow the BAU trend.

[3] The authors would like to sincerely thank an anonymous referee for pointing out this issue.

3. Results and discussion

3.1. Model estimates

Tables 2, 3, and 4 show the final estimates for Eqs. 2, 3, and 3_{bis}, respectively. Because the Breusch-Pagan/Cook-Weisberg test for heteroskedasticity for Eq. 2 rejected the null hypothesis of constant variance ($p = 0.0405$), we applied the robust estimator of variance to the estimate of Eq. 2 (Table 2). We chose final estimates such that all variables are statistically significant at 10% level, and the lowest Akaike information criterion (AIC) scores (for Eq.2 (Table 2), Eq. 3 (Table 3) and Eq. 3bis (Table4)) across all variable combinations tested. We also checked the Bayesian information criterion (BIC) as the robustness check.

Table 2 confirms the EKC such that LN(GDP per capita) has a positive and (LN(GDP per capita))^2 has a negative sign at a statistically significant level. Small islands (geographical), Urban population (social), and Market regulatory quality (regulation and governance) are the components of X_i in Eq. 2, the vector of exogenous variables explaining *Plastic waste per capita*. They were statistically significant predictors and the combination provides the lowest AIC given the available data. The BIC was also the lowest (see Table 1A, 2A and 3A in the Appendix for the comparison of model quality using the AICs and BICs for Eq2, Eq.3, and Eq.3bis). The components of the vector Z_{1i} in Eq. 3 are Middle East and African countries, Latin-American countries, and small islands (Table 3). The component of the vector Z_{2i} in Eq. 3bis is Latin-American countries (Table 4).

For both Eq. 3 and Eq. 3bis, there was no statistically significant predictor representing social aspects (i.e., Population density and Urban population). Both AICs and BICs were the lowest for both models.

As a robustness check, we estimated the determinants of inadequately managed plastic waste using OLS. The results from the robustness check are provided in Appendix Table 4A. These robustness tests were designed to check if the results for the variables of key interest were sensitive to alternative model specifications.[4] As shown, the signs of the estimated coefficients for GDP per capita and (GDP per capita)^2 in all model specifications were mostly consistent with the findings from our baseline empirical model in Table 2. Table 4A also illustrates that the estimated coefficients for the variable corruption control policies had their expected signs and were statistically significant across various model specifications. These results provide additional evidence to support the findings in Table 3. On the contrary, the sign of years of school transitioned to become positive and not significant. We suspect that this insignificant relationship may be attributed to the use of different country samples for the robustness analysis (the lack of data for the variables tested altogether in Table 4A did not allow us to use the same country samples).

Table 2
Linear regression model estimate for Plastic waste per capita (natural logarithm) (Eq. 2).

Variable	Coefficient	Std. Error	*p*-Value	
LN (GDP per capita)	1.573	0.708	0.028	**
(LN (GDP per capita))^2	−0.080	0.039	0.041	**
Small islands	0.562	0.139	0.000	***
Urban population	0.012	0.003	0.001	***
Market regulatory quality	0.008	0.004	0.065	*
Constant	−5.347	3.151	0.092	*
R^2	0.4804			
AIC	326.3714			
BIC	344.3951			
N	149			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3
Logistic model estimate for inadequately managed waste percentage with a focus on corruption control policies (Eq. 3).

Variable	Coefficient	Std. Error	*p*-Value	
LN (GDP per capita)	−1.159	0.410	0.005	***
Corruption control policies	−1.244	0.562	0.027	**
Middle East and African countries	2.215	0.926	0.017	**
Latin American countries	3.057	0.885	0.001	***
Small islands	−1.684	0.809	0.037	**
Constant	9.926	3.683	0.007	***
Pseudo R^2	0.5411			
Log likelihood	−38.8019			
AIC	89.6037			
BIC	106.4278			
N	122			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4
Logistic model estimate for inadequately managed waste percentage with a focus on education policies (Eq. 3bis).

Variable	Coefficient	Std. Error	*p*-Value	
Years of school	−0.437	0.174	0.012	**
LN (GDP per capita)	−1.385	0.387	0.000	***
Latin American countries	3.287	1.120	0.003	***
Constant	16.179	3.717	0.000	***
Pseudo R^2	0.6140			
Log likelihood	−26.7485			
AIC	61.4971			
BIC	71.9177			
N	100			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

3.2. Scenario analyses

All scenarios displayed below were computed using observed data in Models 1 and 2 to simulate the period 1990–2017 and extrapolated data to simulate the period 2018–2050.

3.2.1. Business-as-usual scenario

The BAU forecasts explanatory variables based on past trends

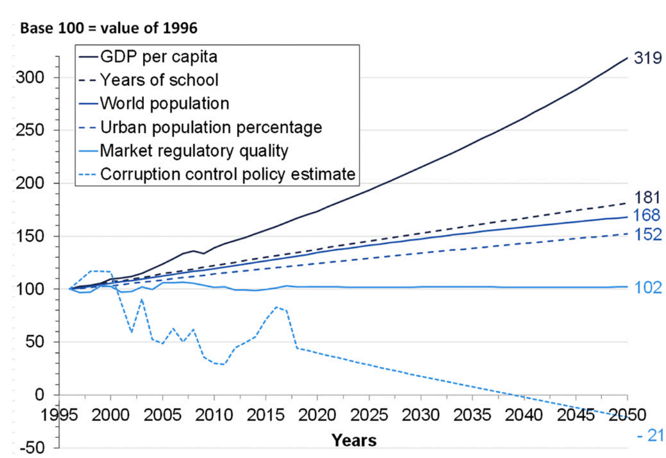

Fig. 1. Evolution of variables explaining global inadequately managed plastic waste in the BAU scenario. Observed data from 1996 to 2017; extrapolated data from 2018 to 2050. All values standardized in base 100 = 1996, that is, the amounts in the year 1996 have been set to 100 and any variation is added to 100 in percentage increase.

[4] We conducted the robustness analysis by using the hierarchical procedure to select the best estimates. Concretely, we retained the variables of income per capita, corruption control policies, and education in the estimated models. We selected other explanatory variables to pursue the highest fitness measured by AIC. We found that the estimated model with the lowest AIC is the model specification (8) (see Appendix Table 4A).

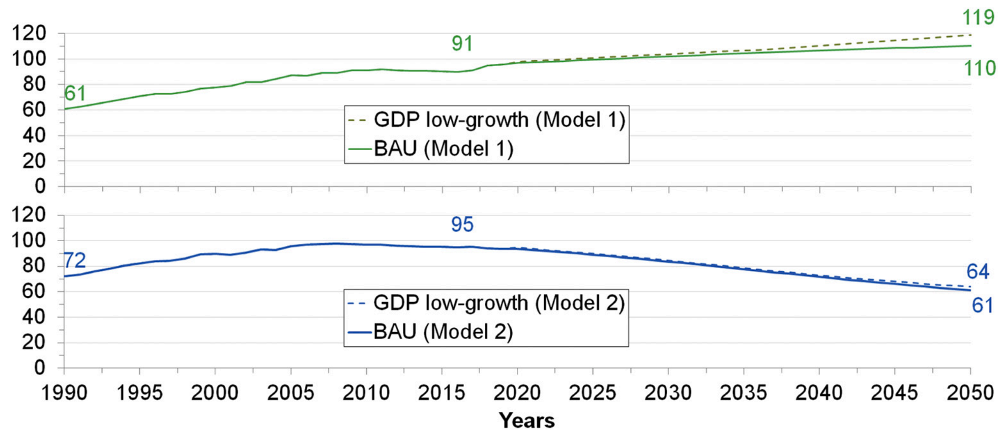

Fig. 2. Annual plastic waste inadequately managed globally (MMT/year) for BAU scenarios in comparison with GDP low-growth scenarios. Note: MMT: million metric tons; BAU: business-as-usual scenario; Model 1: takes into account the weakening trend of corruption-fighting policies; Model 2: takes into account the increasing trend in the number of schooling years.

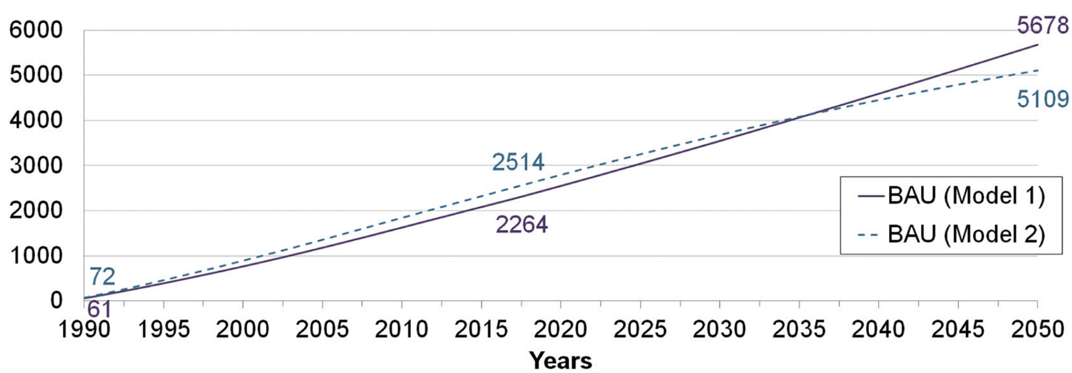

Fig. 3. Global cumulative stock of plastic waste inadequately managed since the reference year 1990 (MMT).

observed from 1996 to 2017 (Fig. 1).

Model 1 shows that under the BAU scenario, annual amounts of inadequately managed plastic waste generated globally increase from 61 million MT per year in 1990 to 110 million MT per year in 2050 (Fig. 2 (scenario *BAU (Model 1)*).

Model 2 tells a different story. It estimates that under the BAU scenario, the annual amounts of inadequately managed plastic waste generated globally will decrease from 72 million MT in 1990 to 61 million MT in 2050 (Fig. 2 (scenario *BAU (Model 2)*).

From the BAU scenarios simulated with Models 1 and 2, we estimate that in the worst case the growth in the annual amount of inadequately managed plastic waste globally is expected to slow over the period 2020–2050 and keep a slight increasing trend. In the best case, it will moderately decrease over 2020–2050 (Fig. 2). If we sum the annual amount of inadequately managed plastic waste generated since 1990 in the BAU scenario, Models 1 and 2 estimate the cumulative stock to 2264–2514 million MT in 2017 and to 5109–5678 million MT in 2050. Both models show the cumulative stock will continue drastically increasing by 2050 (Fig. 3).

Our results are similar to Lebreton and Andrady (2019). They estimate between 60 and 99 million MT of mismanaged plastic waste were produced globally in 2015 (in their study, mismanaged plastic waste = inadequately managed plastic waste +0.1–10% of plastic waste directly littered on the ground by individuals). Our estimation is between 90 and 95 million MT of inadequately managed plastic waste in 2015 as shown in Fig. 2 by Models 1 and 2, respectively.

3.2.2. *Mitigation scenario 1: Capping GDP*

The GDP low-growth scenario (Fig. 2) simulates an economic slowdown capping GDP per capita in all countries at a maximum of $30,000 (PPP international $ at 2011 constant prices) over the period 2020–2050. Without such a cap (BAU scenario), half the countries of the world will probably achieve a GDP per capita greater than $30,000 by 2050 with a world average value at $30,268. With the cap (GDP low-growth scenario), the GDP per capita world average would achieve a level of $21,784 by 2050. We set the cap at $30,000 because it is the GDP per capita threshold beyond which the level of life satisfaction does not increase much.[5] Several authors have raised the question of capping GDP or slow down GDP growth since they have identified beyond a certain level of GDP per capita, education, public health, life expectancy, unemployment, happiness, satisfaction in life, and ecological parameters no longer improve (Haberl et al., 2006; Victor, 2019; Jackson, 2009; Krausmann et al., 2009). Our results show that with such a cap the annual amount of inadequately managed plastic waste slightly increases and reaches 64–119 million MT/year in 2050 (results from Models 2 and 1, respectively) instead of 61–110 million MT/year in the BAU scenario (Fig. 2). This suggests that regarding plastic waste emissions, capping GDP reduces investment capacities in waste treatment systems (which is urgently needed in low- and middle-income countries), increasing inadequately managed plastic waste (Lebreton and Andrady, 2019).

3.2.3. *Mitigation scenario 2: Extending education*

In the education scenario, we simulate a situation in which the 43 countries ranked as generating the most inadequately managed plastic waste (Table 5) would implement education policies by 2050, progressively starting from 2020, ensuring individuals ≥25-years-old will have

[5] Authors' own calculation based on data published by Ortiz-Ospina and Roser (2017).

Table 5
Characteristics of the top 43 countries ranked by mass of inadequately managed plastic waste in 2017.*

	Country	Observed data from World Bank (2018a, 2019b)						BAU scenario (results from Model 2 except in the ranges where results from Models 1 and 2 are shown)			
		Income cate-gory	Corruption control policy estimate		Years of schooling		Popu-lation (million)	Plastic waste generation rate (kg/person/yr)	% Inadequately managed waste	Inadequately managed plastic waste (MMT/yr)	Inadequately managed plastic waste (MMT/yr)
	(Years) ➔		1996	2017	1995	2010	2017	2017	2017	2017	2050
1	India	LMC	−0.38	−0.24 ↗	3.51	5.39 ↗	1338.7	20.2	79.6%	13.85–21.57	4.50–8.98
2	China	UMC	−0.27	−0.27 →	5.69	7.12 ↗	1386.4	31.0	32.2%	12.38–13.82	1.71–10.05
3	Brazil	UMC	−0.02	−0.53 ↘	4.84	7.66 ↗	207.8	44.8	94.0%	8.64–8.75	5.11–8.66
4	Mexico	UMC	−0.51	−0.93 ↘	6.48	8.33 ↗	124.8	45.0	85.1%	4.78–5.29	1.80–7.46
5	Indonesia	LMC	−0.86	−0.25↗	4.21	7.26 ↗	264.6	30.1	53.7%	2.89–4.28	0.78–0.80
6	Pakistan	LMC	−1.22	−0.78↗	2.77	4.45 ↗	207.9	17.8	90.8%	2.77–3.37	3.46–3.49
7	Nigeria	LMC	−1.19	−1.07↗	N.A.	N.A.	190.9	19.4	80.5%	2.91–2.98	7.76–7.99
8	Bangladesh	LMC	−0.97	−0.83 ↗	3.29	4.91 ↗	159.7	15.5	92.1%	2.01–2.29	1.57–1.69
9	Colombia	UMC	−0.51	−0.37 ↗	6.09	8.45 ↗	48.9	46.6	92.8%	2.10–2.12	1.98–3.20
10	Argentina	HIC	−0.10	−0.26 ↘	8.34	9.48 ↗	44.0	44.3	79.4%	1.70–1.55	0.56–1.57
11	Vietnam	LMC	−0.49	−0.58 ↘	4.60	7.45 ↗	94.6	19.6	69.9%	1.16–1.30	0.23–0.67
12	Philippines	LMC	−0.36	−0.48 ↘	7.12	8.18 ↗	105.2	27.0	44.3%	1.26–1.54	0.15–1.16
13	Peru	UMC	−0.40	−0.50 ↘	7.25	8.68 ↗	31.4	45.5	86.8%	1.24–1.34	0.32–1.75
14	Egypt	LMC	−0.47	−0.54 ↘	4.05	6.55 ↗	96.4	19.7	53.8%	1.02–1.68	0.13–2.29
15	Ethiopia	LIC	−0.93	−0.56 ↗	N.A.	N.A.	106.4	9.6	97.6%	0.90–1.00	0.92–1.20
16	Morocco	LMC	−0.11	−0.13 ↘	2.66	4.24 ↗	35.6	29.8	84.6%	0.90–0.93	0.53–1.45
17	Chile	HIC	1.45	1.04 ↘	8.40	9.71 ↗	18.5	61.2	72.3%	0.59–0.82	0.24–0.44
18	Venezuela	UMC	−0.86	−1.36 ↘	5.5	8.16 ↗	29.4	31.2	89.1%	0.82–0.88	0.38–1.09
19	Turkey	UMC	−0.15	−0.19 ↘	4.81	6.56 ↗	81.1	40.4	24.4%	0.56–0.80	0.08–0.17
20	Europe - 28	HIC	1.18	1.09 ↘	9.13	11.23↗	512.2	49.7	3.1%	0.80–1.01	0.07–1.13
21	Tanzania	LIC	−0.70	−0.48 ↗	4.09	5.12 ↗	54.7	15.0	93.1%	0.65–0.77	1.64–1.65
22	Myanmar	LMC	−1.50	−0.56 ↗	2.71	4.09 ↗	53.4	15.8	90.6%	0.55–0.76	0.05–0.15
23	Thailand	UMC	−0.36	−0.39 ↘	4.33	7.30 ↗	69.2	30.4	35.2%	0.64–0.74	0.06–0.55
24	Congo DRC	LIC	−1.65	−1.42 ↗	2.92	3.61 ↗	81.4	8.6	99.3%	0.69–0.70	2.86–2.97
25	Kenya	LMC	−1.16	−0.96 ↗	4.54	6.19 ↗	50.2	15.8	87.5%	0.68–0.69	0.56–1.37
26	Ghana	LMC	−0.34	−0.23 ↗	5.66	6.76 ↗	29.1	25.5	75.3%	0.48–0.56	0.16–0.46
27	Sudan	LMC	−1.24	−1.54 ↘	1.97	3.13 ↗	40.8	14.0	95.2%	0.51–0.55	0.81–1.12
28	Algeria	UMC	−0.57	−0.61 ↘	4.17	5.98↗	41.4	27.2	48.1%	0.54–0.97	0.17–1.52
29	Angola	LMC	−1.17	−1.41 ↘	N.A.	N.A.	29.8	23.1	76.4%	0.53–0.57	2.37–2.70
30	Uganda	LIC	−0.72	−1.04 ↘	3.38	5.42 ↗	41.2	13.0	97.4%	0.49–0.52	1.26–1.33
31	South Afric.	UMC	0.73	−0.01 ↘	8.22	9.43↗	57.0	37.8	22.8%	0.49–0.59	0.06–1.64
32	Côte d'Ivoi.	LMC	−0.26	−0.52 ↘	2.50	4.22 ↗	24.4	21.2	94.2%	0.39–0.49	0.71–0.74
33	Guatemala	UMC	−0.86	−0.74 ↗	3.41	4.30 ↗	16.9	25.3	99.3%	0.42–0.43	0.81–0.79
34	Cameroon	LMC	−1.33	−1.18 ↗	4.15	5.96 ↗	24.6	19.3	87.5%	0.41–0.42	0.53–1.08
35	Dom. Rep.	UMC	−0.42	−0.74 ↘	5.92	7.56 ↗	10.5	42.2	92.5%	0.41–0.42	0.21–0.62
36	Iran	UMC	−0.48	−0.81 ↘	5.26	8.17 ↗	80.7	27.9	18.1%	0.41–1.91	0.02–2.88
37	Ecuador	UMC	−0.68	−0.60 ↗	6.71	7.44 ↗	16.8	24.8	95.3%	0.40–0.40	0.44–0.52
38	Iraq	UMC	−1.60	−1.37 ↗	4.17	6.38 ↗	37.6	26.5	37.8%	0.38–0.93	0.05–1.70
39	Afghanistan	LIC	−1.29	−1.52 ↘	1.86	3.47 ↗	36.3	9.7	98.7%	0.34–0.35	0.90–0.95
40	Yemen	LIC	−0.74	−1.59 ↘	0.65	2.60 ↗	27.8	12.3	98.9%	0.34–0.34	0.73–0.75
41	Senegal	LIC	−0.14	−0.09↗	2.06	1.95 ↘	15.4	21.6	98.4%	0.22–0.33	0.51–0.90
42	Nepal	LIC	−0.64	−0.75 ↘	2.24	3.31 ↗	27.6	12.0	97.4%	0.28–0.32	0.31–0.34
43	Mozambiq.	LIC	−0.42	−0.86 ↘	0.80	1.14 ↗	28.6	10.9	99.7%	0.29–0.31	1.02–1.13
Total 43 countries										77.3–86.9	49.6–90.9
Total world (217 countries)										91.0–95.4	61.2–110.2

* MMT/yr = million MT per year. HIC = High Income Country; UMC = Upper Middle income Country; LMC = Low Middle income Country; LIC = Low Income Country. Corruption control policy estimates range from −2.5 (total lack of public policies to fight corruption) to +2.5 (corruption completely impeded by public policies). Europe - 28: European Union of the 28 member States. N.A.: non-available data. Line 35: Dom. Rep. = Dominican Republic. Line 24: Congo DRC = Democratic Republic of Congo (Congo-Kinshasa).

received a minimum of 12 schooling years. Such an educational target is not easy to achieve; it will be a political and economic challenge. According to the BAU scenario, if current trends continue, only 14 countries in the top 43 will have reached an average number of school years of at least 12 by 2050. The top 43 countries' inadequately managed plastic waste encompassed 91% of the total discarded in the world in 2017 (estimated 91–95 million MT per year – results from Models 1 and 2, respectively). Among the top 43 countries, 30 of them have an average number of schooling years less than 8 (Table 5). Fig. 4 shows the education scenario reduces by 34% the amount of inadequately managed plastic waste in 2050 (40 MMT/year) compared to the BAU scenario (61 MMT/year). This is in line with Otto and Pensini (2017) who assert that a minimum level of education is required to develop the ability to manage contrasting information, a skill that is central to ecological behaviors. Fig. 4 also confirms the results from Hidalgo-Ruz et al. (2018) who show that in the countries with the highest education index, marine waste is decreasing. It also supports Gifford and Nilsson (2014) who recognize knowledge to be a necessary (but not sufficient) condition to pro-environmental behaviors (Gifford and Nilsson, 2014).

3.2.4. Mitigation scenario 3: Fighting corruption

In the fighting corruption scenario, corruption control policies are implemented over 2020–2050 in the top 43 countries, as in the previous scenario. With Model 1, we estimate fighting corruption reduces the global annual amount of inadequately managed plastic waste by 28% in 2050 compared to 1990 levels. This means implementing policies to prevent public power to be used for private gain, including petty and grand forms of corruption and the capture of the state by elites and private interests (World Bank, 2018a; Kaufmann et al., 2010). To reach 28% abatement by 2050, the top 43 countries should progressively raise

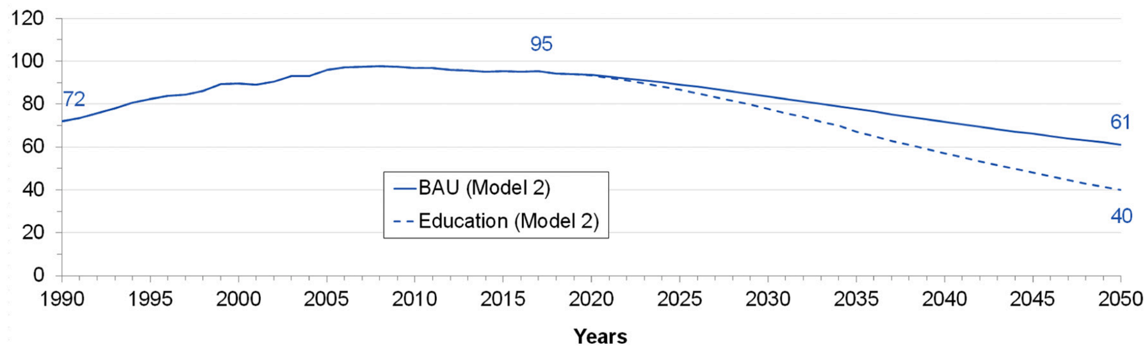

Fig. 4. Annual plastic waste inadequately managed globally (MMT/year) for BAU (Model 2) and Education scenarios (Model 2).

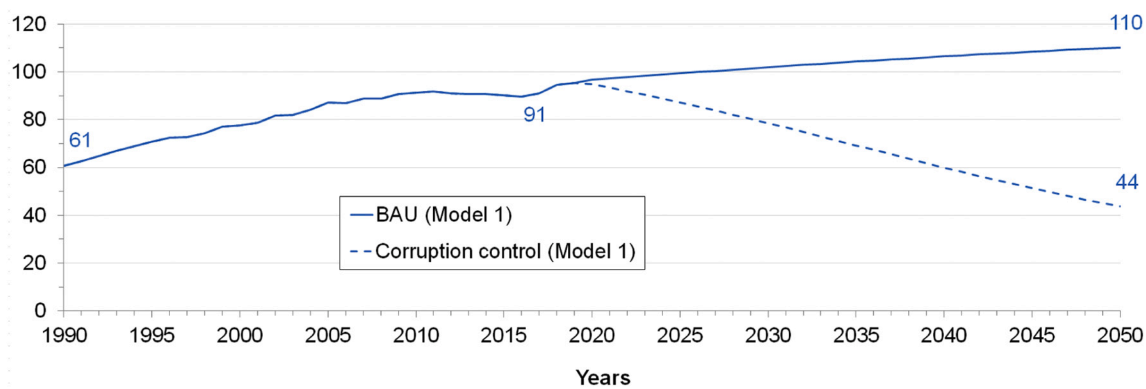

Fig. 5. Annual plastic waste inadequately managed globally (MMT/year) for BAU (Model 1) and Corruption control scenarios (Model 1).

their corruption control policies close to the level of countries such as Uruguay in 2016 or France and Estonia in 2017, that is, a corruption control estimate of 1.24. If such a scenario were implemented (Fig. 5), the estimated global amount of annually inadequately managed plastic waste would fall to 44 million metric tons per year in 2050 instead of 110 million tons per year as in the BAU scenario. This is in line with results from Biswas et al. (2012), who suggest the size of the shadow economy in the top 43 countries is significant enough for corruption-control policies to have an impact in moderating the destructive effects of corruption and industrial lobbying on plastic pollution. Our results further confirm the consensus in previous studies about the environmental consequences of government corruption, in that corruption harms the environment and environmental protection by reducing the stringency of environmental regulations (see Leitão, 2010; Wang et al., 2020; Zhou et al., 2020).

3.3. Limitations of our study

There are seven major limitations of our study. The first relates to observed data for plastic waste. The waste identified by the global database of the World Bank (2018) – used to design our models – exclusively includes quantitative data on municipal solid waste generated by households at home (Kaza et al., 2018). In Europe, for example, approximately 50% of plastics are produced for use by households at home (own estimation based on PlasticsEurope, 2018). The remaining 50% are produced for industrial, building, construction, and agricultural activities and are not captured by our models. Hence, our study of plastic pollution is based on very conservative estimates; we are confident the actual amount of plastic waste is larger than our estimates and therefore the extent of plastic pollution is greater too.

Second, different data sets could lead to different results. We used the World Bank database (except for small island dummies) because it is the most comprehensive and consistent database at the country level. While the robustness check supported the EKC relationship between inadequately managed plastic waste and income per capita, and the significance of corruption control policies as a predictor for inadequately managed plastic waste, education was not robust as a predictor because of its sensitivity to the data availability. Furthermore, due to the limited data used, there are some predictors we did not reflect or used a proxy. For example, environmental legislation and enforcement could directly explain inadequately managed waste but was not reflected in our study because of the lack of data. In addition, because we used country level data, our study has a limitation of not capturing individual behaviors. For example, environmental awareness is a critical predictor, but we used proxies such as urban population and population density; although they are proposed in literature (Otto and Pensini, 2017; Kiessling et al., 2017), they do not represent pure environmental awareness but also other attributes. Furthermore, using a country level dataset restricts us from examining individual attributes and behaviors (e.g., demographic, psychological, and social norms) regarding plastic waste (Hartley et al., 2018).

Third, more importantly, besides the data availability, further studies on the theory explaining inadequately managed plastic waste need to advance. While our study validated the EKC theory hypothesis regarding the relationship between plastic waste per capita and income per capita, other predictors were drawn from various literature, not from a well-accepted theory or framework. While there is a rich literature on individual-level predictors (Hartley et al., 2018; Schultz et al., 2013; Steg and Vlek, 2009), a theory explaining predictors at the country level remain lacking.

Fourth, the model estimates can be improved by using other techniques. Models 1 and 2 used two equations (Eq. 2 and Eq. 3 for Model 1 and Eq. 2 and Eq. 3bis for Model 2). We estimated equations separately by applying ordinary least squares to Eq. 2 and the logit model to Eq. 3 and 3_{bis} by using maximum likelihood. Since there are some common variables used, simultaneous equations model, which include endogeneity (Greene, 2012), could provide better estimates. Alternatively, a single model directly estimating inadequately managed plastic waste could provide a better model for forecasting.

Fifth, we assumed that the share of inadequately managed waste in the waste is identical to the share of inadequately managed plastic waste in the plastic waste as Lau et al. (2020) assumed. We made such an assumption because the raw data for the latter were not available in the World Bank Database. An alternative way could be to use shares sampled from several countries and apply them to other countries; Jambeck et al. (2015, supplemental materials page 2) applied the share obtained from the US data to the other countries. However, to avoid such approximations and conduct more accurate analysis, the generation of raw data awaits.

Sixth, the data for inadequately managed plastic waste needs to be improved. To exclude countries with unclear data (i.e., countries with a high proportion of "Others" and "Unaccounted for" categories), our model estimates were based on 122 countries with a low proportion of these categories (less than 25% in our study). Since the 25% threshold is arbitrary, we tested the 50% threshold. It provides results with the same set of statistically significant predictors with a slightly lower AIC score. While a thorough sensitivity analysis of choosing thresholds could help test the robustness of our estimates, improvement of the data collection in the first place is urgently needed, provided that this dataset is a sine qua non condition to robust modeling.

Seventh, the scenario design was rather arbitrary and has room for further development. There are three main caveats regarding the BAU scenario. First, for the 162 countries for which there were no long-term forecasts from the OECD (2019) and Hawksworth et al. (2017), we arbitrarily chose 2007–2018 as the reference period to compute the average annual growth rate of GDP per capita and we applied it to future years to compute forecasts for 2018–2050. Second, for simplicity, our GDP per capita forecasts assumed a constant annual growth rate. In a further study, country-specific regressions providing variable annual growth rate could better fit observed data. Correcting annual growth rates through expert consultation through the Delphi method (Linstone and Turoff, 1975) could also provide more plausibility. Third, differently from GDP per capita and the other explanatory variables, the trend for corruption control policy does not follow a stable linear trend. However, we applied a linear regression calculated on the 1996–2017 reference period (i.e. the full available data series provided by the World Bank).

Regarding Mitigation scenario 1: capping GDP, we set the cap at \$30,000. However, using the threshold "beyond which the level of life satisfaction does not increase much" is not as accurate. According to the data by Ortiz-Ospina and Roser (2017), the level of life satisfaction first increases with GDP per capita but beyond a certain threshold, it progressively stabilizes following a logarithmic curve. Along such a curve, a single threshold does not exist. It is rather a range that is observed. At the lower margin of the range (~ \$15,000), life satisfaction starts increasing less and less to finally become almost constant beyond the upper margin of the range (~ \$45,000). The cap of \$30,000 we proposed is right in the middle of the range. This choice is a bit arbitrary and in a further study, a sensitivity analysis could use both margins of the range to analyze how results are influenced.

In Mitigation scenario 2: extending education, we considered that spending 12 years at school was the minimum requirement to have cognitive abilities to understand and apply ecological behaviors. However, in some traditional communities, education is not transmitted necessarily by official schools. It is rather transmitted in an informal way by parents and relatives or by elderly people. Although our statistical regressions showed it works, it does not mean there is not another more effective threshold. A sensitivity analysis could help explore other thresholds.

In Mitigation scenario 3: fighting corruption, we proposed to raise corruption control policies closer to the level of countries such as Uruguay in 2016 or France and Estonia in 2017 (i.e., a corruption control estimate of 1.24) rather than less corrupt countries such as Finland (2.22) or Norway (2.24). This was based on the idea that asking too much of highly corrupt countries is unrealistic and asking too little will have only a slight effect on plastic waste management. A sensitivity analysis should help to further study the impact of corruption control policies.

4. Conclusion

While the EKC hypothesis has been validated at a statistically significant level (Eq. 2), our simulations show that the growth of GDP per capita in the BAU scenario will not be sufficient to resolve plastic waste management issues by 2050. Additionally, there is increasing evidence that unlimited economic growth is decreasingly viable in a limited global ecosystem. By developing two worldwide models based on social, political, market regulatory, and governance data, we demonstrate the impact of non-technological solutions to control discarded plastic waste. According to our results, corruption control and education are able to reduce inadequately managed plastic waste; hence, they must be part of implemented interventions.

Additional research should investigate how combining the policy measures suggested in this paper can achieve the highest reduction in mismanaged plastic waste with the lowest effort. Future research should also investigate additional policy options. For example, Models 1 and 2 could be used to study scenarios for policies addressing urban and rural planning. Another way to design policy interventions is by investigating plastic waste policies implemented in the countries with the lowest amount of inadequately managed plastic waste. These policies may include systems that help make repaired and reused products cheaper than new ones. Such policies directly address the reduction of planned product obsolescence and single-use plastic products by favoring longer-lasting, repairable products (Cooper, 2016) and reduce plastic waste discards. Strict regulations of the plastic-producing industry have the potential to bring about significant solutions (e.g. return and deposit systems for plastic bottles, enforcing extended producer responsibility). However, these require higher environmental awareness driven by educational programs especially addressed to children (Kiessling et al., 2017), and a tremendous increase of corruption-control policies in most countries (Table 5). Otherwise, plastic regulations will see their stringency reduced by industrial lobbies (Candau and Dienesch, 2017; Biswas et al., 2012; Milfont and Markowitz, 2016; Damania et al., 2003).

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Author contributions (follows the CRediT taxonomy)

M. C., T. U., J. B., B. J., and H.Y. participated in the conceptualization of this study and wrote the manuscript text. M. C., T. U. and H.Y. contributed to data curation, formal analysis, and the methodology. J. B. contributed to the project administration and organized field observations. J. B. and B. J. contributed to the validation of the results as well as to the review and editing of the manuscript text.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Appendix

Comparison of model quality, using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) scores.

Table 1A
Comparison of the Linear regression model estimate for Plastic waste per capita (Table 2, Eq. 2).*

Rank	Model	AIC	BIC
6	Intercept + LN(GDP per capita)	348.895	354.903
7	Intercept + LN(GDP per capita) + Population Density	350.753	359.765
5	Intercept + LN(GDP per capita) + Small Islands	339.437	348.449
4	Intercept + LN(GDP per capita) + Small Islands + OECD countries	335.933	347.949
3	Intercept + LN(GDP per capita) + Small Islands + OECD countries + Market regulatory quality	333.908	348.928
2	Intercept + LN(GDP per capita) + LN(GDP per capita)ˆ2 + Small Islands + OECD countries + Market regulatory quality	331.430	349.454
1	Intercept + LN(GDP per capita) + LN(GDP per capita)ˆ2 + Small Islands + Urban + Market regulatory quality	326.371	344.395

* Only models with statistically significant independent variables are reported.

Table 2A
Comparison of Logistic model estimate for inadequately managed waste with a focus on corruption control policies (Eq. 3).*

Rank	Model	AIC	BIC
4	Intercept + LN(GDP per capita)	109.004	114.612
3	Intercept + LN(GDP per capita) + Corruption control policies (percentile rank)	105.405	113.817
2	Intercept + LN(GDP per capita) + Corruption control policies (estimate)	104.689	113.101
1	Intercept + LN(GDP per capita) + Corruption control policies (estimate) + Middle East and African countries + Latin American countries + Small islands	89.604	106.428

* Only models with statistically significant independent variables are reported.

Table 3A
Comparison of logistic model estimate for inadequately managed waste with a focus on education policies (Table 4, Eq. 3bis).*

Rank	Model	AIC	BIC
3	Intercept + LN(GDP per capita)	81.848	87.058
2	Intercept + LN(GDP per capita) + Years of school	74.671	82.487
1	Intercept + LN (GDP per capita) + Years of school + Latin American countries	61.497	71.918

* Only models with statistically significant independent variables are reported.

Table 4A
Estimation results for LN(Inadequately managed plastic waste)—robustness checks.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GDP per capita	0.0002**	0.0002*	0.0002*	0.00002*	0.00003**	0.0003*	0.0003**	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.00001)	(0.00002)	(0.0001)	(0.0001)	(0.0001)
$(\text{GDP per capita})^2$	−3.38e-09*	−4.15e-09**	−3.52e-09*			−4.52e-09*	−5.57e-09**	−6.77e-09***
	(1.79e-09)	(1.74e-09)	(1.88e-09)			(2.61e-09)	(2.61e-09)	(2.41e-09)
Years of school				0.0394	0.0684	0.0303	0.039	0.026
				(0.1399)	(0.1515)	(0.1604)	(0.1427)	(0.157)
Corruption control policies (percentile rank)	−0.0412***	−0.0367**	−0.0387**			−0.0524***	−0.0511***	−0.0429***
	(0.0145)	(0.0136)	(0.015)			(0.0147)	(0.0147)	(0.0133)
Market regulatory quality					−0.0134			
					(0.0129)			
Latin-American countries		−0.7172						−1.3499**
		(0.4563)						(0.4944)
Middle-East and African countries			0.8016				1.4826**	
			(0.6442)				(0.6489)	
Constant	−1.3173**	−1.318*	−1.4954**	−2.1006**	−1.8045*	−1.3265	−1.7802	−1.3991
	(0.6363)	(0.6506)	(0.6244)	(1.0176)	(1.0107)	(1.1088)	(1.0619)	(1.1512)
R^2	0.2176	0.2572	0.2525	0.0231	0.0446	0.2862	0.3815	0.3942
N	38	38	38	41	41	32	32	32
AIC	141.6469	141.6719	141.9139	162.7102	163.7981	123.1246	120.5345	119.8734
BIC	146.5597	148.2222	148.4643	167.8509	170.6523	128.9876	127.8632	127.2021

Note: Robust Std. Error into brackets. ***, **, and * denote a significance of 1%, 5% and 10%, respectively.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2020.106930.

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