Is there an empirical environmental Kuznets curve relationship between mismanaged plastic waste per capita and income per capita? A caveat

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Abstract

A study by Barnes (2019) concluded that there exists an empirical environmental Kuznets curve (EKC) relationship between mismanaged plastic waste per capita and income per capita. However, this result needs careful interpretation. The study adopted data that used the World Bank database to compute mismanaged plastic waste amounts. Because data to compute them were not available for all countries, missing data were estimated by relating them to economic classification (i.e., income level). In other words, the data used for the analysis by Barnes simply assumed—without scientific validation—that mismanaged plastic waste amounts are related to economic classification (i.e., income level).

Keywords: Environmental Kuznets curve; plastic waste; income level

A study by Barnes (2019) concluded that there exists an empirical environmental Kuznets curve (EKC) relationship between mismanaged plastic waste per capita and income per capita by using data created by Jambeck et al. (2015). However, the finding needs careful interpretation because not all the data for mismanaged plastic waste were computed using raw data. A substantial amount of data were estimated assuming that there exists a relationship between economic classifications based on national income per capita (HIC = high income; UMI = upper middle income; LMI = lower middle income; LI = low income) and variables computing mismanaged plastic waste when the raw data were not available (Jambeck et al., 2015). In other words, the data Barnes (2019) used were created assuming that income level explains the degree of mismanaged plastic waste per capita.

Mismanaged plastic waste per capita for country i ($i = 1, \ldots, 192$) was computed by Jambeck et al. (2015) as follows:

$$\text{Mismanaged plastic waste}_i/\text{Coastal population}_i = \text{Waste generation rate}_i \times \text{percentage of plastic in the waste stream}_i \times (\text{percentage of inadequately managed waste}_i + \text{percentage of littered waste}) \quad (1)$$

For countries whose raw data were not available to compute equation (1), Jambeck et al. (2015) devised their own estimates based on the following four assumptions. First, for 84 of the 192 coastal countries, they applied average values of waste generation rate for each economic classification based upon gross national income per capita. Second, for 122 of the 192 coastal countries that lacked the data for percentage of plastic in the waste stream, they applied the same method, albeit based upon economic classifications. Third, for 111 of the 192 coastal countries, the percentage of inadequately managed waste was estimated by applying a logistic regression model. The best model, based on Akaike's Information Criterion (AIC) score, includes economic classifications and geographic information as explanatory variables. Fourth, although the model shows a statistically significant relationship between percentage of inadequately managed waste and economic classifications, the computations of the data for the dependent variable (i.e., the probability of inadequate waste management) were based on economic classifications. That is, the data for 81 coastal countries in the model estimation were processed using their respective economic classifications (e.g., landfills in low-income countries are considered to be inadequately managed).

We investigated how the relationship between the percentage of inadequately managed waste and income per capita varies depending on how the percentage of inadequately managed waste is computed. As the data used by Barnes (2019) were not publicly accessible, we used the data provided by Jambeck et al. (2015) and the World Bank (2018) instead. The percentage of inadequately managed waste is computed by combining multiple waste disposal methods, as shown in Table 1. To make the comparison, we created five different rules to compute the percentage of inadequately managed waste, as seen in Table 1. Rule 1 does not make any adjustment based upon the economic classification, whereas the remainder of the rules apply different assumptions regarding the relationship between waste disposal methods and economic classification. For the five different rules, we used the data provided by the World Bank (2018), which are more recent (mostly containing data from 2011–2017), while Barnes (2019) used data from 2010. It should be clearly noted that we do not claim which assumed rule best captures the actual percentage of inadequately managed waste. These rules are just examples to show how the rule chosen to build the data for the percentage of inadequately managed waste impacts the data's relationship with gross domestic product (GDP) per capita.

As shown in Table 1, the results of Barnes (2019) show the largest negative coefficient (−0.7275), indicating the strongest negative relationship between percentage of inadequately managed waste and GDP per capita. Rule 1, which does not use economic classifications, has the weakest negative correlation among alternatives (−0.3416). Moreover, it shows that the correlation varies from −0.3416 to −0.7275 depending on the assumption made.

Table 1. Barnes (2019) and five alternative aggregation rules to estimate the percentage of inadequately managed wastes, and Pearson's correlation coefficients for GDP per capita and various percentages of inadequately managed waste.

		Barnes (2019), based upon Jambeck et al. (2015)	Rule 1	Rule 2	Rule 3	Rule 4	Rule 5
Waste disposal method	Anaerobic digestion						
	Compost (percent)						
	Controlled landfill	X (LIC countries)		X (LIC countries)	X (LIC, LMC, UMC countries)	X (LIC, LMC countries)	X (LIC countries)
	Incineration						
	Landfill (unspecified)	X (LIC countries)		X (LIC countries)	X (LIC, LMC, UMC countries)	X (LIC, LMC countries)	X (LIC countries)
	Open dump	X (All countries)	X (All countries)	X (All countries)	X (All countries)	X (All countries)	X (All countries)
	Other	(Weighting factor for all countries) *		X (LIC, LMC, UMC countries)	X (LIC, LMC, UMC countries)	X (LIC, LMC, UMC countries)	X (All countries)
	Recycling						
	Sanitary landfill, landfill gas system						
	Unaccounted for	(Weighting factor for all countries) *		X (LIC, LMC, UMC countries)	X (LIC, LMC, UMC countries)	X (LIC, LMC, UMC countries)	X (All countries)
	Discarded in waterways and at sea	X (All countries)	X (All countries)	X (All countries)	X (All countries)	X (All countries)	X (All countries)
Correlation coefficient		-0.7275	-0.3416	-0.5504	-0.6987	-0.5978	-0.5022
p-value		< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
N		140	161	161	161	161	161

Note: HIC = high income; UMI = upper middle income; LMI = lower middle income; LI = low income

Empty cells correspond to adequately managed waste disposal methods.

* In some cases, the "Other" and "Unaccounted for" categories of waste disposal methods account for as much as 94% of the total reported fates, although the median share of the reported fates in the "Other" category was 0.015%. Jambeck et al. (2015) accounted for this by using the ratios of waste in the "Other" and "Unaccounted for" categories to the total waste as weights for the data in the regression, thus down-weighting data where there was significant uncertainty with respect to fate.

In conclusion, all three variables—excluding percentage of littered waste, which is assumed to be 2% for all countries—apply economic classifications as assumptions to estimate the missing data. As Jambeck et al. (2015) did not assert that these assumptions have been empirically tested,

they remain just that—assumptions. In other words, the use of economic classifications to fill in the missing data very likely does not serve the purpose at hand. We do not claim that these assumptions are wrong, but we do suggest that they have not been tested robustly and empirically. In addition, these assumptions can result in significant differences, as shown in Table 1. Therefore, we believe that it is crucial to interpret the EKC created by Barnes (2019) with caution as it is based on data derived by assuming relationships between economic classifications and three variables on mismanaged plastic waste per capita. Thus, there is adequate room to revisit and empirically test Barnes' EKC hypothesis.

References

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