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Abstract

Since 2015, the detrimental effects of plastic pollution have attracted media, public, and governmental attention. Considering that economic growth is inevitable and a key driver of plastic contamination, it is worthwhile to analyze the environmental Kuznets curve (EKC) relationship between economic development and plastic pollution. To this end, we contribute by being the first to (i) use the stochastic impacts by regression on population, affluence, and technology model as the theoretical and analytical framework to investigate this EKC relationship; (ii) provide a comprehensive analysis of how demographic factors affect plastic pollution; and (iii) use certain panel model techniques to examine the drivers of plastic pollution. Our empirical results support an inverted U-shaped relationship between plastic pollution and income. The implied turning point, beyond which plastic pollution starts to fall as income rises, is

relatively stable and not very sensitive to variations in model specifications. Our results reveal possible environmental benefits of economic growth and a meaningful response of demographic factors to plastic pollution. At current trends, global plastic pollution (that is, annual discard of inadequately managed plastic waste) is expected to grow from 52 million tons per year in 2020 to 257 million tons per year in 2050.

Keywords: Plastic pollution, environmental Kuznets curve, demographic changes, economic growth, urbanization, STIRPAT model

JEL Classification: O44, Q53, J11

1. Introduction

Plastic pollution is a prevalent and growing problem (Barnes, 2019; Issifu and Sumaila, 2020; Lau et al., 2020). From 1950 to 2015, global plastic production has grown 190 times—from 2 to 380 million metric tons (Geyer et al., 2017; all tons mentioned hereinafter are metric tons). This growth, plus the shift to single-use and inappropriate plastic waste disposal, has led to excessive plastic litter in the natural environment (e.g., oceans and waterways) and extensive environmental damage (Barnes, 2019; Lau et al., 2020). Specifically, persistent marine plastic waste damages ecosystems, curtails biodiversity, and threatens human health (Barnes, 2019; Cordier and Uehara, 2019; GESAMP, 2015; OECD, 2022; Villarrubia-Gómez et al., 2018). Since 2015, these detrimental effects have attracted significant media, public, and governmental attention to policymaking on how to reduce plastic waste generation (Barnes, 2019; Woods et al., 2021). For this purpose, this study examines the factors that impact plastic pollution and the extent of their impact.

However, we found only three studies that investigated the drivers of plastic pollution. Barnes (2019) analyzed the effect of economic development on mismanaged plastic waste using 2010 cross-sectional data of 151 countries and found evidence of an environmental Kuznets curve (EKC) relationship between income per capita and mismanaged plastic waste, with implied turning points ranging from US$ 1,931 to US$ 2,141 per capita (at 2010 prices). The author also incorporated a technology variable in the EKC analysis and showed that investment in scientific and technological research is key to reducing plastic pollution. Chen et al. (2020) applied compositional Bayesian regression to estimate waste generation disaggregated by composition (plastic, glass, etc.) and treatment (incineration, dump, etc.) for every country as a function of economic development. They found that total waste grows at a declining rate with economic

development, but it does not appear to follow the environmental Kuznets curve; that is, no absolute decoupling effect for waste was observed as countries become richer. Cordier et al. (2021) conducted a cross-sectional regression analysis to study the socioeconomic drivers of inadequately managed plastic waste. Their results supported the EKC hypothesis for plastic pollution, but with a high turning point of US$ 18,601 per capita (in US$ at 2011 prices in PPP – *Purchasing Power Parity*).[1] The authors claimed that economic development, corruption control policies, and education are key factors that determine inadequately managed plastic waste. Given the lack of consensus on the existence of an EKC and the unstable implied turning points among studies observing an EKC, a further empirical study is necessary to guide policymaking for curbing plastic pollution.

This paper supplements the scant literature on this topic in three ways. First, it is the first to use the stochastic impacts by regression on population, affluence, and technology (STIRPAT) model as the theoretical and analytical framework to investigate the EKC relationship between economic development and plastic pollution. The STIRPAT model is a widely used analytical technique for understanding the effects of human activities on the environment and the drivers of environmental change (Wei, 2011; York et al., 2003).[2] It allows a precise specification of the functional form of the relationship between the drivers and environmental impacts (York et al., 2003; Zhang et al., 2021). Using the model allows us to analyze several variables that have been neglected by Barnes (2019), Chen et al. (2020), and Cordier et al. (2021), which might have resulted in omitted variable bias.

[1] The turning point of US$ 18,601 (in international US$ at 2011 prices in PPP) is calculated based on the estimation results from Model 1 (Eq. 2) reported by Cordier et al. (2021). For comparison, this turning point is converted into US$ at 2010 prices or $US\$_{2010}$ 12,176.

[2] The STIRPAT model has been used to study the drivers of carbon emissions (see Liu and Han, 2021; Martínez-Zarzoso and Maruotti, 2011; Poumanyvong and Kaneko, 2010), ecological footprint (see Ehigiamusoe et al., 2021; Jia et al., 2009), sulfur oxide emissions (see Xu et al., 2021; Yang and Chen, 2019), and PM2.5 emissions (see Dong et al., 2020; Ji et al., 2018).

Second, to provide reliable information for policymaking and urban planning, this study comprehensively clarifies how demographic changes affect plastic pollution. Currently, the world is experiencing an important demographic transition characterized by changes in both population size and age composition, as well as rapid urbanization. This demographic transition is potentially accelerated by the COVID-19 pandemic by disrupting trends in mortality, fertility, and migration (Charles-Edwards et al., 2021), which raises the question of what implications demographic changes have on plastic pollution. Scholars have focused on demographic changes that contribute to environmental pollution in terms of population size, population aging, population density, urbanization level, and patterns (see Cole and Neumayer, 2004; Goel et al., 2013; Li et al., 2019; Martínez-Zarzoso and Maruotti, 2011; Qin and Wu, 2015; Zhang et al., 2017). However, previous studies mostly treated demographic changes in a fragmentary or overly simplified manner, without providing a multidimensional assessment of the population effect on environmental pollution. Additionally, extant empirical studies show that the relationship between demographic changes and environmental pollution remains an academic puzzle (Li et al., 2019); thus, further investigation of whether demographic factors are robustly linked to plastic pollution is needed.

Finally, we use previously unapplied panel model techniques to investigate the drivers of plastic pollution. These techniques enable capturing the dynamic changes in variables over time (Wooldridge, 2010). They also allow controlling for unobserved country-specific effects that are ignored in a single cross-sectional regression, which creates an omitted variable bias if the unobserved country-specific effects are correlated with the included explanatory variables (Wooldridge, 2010). Therefore, panel model techniques permit more sophisticated research designs to obtain consistent estimates.

The remainder of this paper is organized as follows. Section 2 details the empirical model, variables, and estimation methods. Section 3 describes the empirical findings. Section 4 presents a forecast of plastic pollution up to 2050. Section 5 provides the conclusions, policy implications, limitations of the study, and future research directions.

2. Methods

2.1 Empirical model

We use the STIRPAT model as the theoretical and analytical framework to identify the factors affecting plastic pollution. The STIRPAT model, proposed by Dietz and Rosa (1997), is a stochastic form of the IPAT identity, which was developed in the early 1970s to further debate the principal driving forces of anthropogenic environmental impacts (Feng et al., 2009; York et al., 2003). The IPAT identity specifies that environmental impacts (I) are the multiplicative product of three key drivers: population (P), affluence (A), and technology (T; York et al., 2003). However, it has been criticized for its simplicity and limitations.[3] Unlike the IPAT identity, the STIRPAT model is not an accounting equation and can be used to test empirically the hypotheses on each factor's contribution to the environment (Shafiei and Salim, 2014; York et al., 2003). Furthermore, the STIRPAT model allows for non-monotonic or non-proportional effects of the driving forces (Feng et al., 2009; York et al., 2003). Therefore, the STIRPAT model is commonly used to study the impact of anthropogenic activities on the environment. The basic form of the STIRPAT model is :

[3] The IPAT identity has two fatal limitations. First, it is a mathematical formula and cannot directly test how each factor affects environmental pollution (Poumanyvong and Kaneko, 2010). Second, it assumes that the elasticities of environmental impact to the driving forces are unitary (Poumanyvong and Kaneko, 2010). This implies the proportionate impact of environmental change by changing one factor and simultaneously holding other factors constant (Shafiei and Salim, 2014). Thus, the IPAT identity does not allow for non-monotonic effects of the driving forces, such as an inverted U-shape on the income–environment relationship.

$$I_{it} = aP_{it}^{b}A_{it}^{c}T_{it}^{d}e_{it} \quad (1)$$

The logarithmic form of this model is:

$$lnI_{it} = a + blnP_{it} + clnA_{it} + dlnT_{it} + e_{it} \quad (2)$$

where *I* denotes the environmental impact; *P*, *A*, *T* refer to population, affluence, and technology, respectively; b, c, and d are parameters of *P*, *A*, and *T*, respectively, which indicate the elasticities of each variable to the environmental impact. a is a constant term; e_{it} is the error term, and i and t represent the unit of analysis and time, respectively.

The STIRPAT model is flexible to alternative functional forms and can be extended to meet different research needs (Dietz and Rosa, 1997; Hua et al., 2018; York et al., 2003). Additional factors encompassing rich demographic and economic information can be added to the basic STIRPAT model as long as they are conceptually appropriate for the multiplicative specification of the model (York et al., 2003). Thus, to test whether an EKC is established for plastic pollution, we introduce the square term of affluence into the basic STIRPAT model with reference to the studies of Ji et al. (2018), Salim et al. (2019), Shafiei and Salim (2014), and Wang et al. (2021). We incorporate a range of demographic variables previously considered to affect environmental pollution: population aging, population density, urbanization level, and patterns to understand comprehensively the effect of demographic changes on plastic pollution (see Martínez-Zarzoso and Maruotti, 2011; Pham et al., 2020; Poumanyvong and Kaneko, 2010; Shafiei and Salim, 2014; Xu et al., 2020; Zhang et al., 2017). Following Shi (2003), we decompose the technology term (*T*) into the shares of the manufacturing and service sectors in the economy.[4] We also include

[4] There is no single operational measure of technology (York et al., 2003). Economic production structure and energy intensity have been widely used in the literature as a proxy for technology (see Ji et al., 2018; Martínez-Zarzoso and Maruotti, 2011; Poumanyvong and Kaneko, 2010). Energy intensity was considered in this study;

corruption in the model to control for omitted variable bias, as Leitão (2010) argued that the existence of different income–pollution paths across countries depends on the country's degree of corruption. Based on the panel nature of our data, the expanded STIRPAT model is expressed as follows:

$$lnPP_{it} = \beta_0 + \beta_1 lnGDPPC_{it} + \beta_2[lnGDPPC_{it}]^2 + \beta_3 lnPOP_{it} + \beta_4 lnDF_{it} + \beta_5 lnMAN_{it} + \beta_6 lnSER_{it} + \beta_7 lnCOR_{it} + \varepsilon_{it} \quad (3),$$

where *PP* represents plastic pollution; *GDPPC* is GDP per capita; *POP* denotes population size; *DF* represents the set of demographic factors including population aging, population density, urbanization level, and urban primacy; *MAN* and SER denote the share of the manufacturing and service sectors in the economy; COR is the control of corruption; ε is the error term, and β_0, β_1, β_2, β_3, β_4, β_5, β_6, and β_7 are the coefficients to be estimated. The symbol "*ln*" denotes natural logarithm.

2.2 Data and variables

We construct an unbalanced panel dataset of 128 countries from 1993 to 2017 based on the availability of data for the variables employed.[5] A detailed definition, unit of measurement, and data sources for all variables used in this study are provided in Table 1.

Plastic pollution is measured using inadequately managed plastic wastes, defined as the annual generation of plastic waste, for which waste treatment categories consist of open dumping,

however, its inclusion did not add any further insight or significantly affect the reported findings below. In addition, Shi (2003) noted that the difference in energy intensity can be explained by the difference in the economic structure of each country. Therefore, energy intensity was not included in the estimation.

[5] Indeed, data availability is a challenge and poses several limitations in empirical analyses.

discarding in waterways and marine areas, unaccounted for, and others (see World Bank, 2018).[6] Inadequately managed plastic waste is calculated using data from the World Bank (2012; 2018).

Affluence is represented by GDP per capita at constant prices (2010 US$). The population level is measured using the total population size. Population aging is decomposed into two variables: the percentage of the population aged 1) 14–64 years and 2) 65 years and above in the total population. World Development Indicators define population density as the number of people living per square kilometer of land area. The urbanization level is measured as the percentage of the population living in urban areas. Urban primacy, defined as the percentage of the population in the largest city in the urban population, is used to describe urbanization patterns. The manufacturing (service) sector value-added, as a percentage of GDP, is considered a proxy for the contribution of the manufacturing (service) sector to GDP. The level of corruption in a country is measured by controlling for the corruption index. Worldwide Governance Indicators define corruption as "perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' of the state by elites and private interests." The statistical descriptions of the variables are shown in Table A.1, Appendix A.

Pearson correlation is used to detect potential multicollinearity among the independent variables. The results (Table A.2, available in supplementary materials) show that all the correlation coefficients in absolute value are well below 0.7, except for the coefficients between GDP per capita and urbanization level, and between GDP per capita and control of corruption. As a further check on multicollinearity, variance inflation factor (VIF) tests are performed. The results (Table A.3, available in supplementary materials) show that the mean VIF is 2.59 and the

[6] World Bank (2018) assumes that waste in the category "unaccounted for" is dumped, and waste in "other" is inadequately managed in low- and middle-income countries and thus, is dumped.

VIF values for all the independent variables are less than the empirical value of 10, suggesting that multicollinearity is unlikely to be a major problem with the dataset.

Table 1. Definition of variables

Variable	Definition	Unit of measurement	Data source
Plastic pollution (*PP*)	Annual generation of plastic waste for which waste treatment categories consist of open dumping, discarding in waterways and marine areas, unaccounted for, and other	Metric ton	World Bank (2012, 2018)
GDP per capita (*GDPPC*)	Gross domestic product: 2010 constant price divided by midyear population	US $	World Development Indicators (WDI)
Population size (*POP*)	Midyear population	Number	WDI
Population aging 1 (*AGE1564*)	Percentage of population aged 14–64 years in the total population	Percent	WDI
Population aging 2 (*AGE65*)	Percentage of population aged 65 and above in the total population	Percent	WDI
Population density (*PDEN*)	Number of people living per square kilometer of land area	Number of people/Square kilometer	WDI
Urbanization level (*URB*)	Share of urban population in the total population	Percent	WDI
Urban primacy (*UPRI*)	Percentage of the largest city's population in the urban population	Percent	WDI
Manufacturing sector (*MAN*)	Manufacturing sector value added (percentage of GDP)	Percent	WDI
Service sector (*SER*)	Service sector value added (percentage of GDP)	Percent	WDI
Control of corruption (*COR*)	Perceptions of the extent to which public power is exercised for private gain	Percentile rank, ranging from 0 (corruption is not controlled) to 100 (corruption is well controlled)	WDI

2.3. Estimation methods

We estimate Eq.(3) applying three commonly used panel data estimation techniques: pooled ordinary least squares (POLS), fixed effects (FE), and random effects (RE).[7] The POLS model is used as the baseline and reference case. However, the POLS model neglects unobserved country-

[7] According to Baltagi (2005), panel data provide various advantages over cross-sectional data. For example, panel data give more information, more variability, less collinearity among variables, and higher efficiency.

specific effects and thus, potentially leads to inappropriate parameter estimates (Kimino et al., 2007). By contrast, the FE and RE models allow the intercept to vary over a sample of countries.[8]

We conduct three diagnostic tests, including the F test, Breusch-Pagan Lagrange Multiplier (LM) test, and Hausman test, to evaluate which estimation technique is better suited for our empirical models. The F test is used to determine whether the POLS or FE model is more appropriate. If the F-test rejects the null hypothesis of no significant difference between the individual intercepts at a given significance level, the FE model is preferred. An LM test is conducted to choose between the POLS and RE models. If the LM test rejects the null hypothesis of no random effects intercepted at a given significance level, the RE model is chosen. A Hausman test is performed to compare the FE model with the RE model. If the Hausman test rejects the null hypothesis, which implies that the RE model yields consistent and efficient estimates at a given significance level, then the FE model is chosen.

3. Empirical findings

Table 2 presents the empirical results obtained from the full sample. The F-test and LM test indicate that the FE and RE models outperform the POLS model. In addition, the Hausman test indicates that the RE model is superior to the FE model. Table 2 presents the regression results for the RE model.[9]

[8] The FE model assumes that the unobserved country-specific effects are constant over time, while the RE model assumes that the unobserved country-specific effects are randomly distributed (Park and Lee, 2011). In other words, the FE (RE) model assumes that the intercept is constant over time (a random variable).
[9] The full set of results from the POLS and FE models are available upon request.

Table 2. Determinants of plastic pollution in the random effect regression (full sample)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
lnGDPPC	6.508***	6.512***	5.755***	5.2***	7.73***	5.063**
	(1.398)	(1.406)	(1.551)	(1.478)	(1.523)	(1.983)
$(lnGDPPC)^2$	-0.375***	-0.375***	-0.328***	-0.322***	-0.444***	-0.3***
	(0.079)	(0.079)	(0.084)	(0.081)	(0.087)	(0.105)
lnPOP	0.948***	0.948***	0.945***	0.931***	1.15***	1.052***
	(0.104)	(0.105)	(0.098)	(0.104)	(0.186)	(0.173)
lnPDEN		0.007				0.06
		(0.131)				(0.149)
lnAGE1564			5.072**			5.578**
			(2.224)			(2.458)
lnAGE65			-1.486***			-1.387***
			(0.328)			(0.354)
lnURB				1.444***		0.824
				(0.553)		(0.671)
lnUPRI					0.986**	0.657*
					(0.425)	(0.392)
lnMAN	-0.237	-0.238	0.283	-0.424	-0.252	-0.069
	(0.316)	(0.318)	(0.311)	(0.321)	(0.374)	(0.379)
lnSER	-0.114	-0.129	1.084	-0.252	-0.571	0.557
	(0.886)	(0.94)	(0.882)	(0.874)	(1.031)	(1.093)
lnCOR	-0.657**	-0.657**	-0.52*	-0.581**	-0.515*	-0.41
	(0.288)	(0.289)	(0.272)	(0.285)	(0.29)	(0.275)
Constant	-28.58***	-28.56***	-50.33***	-26.04***	-39.03***	-53.65***
	(6.818)	(6.845)	(8.48)	(6.811)	(8.307)	(9.994)
Turning point	5866	5902	6458	3213	6033	4619
R^2	0.5491	0.5493	0.6266	0.5637	0.4605	0.5657
AIC	1.412	1.423	1.233	1.396	1.429	1.266
BIC	1.539	1.569	1.399	1.542	1.591	1.509
MAE	1.343	1.344	1.262	1.339	1.309	1.201
RMSFE	3.787	3.786	3.088	3.681	3.746	3.015
Obs.	174	174	170	173	148	148
Test statistics:						
F-test (POLS vs. FE)	4.89***	4.83***	3.88***	5.11***	5.19***	4.19***
LM test (POLS vs. RE)	45.28***	44.16***	40.25***	48.12***	43.95***	39.3***
Hausman test (FE vs. RE)	4.49	4.9	3.4	7.9	2.97	8.76

Notes: Standard errors in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Given a large panel of countries with different levels of development and income, we further investigate whether the heterogeneous impact of population, affluence, and technology on environmental pollution varies across the different stages of development. We address this issue by dividing our full sample into two income groups: low- and high-income groups. Low- (high-)

income countries are those with an average per capita GDP lower (higher) than the median GDP per capita of the full sample. Appendix B (available in supplementary materials) lists the countries in each subsample. The POLS (RE) estimation results for the low- (high-) income group are shown in Table 3 (Table 4).[10]

Table 2 shows that the coefficients of GDP per capita and the square of GDP per capita are statistically significant at the 1% or 5% level across alternative model specifications, with a positive and a negative sign, respectively. This indicates that income has an inverted-U shape relationship with plastic pollution and thus, supports the EKC hypothesis for the full sample of countries.[11] This implies that plastic pollution tends to rise during the initial stages of economic growth, but once a threshold level of income (i.e., turning point) is achieved, it then declines with further growth in income. Using the coefficient values obtained for income and square of income, the turning point of income for the inverse U curve ranges from US$ 3,213 to US$ 6,458. These are considerably higher than the range of US$ 1,931 to 2,141 (in US $ at 2010 prices) estimated by Barnes (2019), and much lower than the turning point income of US$ 18,601 (in international US$ at 2011 prices in PPP) reported by Cordier et al. (2021), that is, $US\$_{2010}$ 12,176.[12] The turning points mostly appearing in the literature for various pollutants lie within the income range of US$3,000–10,000 (US$ in 1985 prices), that is, a range of US$ 6,080–20,265 at 2010 prices

[10] For the low-income group, the F-test statistics presented in Table 3 generally suggest accepting the null hypothesis in favor of the POLS model, except for specification (4) in column 5. In specification (4), the F-test rejects the null hypothesis at 10% significance, while conventionally at least 5% significance is required to be confident in rejecting the null hypothesis. In addition, the LM statistics in Table 3 reveal that the POLS is a more efficient estimator than the RE. For the high-income group, as indicated in Table 4, the F-test and the LM test show that the FE and the RE models are preferred over the POLS model. Meanwhile, the Hausman test implies that the RE model is preferred over the FE model.

[11] There are numerous explanations for the EKC hypothesis (see Dinda, 2004 for a detailed discussion). The explanatory factors that commonly appear in the literature are as follows. First, environmental quality is a luxury good whose demand increases only when people have attained sufficiently high incomes to no longer worry about economic struggles (Roca et al., 2001; Sulemana et al., 2017). Second, the relative strengths of the scale, composition, and technique effects over time result in the inverted-U shape between economic development and environmental quality (Churchill et al., 2020). Third, the validity of the EKC hypothesis may result from a displacement of pollution intensive industries from developed economies toward developing ones (Roca et al., 2001).

[12] The conversion into US$ at 2010 prices, not in PPP, is required for comparison with our results.

(Dinda, 2004). Among the six turning points we estimated here, only specification (3) in Table 2 lies within the range (US$$_{2010}$$ 6,458). Specifications (1), (2), and (5) are close to the lower margin of the range (US$$_{2010}$$ 5,866; 5,902; and 6,033, respectively), while specifications (4) and (6) are below (US$$_{2010}$$ 3,213 and 4,619). The implied turning points (Table 2) are relatively stable and not very sensitive to variations in model specification. Moreover, all the implied turning points fall within the data range and thus, may provide a reliable indication of future behavior.[13] Further insights into these results can be gained by calculating the number of years for each country to reach the turning points.[14] The results, sorted by years from small to large, are presented in Table 5.[15] It shows that Belarus will pass the turning point in 1 year and Vanuatu in 7,048 years. Of 59 countries, 52 countries will take more than 10 years to reach the turning point.

Table 3 shows that the estimated coefficient of GDP per capita and its square term have a positive and a negative impact at the 1% or 5% levels of significance, respectively, in all the specifications (except for specifications (3) and (6)) for the low-income countries. Meanwhile, Table 4 shows that the estimated coefficients of GDP per capita and its square term have the signs of an inverted U-shape but not statistically significant in all six specifications for the high-income countries. The evidence of the EKC for low-income countries is plausible. Environmental concern has been a global phenomenon and no longer limited to wealthy nations (Dunlap and Mertig, 1995; Sulemana et al., 2017). The increasing public concern regarding environmental quality in some low-income countries may even make these countries implement environmental

[13] If the implied turning point is extremely high or even out of the sample, it would be less economically meaningful and not recommendable to wait (Lamla, 2009).

[14] The number of years N_i can be calculated as follow: $TP = GDP_{ci} \times (1 + \theta_i)^{N_i}$, where TP is the turning point; GDP_{ci} is country i's current per capita GDP, and θ is the average annual growth rate of per capita GDP. After taking natural logarithms, we obtain: $N_i = Ln(^{TP}/_{GDP_{ci}})/Ln(1 + \theta_i)$.

[15] The calculations of years for each country to reach the turning points presented in Table 5 are based on the implied turning point of specification 3 (column 4, Table 2). The smallest values of the Akaike's information criterion (AIC) and the Bayesian information criterion (BIC) suggest that specification 3 best fits the data.

standards of developed countries at early stages of development (Stern, 2004). The lack of evidence for the EKC hypothesis in the sub-sample of high-income countries could be caused by underestimated amounts of inadequately managed plastic waste.[16]

Table 3. Determinants of plastic pollution for the low-income group

Variable	(1) POLS	(2) POLS	(3) POLS	(4) POLS	(5) POLS	(6) POLS
lnGDPPC	8.03***	7.928***	5.144	7.752***	7.207***	3.166
	(2.882)	(2.891)	(3.126)	(2.864)	(2.71)	(2.836)
$(lnGDPPC)^2$	-0.496**	-0.49**	-0.299	-0.491**	-0.429**	-0.176
	(0.193)	(0.193)	(0.21)	(0.191)	(0.182)	(0.191)
lnPOP	0.878***	0.898***	0.83***	0.885***	1.012***	0.953***
	(0.08)	(0.084)	(0.083)	(0.08)	(0.122)	(0.13)
lnPDEN		-0.089				0.041
		(0.11)				(0.116)
lnAGE1564			4.201*			6.385***
			(2.457)			(2.401)
lnAGE65			-1.274**			-1.592***
			(0.533)			(0.51)
lnURB				0.613*		0.665*
				(0.359)		(0.385)
lnUPRI					0.881***	0.872***
					(0.288)	(0.273)
lnMAN	0.217	0.235	0.341	0.095	0.202	0.171
	(0.27)	(0.271)	(0.278)	(0.277)	(0.256)	(0.264)
lnSER	0.621	0.906	0.763	0.554	0.733	0.876
	(0.761)	(0.841)	(0.767)	(0.758)	(0.749)	(0.793)
lnCOR	-0.323	-0.321	-0.244	-0.281	-0.183	-0.028
	(0.196)	(0.197)	(0.197)	(0.196)	(0.185)	(0.18)
Constant	-36.85***	-37.53***	-42***	-37***	-40.44***	-50.83***
	(11.1)	(11.15)	(12.88)	(11.01)	(10.74)	(12.22)
R^2	0.7319	0.7342	0.7286	0.7392	0.6467	0.7046
Obs.	86	86	84	85	78	78
Test statistics:						
F-test (POLS vs. FE)	1.47	1.56	1.26	1.75*	1.14	1.11
LM test (POLS vs. RE)	1.01	1.05	0.43	1.15	0.57	0.00
Hausman test (FE vs. RE)	5.41	8.33	5.8	10.05	5.63	14.37

Notes: Countries with an average per capita GDP lower than the median GDP per capita are included in the low-income group. The standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

[16] High-income countries declare extremely small amounts of inadequately managed plastic waste. However, these declarations are underestimated since several illegal dumps and uncontrolled landfills are not declared (D'Amatoet al., 2018; Santos et al., 2019; Tisserant et al., 2017). Moreover, none of these appear in official statistics declared by the states in the World Bank databases. Furthermore, the large amount of plastic waste sent by high-income countries to low- and middle-income countries (OECD, 2022) are registered as plastic waste discard in the destination country, not in the originating country.

Table 4. Determinants of plastic pollution for the high-income group

Variable	(1) RE	(2) RE	(3) RE	(4) RE	(5) RE	(6) RE
lnGDPPC	10.82	10.94	7.153	12.17	11.86	7.577
	(11.47)	(11.52)	(11.24)	(11.14)	(14.6)	(15.3)
$(lnGDPPC)^2$	-0.558	-0.563	-0.377	-0.647	-0.604	-0.389
	(0.571)	(0.574)	(0.559)	(0.555)	(0.728)	(0.761)
lnPOP	0.963***	0.964***	0.967***	0.886***	1.315***	1.157***
	(0.207)	(0.208)	(0.195)	(0.203)	(0.369)	(0.368)
lnPDEN		0.007				0.085
		(0.227)				(0.308)
lnAGE1564			7.648			6.148
			(5.603)			(6.71)
lnAGE65			-1.385**			-1.23
			(0.682)			(0.83)
lnURB				2.58**		0.319
				(1.213)		(2.448)
lnUPRI					1.122	0.616
					(0.776)	(0.803)
lnMAN	-0.699	-0.703	0.347	-0.963	-1.149	-0.369
	(0.635)	(0.638)	(0.668)	(0.627)	(0.94)	(1.045)
lnSER	-0.626	-0.662	1.94	-0.722	-3.514	-0.241
	(1.688)	(1.793)	(1.894)	(1.656)	(2.597)	(3.285)
lnCOR	-1.524**	-1.532**	-1.301*	-1.384*	-1.268	-1.269
	(0.768)	(0.774)	(0.728)	(0.762)	(0.805)	(0.804)
Constant	-46.85	-47.28	-71.29	-60.75	-50.07	-64.67
	(55.94)	(56.25)	(53.3)	(54.6)	(70.17)	(67.47)
R^2	0.4351	0.4358	0.5295	0.4627	0.3749	0.4815
Obs.	88	88	86	88	70	70
Test statistics:						
F-test (POLS vs. FE)	6.84***	6.53***	6.2***	6.3***	7.77***	5.41***
LM test (POLS vs. RE)	28***	26.41***	25.64***	30.92***	27.07***	21.72***
Hausman test (FE vs. RE)	7.67	7.45	6.73	6.78	3.66	4.12

Notes: Countries with average per capita GDP higher than the median GDP per capita are included in the high-income group. The standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Years to reach the turning point

Country	Years	Country	Years	Country	Years
Belarus	0.27	Lao PDR	23.9	Mozambique	60.7
Peru	1.55	Sudan	25.4	Honduras	61.6
Serbia	2.33	West Bank and Gaza	27.3	Nepal	61.8
Cuba	3.08	Iraq	28.1	El Salvador	63
Thailand	4.61	Armenia	29	Tuvalu	90.9
Ecuador	7.59	Vietnam	29.7	Pakistan	91.2
Mongolia	8.93	Cambodia	31.6	Burkina Faso	94.3
Sri Lanka	10.5	Bolivia	32.1	Kenya	95
Indonesia	12.2	India	33.6	Cameroon	119
Azerbaijan	12.3	Tonga	35.9	Togo	126
Guyana	15	Ethiopia	36	Benin	153
Kosovo	15.2	Egypt	37.7	Senegal	159
Tunisia	15.9	Papua New Guinea	38	Guinea	160
Algeria	16.4	Bangladesh	41.6	Mauritania	179
Moldova	16.8	Uganda	44.3	Haiti	205
Myanmar	17	Guatemala	44.7	Jamaica	282
Philippines	20.4	Fiji	48.7	Marshall Islands	603
Uzbekistan	20.5	Samoa	52.7	Madagascar	804
Nigeria	21.5	Jordan	53.2	Vanuatu	7,048
Morocco	22.9	Belize	60.3		

As expected, the entire panel results (Table 2) suggest that population size (*lnPOP*) has a significant positive impact on plastic pollution: A 1% increase in the total population increases plastic pollution by approximately 1%. The findings support the Malthusian view that population growth is a crucial factor in environmental degradation. The subsample results in Tables 3 and 4 suggest that the impact of population size on plastic pollution is heterogeneous across countries with different income levels. This is more pronounced in high- than in low-income countries.

Regarding the other demographic factors, the coefficients of population density (*lnPDEN*) are not statistically significant, suggesting the nonsignificant effect of densely populated areas on plastic pollution during the study period. Our findings align with those of Dikareva and Simon (2019), who found no relationship between population density and microplastic abundance. The 15–64 (*lnAGE1564*) and 65 and above (*lnAGE65*) age groups have highly significant positive

and negative effects, respectively, for the full sample of countries. Numerically, a 1% increase in the share of the 15–64 (65 and above) age group is associated with a 5.1% increase (1.5% decrease) in plastic pollution in specification (3) in Table 2. A population's age structure is important because people's patterns of consumption vary by their life stage (Liddle, 2011). Arguably, the working-age population is more involved in socio-economic activities; therefore, their lifestyle is more plastic-intensive than that of older people. The observed effects of the population's age composition also align with previous studies claiming that older people report engaging in more pro-environmental behavior than younger people (see Gifford and Nilsson, 2014; Hartley et al., 2018).

The coefficients for urbanization level (*lnURB*) are significantly positive for the low-income group (Table 3), but they are not uniformly significant for either the full sample of countries (Table 2) or the high-income group (Table 4). Our results corroborate the findings of previous studies suggesting that urbanization may worsen environmental quality, and support the argument of the ecological modernization theory—that societies prioritize economic development over environmental quality at low stages of development. Interestingly, the coefficient of *lnURB* for high-income countries (2.58) is much higher than that for low-income countries (0.61).[17] This seems to support the view of the urban environmental transition theory—that consumption patterns and lifestyles of cities in developed countries tend to be more resource-intensive than those of cities in developing countries (Poumanyvong and Kaneko, 2010). Additionally, urban primacy (*lnUPRI*) has a significantly positive effect for both the full sample and low-income countries but has no effect on high-income countries. One plausible reason for this positive effect is that high primacy usually indicates over-concentration and inefficient urbanization and

[17] See column 5 in Tables 3 and 4.

therefore, may cause substantial urban environmental issues when adequate urban infrastructure support is lacking, especially in developing countries (Zhang et al., 2017).

As for the variables of economic structure, none of their coefficients is statistically significant for both the full sample and the two subsamples. The manufacturing sector is expected to affect plastic pollution positively because plastic-intensive inputs are widely used in various manufacturing industries (e.g., petroleum and chemical products, electrical equipment, and textile industries). However, the sign of the coefficient for the manufacturing sector is negative in some specifications. This may be because the use of alternative biodegradable plastics can help reduce plastic waste. Our results also do not support the generally accepted perspective of an eco-friendly service sector. De facto, the service sector is an aggregate that includes both activities with a weak environmental impact (e.g., banking and consulting) and activities generating a large part of plastic waste (e.g., catering and tourism). Thus, the insignificant impact on the service sector may be due to these two opposing forces. Another reason is the limitations of our study. The waste identified by the global database of the World Bank (2012 and 2018) used to design our models exclusively includes quantitative data on municipal solid waste generated by households at home. Thus, the plastic waste generated by manufacturers or service sectors is not captured by our models.

Lastly, control of corruption is found to be a negative and statistically significant determinant of plastic pollution in majority of the specifications for both the full sample of countries (Table 2) and the high-income group (Table 4). These findings are consistent with theory and empirical experience and supported by Leitão (2010) and Cordier et al. (2021). Our findings support the idea that higher corruption may delay governments' environmental quality concerns and prevent

the implementation of environmental regulations, thus having important implications for environmental degradation (Leitão, 2010; Sulemana et al., 2017).

4. Forecasting plastic pollution

Here, we forecast inadequately managed plastic waste based on specification (6) in Table 2. Accurate forecasting of future growth in country-level plastic pollution allows policymakers to gauge whether a country is on track to maintain its pollution targets. Specification (6) is chosen as the optimal regression model in terms of forecasting and thus, is used to construct forecasts of plastic pollution based on out-of-sample information criteria, including the root mean squared forecast error (RMSFE) and mean absolute error (MAE).[18] We limit the forecasting horizon to 2050.

4.1. Scenario description

Five scenarios are set up: scenarios BAU (business-as-usual), A (slow GDP), B (change in population structure), C (high-speed urbanization level), and D (high-speed urban primacy). These scenarios are governed by the following variables: GDP per capita (GDPPC), population size (POP), population aging 1 (AGE1564), population aging 2 (AGE65), population density (PDEN), urbanization level (URB), urban primacy (UPRI), manufacturing sector (MAN), service sector (SER), and corruption control (COR). The five scenarios share the same assumptions for population size, population density, manufacturing sector, service sector, and corruption control. Thus, we can focus on analyzing the differences among the five scenarios that are due to GDP, population structure, urbanization level, and urban primacy. Thus, the five scenarios demonstrate

[18] We use the measures of out-of-sample forecasting accuracy as a model selection criterion because the in-sample fitness criteria such as AIC and BIC are more suitable for in-sample predictions, as their calculations are based on the in-sample fitness of the regressions. As reported in Table 2, both the MAE and RMSFE show that specification (6) is the optimal specification in terms of the out-sample fitness since the values of the MAE and RMSFE for specification (6) outperform the corresponding values in the other regressions.

the sensitivity of the forecasts to changes in the assumptions regarding these variables. The assumptions for the five scenarios are stated below. For scenarios *A* to *D*, except for the specific variables mentioned, all the other variables grow according to the BAU scenario.

- In the *BAU scenario*, all explanatory variables grow in the same linear trend as in the period 1996–2020, except for some countries where the explanatory variable values decline too fast when using a linear regression. In this case, we use an exponential trend instead of avoiding negative values that would be incompatible with reality.
- In *scenario A*, GDP per capita grows at half the average annual rate of the BAU scenario calculated for 2021–2050.
- In *scenario B*, the 15–64 and ≥ 65 age groups grow at double the average annual rate of the BAU scenario calculated for 2021–2050.
- In *scenario C*, the percentage of the population living in urban areas grows at double the average annual rate of the BAU scenario calculated for 2021–2050.
- In *Scenario D*, the percentage of the urban population living in the largest city of the country increases at double the average annual rate of the BAU scenario calculated for 2021–2050.

4.2. Forecasting results

According to the scenario settings, the forecast results of inadequately managed plastic waste for the world, developing country groups, and developed country groups under the five scenarios are displayed in Figures 1, 2, and 3, respectively.

Figure 1 shows that global plastic waste presents an increasing trend in the five scenarios. Overall, scenario B shows much more clearly marked differences from the BAU, revealing a

substantial increase in global plastic waste. This implies that the future plastic waste reduction potential across the globe is considerable if strict measures are implemented to change the lifestyle of the working-age population. Specifically, by 2050, the global plastic waste will reach 257, 282, 496, 292, and 242 million tons under scenarios BAU, A, B, C, and D, respectively.[19] The BAU amount (257 million tons/year in 2050) is two to four times higher than the estimates provided by Cordier et al. (2021; 61–110 million tons/year in 2050), which may be explained as follows. First, both studies considered inadequately managed plastic waste as waste, for which waste treatment categories consist of open dumping and discarding in waterways and marine areas. However, we follow the World Bank (2018) and consider those from the category "unaccounted for" (and "other") in all (low- and middle-income) countries as "inadequately managed" plastic waste. This treatment increases the amount of inadequately managed plastic waste. Second, our model is based on a panel dataset whereas Cordier et al.'s (2021) is based on a cross-sectional dataset. We believe that our model is more reliable because unlike the previous study, it considers evolution over time. Third, Cordier et al. (2021) based each model on a set of three statistical equations that they multiplied to obtain an estimation of inadequately managed plastic waste. Their multiple-equation approach does not consider the interactions between the explanatory variables from the three equations.[20] Here, each of our models is based on a unique statistical equation to avoid this shortcoming.

[19] The world estimation has been computed applying model specification (6) from Table 2 in Equation (3) for each of the 217 countries and territories of the World Bank database (2012 and 2018). When explanatory variables were unavailable (which was often the case for small islands), we replaced them by data from the closest country, that is, closest in economic and geographical terms.

[20] For example, education in their equation 3b influences demography in equation 1 without this interaction being considered.

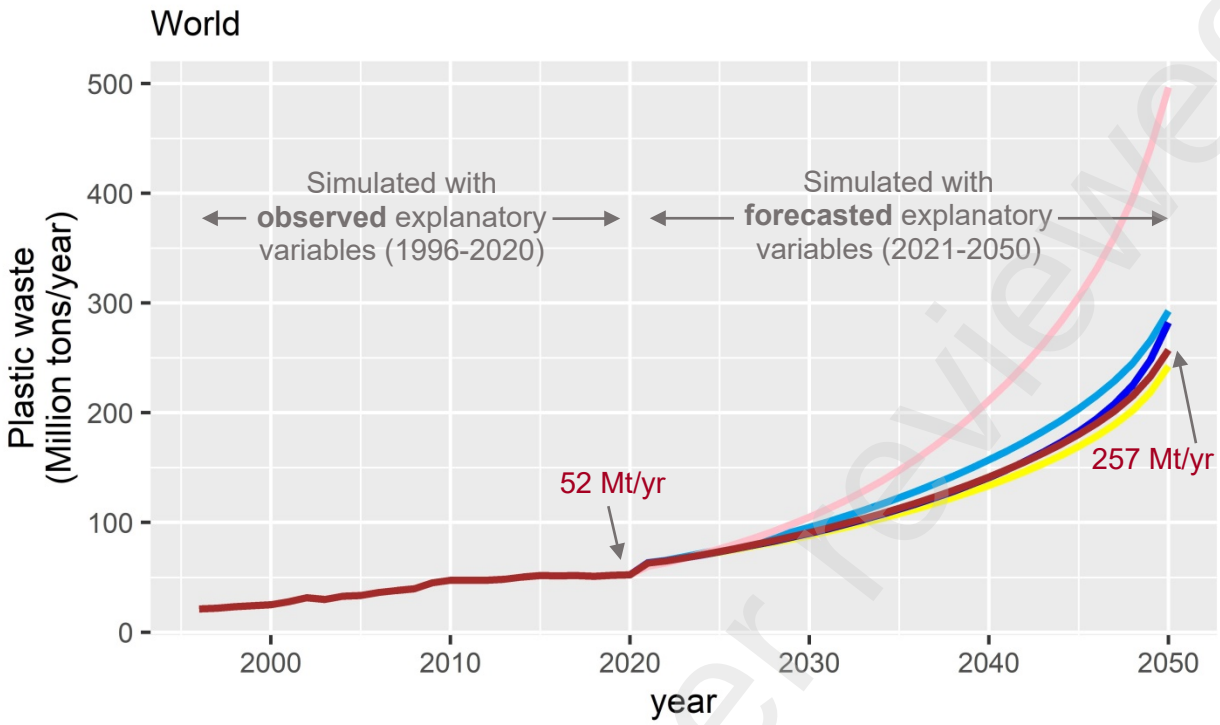

Figure 1. World annual discard of inadequately managed plastic waste over 1996–2050 (million tons per year).

Notes: The results displayed in this graph are estimated with specification 6 from Table 2. Legend for scenarios: BAU = brown curve; A = dark blue curve; B = pink curve; C = light blue curve; and D = yellow curve. Scenario simulations A to D start in 2021. Over 1996–2020, all scenarios follow the BAU scenario.

From a regional perspective, the scenarios display highly diverse possible trajectories (see Figures 2 and 3), which point toward three main conclusions. First, in general, an increase (decrease) in plastic waste under all scenarios for developing country groups except Indonesia (developed groups) for the period 2021–2050 is shown in Figure 2 (Figure 3).[21] The substantial increase in plastic waste in the developing country groups may explain the increasing trend of global plastic waste, as shown in Figure 1. Second, scenario B is associated with an increasing (decreasing) slope of plastic waste for the developing (developed) country groups. This is

[21] In Figure 2, we focus on eight developing countries: India, Bangladesh, China, Nigeria, Mexico, Indonesia, United Arab Emirates, and Iran because they are the top eight greatest plastic polluter countries in 2020, representing 40% of the global annual discard of plastic waste inadequately managed. Developing plastic solutions specifically targeted for these eight countries would help substantially reduce global pollution.

because of the opposite impacts of the 15–64 and ≥ 65 age groups on plastic pollution. As explained in Section 3, the 15–64 age group is keen to consume larger amounts of plastic goods, while the ≥ 65 age group is willing to engage in more pro-environmental behavior. The positive effect of the 15–64 age group on plastic pollution is not enough to compensate for the negative effect of the ≥ 65 age group for the developed country groups.[22] Finally, as expected, plastic pollution is sensitive to scenario C and exhibits a notable increasing trend over the forecasting horizon in most developing countries. This implies that the rapid urbanization process will continue to present tremendous environmental challenges to developing countries. However, an interesting observation from Figure 2 is that in China, plastic pollution will begin to decrease sharply in 2037 under scenario C. This may be because of the more compact development of urban spatial patterns in Chinese cities.[23]

[22] In most developed countries, the average annual growth rate of the 15–64 age group is negative. Thus, doubling it makes it even more negative, drastically reducing the share of the population that consumes large amounts of plastic products.

[23] Recently, China has been strongly promoting the construction of a new type of urbanization, which requires optimizing the layout of urban spatial structure (Lin and Zhu, 2021).

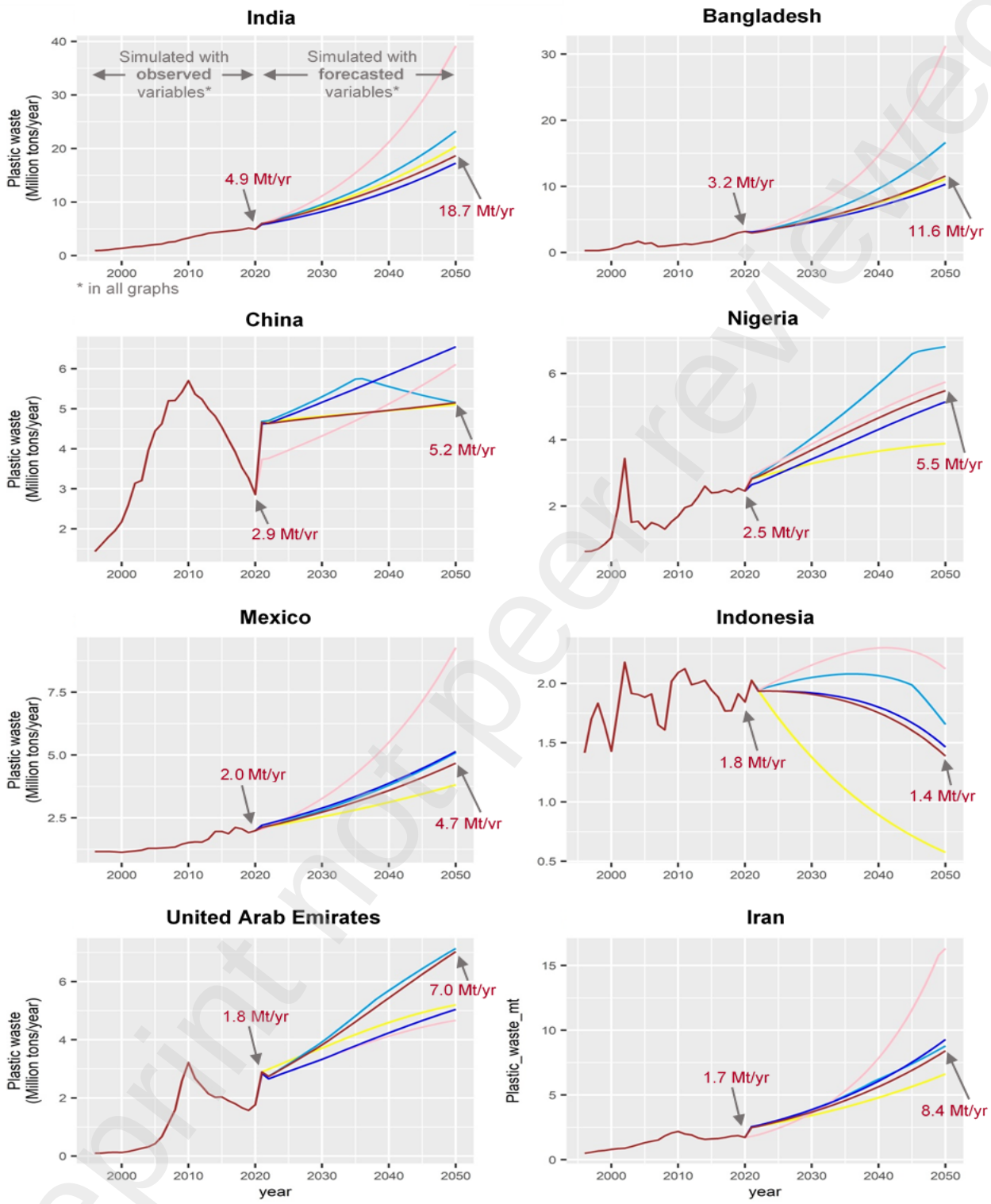

Figure 2. Developing countries: annual discard of inadequately managed plastic waste over 1996-2050 (million tons per year). Note: See Figure 1. Numbers along the curves are business-as-usual (BAU) forecasts.

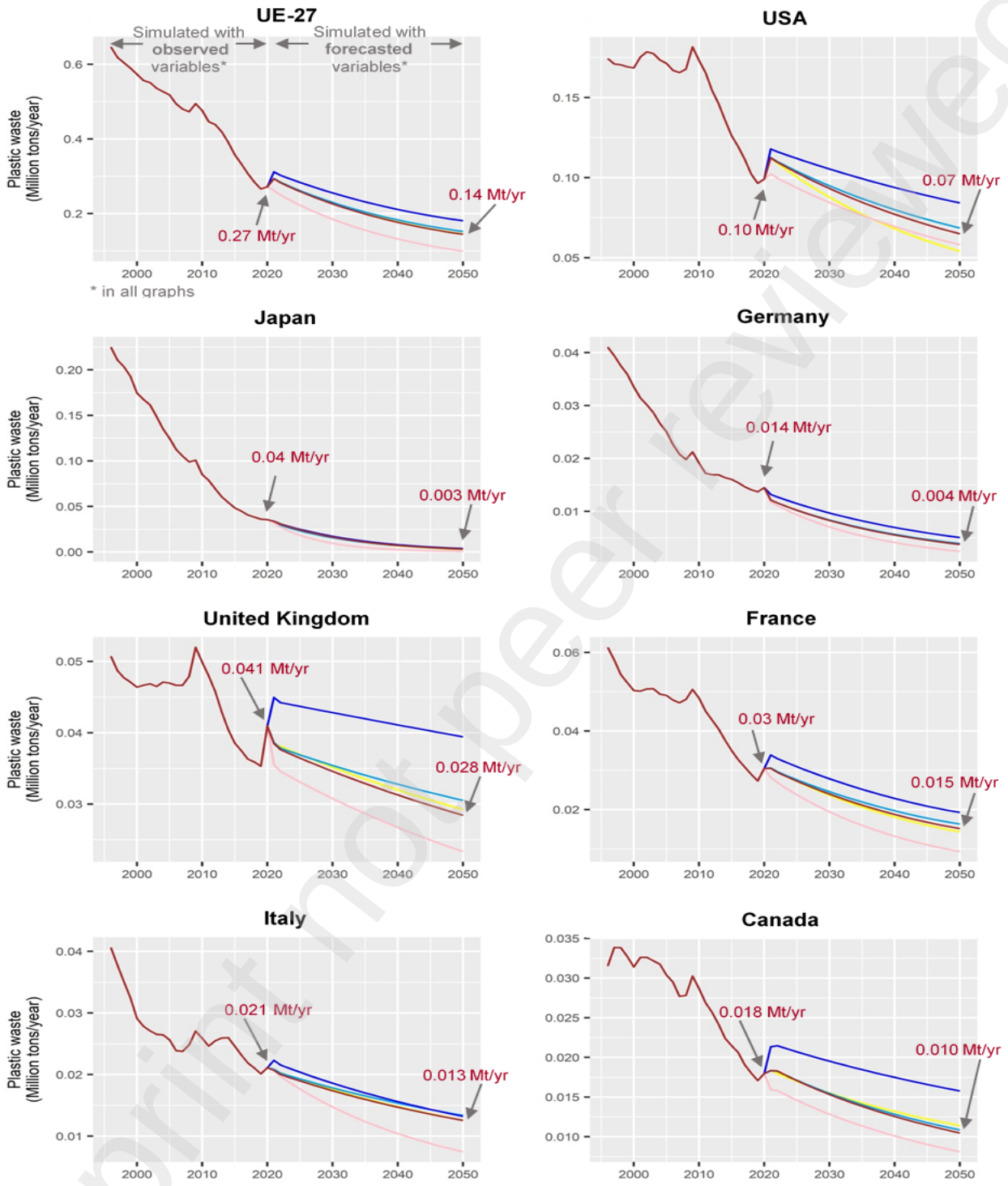

Figure 3. Developed countries: annual discard of inadequately managed plastic waste over 1996-2050 (million tons per year). Note: See Figure 1. Numbers along the curves are business-as-usual (BAU) forecasts.

5. Conclusions

The detrimental effects of plastic pollution have recently caused serious concern over the possible factors affecting plastic waste generation; however, empirical work on this issue is just starting. Hence, this study explores the drivers of plastic pollution using an unbalanced panel dataset of 128 countries for the period 1993–2017 and three different panel model techniques based on the extended STIRPAT model as a theoretical framework.

Our main empirical results suggest that demographic factors play an important role in plastic pollution. Specifically, we find that not only the urbanization level but also the spatial structure of urbanization may affect plastic pollution. We also document the different impacts of population age groups on plastic pollution in terms of sign and size. These findings imply that EKC studies will lead to inaccurate results if they fail to consider such demographic factors. In addition, we provide evidence supporting an EKC relationship between plastic pollution and income. Finally, our results corroborate those of previous studies that advocate corruption control to reduce plastic pollution.

Our findings allow us to highlight policy implications and suggestions for reducing plastic waste generation. First, given the adverse effect of increased working-age population on plastic pollution, policymakers should formulate appropriate policies to change the working-age population's lifestyle. A combination of regulatory, market-based, and behavioral instruments may be required to induce behavioral changes. Regulatory policies and market-based measures have been commonly used. Regulating the consumer market with, for example, bans on single-use plastic products, has been a powerful tool in many countries (Alpizar et al., 2020; Fadeeva and Van Berkel, 2021). To encourage behavioral changes toward plastic products made from materials that are recyclable or biodegradable, market-based instruments have been proposed to

raise the price of goods associated with plastic pollution relative to less damaging alternatives (e.g., recycled plastics), either by taxing or subsidizing the goods (Alpizar et al., 2020). However, recent literature argues that regulatory policies and market-based measures should be complemented by behavioral instruments to produce long-lasting effects on behavior (Alpizar et al., 2020; Kirakozian, 2016). Therefore, government interventions that pinpoint behavioral changes should also adopt softer instruments, such as awareness-raising campaigns, education programs, and nudging.

Second, our findings imply that rapid urbanization introduces severe environmental pressure. This deserves special attention from urban planners, particularly those in developing countries where rapid urbanization is occurring, as the inextricable linkage between the urbanization process and plastic waste management issues increases the urgency of developing effective policy responses to the emerging challenge of plastic waste management (Bari et al., 2012). In this context, urban planners should integrate plastic waste management systems into urban development strategies, following circular economic principles. A circular economy approach aims to reduce the use of raw materials, reuse already processed materials, and recycle wastes (Burneo et al., 2020). Plastic management as part of the circular economy needs more integrated perspectives throughout the entire life cycle, from production to consumption to waste and pollution (Nielsen et al., 2020). A circular economy requires the socio-ecological transformation of urban systems (Williams, 2020). Designating urban forms and infrastructure to facilitate circular actions is essential for socio-ecological transformation (Williams, 2020). Urban spatial planning enables circular actions by relocating producers and consumers of plastic waste within urban areas. In this regard, supporting the delivery of infrastructure is crucial to the socio-

ecological transformation of urban systems (Bolger and Doyon, 2019; Savini, 2019; Williams, 2020).

Third, the EKC evidence does not imply that environmental benefits from economic growth can be achieved automatically. Although the estimation could reveal whether a country is on the rise or decline in the EKC, this does not mean that policymakers can adopt a passive attitude toward the control of plastic pollution. Policymakers must design sustainable growth-oriented policies and strategies to reduce plastic pollution. Finally, the adverse impact of corruption on environmental performance suggests that corruption should be addressed, along with appropriate environmental policies.

Nonetheless, this study provides only preliminary results and has several limitations, which are expected to open promising avenues for future research. First, our analysis was conducted for two periods because of data unavailability. This may limit the ability to capture the dynamic linkages between variables over a reasonable timeframe. Thus, future studies that include more panels could provide more reliable estimates. Second, our findings serve as a pilot study to help advance the knowledge on the impacts of urbanization. Future research could include rural–urban migration, mixed land use, and monocentric/polycentric urban forms to reveal more detailed information about how urbanization affects plastic pollution. Finally, future work could explore the spillover effects of plastic regulation policies imposed on plastic pollution in developing countries.[24]

[24] For example, China designated a ban on the import of plastic waste in 2017. This measure has led to a change in the structure of international plastic waste trade and thus has an additional impact on the distribution of plastic waste pollution.

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Author contributions (follows the CRediT taxonomy)

Huijie Yan: Conceptualization; Data Curation; Formal Analysis; Investigation; Methodology; Software; Writing-Original Draft Preparation

Mateo Cordier: Conceptualization; Data Curation; Formal Analysis; Investigation; Methodology; Project Administration; Resources; Software; Supervision; Validation; Visualization; Writing-Original Draft Preparation; Writing-Revie & Editing

Takuro Uehara: Conceptualization; Data Curation; Funding Acquisition; Project Administration; Software; Supervision; Visualization; Writing – Review & Editing.

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