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Supplementary Materials for

Pathways to reduce global plastic waste mismanagement and greenhouse gas emissions by 2050

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Other supplementary material for this manuscript includes the following:

Data S1

Materials and Methods

Our method coordinates information flows between multiple machine learning regressors each representing different stages of the plastics lifecycle as described in Fig. S1. We then execute policy-specific simulations on top of this "base model" which, in addition to capturing the isolated mechanistic dynamics described herein, account for how those interventions interact with each other. Finally, with these perturbed projections generated, we calculate greenhouse gas (GHG) emissions associated with plastics production and end-of-life.

In order to provide further documentation and reproducibility, we release our code (written in Python, JavaScript / ECMAScript, and a custom domain specific language) implementing these operations as a containerized repeatable pipeline and server (*29*). This open source repository not only further details these methods but also includes the source code for our custom-built interactive simulation platform, software which we make accessible through a public service available at https://global-plastics-tool.org. Researchers can use this online resource through a web browser for further evaluating our modeling as well as for creating additional policy scenarios beyond those specifically explored and reported in this paper (*22*, *23*).

Materials

We build our machine learning-based model using data from multiple sources:

- The business as usual projection is based on historical plastic flow data from 1950 to 2020 (*28*), which extended and regionalized the dataset (*26*) using the original product lifetime methodology and the apparent consumption approach described in (*56*).
- GHG emissions intensities from Zheng and Suh (*13*, *31*).
- Various policy-specific estimations as described in Table S1.
- Socioeconomic data from the Organization for Economic Co-operation and Development's gross domestic product economic projections (*57*) and the United Nations Department of Economic and Social Affairs population estimates (*58*) (Fig. S2) .

Our Zenodo repository (*29*) archive makes some of these materials available for the purposes of reproducibility.

Base model

Tasked with determining the "business as usual" material volumes at each plastic lifecycle stage without any policy intervention, the "base model" consists of four different machine learning regressors as detailed in Table S2. We select these sub-models from a "sweep" of various different regression algorithms (linear / polynomial, SVR, CART, random forest, AdaBoost) under different permutations of hyper-parameters totaling 2,108 candidates. In order to constrain the output range, these regressors predict a given year using a reference value from up to 5 years prior to the state being predicted. Starting from consumption, a "differential" structure originates overall volumes which are then projected into different plastics system steps using ratios predicted by other regressors as further detailed in our open source code. In each case, we prefer a random forest given empirical results. Table S3 outlines the final chosen regressors alongside evaluation from a fully hidden test set, reporting on data withheld from training and model selection.

Following common data engineering conventions, our source archive not only includes a snapshot of execution results but also describes sweep structure and model diagnostic information alongside further documentation outlining a repeatable computational pipeline (*29*). This includes various post-hoc analyses including a temporal-displacement out-of-sample test in which data before 2019 predict 2019 as well as a 4 region-level performance evaluation. These evidence-building trials confirm acceptable performance and general residual symmetry for use in policy simulation with, though often lower in practice, error metrics consistently below 2 Mt.

<u>Policy simulation</u>

Next, we provide a domain-specific programming language for simulation of actions taken on top of business as usual (*23*). In this paper, we report the outcomes of eight policies representative of interventions under consideration in the revised draft of the United Nations plastic pollution treaty (*37*). Three additional policies are depicted in our online interactive tool. We report results in the main manuscript for each of our eight central policies implemented in isolation and for a package that implements four interventions together: 40% minimum recycled content; 2020 virgin production cap; $50B waste management investment; and a plastic packaging tax. These particular four policies were selected for testing in combination with the primary objective of maximizing the reduction of plastic waste mismanagement.

As these individual policies often exercise overlapping effects on the same variables, we employ a “constraints” based approach described in Fig. S3 which allows one intervention to override or build on another. For example, the effects of one policy may serve as “credit” towards meeting the mandate of another like in the form of a first intervention increasing recycling collection which helps meet a secondary production target set by an additional policy. Even so, in situations where this constraints system does not allow for sufficient interaction effect calculation, interventions may directly query each other’s values.

<u>GHG extension</u>

Either under business as usual or a policy scenario, we can next pair predicted volumes with emissions intensities data (*13*) to estimate GHGs associated directly with the production and end-of-life stages. Emissions contributions from waste mismanagement are accounted for following estimations of (*31*). Though the base model and interventions operate at the sector and lifecycle stage, this step requires estimating polymer-level trade volumes. Therefore, an additional random forest regressor as described in Table S2 is chosen from an additional model sweep consisting of 511 candidates which is also further detailed with source code within our pipeline (*29*). Having predicted polymer-level data, iterative backpropagation reduces a small residual error generally under 2 Mt by balancing polymer trade at the region and sector level. As further described in Fig. S4, the live simulation tool performs this calculation under different simulation constraints with a maximum allowed error of 1 Mt. The code for this operation resides in our source code archive alongside further design and diagnostic documentation (*29*).

<u>Modification</u>

In addition to the current eleven policies in our interactive open source tool, our software allows for easy extension by other developers. First, in addition to including the source code and further individual documentation for each existing intervention, our open source data pipeline can accept new policies following a similar structure to be run in a batch process (*29*). Second, not only allowing users to review and live edit the code for each existing intervention alongside supporting documentation, we offer a server running our open source tool which includes a new policy prototype section accessible from a web browser (*23*). These options may support either the creation of new policies or for the modification of existing interventions. Like the data pipeline, our online tool is also open source with supporting documentation (*23*).

Monte Carlo

In our main text, our point estimates use our "best assumed" parameters but Monte Carlo allows us to also report our 95% confidence intervals. In these trials:

- We sample our test set residual distributions to propagate uncertainty into our business as usual projections.
- Where appropriate, we sample residuals from fit curves for policies like in Table S4.
- To support policy intervention simulations, we sample uncertain parameters as ranges including those in Tables S6.

To supplement our main text, we further report the detailed outcomes of our trials in our Zenodo archive (*29*). Additionally, our online tool shows default configuration and allows modification of these trials with re-execution of this error / sensitivity analysis within the browser.

Note that our random forest errors are sampled at the level of region and model type (consumption, end-of-life fate, etc.). Also, having checked for normality and bias (*29*), these residuals are represented as zero centered normal distributions so can optionally be modified within our online tool. See our Zenodo entry for more details (*29*). Finally, our source datasets often do not include uncertainties. Though we cannot currently extend error quantification into underlying inputs, we encourage future datasets to provide error quantification like for plastics volumes or end of life fate propensities.

Color schemes and other resources

Our tools and figures use color blind-resilient schemes from Color Brewer 2 (*59*). Additional open source or community resources supporting our software are documented in our code archive following programming language-specific standards where applicable (*29*). Uses Public Sans (*60*).

Supplemental Text

We offer supplemental text further detailing each of the eleven policy interventions (only 8 of which are reported in the main manuscript) tested which, in some cases, may leverage literature resources as documented in Table S1. Additional individual policy documentation including implementation source code can also be found within our Zenodo repository archive (*29*) and our interactive tool (*23*).

Packaging consumption tax

One economic instrument commonly utilized to address plastic pollution at national and sub-national levels is a tax. We note that there are a diversity of different classes of taxes, fees, and tariffs that have been considered in the context of the UN plastics treaty. Analyses elsewhere have considered the impact that globally implemented taxes would have on plastic producers and upstream actors. In our analysis, we specifically simulate the behavior of one class of such taxes: a per article consumption tax placed on goods in the plastic packaging sector.

Specifically, this policy simulation reduces consumption only in the packaging sector based on a conversion from size of tax to expected reduction in consumption. This packaging consumption tax is assumed to be levied regardless of if primary or secondary materials are used. Therefore, this does not change the end of life fates but does impact consumption. To achieve this, we consider a variety of data sources derived from the study of existing packaging consumption taxes placed upon single-use bags (one of the most common and well-studied plastic consumption taxes) across all four regions as described in Tables S1 and S4. The responses from these empirical examples are projected across all of the packaging sector.

Note that some regions, like China or North America, show signs of non-linearity. To understand this phenomenon, consider each region's low, middle, and high tax example as reported in Table S4. This may arise out of different price sensitivities and consumer behaviors that are regionally-specific.

Therefore, with additional information available in our open source pipeline (*29*), we fit a curve per region for $y(t) = max(min(t^a * b, 1), 0)$ as shown in Table S4 where a and b are learned parameters. This then has the following primary impact:

$$C_{packaging} = C_{packaging} - \Delta_{packaging} = C_{packaging} - (y(t) * C_{packaging})$$

The reduction $\Delta_{packaging}$ is distributed proportionally across waste within the region:

$$W_{fate} = W_{fate} - \frac{W_{fate}}{W_{total}} * \Delta_{packaging}$$

This change in waste is subject to lifecycle distribution delays. Note that imports also change as a result of reduced consumption:

$$T_{import} = T_{import} - \frac{T_{import}}{C_{total}} * \Delta_{packaging}$$

We use the "high" tax level for each region and the Monte Carlo modifies parameters for this policy. However, as the defaults start at a high level, the output distribution may exhibit skew due to diminishing returns. For more details, see our online tool (*23*) or Zenodo archive (*29*).

Minimum recycled content

This intervention is intended to simulate policies that require that new plastics produced contain a minimum percentage of safe and environmentally sound post-consumer recycled plastic. In our results, we specifically report the outcome of using a 40% minimum recycled content mandate.

This intervention redirects waste from other end-of-life fates to recycling in order to meet a minimum amount of secondary plastic production when making new products. This intervention assumes a minimum recycled content target ($\%_{mandate}$) changing over time which can be used to define the required amount of recycled material needed:

$$W_{recycling-need} = \frac{C_{total} * \%_{mandate}}{1 - l_{yield}}$$

Yield loss (l_{yield}) is configurable by the user in the interactive tool (*23*) but see Table S5 for defaults. That in mind, the change in recycling needed becomes:

$$\Delta_{recycling} = max(W_{recycling-need} - W_{recycling}, 0)$$

This delta then either reduces consumption depending on dampening rate ($d_{consumption}$) or redirects waste from other fates to recycling to meet existing consumption demands. Note that our simulation limits $\Delta_{recycling}$ to $[0, W_{non-recycling}]$. Starting with consumption:

$$C_{sector} = C_{sector} - \frac{C_{sector}}{C_{total}} * \Delta_{recycling} * d_{consumption}$$

Next, waste is redirected from other fates to support the need for more recycled materials.

$$W_{fate} = W_{fate} - \frac{W_{fate}}{W_{non-recycling}} * \Delta_{recycling} * (1 - d_{consumption})$$

Afterwards, with these primary effects considered, we turn to further secondary impacts to waste:

$$W_{fate} = W_{fate} - \frac{W_{fate}}{W_{total}} * \Delta_{recycling} * d_{consumption}$$

This change in waste is subject to a delay governed by the lifecycle distributions seen in the change to consumption. In contrast, imports are more immediately reduced due to loss in consumption:

$$T_{import} = T_{import} - \frac{T_{import}}{C_{total}} * \Delta_{recycling} * d_{consumption}$$

Finally, this additional consumption has tertiary effects on exports from other regions. Due to change in imports, see the change trade function. Dampening rate ($d_{consumption}$) is set according to Table S5 by default but this is configurable in our open source tool (*23*).

<u>Minimum recycling collection rate</u>
This intervention seeks to simulate the behavior of policies that would mandate a minimum rate of plastic waste collection for recycling. This rate is defined as the ratio between the amount of waste collected for recycling and the amount of overall waste generation. In our results, we

report the outcome of using a 40% minimum recycling collection rate but other levels can be considered in our open source tool (*23*).

This intervention functions by redirecting waste from other end of life fates to recycling in order to meet a collection requirement, assuming a minimum mandate ($\%_{mandate}$) changing over time:

$$\Delta_{recycling} = max(W_{recycling}, \%_{mandate} * W_{total}) - W_{recycling}$$

This delta is then offset for the non-recycling fates like so:

$$W_{fate} = W_{fate} - \frac{W_{fate}}{W_{non-recycling}} * \Delta_{recycling}$$

Due to virgin displacement rate (d_{virgin}), we anticipate new consumption to account for the part not displaced:

$$C_{sector} = C_{sector} + \frac{C_{sector}}{C_{total}} * \Delta_{recycling} * d_{virgin}$$

This additional consumption has tertiary effects on trade and waste. New virgin plastics has an impact on imports like so:

$$T_{import} = T_{import} - \frac{T_{import}}{C_{total}} * d_{virgin} * \Delta_{recycling}$$

Furthermore, the increase in consumption has downstream effects on waste as follows:

$$W_{fate} = W_{fate} - \frac{W_{fate}}{W_{total}} * \Delta_{recycling} * d_{virgin}$$

This is time delayed based on the sector lifetime distributions of change in the consumption. Finally, note this change in imports has an additional downstream effect on other region's exports (see change trade function). Additionally, one of the end of life fates impacted is waste trade and other regions experience secondary effects in the simulation (see waste trade interventions). Though configurable in our open source tool (*23*), displacement rate (d_{virgin}) for recycling collection is set according to Table S5 by default.

<u>Minimum packaging reuse rate</u>
This intervention simulates the behavior of policies that would promote plastic reuse by setting a minimum reuse target by mass. In our results we report the outcome of applying this intervention only to the packaging sector and adopting a minimum 40% reuse target but our model and accompanying tool can be configured to target other sectors as well (*23*).

Either at our selected mandate or another provided in our interactive tool, this intervention extends the lifecycle duration of products, reducing consumption and waste in the process.

Starting with the effect of consumption, the following occurs in repetition longitudinally where Δ_{reuse} refers to drop in consumption due to reuse but $\Delta_{product}$ refers to increased material usage in products to support reusability:

$$C_{sector} = C_{sector} - \Delta_{reuse} + \Delta_{product}$$

The iterative nature of this intervention is further described in our data pipeline (1). Regardless, we can expand these terms:

$$\Delta_{reuse} = C_{sector} * \%_{mandate} * (1 - r_{reuse}) - l_{yield} * C_{sector} * \%_{mandate}$$
$$\Delta_{product} = (C_{sector} * \%_{mandate} + l_{yield} * C_{sector} * \%_{mandate}) * x_{reuse}$$

Though configurable in our interactive tool, x_{reuse} describes some marginal percent change in material consumption to support reusable products which conclude their life at a retirement rate (r_{reuse}). We assume both to be set according to Table S5 by default. That in mind, as product retirement into recycling is expected:

$$W_{recycling} = W_{recycling} + \%_{mandate} * r_{reuse} * C_{sector}$$

The decrease in consumption causes a reduction in waste and trade. Starting with waste:

$$W_{fate} = W_{fate} - \frac{W_{fate}}{W_{total}} * \Delta_{reuse}$$

Next, imports are reduced due to loss in consumption:

$$T_{import} = T_{import} - \frac{T_{import}}{C_{total}} * \Delta_{reuse}$$

This additional consumption has tertiary effects on exports from other regions.

$$T_{region-export} = T_{region-export} - \frac{T_{region-export}}{T_{total-export}} * \Delta_{import}$$

Note that this incurs an effect on GHG in exporter regions.

<u>Investment in recycling infrastructure</u>
This intervention is intended to simulate a financial investment made in recycling systems and infrastructure. Funding for such an investment could be generated by programs such a plastic fee, tax, repurposed subsidies, or other facets included within extended producer responsibility schemes. In our results, we report the impact of a simulated $100B USD total investment.

This intervention specifically increases recycling through capacity for collection and processing of waste towards input into the secondary production stream. To support this implementation, we use cost information as reported in Table S6 though these values can be changed in our interactive simulation tool (*22*). Specifically, this intervention assumes a mass of incineration ($m_{recycling}$) costing some annual operating cost (c_{opex}) and capital expenditure (c_{capex}) over an operating lifetime ($l_{capital}$).

With those parameters in mind, this policy applies a recycling increase ($m_{increase}$) over time:

$$\Delta_{recycling} = min(m_{increase}, W_{non-recycling})$$

This is extended to recycling:

$$W_{recycling} = W_{recycling} + \Delta_{recycling}$$

This delta is then offset for the non-recycling fates like so:

$$W_{fate} = W_{fate} - \frac{W_{fate}}{Wnon - recycling} * \Delta_{recycling}$$

Note that investment is a mix of capital and operating expense which is summarized in Table S6:

$$c_{annual} = c_{opex} + \frac{c_{capex}}{l_{capital}}$$

This intervention assumes a potential change in the recycling ($m_{increase}$) over time based on an investment I:

$$m_{increase} = I * \frac{m_{recycling}}{c_{annual}}$$

Due to virgin displacement rate (d_{virgin}), there is actually new consumption to account for the part not displaced:

$$C_{sector} = C_{sector} + \frac{C_{sector}}{C_{total}} * \Delta_{recycling} * d_{virgin}$$

This causes tertiary effects on both waste and trade. New virgin plastics has an impact on imports like so:

$$T_{import} = T_{import} - \frac{T_{import}}{C_{total}} * d_{virgin} * \Delta_{recycling}$$

Note that this change in imports has an additional downstream effect on other region's exports (see the change trade function). Meanwhile, the increase in consumption has downstream effects on waste as follows:

$$W_{fate} = W_{fate} - \frac{W_{fate}}{W_{total}} * \Delta_{recycling} * d_{virgin}$$

This is time delayed based on the sector lifetime distributions of change in consumption. Note that one of the end of life fates impacted is waste trade and other regions experience secondary effects in the simulation. Additional values beyond $100B can be explored in our interactive tool (*23*).

Reduction of single-use packaging

This intervention is intended to simulate the behavior of a ban on short-lived, single-use plastic products in the packaging sector - i.e., products used only once for a short period before they are disposed of or recycled. Our assumptions for this definition and associated Monte Carlo parameterization are described in Table S5. We assume a 90% reduction of single-use packaging in this policy to approximate imperfect implementation and any policy exceptions (e.g. medical use). We recognize that there are a diversity of definitions for single-use plastics (*61*) and, as in all such cases, we invite users to explore alternate definitions of single-use plastics in the interactive tool.

This policy operates by simply subtracting consumption and sending that delta "onwards" to waste and trade.

$$C_{packaging} = C_{packaging} - \Delta_{packaging}$$

The change in packaging can be defined by:

$$\Delta_{packaging} = C_{packaging} * \%_{packaging-SU} * \%_{reduction-SU}$$

The reduction $\Delta_{packaging}$ is distributed proportionally across waste within the region:

$$W_{fate} = W_{fate} - \frac{W_{fate}}{W_{total}} * \Delta_{packaging}$$

This change in waste is subject to lifecycle distribution delays. Note that imports also change as a result of reduced consumption:

$$T_{import} = T_{import} - \frac{T_{import}}{C_{total}} * \Delta_{packaging}$$

Here C_{total} is all input plastics (consumption) including domestic production and imports.

Virgin plastic production cap

This intervention simulates a policy which would place a cap on global virgin plastic production. In our results, we report the impact of a cap set to not exceed 2020 production levels.

Specifically, this intervention imposes a maximum allowed amount of virgin plastic production ($M_{mandate}$) changing over time. This leads to a requirement for a change in primary production:

$$\Delta_{required} = P_{primary} - min(P_{primary}, M_{mandate})$$

The intervention first tries to increase recycling to compensate given a configurable backfill rate ($b_{secondary}$) and yield loss rate for converting end of life recycling stream to new secondary production (l_{yield}):

$$\Delta_{secondary} = min(W_{non-recycling} * l_{yield}, \Delta_{required} * b_{secondary})$$

This reflects into production:

$$P_{secondary} = P_{secondary} + \Delta_{secondary}$$

In practice, the simulation takes time delays between end-of-life and production into account. In the event that not enough recycling is available, consumption sees a change:

$$\Delta_{consumption} = \Delta_{required} - \Delta_{secondary}$$

These change is distributed across consumption sectors like so:

$$C_{sector} = C_{sector} - \frac{C_{sector}}{C_{total}} * \Delta_{consumption}$$

These two changes have secondary effects in waste and imports. First, the change in recycling cannibalizes other waste fates. Starting with recycling itself:

$$W_{recycling} = W_{recycling} + \frac{\Delta_{secondary}}{l_{yield}}$$

Then, updating the others:

$$W_{fate} = W_{fate} + \frac{W_{fate}}{W_{non-recycling}} * \frac{\Delta_{secondary}}{l_{yield}}$$

Next, the change in consumption is propagated across all waste fates.

$$W_{fate} = W_{fate} - \frac{W_{fate}}{W_{total}} * \Delta_{consumption}$$

This impact is time delayed based on the distribution of the change to consumption across sectors. Regardless, imports are reduced due to loss in consumption:

$$T_{import} = T_{import} - \frac{T_{import}}{C_{total}} * \Delta_{consumption}$$

This additional consumption has tertiary effects on exports from other regions. Our simulation tool (2) assumes a default yield loss and backfill rate as defined in Table S6 but the user may change this within the online software.

Investment in waste management infrastructure

This intervention is intended to simulate a financial investment made in waste management systems and infrastructure (e.g., landfill and incineration capacity). As above, funding for such an investment could be generated by programs such a plastic fee, tax, repurposed subsidies, or other elements included in extended producer responsibility schemes. In our results, we report the impact of a simulated $50B USD total investment in waste management.

This intervention specifically increases capacity for collection and processing of waste into a target end-of-life fate. To support this implementation, we use cost information as reported in Table S6 though these values can be changed in our interactive simulation tool (2). This intervention assumes a mass of fate (m_{fate}) costing some annual operating cost (c_{opex}) and capital expenditure (c_{capex}) over an operating lifetime ($l_{capital}$). This arrives as the following primary impact where investment is a mix of capital and operating expense as shown in Table S6:

$$c_{annual} = c_{opex} + \frac{c_{capex}}{l_{capital}}$$

This intervention assumes a potential change in the incineration ($m_{increase}$) over time based on an investment level I:

$$m_{increase} = I * \frac{m_{incinerated}}{c_{annual}}$$

With this potential change defined, the target for plastics is limited by other fates from which they are redirecting ("source" fates):

$$\Delta_{fate} = min(m_{increase} * \%_{plastic}, W_{source})$$

This is then applied to the overall fate rate:

$$W_{fate} = W_{fate} + \Delta_{fate}$$

Finally, this intervention updates other fates such as mismanaged:

$$W_{other} = W_{other} - \Delta_{fate} * \frac{W_{fate}}{W_{source}}$$

This has the effect of proportional distribution of impact across end-of-life fates. Note that, while configurable in our tool (*23*), the waste infrastructure investment scenario follows a user configurable split between incineration and landfill that defaults to even. Both incineration and landfill redirect from mismanaged but incineration may redirect from landfill depending on the set of policies enabled. For more information, see the policy source code (*29*).

<u>Change trade function</u>
A number of policy simulations involve changes to trade and effects are propagated like so:

$$T_{region-export} = T_{region-export} - \frac{T_{region-export}}{T_{total-export}} * \Delta_{import}$$

Note that Δ_{import} comes from the region in which the intervention was introduced.

Fig. S1.

Overview of our business as usual prediction model. Each box in this diagram may be modified by a policy intervention whose code can be found within our online tool. Variables included here map to the aforementioned equations that define the structure of each policy intervention that we simulated. Our open source Zenodo archive (*29*) also includes more detailed information including intervention and data pipeline source code provided alongside a copy of our interactive tool (*23*). This also records license information about our work and for software used.

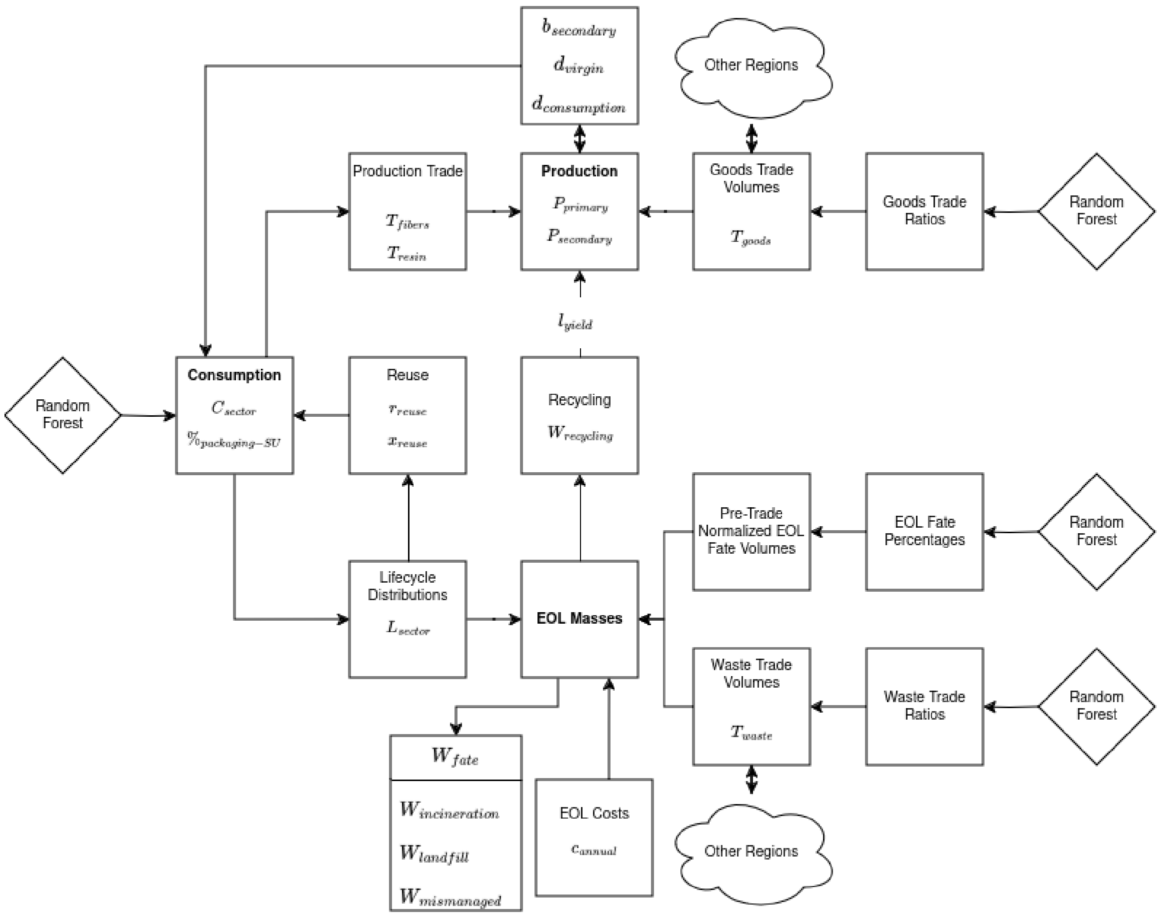

Fig. S2.

(A-B) Bar charts displaying Gross Domestic Product (GDP) by year across each of four world regions: China, EU30, North America (NA), and Majority World (MW) (*57*). (A) GDP by year based on Purchasing Power Parity (PPP) in billions in each region and globally (Total) (B) Percent change in GDP over each year. (C-D) Bar charts displaying population by year across each region (*58*). (C) Population in millions by year. (D) Percent change in population over each year. The spike in population seen in EU30 is attributed to increased migratory movements (*62*).

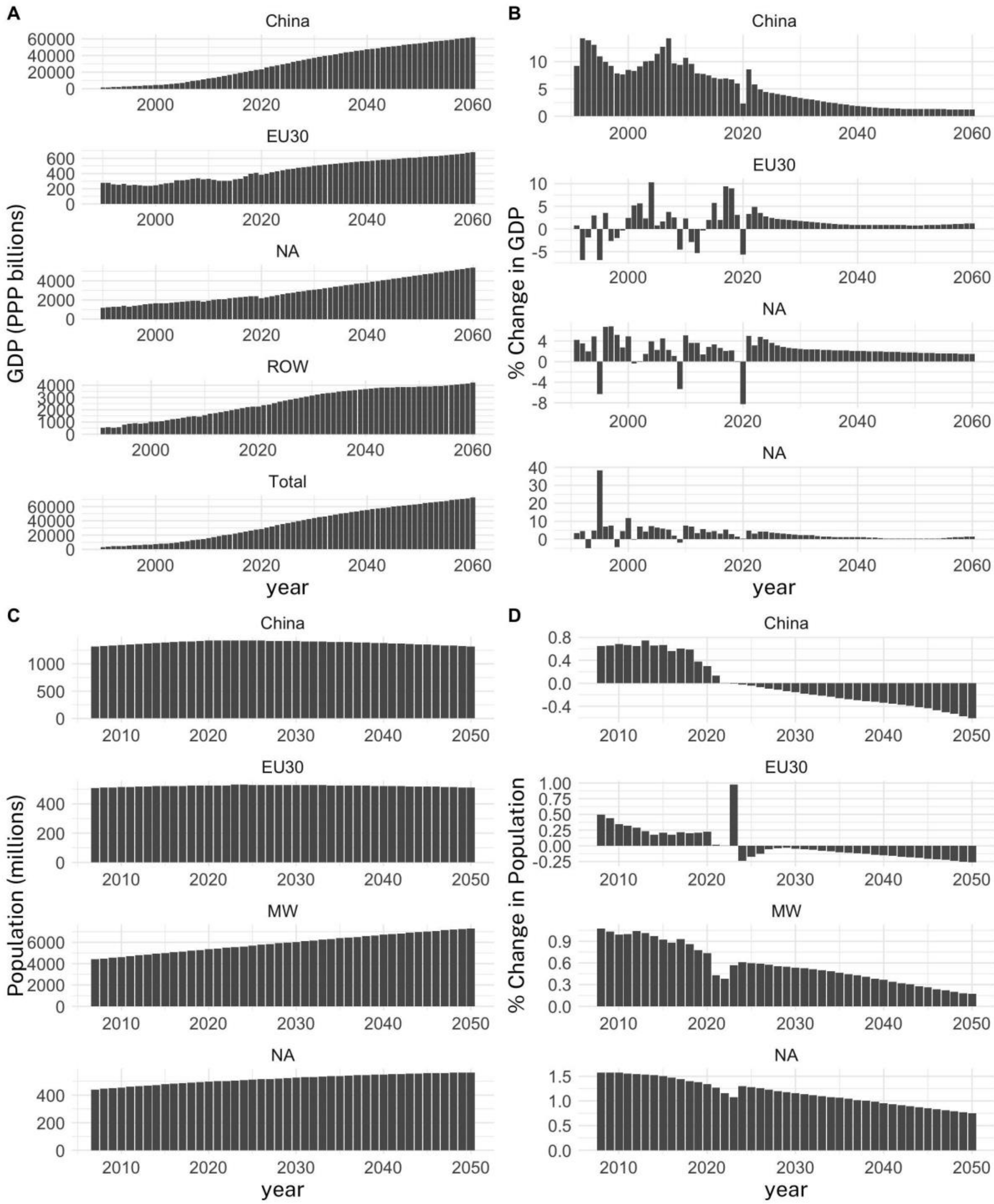

Fig. S3.

Diagram describing the policy constraints-based system. If multiple interventions are enabled, they independently apply constraints such as a minimum recycling collection rate. In the instance that multiple interventions modify the same simulation parameter, our software applies the "strongest" constraint that satisfies all active policy requirements. For example, in this figure, perhaps Effect 1 represents minimum recycled content, Effect 2 represents minimum recycling collection rate, and Effect 3 comes from recycling infrastructure investment. All may impact the minimum collection rate but the highest required (from minimum recycled content or "Effect 1") is ultimately applied by the simulation. As indicated, this may change over time.

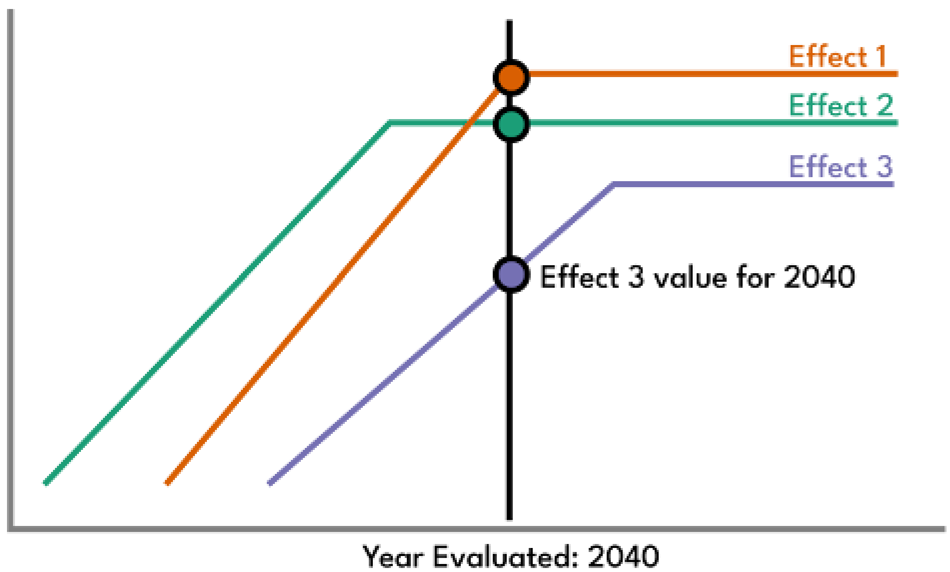

Fig. S4.

Diagram describing optimization using error back-propagation of traded goods in which each row represents a region and each column represents a sector. In a balanced system, the following invariants apply: the sum of rows results in the overall trade volume for that region to other regions while the sum of all columns equals zero (sum of all transportation exports equals the sum of all transportation imports). However, as the data informing the columns and rows may come from different sources or estimations, small errors or discrepancies can occur. Following a back propagation-like algorithm described in our Zenodo entry (*29*), the values in this frame are offset iteratively between rows and columns based on the errors (put formally, the values are proportionally offset based on errors residuals determined by invariants). This ensures that all imports and exports are effectively balanced across regions and sectors after a small number of iterations. See Zenodo entry for performance (*29*).

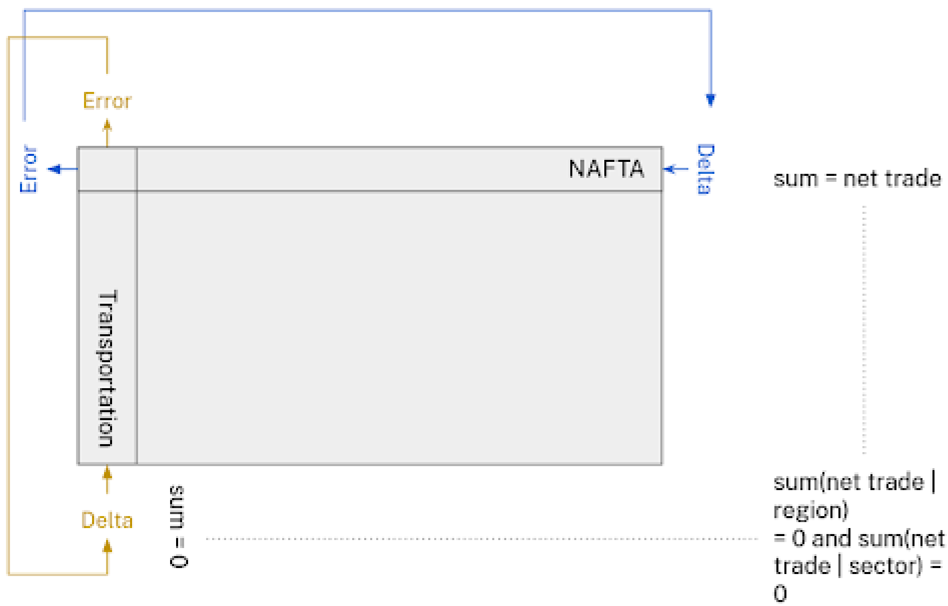

Table S1.
List of references from which parameters were selected for respective policies. Some policies require and are modeled on historic data. Others are "mechanistic" and thus do not require external data but have been provisionally parameterized in general concordance with policies that have been implemented or proposed at national and sub-national contexts. All parameters can be adjusted in the online tool to match alternate assumptions of users.

Policy	**Reference**	**Details**
Packaging consumption tax	(*63–76*)	Regionally specific taxation levels and observed responses.
Minimum recycled content	None	Mechanistic intervention
Minimum recycling collection rate	None	Mechanistic intervention
Minimum packaging reuse rate	None	Mechanistic intervention
Investment in recycling infrastructure	(*24*)	Regionally specific capital expenditure (capex) and operating expenditure (opex) for waste volumes.
Ban on single-use packaging	None	Mechanistic
Virgin plastic production cap	None	Mechanistic
Investment in waste management infrastructure	(*24*)	Regionally specific capital expenditure (capex) and operating expenditure (opex) for waste volumes.
Change trade function	None	Mechanistic

Table S2.
Model inputs and outputs for business as usual regressors with these structures and ratio scalings found through our open source data pipeline (*29*).

Name	**Inputs**	**Response Variable / Output**
Consumption	Number of years elapsed GDP change Population change Region (one-hot) Sector (one-hot)	Change in consumption for sector and region.
Goods Trade	Number of years elapsed Change in GDP Change in population Region (one-hot) Good type (article, fiber, etc. as one-hot) Start goods trade ratio	New goods trade ratio (trade volume / total consumption) from which an offset is to be applied to consumption.
Waste Trade	Number of years elapsed Change in GDP Change in population Region (one-hot) Reference waste ratio Flag: China Sword active.	New waste trade ratio (waste trade / total consumption) from which an offset is to be applied to waste. Not dividing total waste to avoid circular dependency.
End of Life Fate	Number of years elapsed Change in GDP Change in Population Region (one-hot) Fate (one-hot) Reference waste fate ratio	New waste fate ratio (percent for fate) from which percentages of mass will be assigned to different end-of-life streams
Polymer Trade	Number of years elapsed GDP change Population change Sector (one-hot) Region (one-hot) Polymer (one-hot) Prior polymer trade ratio	Polymer trade ratio (sector trade for a polymer / total trade for polymer) from which sector level trade will be inferred.

Table S3.

Chosen models for business as usual prediction with mean absolute errors (MAE) converted to million metric tonnes (Mt). Results presented prior to backpropagation. These reported family-level performances only quantify prediction errors in a fully hidden test set. These estimations importantly ignore the measurement errors of the underlying datasets which are not made available by those sources. That measurement error is likely to significantly exceed that of our reported MAEs. Model test set residuals are sampled in Monte Carlo.

Model	**Algorithm**	**Test MAE in Mt**	**Estimators**	**Max Depth**	**Feature Limit**
Consumption	Random Forest	1.04	25	7	None
Goods Trade	Random Forest	1.96	25	16	log2
Waste Trade	Random Forest	1.31	5	17	None
End of Life Fate	Random Forest	0.02	30	15	log2
Polymer Trade	Random Forest	0.20	25	8	log2

Table S4.

For the consumption tax intervention, we summarize (*63–76*) with the high, middle, and low impact estimates derived from literature after conversion to cents in 2023 USD purchasing power parity (PPP). For these estimates, we use single-use plastic bag taxes given the broader data available for this type of consumer tax as an example before applying this across all packaging. In the main manuscript, we report the impact of utilizing a "high" implementation of this tax policy so as to view the upper bound impact of this intervention. However, we invite users to explore alternate parameterization in the accompanying online tool. We note, however, that the behavioral response to such a tax for other packaging products may vary. One curve is fit per region using these data with model parameters found for the following function: $y(t) = max(min(t^a * b, 1), 0)$.

		China	**EU30**	**NA**	**MW**
Low	**Price Original**	0.21	0.05	0.05	0.3
	Year Reporting	2008	2015	2013	ZAR
	Inflation Adjustment	1.35	1.28	1.3	2.17
	PPP Adjust	3.64	0.67	1	7.28
	Effective 2023 USD PPP	0.08	0.1	0.07	0.09
	Response	-49%	-29%	-60%	-48%
	Source	(*63*)	(*64*)	(*65*)	(*66*)
	Notes	1 std below.	Population scaled average.	Follow up survey.	Avg across retailers at 2008 norm to 30 cents.
Mid	**Price Original**	0.36	0.1	0.07	0.1
	Original Units	CNY	Euro	USD	2018
	Inflation Adjustment	1.35	1.18	1.24	1.07
	PPP Adjust	3.64	0.52	1	0.88
	Effective 2023 USD PPP	0.13	0.23	0.09	0.12

	Response	-64%	-74%	-40%	-38%
	Source	(*63*)	(*67*)	(*68*)	(*70*)
	Notes	Mean.	Overall consumption.	Chicago only - see also (H) (*69*)	ANLA. Using updated pricing.
High	**Price Original**	0.5	0.15	0.1	4
	Original Units	CNY	Euro	USD	Yen
	Inflation Adjustment	1.35	1.45	1.28	3.26
	PPP Adjust	3.64	0.75	1	94.68
	Effective 2023 USD PPP	0.19	0.29	0.13	0.14
	Response	-77%	-93%	-70%	-69%
	Source	(*63*)	(*71*)	(*72*)	(*73*)
	Notes	1 std above.	Avg all Table 2.	City-reported.	Num bags before / after.
Model	**Parameter a**	0.519	1.082	0.247	0.862
	Parameter b	0.168	0.024	0.329	0.062
	Tax Level 2023 USD PPP	0.19	0.29	0.13	0.14
Other Sources	**Index**	(*74*)			
	PPP Adjust	(*75*)			
	Inflation Adjustment	(*76*)			

Table S5.
Starting default but configurable approximate policy assumptions to represent expected general intervention system dynamics. Values informed by literature and expert consultation but configurable within our online interactive tool.

Variable	Default Value	Description	References	Sampling Range
$d_{consumption}$	0%	Dampening of consumption due to recycling mandates.	Simulation tool allows use of this variable but, lacking data, it is currently dormant.	
d_{virgin}	80%	Virgin displacement rate or how much virgin production is reduced in response to increased secondary production (circular economy rebound).	10. Zheng & Suh, Nat. Clim. Chang. 2019 Lowe et al. (2024) Methods to estimate the circular economy rebound effect: A review, Journal of Cleaner Production 443 (2024) 141063	70% - 90%
r_{reuse}	10%	Retirement rate for reusable goods (rate per typical product lifecycle).	UBA, Prüfung und Aktualisierung der Ökobilanzen für Getränkeverpackungen, 2016	5 - 15%
x_{reuse}	150%	Scaling factor for making products reusable.	UBA, Prüfung und Aktualisierung der Ökobilanzen für Getränkeverpackungen, 2016	150 - 250%

l_{yield}	25%	Yield loss for recycling.	Plastics Europe, The Circular Economy for Plastics, p.71, March 2024 NAPCOR, 2020 PET Recycling Report, pp.7&9, Nov 2021	20 - 30%
$b_{secondary}$	50%	Backfill rate or how much increased secondary production will attempt to make up for lost primary production as opposed to reduced consumption.	Lowe et al. (2024) Methods to estimate the circular economy rebound effect: A review, Journal of Cleaner Production 443 (2024) 141063	40% - 60%
$\%_{packaging-SU}$	50%	Percent of packaging comprised of single-use.	Literature does not currently provide robust consensus.	40 - 60%

Table S6.

Reference points for investment interventions used from Lau et al. having converted capex and opex to overall amortized annual cost as USD / ton assuming a capex lifetime of 50 years (*77*).

EoL Fate / Invest Type	**China**	**EU30**	**NA**	**MW**
Landfill	$126 / ton	$225 / ton	$175 / ton	$74 / ton
Incineration	$151 / ton	$292 / ton	$221 / ton	$99 / ton
Recycling	$815 / ton	$1105 / ton	$960 / ton	$530 / ton

Data S1. (separate file)

Simplified longitudinal prediction of future mass flows under the business as usual scenario until 2050 along with predictions under the different policy scenarios discussed. This uses best assumption parameters for point estimates. Our Zenodo archive offers data files describing Monte Carlo outcomes (*29*).

References and Notes

1. R. Geyer, *Plastic Waste and Recycling*, T. Letcher, Ed. (Academic Press, 2020).

2. J. R. Jambeck, R. Geyer, C. Wilcox, T. R. Siegler, M. Perryman, A. Andrady, R. Narayan, K. L. Law, Marine pollution. Plastic waste inputs from land into the ocean. *Science* **347**, 768–771 (2015). doi:10.1126/science.1260352 Medline

3. G. Lamichhane, A. Acharya, R. Marahatha, B. Modi, R. Paudel, A. Adhikari, B. K. Raut, S. Aryal, N. Parajuli, Microplastics in environment: Global concern, challenges, and controlling measures. *Int. J. Environ. Sci. Technol.* **20**, 4673–4694 (2023). doi:10.1007/s13762-022-04261-1 Medline

4. D. Allen, S. Allen, S. Abbasi, A. Baker, M. Bergmann, J. Brahney, T. Butler, R. A. Duce, S. Eckhardt, N. Evangeliou, T. Jickells, M. Kanakidou, P. Kershaw, P. Laj, J. Levermore, D. Li, P. Liss, K. Liu, N. Mahowald, P. Masque, D. Materić, A. G. Mayes, P. McGinnity, I. Osvath, K. A. Prather, J. M. Prospero, L. E. Revell, S. G. Sander, W. J. Shim, J. Slade, A. Stein, O. Tarasova, S. Wright, Microplastics and nanoplastics in the marine-atmosphere environment. *Nat. Rev. Earth Environ.* **3**, 393–405 (2022). doi:10.1038/s43017-022-00292-x

5. N. Qian, X. Gao, X. Lang, H. Deng, T. M. Bratu, Q. Chen, P. Stapleton, B. Yan, W. Min, Rapid single-particle chemical imaging of nanoplastics by SRS microscopy. *Proc. Natl. Acad. Sci. U.S.A.* **121**, e2300582121 (2024). doi:10.1073/pnas.2300582121 Medline

6. M. MacLeod, H. P. H. Arp, M. B. Tekman, A. Jahnke, The global threat from plastic pollution. *Science* **373**, 61–65 (2021). doi:10.1126/science.abg5433 Medline

7. M. Bergmann, F. Collard, J. Fabres, G. W. Gabrielsen, J. F. Provencher, C. M. Rochman, E. van Sebille, M. B. Tekman, Plastic pollution in the Arctic. *Nat. Rev. Earth Environ.* **3**, 323–337 (2022). doi:10.1038/s43017-022-00279-8

8. X. Zhu, C. M. Rochman, B. D. Hardesty, C. Wilcox, Plastics in the deep sea – A global estimate of the ocean floor reservoir. *Deep Sea Res. Part 1 Oceanogr. Res. Pap.* **206**, 104266 (2024).

9. R. Marfella, F. Prattichizzo, C. Sardu, G. Fulgenzi, L. Graciotti, T. Spadoni, N. D’Onofrio, L. Scisciola, R. La Grotta, C. Frigé, V. Pellegrini, M. Municinò, M. Siniscalchi, F. Spinetti, G. Vigliotti, C. Vecchione, A. Carrizzo, G. Accarino, A. Squillante, G. Spaziano, D. Mirra, R. Esposito, S. Altieri, G. Falco, A. Fenti, S. Galoppo, S. Canzano, F. C. Sasso, G. Matacchione, F. Olivieri, F. Ferraraccio, I. Panarese, P. Paolisso, E. Barbato, C. Lubritto, M. L. Balestrieri, C. Mauro, A. E. Caballero, S. Rajagopalan, A. Ceriello, B. D’Agostino, P. Iovino, G. Paolisso, Microplastics and nanoplastics in atheromas and cardiovascular events. *N. Engl. J. Med.* **390**, 900–910 (2024). doi:10.1056/NEJMoa2309822 Medline

10. R. E. Zurub, Y. Cariaco, M. G. Wade, S. A. Bainbridge, Microplastics exposure: Implications for human fertility, pregnancy and child health. *Front. Endocrinol.* **14**, 1330396 (2024). doi:10.3389/fendo.2023.1330396 Medline

11. R. U. Halden, Plastics and health risks. *Annu. Rev. Public Health* **31**, 179–194 (2010). doi:10.1146/annurev.publhealth.012809.103714 Medline

12. B. J. Seewoo, L. M. Goodes, L. Mofflin, Y. R. Mulders, E. V. Wong, P. Toshniwal, M. Brunner, J. Alex, B. Johnston, A. Elagali, A. Gozt, G. Lyle, O. Choudhury, T. Solomons, C. Symeonides, S. A. Dunlop, The plastic health map: A systematic evidence map of human health studies on plastic-associated chemicals. *Environ. Int.* **181**, 108225 (2023). doi:10.1016/j.envint.2023.108225 Medline

13. J. Zheng, S. Suh, Strategies to reduce the global carbon footprint of plastics. *Nat. Clim. Chang.* **9**, 374–378 (2019). doi:10.1038/s41558-019-0459-z

14. Organisation for Economic Co-operation and Development (OECD), "Plastics" (Policy sub-issue, 2023); https://www.oecd.org/en/topics/plastics.html.

15. N. Karali, N. Khanna, N. Shah, Climate Impact of Primary Plastic Production. (Berkeley Lab, Energy Analysis & Environmental Impact Division report, 2024); https://energyanalysis.lbl.gov/publications/climate-impact-primary-plastic.

16. J. Moffett, The Disproportionate Burden on Vulnerable Communities in the Trade of Plastic Waste: How Environmental Justice Should be Integrated into the United Nations Treaty on Plastic Pollution. *UC Law Environmental Journal* **30**, 177 (2024).

17. C. Velis, Waste pickers in Global South: Informal recycling sector in a circular economy era. *Waste Manag. Res.* **35**, 329–331 (2017). doi:10.1177/0734242X17702024 Medline

18. A. L. Brooks, S. Wang, J. R. Jambeck, The Chinese import ban and its impact on global plastic waste trade. *Sci. Adv.* **4**, eaat0131 (2018). doi:10.1126/sciadv.aat0131 Medline

19. N. Simon, K. Raubenheimer, N. Urho, S. Unger, D. Azoulay, T. Farrelly, J. Sousa, H. van Asselt, G. Carlini, C. Sekomo, M. L. Schulte, P.-O. Busch, N. Wienrich, L. Weiand, A binding global agreement to address the life cycle of plastics. *Science* **373**, 43–47 (2021). doi:10.1126/science.abi9010 Medline

20. UNEP, Initial Considerations for the Intergovernmental Negotiating Committee on the UNEA Resolution 5/14 to End Plastic Pollution: Towards an International Legally Binding Instrument (UNEP, 2022); https://wedocs.unep.org/bitstream/handle/20.500.11822/38522/k2200647_-_unep-ea-5-l-23-rev-1_-_advance.pdf?sequence=1&isAllowed=y

21. Materials and methods are available as supplemental materials.

22. A. S. Pottinger, N. Biyani, R. Geyer, D. J. McCauley, M. de Bruyn, M. R. Morse, N. Nathan, K. Koy, C. Martinez, Combining Game Design and Data Visualization to Inform Plastics Policy: Fostering Collaboration between Science, Decision-Makers, and Artificial Intelligence, arXiv.2312.11359 [cs.HC] (2023).

23. A. S. Pottinger, R. Geyer, N. Biyani, C. C. Martinez, N. Nathan, M. R. Morse, M. de Bruyn, E. Baker, D. McCauley, Global Plastics AI Policy Tool (2024); https://global-plastics-tool.org.

24. W. W. Y. Lau, Y. Shiran, R. M. Bailey, E. Cook, M. R. Stuchtey, J. Koskella, C. A. Velis, L. Godfrey, J. Boucher, M. B. Murphy, R. C. Thompson, E. Jankowska, A. Castillo Castillo, T. D. Pilditch, B. Dixon, L. Koerselman, E. Kosior, E. Favoino, J. Gutberlet, S. Baulch, M. E. Atreya, D. Fischer, K. K. He, M. M. Petit, U. R. Sumaila, E. Neil, M. V.

Bernhofen, K. Lawrence, J. E. Palardy, Evaluating scenarios toward zero plastic pollution. *Science* **369**, 1455–1461 (2020). doi:10.1126/science.aba9475 Medline

25. S. B. Borrelle, J. Ringma, K. L. Law, C. C. Monnahan, L. Lebreton, A. McGivern, E. Murphy, J. Jambeck, G. H. Leonard, M. A. Hilleary, M. Eriksen, H. P. Possingham, H. De Frond, L. R. Gerber, B. Polidoro, A. Tahir, M. Bernard, N. Mallos, M. Barnes, C. M. Rochman, Predicted growth in plastic waste exceeds efforts to mitigate plastic pollution. *Science* **369**, 1515–1518 (2020). doi:10.1126/science.aba3656 Medline

26. R. Geyer, J. R. Jambeck, K. L. Law, Production, use, and fate of all plastics ever made. *Sci. Adv.* **3**, e1700782 (2017). doi:10.1126/sciadv.1700782 Medline

27. UNEP, *Practical guidance on the development of inventories of plastic waste* (UNEP, 2022).

28. L. Chao, R. Geyer, S. Hu, 100 years of plastic: using the past to guide the future.

29. A. S. Pottinger, R. Geyer, N. Biyani, C. C. Martinez, N. Nathan, M. R. Morse, L. Chao, S. Hu, M. de Bruyn, E. Baker, D. McCauley, Data Pipeline and Tool Source Code for the Global Plastics AI Policy Tool, Zenodo (2024); https://doi.org/10.5281/zenodo.12615011.

30. S. Kaza, L. Yao, P. Bhada-Tata, F. Van Woerden, *What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050* (World Bank Publications, 2018).

31. J. W. Cottom, E. Cook, C. A. Velis, A local-to-global emissions inventory of macroplastic pollution. *Nature* **633**, 101–108 (2024). doi:10.1038/s41586-024-07758-6 Medline

32. OECD, Global Plastics Outlook: Policy Scenarios to 2060 (Green Talks LIVE, Webinar, 2022); https://www.oecd.org/en/events/2022/06/Global-plastics-outlook-policy-scenarios-to-2060.html.

33. B. Nyberg, P. T. Harris, I. Kane, T. Maes, Leaving a plastic legacy: Current and future scenarios for mismanaged plastic waste in rivers. *Sci. Total Environ.* **869**, 161821 (2023). doi:10.1016/j.scitotenv.2023.161821 Medline

34. L. Fok, I. N. Y. Cheng, Y. Y. Yeung, *Environmental Sustainability and Education for Waste Management: Implications for Policy and Practice*, W. W. M. So, C. F. Chow, J. C. K. Lee, Eds. (Springer, 2019), pp. 57–71.

35. L. Lebreton, A. Andrady, Future scenarios of global plastic waste generation and disposal. *Palgrave Commun.* **5**, 6 (2019). doi:10.1057/s41599-018-0212-7

36. S. Dhakal, J. C. Minx, F. L. Toth, A. Abdel-Aziz, F. L. Figueroa Meza, K. Hubacek, I. G. C. Jonckheere, Y.-G. Kim, G. F. Nemet, S. Pachauri, X. C. Tan, in *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge Univ. Press, 2023), pp. 215–294.

37. UNEP, Compilation of draft text of the international legally binding instrument on plastic pollution, including in the marine environment. (2024); https://wedocs.unep.org/bitstream/handle/20.500.11822/45858/Compilation_Text.pdf.

38. A. Stöfen-O'Brien, The Prospects of an International Treaty on Plastic Pollution. *Int. J. Mar. Coast. Law* **37**, 727–740 (2022). doi:10.1163/15718085-bja10108

39. OECD, Extended Producer Responsibility (OECD Environment Policy Papers, No. 41, 2024); https://www.oecd-ilibrary.org/environment/extended-producer-responsibility_67587b0b-en

40. EU, Packaging and packaging waste. (EU, 2020); https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=LEGISSUM:l21207.

41. SB 54 Plastic Pollution Prevention and Packaging Producer Responsibility Act Permanent Regulations (CalRecycle, 2024). https://calrecycle.ca.gov/Laws/Rulemaking/SB54Regulations/.

42. T. Dey, L. Trasande, R. Altman, Z. Wang, A. Krieger, M. Bergmann, D. Allen, S. Allen, T. R. Walker, M. Wagner, K. Syberg, S. M. Brander, B. C. Almroth, Global plastic treaty should address chemicals. *Science* **378**, 841–842 (2022). doi:10.1126/science.adf5410 Medline

43. J. D. Meeker, S. Sathyanarayana, S. H. Swan, Phthalates and other additives in plastics: Human exposure and associated health outcomes. *Philos. Trans. R. Soc. B.* **364**, 2097–2113 (2009). doi:10.1098/rstb.2008.0268 Medline

44. M. Bergmann, B. C. Almroth, S. M. Brander, T. Dey, D. S. Green, S. Gundogdu, A. Krieger, M. Wagner, T. R. Walker, A global plastic treaty must cap production. *Science* **376**, 469–470 (2022). doi:10.1126/science.abq0082 Medline

45. Minderoo Foundation Limited, The Polymer Premium: A Fee on Plastic Pollution. (Minderoo Foundation, 2024); https://cdn.minderoo.org/content/uploads/2024/04/21232940/The-Polymer-Premium-a-Fee-on-Plastic-Pollution.pdf.

46. The Circular Economy for plastics – A European Analysis 2024. (Plastics Europe, 2024); https://plasticseurope.org/knowledge-hub/the-circular-economy-for-plastics-a-european-analysis-2024/.

47. T. Zink, R. Geyer, Circular economy rebound. *J. Ind. Ecol.* **21**, 593–602 (2017). doi:10.1111/jiec.12545

48. C. A. Choy, B. H. Robison, T. O. Gagne, B. Erwin, E. Firl, R. U. Halden, J. A. Hamilton, K. Katija, S. E. Lisin, C. Rolsky, K. S. Van Houtan, The vertical distribution and biological transport of marine microplastics across the epipelagic and mesopelagic water column. *Sci. Rep.* **9**, 7843 (2019). doi:10.1038/s41598-019-44117-2 Medline

49. L. Roman, B. D. Hardesty, G. H. Leonard, H. Pragnell-Raasch, N. Mallos, I. Campbell, C. Wilcox, A global assessment of the relationship between anthropogenic debris on land and the seafloor. *Environ. Pollut.* **264**, 114663 (2020). doi:10.1016/j.envpol.2020.114663 Medline

50. N. Rangel-Buitrago, W. Neal, A. Williams, The Plasticene: Time and rocks. *Mar. Pollut. Bull.* **185**, 114358 (2022). doi:10.1016/j.marpolbul.2022.114358 Medline

51. M. Kida, S. Ziembowicz, P. Koszelnik, Decomposition of microplastics: Emission of harmful substances and greenhouse gases in the environment. *J. Environ. Chem. Eng.* **11**, 109047 (2023). doi:10.1016/j.jece.2022.109047

52. S.-J. Royer, S. Ferrón, S. T. Wilson, D. M. Karl, Production of methane and ethylene from plastic in the environment. *PLOS ONE* **13**, e0200574 (2018). doi:10.1371/journal.pone.0200574 Medline

53. P. Stegmann, V. Daioglou, M. Londo, D. P. van Vuuren, M. Junginger, Plastic futures and their CO_2 emissions. *Nature* **612**, 272–276 (2022). doi:10.1038/s41586-022-05422-5 Medline

54. C. Richon, T. Gorgues, M. Cole, I. Paul-Pont, C. Maes, A. Tagliabue, C. Laufkötter, Model exploration of microplastic effects on zooplankton grazing reveal potential impacts on the global carbon cycle. *Environ. Res. Lett.* **19**, 074031 (2024). doi:10.1088/1748-9326/ad5195

55. R. D. Lamboll, Z. R. J. Nicholls, C. J. Smith, J. S. Kikstra, E. Byers, J. Rogelj, Assessing the size and uncertainty of remaining carbon budgets. *Nat. Clim. Chang.* **13**, 1360–1367 (2023). doi:10.1038/s41558-023-01848-5

56. UNEP, Practical guidance on the development of inventories of plastic waste. (UNEP, 2022); http://www.basel.int/Portals/4/download.aspx?d=UNEP-CHW-NREP-INVENT-GUID-PlasticWaste-2022.English.pdf.

57. OECD, Real GDP Long-Term Forecast. (2023); https://www.oecd.org/en/data/indicators/real-gdp-long-term-forecast.html.

58. DESA, World Population Prospects. (United Nations Department of Economic and Social Affairs, 2022); https://population.un.org/wpp/Download.

59. C. A. Brewer, M. Harrower, B. Sheesley, A. Woodruff, D. Heyman, ColorBrewer 2.0. (2013); https://colorbrewer2.org/#type=sequential&scheme=Blues&n=3

60. General Services Administration, Public Sans: A strong, neutral typeface for interfaces, text, and headings. (US Web Design System, 2024); https://public-sans.digital.gov/

61. UNEP, Single-use plastics: A roadmap for sustainability. (UNEP, 2018); https://www.unep.org/resources/report/single-use-plastics-roadmap-sustainability.

62. Population and population change statistics. (Eurostat, 2024); https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Population_and_population_change_statistics.

63. H. He, Effects of environmental policy on consumption: Lessons from the Chinese plastic bag regulation. *Environ. Dev. Econ.* **17**, 407–431 (2012). doi:10.1017/S1355770X1200006X

64. G. O. Thomas, E. Sautkina, W. Poortinga, E. Wolstenholme, L. Whitmarsh, The English Plastic Bag Charge Changed Behavior and Increased Support for Other Charges to Reduce Plastic Waste. *Front. Psychol.* **10**, 266 (2019). doi:10.3389/fpsyg.2019.00266 Medline

65. DDOE, Alice Ferguson Foundation, D.C. Resident and Business Bag Use Surveys. (DDOE, 2013); https://doee.dc.gov/sites/default/files/dc/sites/ddoe/publication/attachments/DDOE%202013%20Bag%20Law%20Survey%20Final%20Report%20%282%29.pdf.

66. J. Dikgang, A. Leiman, M. Visser, Analysis of the plastic-bag levy in South Africa. *Resour. Conserv. Recycling* **66**, 59–65 (2012). doi:10.1016/j.resconrec.2012.06.009

67. G. Martinho, N. Balaia, A. Pires, The Portuguese plastic carrier bag tax: The effects on consumers' behavior. *Waste Manag.* **61**, 3–12 (2017). doi:10.1016/j.wasman.2017.01.023 Medline

68. T. Homonoff, L.-S. Kao, J. Selman, C. Seybolt, *Skipping the Bag: The Intended and Unintended Consequences of Disposable Bag Regulation* (National Bureau of Economic Research, 2021).

69. T. Homonoff, ideas42, University of Chicago Energy & Environment Lab, Preliminary study suggests Chicago's bag tax reduces disposable bag use by over 40 percent. (2017); https://urbanlabs.uchicago.edu/attachments/4d5115b55b216984be9d0c3c20e3b0fc42096fa5/store/bc678f1fd91593abc69c737c5c8a6da925a2ba8bce03b1dade052e095e58/Bag-tax-results-memo-PUBLIC.FINAL_.pdf.

70. M. Rokoua, Infrastructure: A short study on Fiji's Environmental & Climate Adaptation Levy (ECAL). (2021); https://doi.org/10.13140/RG.2.2.34852.81285.

71. F. Convery, S. McDonnell, S. Ferreira, The most popular tax in Europe? Lessons from the Irish plastic bags levy. *Environ. Resour. Econ.* **38**, 1–11 (2007). doi:10.1007/s10640-006-9059-2

72. City of Boulder, Disposable Bag Fee (2023); https://bouldercolorado.gov/services/disposable-bag-fee.

73. A. Nishijima, J. Nakatani, Survey and analysis on the use and disposal of plastic shopping bags before and after the introduction of charges. *J. Mater. Cycles Waste Manag.* **26**, 741–754 (2024). doi:10.1007/s10163-023-01856-9

74. Scientist Action and Advocacy Network, Effectiveness of plastic regulation around the world. (2019); https://web.archive.org/web/20210129061143/https://plasticpollutioncoalitionresources.org/wp-content/uploads/2017/03/Effectiveness_of_plastic_regulation_around_the_world_4_pages.pdf.

75. World Bank Group (WBG), PPP conversion factor, GDP (LCU per international $). (WBG, 2023); https://data.worldbank.org/indicator/PA.NUS.PPP.

76. World Bank Group (WBG), Inflation, consumer prices (annual %). (WBG, 2023); https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG.

77. J. Davis, R. Geyer, J. Ley, J. He, R. Clift, A. Kwan, M. Sansom, T. Jackson, Time-dependent material flow analysis of iron and steel in the UK: Part 2. Scrap generation and recycling. *Resour. Conserv. Recycling* **51**, 118–140 (2007). doi:10.1016/j.resconrec.2006.08.007