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Household waste practices: New empirical evidence and policy implications for sustainable behaviour

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Environment Working Paper No.249

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Keywords: residential waste practices, household behaviour, circular economy, recycling, waste prevention, discrete choice experiment

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Abstract

This report presents findings from analysis of data from the 2022 OECD household survey on Environmental Policies and Individual Behaviour Change (EPIC) conducted in nine countries. The analysis provides new evidence and insights on the most important drivers of outcomes related to waste generation, prevention, and recycling at the household level. The survey also gathers information on households' preferences and attitudes, as well as the availability of a variety of recycling collection services for different materials and whether and how households were charged for their municipal waste collection. These data enable an analysis of the associations between policy measures and reported behaviour, controlling both for observed household characteristics, general attitudes towards environmental problems and governance, as well as unobserved country-level factors.

The analysis identifies four major attitudinal profiles among households, including *environmental prioritisers* (40% of the sample), *technological optimists* (17%), *economic prioritisers* (12%), and the *environmentally neutral* (31%). Findings also indicate that attitudes are significantly and consistently associated with households' waste-related choices. With respect to the impact of waste-related policies on household behaviours, the analysis finds that recycling collection services are associated with significantly lower mixed waste generation and greater engagement in waste prevention behaviours. The presence of charging schemes is associated with increased recycling volumes, a greater effectiveness of recycling collection services in reducing mixed waste, and higher engagement in waste prevention behaviours.

Survey results indicate that most households generate at least some food waste. Correlations between the number of types of food wasted and several socioeconomic and policy-related factors raise pertinent questions relevant to waste management policies and call for further research. Finally, findings from a discrete choice experiment indicate that households fall into one of three primary groups regarding their packaging preferences and willingness to pay for sustainable packaging. Two of these groups (constituting most households in all countries surveyed) are willing to pay a price premium for products with sustainable packaging, while the third group would require a price discount in order to opt for sustainable packaging. The presence of recycling services and charging schemes are notably associated with a greater preference for sustainable packaging, which suggests that waste prevention incentives for consumers may influence their purchasing decisions.

Taken together, findings of the analysis suggest that aligning waste policies with sustainable consumption goals can be a strategy for stimulating sustainable waste practices and demand for more sustainable consumption. The report concludes with an appraisal of policy implications from the analysis.

Keywords: residential waste practices, household behaviour, circular economy, recycling, waste prevention, discrete choice experiment

JEL Codes: D01, D12, Q53, D91, C25

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Executive Summary

This report analyses new survey data on household waste generation, prevention, and recycling. The aim of the analysis is to provide new evidence and insights on the most important drivers of key waste-related outcomes at the household level. The analysis is based on survey data from the 2022 OECD Survey on Environmental Policies and Individual Behaviour Change (EPIC), elicited from 8,569 households across nine OECD countries.[1] The survey gathers information on household waste generation, recycling rates, as well as waste-related behaviours, preferences and attitudes. Importantly, households also reported the availability of a variety of recycling collection services for different materials, as well as whether and how they were charged for their municipal waste collection. This information notably enables an assessment of the association between policies and household behaviour.

The report investigates associations between policy measures and reported behaviour, controlling both for observed household characteristics (e.g. income, household size), general attitudes towards environmental problems and governance, as well as unobserved country-level factors. Several main findings of the analysis include:

- **Four major attitudinal profiles across countries are help explain households' waste-related choices.** The four attitudinal profiles include *environmental prioritisers* (40% of the sample), *technological optimists* (17%), *economic prioritisers* (12%), and the *environmentally neutral* (31%). *Environmental prioritisers* value environmental protection over economic growth and *environmentally neutral* households exhibit relative indifference between economic and environmental issues. The other two profiles, *technological optimists* and *economic prioritisers*, both place greater weight on economic security than the previous two classes, with *technological optimists* attaching a greater importance to environmental problems. The association of attitudes with waste-related behaviours points to the relevance of information that impact environmental awareness as a means to foster sustainable household choices.
- **The provision of recycling collection services is associated with 15% lower mixed waste generation, as well as greater engagement in waste prevention behaviours**. These findings point to the critical role of providing recycling collection services for households as a low-cost and convenient option for diverting material from mixed waste streams.
- **The presence of charging schemes is associated with increased recycling but not with a change in the total volume of waste, in contrast to earlier literature.** Charging schemes are also associated with a greater effectiveness of recycling collection services in reducing mixed waste, and higher engagement in waste prevention behaviours. However, the fact that these schemes are not significantly associated with a change in the volume of waste, suggests that households may face other structural constraints (e.g. in the form of local norms, lack of availability of sustainable products or high opportunity costs of time) that limit the extent to which they are able to alter their mixed waste generation volumes. This possible explanation aligns

[1] Participating countries included Belgium, Canada, the Netherlands, Israel, France, Sweden, Switzerland, the United Kingdom and the United States,

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with other findings, notably that households rate enhanced financial incentives (e.g. saving or receiving money), the provision of kerbside waste/recycling services, and more collection or drop-off services as the most important factors in encouraging them to recycle and compost more.

- **Most households in most surveyed countries throw away at least some food.** Composting service provision and living in an urban area are significantly associated with households throwing more types of food away more frequently. Multiple policy-relevant explanations could be consistent with these findings. For example, households may feel more at liberty to throw food away when it is composted vs. discarded with mixed waste. Additionally, households that tend to throw away more food may also have a higher propensity to sign up for composting services (when such municipal-level services are not mandatory). As these two alternative explanations imply different policy responses (e.g. complementary policies to mitigate food waste in the case of the former, vs. expanding composting service provision in the case of the latter), this finding calls for further research to identify the principal explanatory mechanism.
- **A majority of households are willing to pay a premium for sustainable packaging.** Households fall into one of three primary groups regarding their packaging preferences and willingness to pay for sustainable packaging. Two of these groups (constituting most households in all countries surveyed) are willing to pay a price premium for products with sustainable packaging, while the third group would require a price discount in order to opt for sustainable packaging. The presence of recycling services and charging schemes are also associated with a greater preference for sustainable packaging, which suggests that **aligning waste policies with sustainable consumption goals can be a strategy for stimulating sustainable waste practices and demand for more sustainable consumption**.

The analysis points to several useful areas for future work, including assessing the extent to which the waste policies that respondents report being in place (e.g. recycling collection services and mixed waste charging schemes) correspond with actual coverage, which could identify lack of awareness of such policies. Country-specific analyses could explore whether differences in the surveyed populations could contribute to differences in attitudinal profiles and behaviours observed across countries. The results found in this analysis also indicate the need for further work to better understand the relationship between composting service provision and food waste generation in order to confirm the positive association found here and identify the driving mechanism. In addition to mixed waste and recyclable waste, future data collection efforts could also focus on eliciting a measure of food waste volumes generated.

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1. Introduction

Household consumption inevitably generates waste. Higher incomes and consumption are generally associated with more waste generation. Although waste that is incinerated, landfilled or otherwise disposed of has declined in OECD countries over the last two decades, nearly two thirds of this waste remained unrecovered in 2020 (OECD, 2023[1]). In fact, recent research suggests that recycling rates in these countries have plateaued (Kinnaman and Yamamoto, 2023[2]). On a global basis, the World Bank estimates that in 2020, nearly 83% of global waste generation is unrecovered (Kaza, Siddarth and Sarur, 2021[3]). The World Bank also estimates that if current relationships between income and waste generation continue, then income and population growth could drive global waste generation to grow by 73%, the unrecovered portion of which growing by 79% by 2050 compared to 2020.

With increased waste generation comes increased environmental damage. This includes air, water and terrestrial pollution directly attributable to landfills, incineration, or open dumping, including micro- and macro-plastics, airborne particulate matter, and toxic chemicals and metals (Scherhaufer et al., 2018[4]; Liu et al., 2023[5]; OECD, 2023[1]). Indirect negative environmental impacts from waste generation are also incurred from the environmental footprints of upstream resource extraction and agricultural activities that could be displaced through more effective waste prevention and the safe recycling and reuse of discarded materials (Scherhaufer et al., 2018[4]; Liu et al., 2023[5]).

The significant and growing challenges from waste generation and its environmental consequences point to a clear need for more efficient and effective waste management policies (OECD, 2023[1]). In particular, neither consumers nor producers face the full benefits and costs, i.e. accounting for environmental and public health impacts, of their decisions to discard or recycle materials or to manufacture more durable, reparable, or sustainably packaged goods. Addressing these externalities therefore requires effective public policies. And with household consumption being a major source of total waste generation (OECD, 2023[1]), an important subset of these policies are those that reduce households' generation of unrecovered waste. Reductions come from a combination of diverting more household waste to recycling services, reducing waste generated per unit of consumption, or reducing the amount of material consumption itself.

This report analyses responses to survey questions related to household waste generation, recycling and waste prevention in the 2022 OECD Survey on Environmental Policies and Individual Household Behaviour Change (EPIC) (Box 1.1). It builds on a descriptive analysis of these data provided in OECD (2023[1]). The aim of the present report is to provide an in-depth analysis of the determinants of households' reported waste-related behaviours, including the impact of waste-related policies and of households' attitudes towards the environment and the economy.

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Box 1.1. Aim and scope of the EPIC Survey

The third OECD Survey on Environmental Policies and Individual Behaviour Change (EPIC) explores households' environmental attitudes and actions in the areas of energy, transport, waste and food across nine OECD countries. The survey collects information on reported environmental behaviours. It also records the socioeconomic characteristics of households and households, as well as the characteristics of their residence and residential location. As such, the survey provides information on a wide range of factors that can influence environmentally relevant household decisions. The questionnaire and further information on the implementation of the survey are available in (OECD, 2023[1]).

Table 1.1. OECD EPIC surveys: Coverage, thematic areas and sample sizes

	2008	2011	2022
Countries included	Australia	Australia	Belgium
	Canada	Canada	Canada
	Czech Republic	Chile	France
	France	France	Israel
	Italy	Israel	The Netherlands
	Korea	Japan	Sweden
	The Netherlands	Korea	Switzerland
	Norway	The Netherlands	United Kingdom[1]
	Mexico	Spain	United States
	Sweden	Sweden	
		Switzerland	
Total sample size	10 000	12 303	17 216
Methodology for measuring preferences and behaviour	Self-reporting	Self-reporting	Self-reporting + choice experiments
Number of thematic areas	5	5	4
Possibility to test hypothetical policy interventions	No	No	Yes
Distributional issues addressed	No	No	Yes

Note: [1]The sample from the United Kingdom includes households in England, Northern Ireland, Scotland and Wales.

The third EPIC Survey was implemented in June-July 2022, more than a decade after the second round of the survey, in 2011. Changes since then pertain to the environmental, political, technological and economic context and have all contributed to a need to reassess environmental attitudes and behaviours, as well as the effectiveness of environmental policies. At the time of implementation, most significant COVID-19-related restrictions (lockdowns and international travel bans), had been lifted in all the countries sampled. However, the period continued to be characterised by historically high energy prices, inflation and geopolitical tensions. The particularities of this context could have several implications for survey responses. Self-reported levels of support for tax instruments, for example, may be lower, while support for policy measures involving financial support (e.g. grant and subsidies) may be higher. Increasing economic concerns may reduce the political acceptability of disincentives (e.g. taxes); however, the same concerns could make measures that align sustainable habits with monetary savings (e.g. energy conservation) more likely to be adopted. Further, the energy crisis may have also led to increased interest in energy efficiency technologies that reduce energy costs over the long term.

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The report is organised as follows: Section 2 provides a literature review of previous empirical work examining the effects of different policies and interventions on household behaviours and waste generation outcomes. Section 2 examines the determinants of households' waste generation volumes and describes how the attitudinal data were prepared and synthesised for inclusion in the empirical analysis. Sections 3 and 4 examine the determinants of households' waste prevention efforts and specific household-level outcomes related to food waste. Section 5 analyses the determinants of households' expressed preferences for different types of waste management policies, such as incentive-based or information-based interventions. Section 6 examines households' hypothetical demand and willingness to pay (WTP) for more sustainably packaged staple consumer products using a discrete choice experiment (DCE). Finally, Section 7 offers a number of policy considerations yielded by the above analyses.

1.1. Literature review

Previous research (including analysis of the previous round of the EPIC survey in 2011) has found that kerbside recycling collection services have generally been associated with significant reductions in mixed (i.e. unrecovered) waste generation and concomitant increases in recycling, although effects vary by context. Likewise, in prior studies across several OECD countries, waste charging systems have been associated with 18% to 50% reductions in mixed waste generation. Beyond these policies, a wide variety of behavioural interventions, ranging from social marketing and awareness-building to behavioural 'nudges,' have been studied in the waste management literature. If well-designed and backed with sufficient investments, previous meta-analyses suggest that behavioural interventions can be among the most effective measures in shifting household waste generation and prevention behaviours.

Much of the empirical economic research on policies for reducing household mixed waste has focused on the effects of recycling services or mandates as well as unit-based waste fees on household waste generation. These policies have been widely implemented across OECD countries over the last several decades (OECD, 2023[6]). Evidence across many contexts indicates that increased recycling service availability and recycling mandates reduce household mixed waste generation, though the magnitude of effects varies considerably.

In their econometric analysis of the 2011 EPIC data (which included 11 OECD countries, 6 of which are also included in the 2022 EPIC data analysed in this report), Palatnik et al. (2014[7]) characterise the literature as showing a mix of positive, null, and negative results, with positive associations overall. They find that medium to high levels of recycling services are associated with approximately a 10% to 25% reduction in mixed (i.e. unrecovered) waste generation volumes. Studying 95 Italian municipalities for the years 1999-2008, Bucciol et al. (2015[8]) find that kerbside recycling services reduced mixed waste generation by around 30%. In contrast, a recent study by Maier et al. (2023[9]) in the US state of North Carolina finds that kerbside recycling programs had no statistically significant effect on household mixed waste generation and increased overall household waste generation (including both mixed and recyclable waste) by around 10%.

It is worth noting that most studies of recycling program impacts appear to focus on material-specific separation rates, i.e. the portion of a disposed material that is recycled (e.g. Jenkins et al., (2003[10]) and Struk (2017[11]), or on households' recycling and waste prevention behaviours (see Allison et al. (2022[12]) for a meta-analysis). Less frequently examined in prominent peer-reviewed literature is the effect of recycling programs on total or mixed waste generation volumes, despite the fact that these outcomes are ultimately those of most policy interest in light of the environmental challenges described above. Current systematic reviews or meta-analyses of the effects of recycling programs on these key outcomes appear to be lacking.

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As with the research on recycling programs, a long-running thread of research on unit-based waste charges (overlapping in part with the recycling literature) has shown that in general such waste charging schemes are effective at reducing household mixed waste. These systems, commonly referred to as 'pay-as-you-throw', include charging by weight, volume, or collection frequency. Like recycling policies, their effectiveness varies by the form of implementation and by context.

In addition to evaluations of recycling programs, Palatnik et al. (2014[7]) also review the evidence for charging scheme effects and conclude that the literature generally supports the effectiveness of these schemes on reducing mixed waste. Analysing the 2011 EPIC data, they find that charging schemes were generally associated with a 20-22% average reduction in mixed waste generation volumes (Table 1.2). Studies published since then have applied increasingly sophisticated econometric methods to analyse the impacts of charging schemes. In particular, a series of studies analyse panel data on charging scheme effects using a 'difference-in-differences' (DID) methodology in which outcomes are analysed before and after a charging scheme is implemented. These differences are compared to differences over time in otherwise comparable areas/households that were never subject to a charging scheme. Bucciol et al. (2015[8]), Pfister and Mathys (2022[13]), and Andersson and Stage (2018[14]) use this methodology to analyse the effects of charging schemes in municipalities in Italy, Switzerland and Sweden respectively, and find effect sizes comparable to the associations reported in Palatnik et al. (2014[7]) (Table 1.2).

The most recent and sophisticated analysis of the causal effects of charging schemes on mixed waste generation is provided by Valente (2023[15]), using recent data from Italian municipalities. Valente finds a much higher mean effect of a charging scheme, amounting to a 50% reduction in household mixed waste, with a 32% increase in recycled waste (implying that a substantial portion of the mixed waste reduction was due to waste prevention). Using advanced econometric techniques that allow for an estimation of heterogeneous effects of charging schemes between municipalities with different charging scheme price levels, this work also estimated price elasticities of demand for mixed waste generation/collection. The analysis finds that these elasticities are nonlinear, with waste generation being relatively insensitive to the charging level when low but becoming more sensitive as the charging level increases.

Research on charging scheme systems has also examined potential unintended consequences such as increases in illegal dumping. Evidence for these effects, to the extent that it exists (e.g. Bucciol et al. (2015[8])), suggests that they are relatively marginal in relation to the magnitude of the positive impacts of a charging scheme. In summary, given the now large body of econometric work showing the positive effects of waste charging schemes on reducing waste generation volumes, the time appears ripe for a meta-analysis of the estimated effects across the literature in order to examine broader heterogeneity in these effects (e.g. to distinguish between the average impact of a charging scheme and marginal effects at different price levels).

Table 1.2. Recent evidence on the effect of waste charging schemes on mixed waste generation

Study	Mean effect	Study Context	Notes
Valente (2023)	50% reduction	Italy 2010-2015	Panel data, difference-in-differences (DID) with heterogeneous treatment effects; Estimates price elasticities
Pfister & Mathys (2022)	26% reduction	Swiss cantons 2010-2017	Panel data DID
Andersson & Stage (2018)	18-20% reduction	Sweden 2007-2014	Panel data DID; Maximum effect reported which occurred by year 3 of the charging scheme
Bucciol et al. 2015	22-30% reduction	Italy 1999-2008	Panel data DID
Palatnik et al. (2014)	20-22% reduction	EPIC 2011 (11 OECD countries)	Cross-sectional regression analysis

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Finally, a significant body of research ranging across economics, psychology and other social sciences has examined several behavioural interventions and mechanisms that shape households' waste disposal decisions in different policy contexts. These studies appear to generally fall into three broad categories relevant for this report: education and social marketing; rebound and other unanticipated effects; and behavioural 'nudges.'

The first category constitutes the longest running research stream of the three, with work going back to the 1970s. This research examines the role of education, public information and advocacy campaigns or related approaches, such as social modelling or community-based social marketing (CBSM) interventions (e.g. Haldeman and Turner (2009[16])) on household waste behaviours. In separate meta-analyses, Xia et al. (2023[17]), Allison et al. (2022[12]), and Varotto and Spagnolli (2017) find that collectively these interventions are among the most effective at increasing household recycling, but with large heterogeneity in their effects. These studies also generally agree that the most effective forms of these interventions are those that are most intensive and costly, i.e. social modelling of recycling behaviours in one-on-one interactions or focus groups.

The second category of behavioural research related to waste concerns potential 'rebound effects' and other unanticipated responses from waste reduction policies. For example, expanding recycling programs may sometimes lead to increased overall household waste generation (Maier, Geyer and Steigerwald, 2023[9]). Such rebound effects are considered to arise in part due to changes in economic incentives. For example, expanding recycling programs in the presence of a charging scheme effectively reduces the marginal cost of waste disposal to households, which could increase overall generation volumes. Another example of an unanticipated response to a waste prevention policy arising from altered incentive structures concerns disposable shopping bag bans in the US state of California. Taylor (2019[18]) found that while bans on disposable carryout bags from restaurants eliminated 40 million pounds from the waste stream, they increased consumer purchases of trash bags by 12 million pounds, evidently to offset the 'second life' of carryout bags as trash bags in homes. Rebound-type effects may also arise for other behavioural reasons, e.g. households purchasing products with 'eco-labels' feeling a moral license to consume more as a result (Barkemeyer et al., 2023[19]; Dorner, 2019[20]).

A particularly relevant empirical example of rebound in waste policies concerns food waste. For at least the last decade, food waste has a been a growing concern for policymakers in OECD countries (Schanes, Dobernig and Gözet, 2018[21]; Thyberg and Tonjes, 2016[22]). At the same time, municipal composting has been increasingly advocated as a means for better managing this waste stream and reducing its environmental damage (Farhidi, Madani and Crichton, 2022[23]). However, recent global economic modelling of food waste reductions suggest that rebound effects could offset between 53% and 71% of anticipated reductions from food waste prevention policies, due to cheaper effective food prices and increased demand that could result from such policies (Hegwood et al., 2023[24]). In addition, composting programs may have unanticipated effects on food waste generation: In a small case study in an institutional setting, Qi and Roe (2017[25]) find that, when university students and staff were informed that their food waste from a freely provided lunch would be composted, they generated more food waste compared to a comparable group without this composting information. Although coming from a small-scale case study, this finding and the theory underlying it is relevant for the analysis of food waste prevention behaviours analysed later in this report.

A third category of behavioural research focuses on 'nudges' that can cost-effectively reduce household waste generation or increase recycling. An illustrative recent example for household waste prevention is provided by Akbulut-Yuksei and Boulatoff (2021[26]). The authors study the effects of a 'clear bag policy' in an urban Canadian municipality, whereby households are required to dispose of their mixed waste in clear bags so that waste collectors can screen in order to refuse bags containing recyclable materials. The authors find that this policy reduced mixed waste weight by 15% and total waste by 27%,

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with an accompanying 15% increase in recycling. The previously discussed meta-analyses of behavioural interventions (Xia et al., 2023[17]; Allison et al., 2022[12]; Varotto and Spagnolli, 2017[27]) also include examples of such nudges in their analyses, and find such approaches generally have small effects (though accompanied by small costs). To reconcile these systematic conclusions with the above example, it is important to stress the great variety in behavioural nudges that can be devised for waste prevention, and that the behavioural and economic sciences continue to offer innovative types of nudges. Future meta-analyses, specifically on the cost-effectiveness of waste prevention and recycling nudges, would be useful for informing policy.

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2. Survey sample

2.1. Data description and considerations

The EPIC Survey relies on a stated preference empirical approach to data collection. As opposed to revealed preference approaches, which make use of data on observed behaviours, stated preference approaches use data gathered by asking individuals to either report their actual behaviour, or report how they would behave in a given hypothetical situation. Although revealed preference approaches have high reliability and validity because they reflect the real-world constraints faced by individuals, this also constitutes a limitation insofar as analyses are limited to addressing only those choices and conditions that are available in real-world contexts. The main challenges of stated preference approaches, on the other hand, include response bias and sample representativeness.

Generally speaking, limitations of analyses based on survey data arise from the extent to which reported responses may differ from actual behaviours (i.e. hypothetical bias), as well as the extent to which the characteristics of survey respondents may diverge from those of the actual population. Care should therefore be taken to evaluate the representativeness of survey samples when extrapolating findings to the general population.[2] Despite these challenges, stated preference approaches offer a number of advantages over revealed preference approaches when it comes to ex-ante policy evaluation (OECD, 2018[28]). Discrete choice experiments, for example, are well-suited to analysing choices in the context of relatively complex, multi-dimensional issues (Bateman et al., 2002[29]; OECD, 2018[28]).

It should also be noted that, as the analyses carried out in this paper simultaneously control for a variety of factors on reported behaviour, they provide evidence of association, but do not provide evidence of causation strictly speaking. The stated preference and observational nature of the EPIC data mean that some uncertainty remains regarding the effects of policies on behaviour. An assessment of the consequences of policy settings on different outcomes requires an ex-post policy evaluation framework. As such, a cross-sectional survey of self-reported preferences, behaviours and investments is not the appropriate tool for robust policy evaluation, and this study does not call into question the results of evaluations that have sought to identify the causal impact of a specific policy interventions. Following the convention in the environmental economics literature, however, the independent variables used in the analysis are sometimes referred to as determinants.

The waste section of the third EPIC survey contains data from 8,569 respondents, about half of the overall EPIC survey sample size (see Box 1.1; respondents were randomly selected for participating in each of the four thematic sections). Summary statistics for socioeconomic characteristics of this sample, as well as can be found in Table A A.1 in the Annex. General environmental attitudes were also elicited in the survey and are profiled using latent class analysis (Box 2.1). Both socioeconomic characteristics and environmental attitudinal profiles (described in the following section) are used in subsequent analyses as possible factors associated with waste-related outcomes.

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[2] To ensure a representative survey and avoid sample bias, the target sample for the EPIC Survey was stratified by income, age, gender and region in each country. Following implementation, to correct for divergences between the sample and the population with respect to age, gender, region and income, weighting factors were calculated to ensure representativeness at the population level. Post-stratification weights were calculated on a country-by-country basis based on age, gender, region and income variables. Additional details about the implementation of the EPIC Survey are provided in (OECD, 2023[1]).

2.2. Environmental attitude profiles

To examine how general environmental attitudes affect waste prevention and separation behaviours, a latent class analysis (LCA) of selected attitudinal questions was conducted (Hagenaars and McCutcheon, 2002[30]; StataCorp, 2023[31]). Box 2.1 provides an overview of latent class analysis. In the analyses in subsequent sections, individuals' predicted probabilities of belonging to the attitudinal profiles generated here are used as a parsimonious way of examining how overall environmental attitudes are associated with the waste prevention and separation outcomes and behaviours elicited in the survey.

LCA is used to examine response patterns to the following survey questions: How important is climate change (e.g. rising average temperatures, extreme weather events) or other environmental issues (e.g. pollution) to you personally? Respondents could indicate the importance of the issue based on a 5-point Likert scale ranging from "Not at all important" to "Very important". The second question upon which the LCA is based is: To what extent do you agree with each of the following statements? Respondents could indicate their agreement on a 5-point Likert scale ranging from "Strongly disagree" to "Strongly Agree". The statements included: Environmental impacts are frequently overstated, I am willing to make compromises in my current lifestyle for the benefit of the environment, protecting the environment can boost the economy, environmental issues should be dealt with primarily by future generations, environmental issues should be resolved mainly through public policies, environmental policies introduced by the government should not cost me extra money, environmental issues will be resolved primarily through technological progress, and environmental issues will be resolved mainly through individuals voluntarily changing their behaviour.

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Box 2.1. An overview of latent class analysis

Latent class analysis (hereafter, LCA) is a statistical procedure used to identify different subgroups (or latent classes) of households based on patterns in their behaviour (Lazarsfeld, 1950[65]; Goodman, 1974[66]; Eliason and Hagenaars, 1990[67].[3] LCA assumes that observed behaviours, in this case self-reported energy conservation and investment in energy efficiency equipment, are driven by membership in unobserved household profiles. The latent variable is considered to be an unordered categorical variable.

Once the number of latent classes is specified, LCA uses maximum likelihood estimation to determine the proportion of observations that fall into each latent class. For each latent class, it also estimates the likelihood of observing each response option. Specifically, it maximises the statistical independence of the observed variables of a household conditional on its latent class. This process assigns households with similar behaviours to the same latent class. In a well-performing LCA model, each observation is estimated to have a high likelihood of belonging to one class and a low likelihood of belonging to the other classes. Common indicators of the statistical fit of latent class models include the Bayesian Information Criterion (BIC), the Akaike information criterion (AIC) and likelihood-ratio tests (LRT). In addition to statistical criteria, an important theoretical criterion for selecting the number of latent classes is the identification of distinct and interpretable classes.

LCA derives clusters using a probabilistic model that describes the distribution of the data and has a number of advantages over simpler algorithm-based approaches. It can account for class size during the allocation process and accommodate different types of data (e.g. categorical and numerical). Because LCA models the latent structure of data rather than simply identifying similarities, it also allows for tests of goodness-of-fit and significance and thus can measure the degree of uncertainty in the resulting classifications.

Formally, the probability of obtaining response pattern $\boldsymbol{y}$, $P(\boldsymbol{Y} = \boldsymbol{y})$, is a weighted average of the C class-specific probabilities $P(\boldsymbol{Y} = \boldsymbol{y}|X = x)$:

$$P(\boldsymbol{Y} = \boldsymbol{y}) = \sum_{x=1}^{C} P(X = x)\, P(\boldsymbol{Y} = \boldsymbol{y}|X = x)$$

Table 2.1 reports the classes identified through the LCA in relation to the above survey questions.[4] Four classes were estimated: e*nvironmental prioritisers*, *technological optimists, economic prioritisers*, and the *environmentally neutral*. The *environmental prioritiser* and *technological optimist* profiles rated climate and environmental issues as relatively more important than the other two classes. These two profiles also both viewed environmental protection as boosting the economy and expressed a relatively greater willingness to make compromises on behalf of the environment. However, *environmental prioritisers* and *technological optimists* fundamentally differed in their views on whether environmental problems tend to be overstated, the responsibility of future versus present generations in protecting the environment, the role of technology in solving environmental issues, whether environmental policies

[3] See also, for example, Linzer and Lewis, 2011[2] and Weller, Bowen and Faubert, 2020[3].

[4] The LCA is implemented by first aggregating the strongly agree and agree responses into an 'agree' category, and the strongly disagree or disagree responses into a single 'disagree' category, and separately retaining the 'neither agree or disagree' and 'prefer not to say' responses. For robustness, the LCA is compared with the original response categories and the relevant findings are qualitatively the same.

should cost them extra money, and whether environmental issues are primarily the responsibility of future versus current generations.

Among the profiles, *economic prioritisers* viewed climate and environmental issues as least important. This group also agreed most frequently with the statement that environmental impacts are frequently overstated. They were the only class to exhibit a net unwillingness to make compromises in their lifestyle for the benefit of the environment and to disagree with the idea that protecting the environment can boost the economy.

The *environmentally neutral* most frequently selected more neutral responses to all statements. While they tend to agree that climate and environmental issues are important, their net agreement/disagreement was the most neutral of all the classes. The statement for which they had the highest net agreement or disagreement was agreement with the sentiment that 'Environmental policies introduced by the government should not cost me extra money.'

Table 2.1. Net agreement with attitudinal statements, by estimated latent classes

Survey item	Environmental prioritisers	Technological optimists	Economic prioritisers	Environmentally neutral
Climate and environmental issues are important	0.90	0.74	-0.60	0.34
Environmental impacts are frequently overstated	-0.85	0.51	0.64	0.06
I am willing to make compromises in my current lifestyle for the benefit of the environment	0.88	0.84	-0.39	0.38
Protecting the environment can boost the economy	0.80	0.91	-0.26	0.40
Environmental issues should be dealt with primarily by future generations	-0.74	0.77	-0.21	-0.19
Environmental issues should be resolved mainly through public policies	0.45	0.91	-0.05	0.30
Environmental policies introduced by the government should not cost me extra money	0.24	0.86	0.74	0.57
Environmental issues will be resolved primarily through technological progress	0.07	0.83	0.22	0.22
Environmental issues will be resolved mainly through individuals voluntarily changing their behaviour	0.33	0.87	0.01	0.35

Note: Net agreement calculated as the fraction within each class agreeing or strongly agreeing with statement minus the percentage disagreeing or strongly disagreeing.

Table 2.2. Distribution of attitudinal profiles across countries

Country	Environmental prioritisers	Technological optimists	Economic prioritisers	Environmentally neutral
BEL	37%	16%	12%	35%
CAN	44%	15%	11%	30%
CHE	50%	9%	11%	30%
FRA	43%	18%	10%	30%
GBR	41%	20%	10%	30%
ISR	29%	30%	13%	28%
NLD	41%	12%	14%	34%
SWE	44%	9%	15%	32%
USA	34%	21%	15%	30%

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Table 2.3. Marginal effects of socioeconomic factors on environmental class membership

Variable	Environmental prioritisers	Technological optimists	Economic prioritisers	Environmentally neutral
Age	0.00219*	-0.00255***	-0.000959	0.00132
	(0.00128)	(0.000914)	(0.00132)	(0.00133)
Gender (Base = male)				
Female	0.0683***	-0.0307***	-0.0675***	0.0300***
	(0.00845)	(0.00486)	(0.00538)	(0.00727)
Other	0.152**	0.0180	-0.0564*	-0.114***
	(0.0678)	(0.0668)	(0.0303)	(0.0345)
Log(income)	0.0199**	0.0111*	-0.0170***	-0.0141***
	(0.00838)	(0.00583)	(0.00480)	(0.00437)
Log(household size)	-0.0196***	0.0109***	0.00649	0.00221
	(0.00610)	(0.00355)	(0.00520)	(0.00390)
Children in the household (Base = no)	-0.0788***	0.0770***	3.82e-05	0.00172
	(0.0124)	(0.0110)	(0.00528)	(0.00854)
Log(home size)	-0.00509	-0.0170**	0.0166***	0.00549
	(0.00635)	(0.00726)	(0.00474)	(0.00513)
Renter (Base = no)	-0.00877	-0.0221***	0.00707	0.0238***
	(0.00816)	(0.00684)	(0.00544)	(0.00740)
Higher education (Base = no)	0.112***	0.0133*	-0.0238***	-0.101***
	(0.00798)	(0.00683)	(0.00432)	(0.00425)
Residential location type (Base = urban)				
Suburban	0.0138	-0.0538***	0.0183***	0.0217***
	(0.0146)	(0.0120)	(0.00517)	(0.00736)
Town/village	0.0215***	-0.0809***	0.0325***	0.0269***
	(0.00712)	(0.00892)	(0.00493)	(0.00591)
Rural	-0.0293*	-0.0815***	0.0798***	0.0310***
	(0.0172)	(0.0124)	(0.0215)	(0.0106)
Employment status (Base = employed)				
Homemaker/retired	0.0165**	-0.0222***	-0.000609	0.00637
	(0.00716)	(0.00766)	(0.00612)	(0.00669)
Unemployed	0.0258	-0.0423***	-0.00897	0.0254
	(0.0203)	(0.0143)	(0.0102)	(0.0213)
Student	0.0971***	-0.0593***	-0.0278***	-0.00999
	(0.0167)	(0.00809)	(0.0105)	(0.0153)
Other (e.g. disability)	0.0275***	-0.0449***	0.00523	0.0123
	(0.00763)	(0.0109)	(0.00891)	(0.0125)
Country fixed effects included	Yes			
Observations	17,215			

Note: Results of a fractional multinomial logit model estimation. Outcome variables (column headers) reflect the estimated marginal effect on the probability of belonging to each class (s.e). Age^2 was also included as a control but was not significant.

Table 2.2 shows the country-level distributions of these environmental attitude types. *Environmental prioritisers* were most prevalent in Switzerland and least prevalent in Israel. *Technological optimists* were most prevalent in Israel and least prevalent in Sweden and the UK. *Economic prioritisers* were most prevalent in Sweden and the US. The *environmentally neutral* were most prevalent in Belgium and least prevalent in Israel. In all countries, the *environmentally neutral* are the most prevalent of the four classes. In terms of the two classes that viewed climate and environmental issues as highly

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important (*environmental prioritisers* and *technological optimists*), in all countries except for Israel, *environmental prioritisers* were more prevalent than *technological optimists*.

Table 2.3 shows the estimated marginal effects of several socioeconomic factors on whether an individual is more or less likely to belong to each of the four attitudinal profiles. A fractional multinomial logit statistical regression model was used for this analysis. Older respondents and female respondents are more likely to be *environmental prioritisers* versus their counterparts, who are more likely to be *technological optimists* or *economic prioritisers*. Family size and the presence of children in the household are associated with greater likelihood of being a *technological optimist* and a relatively lower likelihood of being an *environmental prioritiser*. Higher incomes, having a higher education, owning one's primary residence, and living in an urban area are associated with a significantly greater likelihood of being an *environmental prioritiser* and *technological optimist* and a lower likelihood of being an *economic prioritiser* or *environmentally neutral*.

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3. Mixed waste generation and recycling behaviour

This section explores the factors that determine how much mixed and recyclable waste households generate. The outcomes of interest reflect two survey items regarding these behaviours.[5] The first survey item asked households to estimate how many 30 litre (7.5 gallon) bags/bins of mixed waste (i.e. non-recyclable and non-compostable waste) they generate each week. An illustration was included in the questionnaire to provide an indication of the size of the bag/bin relative to a person. Households were asked the same question with respect to the amount of recyclable (not including compostable) waste they generate per week.

Three categories of explanatory variables are assumed to impact the generation of mixed waste (M) and recyclables (R). The determinants of household i's volume V_i^w generated for waste type $w \in \{\mathrm{M}, \mathrm{R}\}$ was estimated using a log-linear regression of the form:

$$\log V_{ic}^{w} = \beta_0 + \boldsymbol{\beta}'_{pol}\boldsymbol{x}_i^{pol} + \boldsymbol{\beta}'_{SEC}\boldsymbol{x}_i^{SEC} + \boldsymbol{\beta}'_{attd}\boldsymbol{x}_i^{attd} + \alpha_c + \epsilon_{ic}$$

Here, three sets of covariates are represented by three vectors covering waste policy ($\boldsymbol{x}_i^{pol}$), socio economic characteristics ($\boldsymbol{x}_i^{SEC}$) and attitudinal factors ($\boldsymbol{x}_i^{attd}$). The β's are the estimated partial associations between the variables and waste generation volume, α_c is a country fixed effect, and ϵ_{ic} is estimation error.[6]

Following Palatnik et al.'s (2014[7]) analysis of similar data from the 2011 EPIC survey, policy variables analysed include a binary indicator for whether the household stated that a waste charging scheme (by either weight, volume or frequency) was used for mixed waste collection. The reported level of recyclable collection service availability was also included as a policy variable. Following Palatnik et al. (2014[7]), an aggregate 'separation service level' variable is created based on the reported availability of different levels of service (e.g., none, drop-off, kerbside) for each of five types of separated waste studied in the survey: glass, plastic containers, metal, and paper (including cardboard, which is collected separately from paper in Israel).[7] A "high level" of overall separation services is therefore defined as kerbside pickup services for at least three (four for Israel) of the four considered materials (five for Israel, with cardboard separate from other paper). A "medium" level of service is defined as drop-off services available for at least three of the four materials and at least one pickup service (but less than three). A

[5] The complete survey questionnaire is provided in OECD (2023[1]).

[6] Based on specification testing, the error term is modelled as heteroskedastic between countries with $\mathrm{Var}[\epsilon_{ic}] = \sigma_c^2$. The model was estimated using maximum likelihood using the *hetregress* command in Stata.

[7] Plastic packaging and batteries collection is excluded from the definition of service levels because households indicated availability of pickup services for these items at greater frequencies than is realistic in a number of countries. Food waste is also excluded from service levels, because food waste collection services are highly heterogeneous in their structure, e.g. in the US, they are frequently provided by households opting in to a paid service provided by a private company.

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"low" level of service is defined as at least one drop-off service (but less than the other service categories). The vector of policy variables $\boldsymbol{x}_i^{pol}$ is also specified to include interactions effects between the presence of a charging scheme and different separation service levels.[8] The socioeconomic characteristics included in waste volume regressions ($\boldsymbol{x}_i^{SEC}$) match those that were used to study determinants of the environmental attitudinal class membership, with the addition of the estimated latent attitudinal classes described in section 2.1, with the estimated membership probabilities included as respondent characteristics in the regression analysis.[9]

Table 3.1 shows the distributions of service levels and their interaction with charging schemes. There is significant between-country heterogeneity in the level of collection services: The prevalence of low/no separation services are less than 11% in all surveyed countries, except Israel and the US. These numbers also show that charging schemes are much more prevalent in conjunction with medium and high levels separation services. It is also important to emphasise the likelihood of survey-based measurement error and incorrect responses in stated service availability and charging schemes. This is particularly relevant for the cases where very small percentages (<1%) of households indicated a charging scheme with no or low separation services and should be borne in mind when considering the regression results.

Table 3.1. Reported coverage of charging schemes and recycling collection service levels by country

	BEL	CAN	CHE	FRA	GBR	ISR	NLD	SWE	USA
Charging scheme mixed waste pricing	40.5%	9.6%	53.2%	7.2%	7.4%	5.3%	19.6%	8.0%	16.1%
Separation service level									
No service	0.8%	6.5%	0.5%	3.3%	4.8%	31.3%	1.3%	3.5%	15.4%
Low service	2.2%	3.9%	1.8%	3.5%	2.4%	59.5%	6.4%	5.0%	8.7%
Medium service	19.8%	31.8%	95.2%	43.8%	17.1%	9.2%	67.9%	68.7%	32.6%
High service	77.3%	57.8%	2.5%	49.4%	75.7%	0.0%	24.4%	22.8%	43.3%
Charging scheme X separation service level									
No Charging scheme, no service	0.7%	6.3%	0.5%	3.2%	4.4%	29.3%	1.0%	3.3%	14.6%
Charging scheme, no service	0.1%	0.2%	0.0%	0.1%	0.3%	2.0%	0.2%	0.2%	0.7%
No Charging scheme, low service	1.3%	3.1%	1.0%	2.5%	1.3%	56.8%	6.1%	4.0%	6.4%
Charging scheme, low service	0.9%	0.8%	0.8%	0.9%	1.1%	2.7%	0.3%	0.9%	2.4%
No Charging scheme, medium service	12.4%	26.9%	43.9%	39.8%	11.8%	8.6%	54.7%	62.4%	23.2%
Charging scheme, medium service	7.4%	5.0%	51.4%	4.0%	5.2%	0.7%	13.2%	6.4%	9.4%
No Charging scheme, high service	45.2%	54.2%	1.5%	47.2%	75.1%	0.0%	18.6%	22.3%	39.7%
Charging scheme, high service	32.1%	3.6%	1.0%	2.2%	0.7%	0.0%	5.8%	0.5%	3.5%

[8] Due to the small incidence and measurement issues of a charging scheme with low or no separation services (Table 3.1), interactions between a charging scheme and these service levels are not included.

[9] The survey also contained several attitudinal variables pertaining specifically to waste generation: For example, whether respondents ranked plastic pollution or resource depletion as among the most concerning of environmental issues from a list of eight different environmental problems. However, these variables are excluded as determinants in the regression analysis due to concerns about endogeneity (e.g. omitted variable bias or reverse causality).

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Table 3.2 presents the regression results for reported volume of mixed waste and recyclables.[10] The determinants included in this analysis explain approximately 20% of the within-country variation in mixed waste generation volumes, leaving nearly 80% of the variation unexplained, which suggests considerable heterogeneity and idiosyncrasies in household waste production. In terms of socioeconomic determinants, estimated effects are very similar between mixed waste and recyclables generation. General environmental attitudes were found to be significant determinants of waste generation volumes: *environmental prioritisers* are associated with both lower mixed waste (-15%) and recycling (-25%) volumes compared to the *environmentally neutral*, whereas the opposite is the case for *technological optimists* class (+22% mixed waste and +220% recycling volumes). The *economic prioritiser* class does not exhibit significantly different waste generation volumes compared to the *environmentally neutral*.

Age is associated with lower waste generation, but in the case of recycling volumes this effect is nonlinear and diminishes with older households (i.e. the positive and significant coefficient on age^2). Female respondents indicated that their household generated around 3% lower mixed waste and 13% lower recycling volumes compared to male respondents. The estimated income elasticity of mixed waste generation is statistically significant but less than 1%, controlling for other socioeconomic characteristics. For recyclables generation, the estimated income elasticity is estimated at 0.27%. Together, these income elasticities imply recyclables generation is more sensitive to income than mixed waste generation. Household size is also a significant determinant of waste generation, with an increase in household size from one to two members (100% increase) implying a 36%(=100%*[exp(0.309)-1]) increase in mixed waste generation and a 177% increase in recyclables generation. The presence of children in the home is only a statistically significant determinant of recyclables generation, associated with a 46% increase in this outcome. Renters are significantly associated with a 5.2% increase in mixed waste generation. There is a clear pattern of lower population density areas being associated with less waste generation (both mixed and recyclable). Residing in an urban area is associated with 18% greater mixed waste generation and 42% greater recyclables generation than residing in a rural area, controlling for other factors. Employment status was not found to be significantly associated with waste generation volumes.

When examining how the policy variables are associated with the volume of recycled material generated (Figure 3.2), the results are more nuanced, but significant associations are present. Without a charging scheme, there appear to be no significant differences in recycling volumes between low and medium service levels, holding other factors constant. With a charging scheme, medium- versus low-service is associated with 60% greater recycling volumes, though the difference is not precisely estimated. High- versus medium-service levels are counterintuitively associated with lower recycling volumes. Without a charging scheme, high- versus medium-service levels are associated with 13% lower recycling volumes; with a charging scheme, there is an estimated 87% difference between these levels. The correlation between a charging scheme and recycling volumes appears strongest at medium service levels, and the direction of the correlation is intuitive (assuming households are incentivised by a charging scheme to direct more waste to recycling versus mixed waste). In these cases, a charging scheme is associated with an 16% increase in recycling. At high recycling service levels, a charging scheme is associated with an 8% increase in recycling (though this association is not statistically

[10] As the outcomes analysed in the regression analysis are logs of volumes, the regression coefficients for the categorical determinants require transformations to obtain percentage changes in volumes associated with a given factor. The estimated percentage associations from a binary explanatory factor should be calculated as $\exp(\hat{\beta}) - 1$, where $\hat{\beta}$ is the estimated regression coefficient (i.e. the values reported in Table 3.2). For non-binary categorical factors, the estimated percentage change associated with a change from level l of the variable to level k is given by $\exp(\hat{\beta}_k) - \exp(\hat{\beta}_l)$. The standard errors and 95% confidence intervals for these estimated percentage changes are calculated using the delta method via the *nlcom* command in Stata.

significant). Figure 3.1 and Figure 3.2 present these estimates for mixed waste and recycling volumes respectively.

The only policy measures significantly associated with changes in mixed waste generation are those with high levels of separation services. High-level separation services are associated with a 15% reduction in mixed waste generation, relative to the no-separation-service case. However, no association is found between waste charging schemes and generation volumes, after controlling for other observed household characteristics and heterogeneous baseline household waste volume distributions across countries. This diverges notably with prior literature examining the causal effects of charging schemes on waste generation volumes, including results from the previous EPIC Survey, which overall indicates that such incentives reduce household mixed waste generation at estimated effect sizes ranging from 18% to 50% reductions across a range of (mostly European) OECD countries (Table 1.2).

A difference between the current analysis and the prior literature may be due in part to genuine distinctions in the relationships found for these countries and years (e.g. post-COVID). It is also likely due to the nature of data, which is cross-sectional data on self-reported waste generation volumes collected from countries of highly heterogeneous sizes, waste collection systems, and social norms surrounding waste disposal, which could lead to measurement errors that obscure the true correlation between charging schemes and actual waste generation.[11] Despite the limitations of this self-reported data, it remains useful insofar as it provides simultaneous and comparable information across a set of countries that provide a signal of the drivers of behaviour within and across countries.

Table 3.2. Regression results of waste and recycling generation (volume)

Determinants	Outcome			
	Log (mixed waste volume)		Log (recycling volume)	
Charging scheme X separation service level (Base = no charging scheme, no separation services)				
Low service	0.0690	(0.0478)		
Medium service, no Charging scheme	-0.0183	(0.0396)	-0.246	(0.182)
Medium service, Charging scheme	0.0506	(0.0479)	0.467*	(0.248)
High service, no Charging scheme	-0.161***	(0.0431)	-0.426*	(0.224)
High service, Charging scheme	-0.176**	(0.0691)	-0.302	(0.286)
Age	-0.0149***	(0.00571)	-0.0619***	(0.0164)
Age^2	9.04e-05	(5.90e-05)	0.000455***	(0.000164)
Gender (Base = male)				
Female	-0.0340*	(0.0184)	-0.137*	(0.0828)
Other	0.128	(0.0850)	0.441	(0.560)

[11] For example, eliciting household self-reports of waste volumes is subject to an array of recall and perceptual biases (e.g. difficulty in estimating cumulative weekly volume from recall). The survey data also do not record whether the respondent regularly disposes of their waste (versus another household member typically doing this). This issue extends to estimated associations with recycling volumes. For example, in these data, lower recycling volumes appear to be weakly associated with *higher* recycling service levels, controlling for other observed factors and country-level baseline differences in distribution volumes. While such counterintuitive findings have been reported in other specific instances in the literature, it is also worth recognising that the form of recycling service could influence how households recall recycling volumes in self-reports. For example, households that usually drive their recycling to a drop-off centre (loading and unloading it from their vehicle) may have a more accurate sense of their recycling volume than those with kerbside service who may more frequently deposit smaller volumes with perhaps irregularly sized containers (e.g. cardboard boxes or bags of various sizes) in their collection bins. Unfortunately, this means that recall bias may vary systematically with separation service availability.

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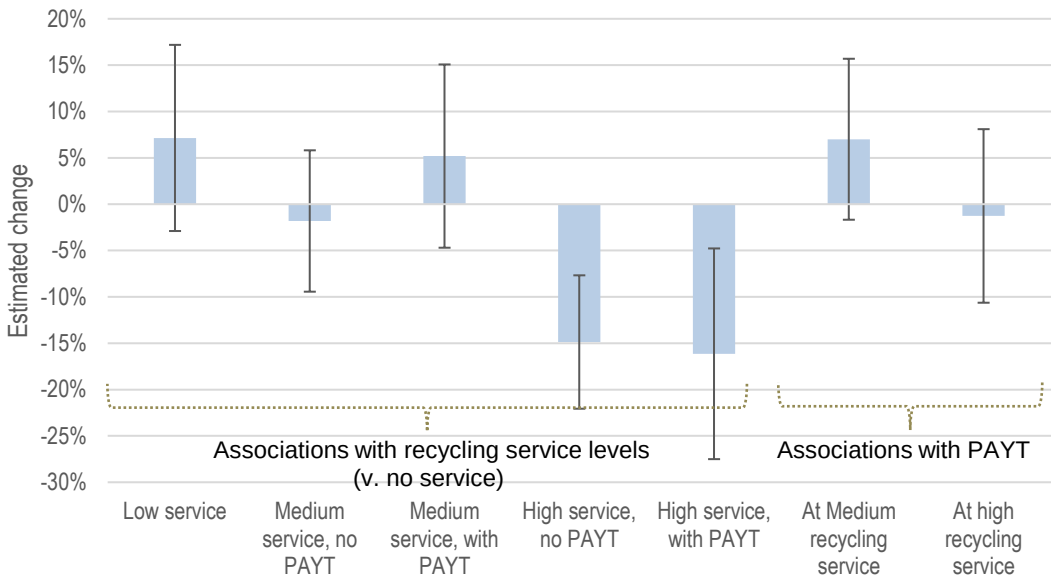
Log(income)	0.0732***	(0.0142)	0.278***	(0.0643)
Log(household size)	0.309***	(0.0265)	1.024***	(0.0950)
Children in the household (Base = no)	0.0484	(0.0295)	0.375***	(0.123)
Log(home size)	0.0162	(0.0178)	0.0782	(0.0746)
Renter (Base = no)	0.0515**	(0.0235)	-0.0555	(0.0801)
Higher education (Base = no)	-0.0320	(0.0198)	0.00741	(0.0663)
Residential location (Base = urban)				
Suburban	-0.0454**	(0.0198)	-0.0341	(0.0731)
Town/village	-0.122***	(0.0222)	-0.354***	(0.0837)
Rural	-0.200***	(0.0379)	-0.537***	(0.144)
Employment status (Base = employed)				
Homemaker/retired	0.0232	(0.0275)	0.0303	(0.0823)
Unemployed	0.0497	(0.0384)	-0.101	(0.170)
Student	-0.0694	(0.0474)	-0.128	(0.156)
Other (e.g. disability)	-0.0101	(0.0385)	0.0946	(0.132)
Environmental attitude profile (Base = environmentally neutral)				
Environmental prioritiser	-0.158***	(0.0261)	-0.287***	(0.0896)
Technological optimist	0.236***	(0.0326)	1.166***	(0.134)
Economic prioritiser	-0.0317	(0.0319)	-0.171	(0.126)
Country Fixed effects	Yes		Yes	
Observations	8,569		7,871	
Within R2	0.205		0.210	

Note: Country-level heteroskedastic linear regression estimated via maximum likelihood (hetregress command in Stata), with standard errors clustered by subnational regions. Statistical significance levels: *** < 1%, ** < 5%, * < 10%.

Figure 3.1. Self-reported mixed waste generation volume, estimated policy associations



Note: Calculated from regression results in reported in Table 3.2. Error bars are 95% confidence intervals.

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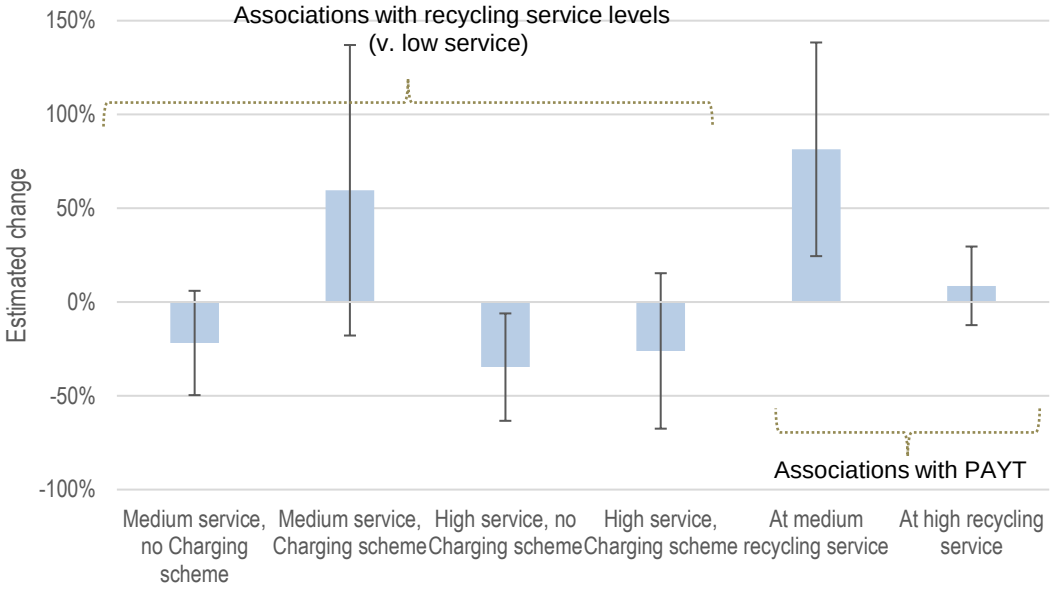
Figure 3.2. Self-reported recycling generation volume, estimated policy associations



Note: Calculated from regression results in reported in Table 3.2. Error bars are 95% confidence intervals.

To explore how policies, socioeconomic characteristics and attitudes associate with separation behaviours in more detail, fractional logit regressions are run on the percentage of each material separated. For each of the seven types of materials for which this outcome was measured, the reported percentage of material recycled per week was regressed on the same socioeconomic and attitudinal determinants as in the regressions in Table 3.2. The estimation sample for each of these regressions was specified as those who stated having at least some separation service available for that material. The policy variables included in these regressions are specific to the material type. Due to their size, regression results are presented in the Annex in Table A A.2.[12]

Regarding socioeconomic correlates of recyclables separation, age is significantly associated with greater percentage separation, though the relationship is nonlinear and diminishes among older respondents (given the consistently negative and significant coefficient on age^2). Female respondents report consistently lower separation percentages than male respondents. Income does not appear significantly associated with the number of specific materials recycled. Household size is associated with greater engagement in separation, though the presence of children in the household is associated with less engagement. One hypothesis explaining this pattern is that households with children face a more significant opportunity cost of time in the home, diminishing the incentive to sort waste types. Larger homes are associated with significantly more separation, which is intuitive insofar as greater space in the home reduces the inconvenience of having multiple receptacles for different waste types. This association is somewhat mirrored in the population density variables though the relationship is nonlinear, with residents in suburban and towns separating more versus those in cities or in rural areas, (perhaps due to greater transport time/cost/inconvenience in rural areas). Households that rent rather than own their primary residence are also significantly associated with lower percentage separation.

[12] For presentation purposes, standard errors are omitted from the table and only qualitative significance levels (1%, 5%, 10%) are shown.

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This result could be in part driven by the fact that the separation and disposal of separate waste streams are more difficult in apartment buildings with shared collection containers.

Regarding the attitudinal variables, *environmental prioritisers* separate more in percentage terms than the other attitudinal classes, whereas *technological optimists* separate the least percentage of their waste. This is counterintuitive given that these individuals tend to state that technological solutions (e.g. recycling) provide the main ways of dealing with environmental problems. It is also noteworthy that *technological optimists* are also associated with significantly more overall recycling volumes than *environmental prioritisers* (Table A A.2). This implies significantly less overall waste generation and more waste prevention among *environmental prioritisers* versus *technological optimists*, with *environmental prioritisers* recycling a greater percentage of the smaller amount of total waste that they generate.

The policy factor most consistently associated with greater self-reported recycling is the presence versus absence of a unit-based charge for mixed waste when there is drop-off recycling collection for a given material. For example, a charging scheme is associated with an approximately 10% increase in the ratio between the percent recycled versus percent disposed in glass, plastic packaging, and plastic containers; and an approximately 20% increase in this ratio for metal waste. Associations between percent separated and material-specific recycling service levels are inconsistent: kerbside programs are associated with lower separation versus drop-off for glass, but higher separation with plastics and metal waste. These inconsistencies may suggest selection issues with causal interpretation of these regressions (e.g. that kerbside recycling may be more likely to be implemented in areas with higher awareness and prevention effort regarding waste generation and recycling).

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4. Waste prevention behaviours

This section explores the determinants of household engagement in actions that prevent the generation of waste. It analyses survey responses that focus on how frequently households practiced nine different waste prevention behaviours: buying paper with recycled content, buying products that are less environmentally harmful (e.g. cleaning products), using refillable containers for purchases, using reusable shopping bags, renting or borrowing items (e.g. home improvement tools) instead of buying them, making homemade products (e.g. beauty or cleaning products), buying second-hand items, buying high quality items that will last, and repairing damaged items instead of buying new ones. Analysing the policy, socioeconomic, and attitudinal determinants of these behaviours is a complementary exercise to analysing the determinants of waste volumes generated. While the latter is the ultimate outcome of focus for environmental policies, waste prevention behaviours are instrumental for determining this outcome and can be easier for households to recall and answer, thus reducing potential measurement error.

Using the survey measurements on the above list of behaviours, a waste prevention index is constructed that sums the Likert-scale responses across all nine behaviours, with responses coded as 0 = 'Never / Don't Know', 1 = 'Occasionally', 2 = 'Often', 3 = 'Always'. To facilitate interpretation of the regression results, the index is then divided by three, so that a one-unit change in the index can be interpreted as the difference between never and always engaging in one of the nine listed behaviours. Annex Figure A A.1 shows the country-level distributions (i.e. histograms) for this index.

Table 4.1 reports the results from a linear regression of this index allowing for country-level heteroskedasticity, considering the same determinants as those used in Section 3. The table shows the estimated regression coefficients and marginal impacts (i.e. predicted percent change in the index score associated with a one-unit change in the explanatory variable). Regression results show strong and intuitive statistical associations between the waste policy variables and waste prevention behaviours. The presence of a unit-based charging scheme and separation services are significantly associated with greater engagement in waste prevention behaviours. Medium and high levels of recycling separation services, without a charging scheme, are associated with approximately 11-16% higher waste prevention scores. The presence of a charging scheme increases this association to 18-26%, controlling for other factors.

Socioeconomic characteristics that are positively and significantly associated with greater waste prevention effort include household size, the presence of children, and whether the respondent has a higher education. Households in suburbs and towns have lower waste prevention scores compared to those in urban and rural areas. Finally, attitudinal profiles are also highly predictive of waste prevention scores. *Environmental prioritisers* and *technological optimists* are respectively associated with an approximately 17% and 30% increase in waste prevention scores versus the *environmentally neutral*, and *economic prioritisers* are associated with a 7% decrease. The fact that *environmental prioritisers* and *technological optimists* are both associated with greater waste prevention (and *technological optimists* even more so than the *environmental prioritisers*) is notable given the contrasting effects on waste generation volumes seen in Table 3.2.

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Table 4.1. Determinants of waste prevention behaviours

	Waste prevention score (min = 0, max = 7)		Marginal impact on waste prevention score (∂ log(score)/ ∂x)	
Charging scheme X separation service level				
Low service	0.654***	(0.105)	0.163***	(0.0262)
Medium service, no charging scheme	0.649***	(0.0865)	0.161***	(0.0229)
Medium service, charging scheme	1.085***	(0.102)	0.256***	(0.0257)
High service, no charging scheme	0.448***	(0.0943)	0.114***	(0.0248)
High service, charging scheme	0.750***	(0.122)	0.184***	(0.0301)
Age	-0.00764	(0.00765)	-0.00178	(0.00178)
Age^2	2.98e-05	(8.14e-05)	6.94e-06	(1.90e-05)
Gender (Base = male)				
Female	0.178***	(0.0359)	0.0417***	(0.00838)
Other	-0.0262	(0.153)	-0.00628	(0.0366)
Log(income)	-0.0222	(0.0337)	-0.00517	(0.00785)
Log(household size)	0.195***	(0.0368)	0.0455***	(0.00866)
Children in the household	0.0992**	(0.0470)	0.0230**	(0.0109)
Log(home size)	0.0345	(0.0444)	0.00805	(0.0104)
Renter	-0.0636**	(0.0298)	-0.0149**	(0.00696)
Higher education	0.197***	(0.0318)	0.0456***	(0.00731)
Residential location type (Base = urban)				
Suburban	-0.160***	(0.0463)	-0.0371***	(0.0108)
Town/village	-0.187***	(0.0504)	-0.0436***	(0.0118)
Rural	-0.0264	(0.0924)	-0.00602	(0.0211)
Employment status (Base = employed)				
Homemaker/retired	-0.0594	(0.0415)	-0.0139	(0.00973)
Unemployed	-0.0729	(0.0888)	-0.0171	(0.0209)
Student	-0.0881	(0.0818)	-0.0207	(0.0193)
Other (e.g. disability)	0.00849	(0.0657)	0.00197	(0.0152)
Environmental attitude profile (Base = environmentally neutral)				
Environmental prioritiser	0.735***	(0.0587)	0.172***	(0.0140)
Technological optimist	1.268***	(0.0797)	0.296***	(0.0190)
Economic prioritiser	-0.299***	(0.0831)	-0.0697***	(0.0194)
Country fixed effects	Yes			
Sample mean of dependent variable	4.40			
Observations	8,569			
Within R-squared	0.1781			

Note: Country-level heteroskedastic linear regression estimated via maximum likelihood (hetregress command in Stata), with standard errors clustered by subnational regions. Marginal impacts computed for discrete variables as discrete changes (using margins command). Statistical significance levels: *** < 1%, ** < 5%, * < 10%.

The fact that households appear to respond to charging schemes in their prevention behaviours as reported above, but not in the amount of waste that they generate (as reported in Section 3) suggests further studies are needed to determine whether this finding stems mainly from measurement error in the survey-elicited waste volumes or points to potential ineffectiveness in household waste prevention efforts. Such ineffectiveness could arise from systemic constraints that households face in reducing the amount of waste that they generate, such as a lack of availability of minimally packaged consumer products

5. Food waste generation

This section examines the correlates of household food waste generation. The survey asked respondents about the frequency with which their households "usually" throw away each of six different types of food (fruits/vegetables, bread, meat/seafood, dairy/eggs, packaged shelf-stable foods, meal leftovers).[13] For analysis, these responses are aggregated into a single household food waste behaviour index similar to the waste prevention index in Section 4, here by summing the number of items a household indicates as "frequently" throwing away.[14] Like the waste prevention index in Section 4, the food waste behaviour index analysed here has advantages (better respondent recall, lower measurement error) and disadvantages (instrumental and unobserved relationships with target policy outcomes) compared to physical quantity measures. Table 5.1 shows the summary outcomes by country.[15]

Table 5.1. Percentage of households indicating that they usually throw away food

Country	No food items	Some food items	All food items listed
BEL	43%	53%	4%
CAN	38%	59%	4%
CHE	50%	49%	1%
FRA	54%	44%	2%
GBR	35%	62%	3%
ISR	15%	75%	10%
NLD	35%	59%	6%
SWE	34%	62%	4%
USA	28%	64%	8%

The factors that could be correlated with food waste behaviours investigated in this analysis include socioeconomic and household characteristics, environmental attitudes, as well as certain waste policies. One policy-related variable that is notably included is the provision of food waste collection services. Based on the literature review in Section 1.1, the correlation between having a composting service available and the number of types of food thrown away is not clear, particularly when a charging scheme for mixed waste generation is also in place. On the one hand, the presence of municipal or

[13] The survey did not specify whether 'throw away' included disposal in separated compost, though we interpreted this to be the case. However, it should be noted that without specification in the survey, respondents could have interpreted this wording differently (e.g. 'throw away' specifically meaning disposal with mixed waste only and not with separated compost).

[14] These data are analysed using a fractional logit regression model, where the index is rescaled as the fraction of the six listed items households indicated as frequently throwing away. For the policy variables in this regression, an aggregated food-waste-specific (i.e. compost) collection service is defined as either "kerbside," "drop-off, bring to store or 'other'," or "none / I don't know". Robustness of the regression results was confirmed with a standard linear OLS as well as several other models.

[15] Country-specific histograms of the constructed index are provided in the Annex Figure A A.2.

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commercial composting services may enhance household awareness of food waste and thereby contribute to fewer types of food being discarded. On the other hand, easy access to composting could lessen negative feelings about throwing away food and, in the presence of a charging scheme pricing, the marginal cost of throwing away food (e.g. Qi and Roe, (2017[25])).

Table 5.2 presents the estimated marginal impacts of various factors on the food waste index, i.e. the predicted percent changes in the number of food types discarded associated with a one unit increase in each explanatory factor. Kerbside composting availability is significantly associated with a 9.6% higher food waste score. The direction of this association is consistent with multiple explanations: One possibility is that individuals feel more licensed to throw a higher number of food types away if they compost. Another possibility is that those who generate more types of food waste *ex ante* may select into kerbside composting programs when such programs are opt-in. Unit-based charging schemes are not significantly associated with greater or fewer types of food waste. Regarding socioeconomic characteristics, male and female respondents do not appear to exhibit significantly different food waste scores, but those indicating their gender as 'other' or 'prefer not to say' are associated with a 43% higher food waste score. In contrast to the waste prevention behaviour regressions (Table 4.1), income and household size show no significant association with the number of different types of food discarded. However, the presence of children is associated with a 12% higher food waste score. Households that rent versus own their primary residence also appear to throw away significantly more food types, as do individuals living in urban areas, with those in rural areas associated with a 33% lower food waste score compared to those in urban areas. Retirees and those who report being a homemaker have 24% lower food waste scores. Of the attitudinal classes, *technological optimists* have 26% higher food waste scores compared to the other classes.

One important caveat in interpreting these regression results is a potentially large heterogeneity in composting service provision as compared to other wase separation services. For example, a recent survey of composting facilities in the US found that 75% of surveyed facilities were commercially owned (Biocycle, 2023[32]), and a number of commercial operators around the US sell collection services to households on a voluntary basis. In other areas and countries, food waste collection is provided as a municipal service and separation is sometimes compulsory (e.g. Milan (MiZA, 2022[33])). This complicates the interpretation of estimated associations between the types of food discarded and compost services. For instance, selection issues may exist if households that discard many types of food decide that they wish to pay for a commercial service and if households that discard fewer types of food are not aware of such commercial services if they perceive no need for them.

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Table 5.2. Determinants of number of food types discarded

Semi-elasticities for food waste index

	Marginal impact on food waste index	
	Estimate	s.e.
Composting service availability (base = no availability)		
Drop-off compost collection available	0.0118	(0.0539)
Curbside compost collection available	0.0960**	(0.0442)
Collective compost facility vs. at home composting	0.0418	(0.0353)
Waste charging scheme in place	0.0113	(0.0299)
Age	-0.000469	(0.00663)
Gender (Base = male)		
Female	0.00277	(0.0296)
Other	0.430***	(0.147)
Log(income)	0.0266	(0.0309)
Log(household size)	0.0432	(0.0328)
Children in the household (Base = no)	0.122***	(0.0471)
Log(home size)	0.0817***	(0.0280)
Renter (Base = no)	0.102***	(0.0311)
Higher education (Base = no)	0.0164	(0.0339)
Residential location type (Base = urban)		
Suburban	-0.0851*	(0.0443)
Town/village	-0.0952***	(0.0349)
Rural	-0.334***	(0.0655)
Employment status (Base = employed)		
Homemaker/retired	-0.244***	(0.0448)
Unemployed	-0.00952	(0.0787)
Student	-0.136**	(0.0599)
Other (e.g. disability)	-0.0757	(0.0780)
Environmental attitude profile (Base = environmentally neutral)		
Environmental prioritiser	0.0111	(0.0458)
Technological optimist	0.259***	(0.0530)
Economic prioritiser	0.0689	(0.0594)
Country fixed effects	Yes	
Sample mean index (fraction of items thrown away)	0.254	
Observations	6,155	
Within Pseudo-R^2	0.308	

Note: Fractional logit regression model, dependent variable is fraction of six listed food items household throws away (Stata command is fracreg logit). Standard errors clustered by subnational regions. Marginal impacts computed for discrete variables as discrete changes (using margins command). Statistical significance levels: *** < 1%, ** < 5%, * < 10%. Age2 was also controlled for but was not significant.

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6. Preferences for waste-related policies

This section explores the determinants of household preferences for waste-related policies. The survey asked households to identify the three most important factors that would encourage them to recycle or compost more, from a list of nine possible items, including: more practical information on how to engage in recycling or composting, greater financial incentives (e.g. saving or receiving money), more space at home for recycling or composting, simpler requirements for recycling (e.g. less sorting needed), more accessible collection or drop-off services, more frequent collection of recyclable or compostable items, better evidence of the environmental benefits of recycling, having the option to get recycled/composted waste collected from one's home, and cleaner containers to use for recycling and composting.

A descriptive analysis of these data in OECD (2023[1]) show that on average households judge 'more money', 'home collection,' and 'more accessible' collection as the most important factors in encouraging them to recycle and compost more. Here, socioeconomic characteristics, existing policies, and environmental attitudinal profiles are examined as potential factors that could be correlated with policy preferences. Given that survey respondents provided a partial ranking of the nine different potential policy changes, a partially-rank-ordered logit regression model is used to estimate the relationships between these potential correlates and respondents' waste policy preferences. Given the large volume of estimation results from this regression model, they are provided in Annex Table A A.3. Figure 6.1 below summarises the results regarding estimated associations between the existing policy context and respondents' views on policy factors to target for improvement.

Controlling for respondent socioeconomic and attitudinal characteristics, the regression results in Figure 6.1 show that respondents subject to a unit-based charging scheme viewed evidence of environmental benefits and home collection as relatively more important factors encouraging more recycling. The existing level of recyclables separation services is also associated with program preferences in intuitive ways. Greater accessibility is a relatively less important factor in areas with already high levels of separation and collection services. However, in such areas, households are more likely to rank financial incentives and collection frequency as the most important ways to encourage more recycling. This suggests that residents in such areas may face capacity constraints, as well as incur more opportunity costs of time in sorting and separating recyclables. Meanwhile, respondents with medium levels of separation services were relatively more likely to rank cleaner containers as a more important factor.

Socioeconomic characteristics also correlate with stated factor rankings in intuitive ways (Table A A.3). Higher incomes are associated with a decreased relative importance placed on financial incentives, whereas the presence of children in the household increases the relative importance of more space, simpler sorting, and more frequent collection. Households that rent versus own their primary residence place more importance on more space, more accessibility, and cleaner containers, which could be due to communal containers in multi-unit settings. Relative to urban households, those in small towns and villages expressed relatively greater preferences for more accessible services, simpler sorting, home collection, and greater financial incentives. General environmental attitudes are also associated with waste policy preferences: *environmental prioritisers* placed significantly less relative importance on financial incentives, simpler sorting, better evidence of environmental benefits, and cleaner containers, whereas *economic prioritisers* ranked financial incentives, simpler sorting, and better evidence of benefits as significantly more important.

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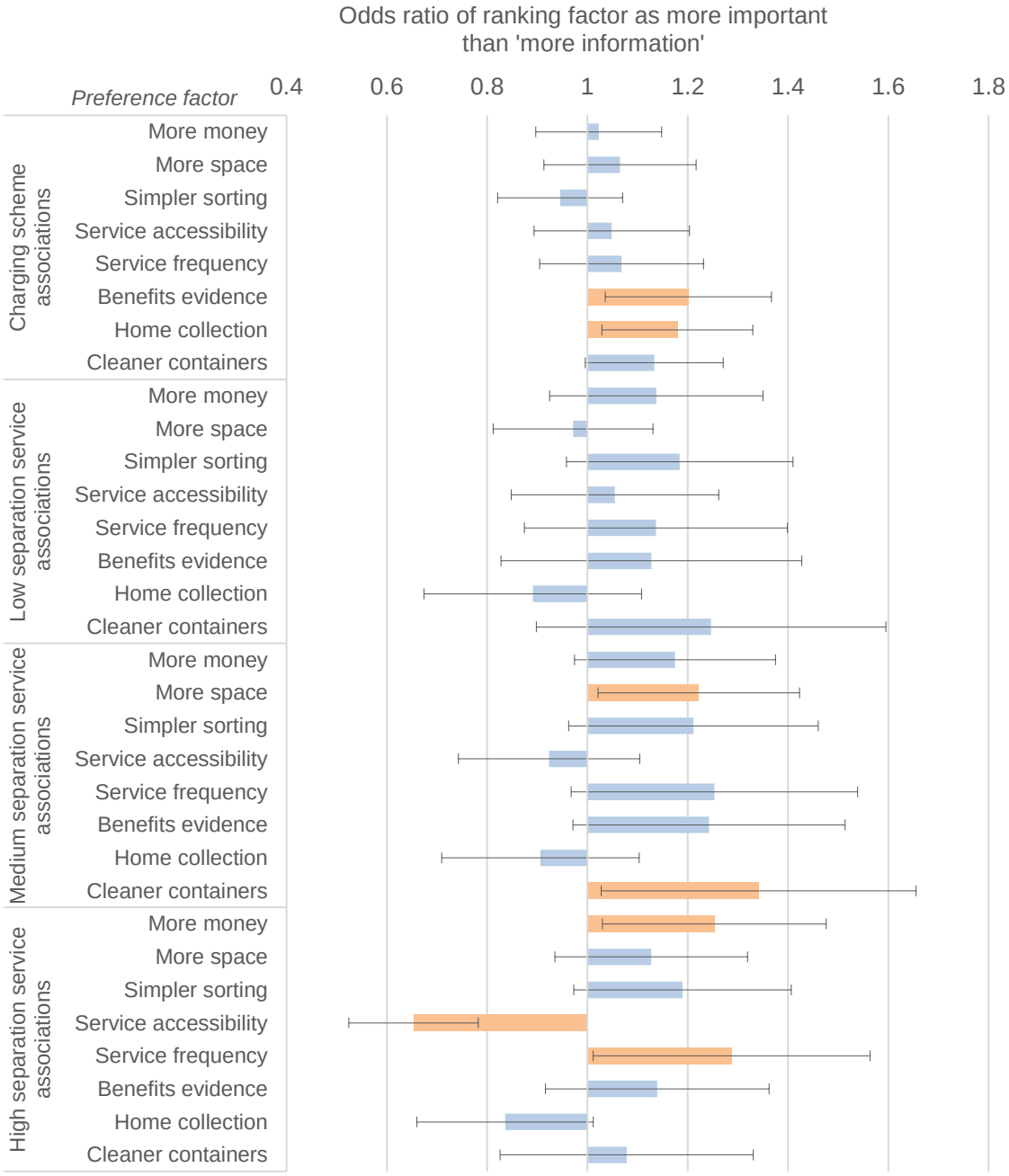
Figure 6.1. Waste policy associations with factors ranked by respondents as most important in encouraging recycling and composting.



Note: Estimates from a rank-ordered logit model with country fixed effects. Error bars are 90% confidence intervals; bars in orange are statistically different from one (i.e. no change in the odds ratio). Odds ratios (OR) shown here are obtained from the log-odds (LO) reported in Table A A.3 by the formula $\mathrm{OR} = \exp(\mathrm{LO})$, with odds ratio confidence intervals calculated using the delta method. Under charging scheme associations, for example, an odds ratio of 1.20 for 'benefits evidence' means that those who are subject to a charging scheme for mixed waste generation have 1.2 times the odds of rating evidence of the benefits of recycling as more important than generic information on how to recycle, compared to respondents not subject to a charging scheme. Within-country generalised (Cox and Snell) $R^2 = 0.09$. See Annex Table A A.3 for full estimates.

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7. Willingness to pay for more sustainable product packaging

This section presents the results of the discrete choice experiment (DCE) regarding household waste behaviour included in the 2022 EPIC Survey. In this experiment, households were asked to consider hypothetical purchase scenarios in which different laundry detergents were available for purchase. The purpose of this DCE was to investigate the degree to which respondents preferred and were willing to pay for more sustainable packaging, including recyclable and reusable deposit-refund options. More information on discrete choice experiments is provided in Box 7.1

Box 7.1. Using discrete choice experiments to a better understand decision-making

In discrete choice experiments, subjects are asked to make hypothetical choices by selecting a preferred alternative from a menu of options (Bateman et al., 2002[29]; OECD, 2018[28]). Stated preference data generated by discrete choice experiments enable an estimation of how much respondents value the various characteristics of the options presented. These characteristics could relate to products (e.g. the price of, or GHG emissions from, energy supply); actions (e.g. convenience of using disposable rather than refillable containers); or elements directly affected by environmental policies (e.g. the cost and convenience of owning an electric car).

Despite the challenges of survey-based research noted in Section 2.1, stated preference approaches offer a number of significant advantages over revealed preference approaches when it comes to ex-ante policy evaluation (OECD, 2018[28]). Discrete choice experiments, for example, are well-suited to analysing choice in the context of relatively complex, multi-dimensional issues (Bateman et al., 2002[29]; OECD, 2018[28]). Flexibility to define decision scenarios allows for an evaluation of the impact of hypothetical policy interventions. Stated preference approaches also generate valuations of changes in health status and environmental quality that provide critical input into cost-benefit analyses.

Discrete choice experiments also generate data that provide a richer picture of preferences than simpler stated preference elicitation methods. The data generated by choice experiments allow for an estimation of how much respondents value the characteristics of the options being considered, also known as willingness-to-pay. Examples include travel time, travel cost, and comfort for transport mode options, or cost and convenience for waste reduction practices. The data can also provide insights into how respondents make trade-offs between these characteristics and how sensitive their choices are to changes in the characteristics of the options presented. The EPIC Survey data allow for disaggregation at the household level to understand how these values and sensitivities vary across the population according to location or socioeconomic variables such as age, income and gender.

Previous recent literature has found that consumers value the environmental benefits of more sustainable packaging (e.g. De Marchi et al. (2020[34])) but also consider the cost, perceived safety, time and convenience involved with these different options (Berck et al., 2024[35]) Consumers may also consider their waste collection service policies in place when valuing such alternatives: For example, unit-based mixed waste charging increases the cost of disposing of non-recyclable packaging, whereas a lack of recycling separation service limits the effective environmental impact consumers can achieve

by purchasing products with recyclable packaging. The analysis here addresses these hypotheses and adds to prior literature by expanding the geographic scope of existing work, which contributes to establishing greater externality validity of findings.

The menu of products in the DCE was experimentally varied according to their price and the type of packaging used, holding other attributes of the product constant. Four types of packaging were considered: a disposable container, a recyclable paper container, a recyclable plastic container, and a reusable container in which a deposit is made for initial purchase. Respondents were asked to make this choice six times, and the menu of products varied between each choice task.[16] The experiment allows for the estimation of households' willingness to pay (WTP) for these products.[17]

Results indicate that different groups of households have different preferences regarding sustainably packaged products (Table 7.1).[18] One group of households (21% of sample) avoid the sustainably packaged options in the DCE, requiring discounts between 14-36% relative to the price of the disposable product to purchase them. A second group (19% of sample) are willing to pay a premium for the more sustainably packaged products, and are willing to pay a 105% premium for the paper recyclable option and a 55% premium for the recyclable plastic option, and a 15% premium for the deposit-refund reusable option (vs. the disposable option). A third group, the largest in all countries of the sample and 57% overall (Table 7.1), prefers the reusable product most and is willing to pay somewhat less for sustainably packaged products over the disposable option. In particular, this group of households demonstrated a willingness to pay a 60% premium for the reusable packaging, a 18% premium for recyclable paper option and a 20% premium for a recyclable plastic option, vs. the disposable option. A small remaining group of households (4% of the sample) appear insensitive to the product price, as seen by the regression coefficient on the cost attribute for this class, which is statistically indistinguishable from zero.[19]

[16] An example choice set is provided in the Annex.

[17] Further details on the choice model used in the analysis of the discrete choice experiment are provided in the Annex.

[18] Results from a base conditional logit model as well as a four-class latent class choice model (LCCM) are reported in the Annex. The LCCM performs better than the homogenous preference model based on conventional statistical measures (e.g. Bayesian or Akaike information criteria), despite having far more parameters (primarily from the class membership model).

[19] As a consequence, the WTP of this class for the different products cannot be computed.

Table 7.1. Results from sustainable packaging choice experiment

Parameter estimates for packaging type attributes and WTP estimates for each packaging type

	Pooled results (conditional logit)	*Results by household group* (latent class logit)			
		Avoids sustainable packaging	*Prefers recyclable packaging*	*Prefers reusable packaging*	*Price indifferent*
Percent of sample		21%	19%	57%	4%
Parameter estimates (s.e)					
log(Cost)	-3.146***	-2.286***	-3.043***	-5.928***	-0.298
	(0.154)	(0.278)	(0.307)	(0.324)	(0.808)
Recyclable paper	0.490***	-0.983***	2.187***	0.987***	0.276
	(0.0398)	(0.189)	(0.282)	(0.0568)	(0.299)
Recyclable plastic	0.588***	-0.337***	1.330***	1.102***	3.253***
	(0.0205)	(0.0804)	(0.200)	(0.0493)	(0.271)
Reusable	0.919***	-1.036***	0.436***	2.768***	0.0576
	(0.0452)	(0.181)	(0.107)	(0.0806)	(0.334)
Class distribution		20.60%	18.80%	56.50%	4.10%
Willingness to pay, as % percent of disposable price (s.e)					
Recyclable paper	16.9% ***	-35.0%***	105.2% ***	18.1% ***	-
	(1.47%)	(3.98%)	(14.1%)	(1.44%)	
Recyclable plastic	20.6% ***	-13.7% ***	54.8% ***	20.4%***	-
	(1.34%)	(2.16%)	(8.04%)	(1.45%)	
Reusable	33.9%***	-36.4% ***	15.4% ***	59.5% ***	-
	(2.72%)	(3.10%)	(4.52%)	(5.10%)	
Respondent type description	(full sample representative consumer)	Avoids all sustainable packaging	Prefers recyclable paper & plastic	Prefers reusable	Price insensitive (prefers recyclable plastic)
Respondents	8,569	8,569			
Choice tasks	51,414	51,414			
Parameters	4	50			
Log-likelihood	-45,735	-38,662			

Note: Conditional logit model estimated via maximum likelihood. Latent class logit estimated via hybrid EM-maximum likelihood algorithm using the user-written lclogit2 package in Stata (Yoo, 2020[36]). Standard errors clustered by subnational regions in parentheses. Percent WTP estimates are obtained using the formula for θ_j^{WTP} with standard errors estimated using the delta method (nlcom command in Stata). See the Annex for latent class membership prediction model. Statistical significance levels: *** < 1%, ** < 5%, * < 10%.

The group of households that are indifferent to price appears to have focused only on the recyclable plastic product in the DCE, as the full set of fitted regression coefficients for this class imply that this product would be selected on over 90% choice occasions that include this option versus any other alternative. Price insensitivity is a form of attribute non-attendance in DCEs, a common challenge to which much prior research in has been devoted to identifying and reducing (see Johnston et al. (2017[37])). Given that the scope of the problem in this application evidently pertains to only 4% of the sample, this class is excluded when analysing WTP for the different types of sustainable packaging.[20]

[20] It is worth noting that excluding this 4% could substantively affect mean WTP estimates to the extent that this small subsample may have large WTP values (since their marginal utility of money is evidently small and insignificant).

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To analyse the types of individuals belonging to these different classes and to examine their varying distributions between countries, two additional tables are provided. Table A A.4 in the Annex shows the policy and household characteristics that are associated with household membership in each group, and Table 7.2 shows the distributions of the classes and the estimated mean WTP for each product across countries.

Several policy, socioeconomic, and attitudinal characteristics appear to be associated with preferences and WTP in the DCE. As seen in household income and size are positively associated with preferences for sustainable options, with a 10% increase in income or an increase of household size from one to two members associated respectively with a 0.2-0.3% and a 3% shift towards the likelihood of preferring the recyclable over the reusable alternatives. This finding could suggest that the inconvenience of the reusable option may limit its desirability.

Regarding policy factors, higher levels of recycling services are systematically and progressively associated with a 6-13% decrease in the likelihood of avoiding all the sustainable packaging options (Table 7.2). This finding is intuitive and aligns with economic theory. Assuming that households generally prefer to make sustainable choices, all else equal, those with more extensive recycling collection services should be more inclined to choose recyclable packaging, and the motivation to do so should become even stronger in the presence of an economic incentive such as a unit-based waste charging scheme. Indeed, results indicate that the presence of a unit-based charging scheme is associated with an approximately 8-10% increase in the likelihood of the household preferring recyclable packaging over reusable alternatives.

Concerning the impact of attitudes, *environmental prioritisers* (versus the *environmentally neutral*) are 24% less likely to avoid the sustainably packaged options in the DCE, and 4% and 19% more likely to prefer the recyclable and reusable packaging, respectively (Table 7.2). *Technological optimists*, meanwhile, are associated with a 13% greater likelihood of preferring the recyclable options and a concomitant lower likelihood of preferring the reusable option. *Economic prioritisers* are unsurprisingly the most likely to avoid the more sustainably packaged products.

In terms of differences across countries, the Netherlands, Belgium and Switzerland display the highest prevalence of households that most preferred the reusable container (over 62%), with associated mean WTP premia for this product of over 33% (Table 7.2). Sweden has a high prevalence of households that most prefer the recyclable options (32%), with a mean WTP premium of 36% for the recyclable paper option (higher than the country's mean WTP for either the recyclable plastic or reusable options). The US has the highest prevalence of households that sought to avoid any of the sustainably packaged alternatives in the DCE, and consequently had among the lowest mean WTPs (along with Israel) for any of the recyclable or reusable options.

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Table 7.2. Country-level mean willingness to pay estimates and latent class distributions

	BEL	CAN	CHE	FRA	GBR	ISR	NLD	SWE	USA
Household groups									
Avoids sustainable packaging	19.6%	17.8%	14.1%	17.9%	22.9%	26.1%	18.7%	19.3%	29.0%
Prefers recyclable packaging	14.8%	14.1%	21.3%	17.9%	16.9%	15.2%	14.7%	31.5%	18.5%
Prefers reusable packaging	62.7%	61.4%	62.5%	59.7%	58.3%	56.5%	63.1%	47.4%	45.2%
Price indifferent	2.9%	6.8%	2.1%	4.5%	2.0%	2.2%	3.5%	1.8%	7.3%
Mean WTP among the price sensitive (as percent of the price of an item with disposable packaging)									
Recyclable paper	20.6%	21.1%	29.4%	24.5%	20.7%	17.5%	21.1%	35.7%	19.0%
Recyclable plastic	18.8%	19.1%	23.0%	20.5%	18.4%	16.7%	19.0%	24.8%	16.7%
Reusable	33.4%	34.8%	36.1%	33.4%	29.7%	27.1%	34.3%	26.6%	21.2%

Results pointing to a possible link between waste policies such as recycling collection service provision and preferences for sustainable packaging is policy-relevant in light of policy goals to reduce plastic pollution and the use virgin plastics in consumer products, as exemplified by the implementation of taxes on packaging containing non-recycled or non-recyclable plastics in several OECD countries and subnational jurisdictions (OECD, 2022[38]) Such taxes are expected to increase the cost of such products, and ultimately for consumers, thereby decreasing the demand for them. The finding that consumer demand for more sustainably packaged products is associated with residential waste management policies in place suggests that achieving a more circular economy in consumer products will involve interactions between both policies that involve traditional waste management measures and policies oriented towards extended producer responsibility (Tumu, Vorst and Curtzwiler, 2023[39]). The consumer welfare implications of these interactions are also important for policymakers to consider. For example, these choice experiment results would suggest that the welfare losses to consumers from increased taxes on a non-recyclable detergent would be lower when greater levels of recycling services are available. Further analyses of such consumer welfare effects using observed product sales data will be important for assessing net economic impacts, as more experience is gained with the implementation of such taxes.

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8. Policy considerations for waste prevention and management

The comparative advantage of the EPIC Survey data for examining household waste behaviour lies in the breadth of the specific behaviours and attitudes elicited, in conjunction with detailed household characteristics and the broad contextual variation within and between countries. Within the EPIC data, the waste-related data is distinguished because it includes information on a number of policies regarding households' waste-related choices, enhancing the suitability for evaluating the potential impact of policies on household behaviour. The analyses contained here highlight the importance of a variety of factors in determining households' waste-related choices.

Specifically, the analysis points to four major attitudinal profiles among households: *environmental prioritisers, technological optimists, economy prioritisers,* and the *environmentally neutral*. The analysis shows that pro-environmental attitudes are associated with more sustainable household choices with respect to a variety of waste-related practices including waste generation, waste prevention, as well as preferences for sustainably packaged products. To the extent that informational campaigns, education, and social marketing can influence environmental attitudes, these findings point to the general relevance of such efforts in fostering sustainable household choices related to waste generation. Between-country variation in both waste-related behaviours analysed here and in environmental attitudes means that country-specific conditions should be considered in determining optimal policy approaches to the management of household waste .

Recycling collection supports reduced mixed waste generation. With respect to the impact of waste polices on household behaviour, the analysis provides strong evidence that recycling collection services are associated with reduced volumes of household mixed waste generation. The results also indicate that the presence of recycling collection services is associated with greater engagement in waste prevention behaviours. These findings agree with existing literature and point to the critical role of recycling collection service provision in providing households with a low-cost and convenient option for diverting discarded material from the stream of mixed waste.

Compost services should be combined with measures to reduce food waste. A counter-intuitive finding with respect to food waste is that kerbside compost services and residing in an urban area are associated with households throwing away more types of food. Given the number of possible policy-relevant explanations for this finding, further empirical investigation is warranted. In light of current policy focus on composting as a component of policy options to reducing food waste (UNEP, 2023[40]) as well as on urbanisation and densification as strategies for sustainable development (Pont et al., 2021[41]), analysis of the present data therefore points to a need to better understand and anticipate unintended consequences from scaling up municipal composting, such as increases in the number of types of food discarded as food waste (even if a higher proportion of that waste is diverted to composting) and higher-than-anticipated production of compost. High-quality causal assessments of the effects of municipal compost programs on food waste generation remain lacking.

Charging schemes and collection services can stimulate sustainable practices and support demand for sustainable consumption. While no association is found between unit-based waste

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charging schemes and reported waste generation,[21] the presence of charging schemes is associated with increased recycling volumes as well as a stronger association between recycling collection services and reduced mixed waste. The lack of evidence for a significant direct association between charging schemes and waste generation volumes could be due to several data-related factors that call for further empirical analysis.[22] Waste charging schemes are, however, significantly associated with greater waste prevention behaviours. This finding is important because waste prevention behaviours are instrumental precursors to waste generation, and the association found here between charging schemes and instrumental behaviours suggests that charging schemes may have causal effects on instrumental behaviours. Research exploring such potential causation is currently needed. Furthermore, the analysis also suggests that survey respondents with higher levels of recycling collection services are willing to pay more for products with recyclable or reusable packaging. While more research is needed to determine whether this association is causal in nature, it suggests that waste policies could play a role in stimulating demand for sustainable consumption.

[21] A discussion on the possible reasons for this finding are provided in Section 3.

[22] Potential data-related factors that could explain this result are discussed further in Section 3.

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Annex A

Supplementary material for Section 2

Descriptive statistics

Table A A.1. Summary of respondent socioeconomic characteristics

Variable	Mean / Total	Standard Deviation
Respondents	8,569	
Age	49.2	17.8
Gender		
Male	45%	50%
Female	54%	50%
other / prefer not to say	1%	9%
Annual household income (USD)	$91,806	$107,811
Household size	2.6	2.0
Number of children in household	0.7	1.6
Any children in household	30%	46%
Home size (sq. m.)	110	57
Renters	36%	48%
Higher education	43%	49%
Residential location		
Urban	34%	47%
Suburban	26%	44%
Town/village	35%	48%
Rural	5%	21%
Employment status		
Employed	57%	49%
Homemaker/retired	28%	45%
Unemployed	4%	20%
Student	5%	21%
Other (e.g. disability)	6%	24%

Table A A.1 presents the means and standard deviations of the socioeconomic characteristics that are used as covariates throughout the analysis here to explain waste outcomes. The statistics pertain to the waste-specific subsample of the survey, which are nearly identical to those from the full sample of 17,216 respondents due to the random assignment of respondents to different sections. The statistics are mainly presented in this table to describe a representative respondent in the sample. They are older middle-aged, roughly equally likely to be male or female, have roughly a three-in-five chance of being employed, and a two-in-five chance of having attained higher education (college or greater). They usually live with at least one other person, with a 30% chance of a child being present, earning a combined $92 thousand USD in annual household income, in a 110 square meter home that is typically owned, located with roughly equal likelihood in a large urban or suburban area or small town.

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Data preparation and econometric notes

Survey weighting, standard errors and country fixed effects

Survey weights are applied in regression analyses.[23] Asymptotic standard errors are computed by clustering at the sub-national, region level, which allows for potential serial correlation in econometric error within region (more conservative standard error estimates). Country fixed effects are included throughout, implying that all estimated effects reflect *within* country variation in outcomes and determinants. Country fixed effects are considered as a middle ground between only running country-level regressions which greatly reduces statistical power, and running a single pooled regression with one regression constant, which is overly restrictive given the cross-country nature of the data. In addition to country fixed effects, in some linear regression models based on specification tests, parametric country-level heteroskedasticity is considered in estimation (not just standard error computation). This models country-level differences in the conditional means *and* variances of the dependent variable.[24] This model is less restrictive and thus more robust than the simple linear fixed effects model.

Interval data imputation

A number of the outcomes analysed in this report were measured using survey questions involving interval responses, e.g. income, mixed waste and recyclables generation and percentage separation. For these variables, a continuous outcome measure is imputed using a country-level interval regression without covariates other than a constant. This is particularly useful for determining a finite, data-guided imputed value for responses on an unbounded interval (e.g. households indicating their income or mixed waste generation is greater than *X* USD or litres). The interval regression specifies the unobserved outcome y_{ic} for household i in country c as following a transformed normal distribution:

$$f(y_{ic}) = \mu_c + \epsilon_{ic}$$

where $f(\cdot)$ is an appropriately specified, strictly monotonic transformation function (e.g. the logarithm of income), μ_c is the country-level mean for the outcome and $\epsilon_{ic} \sim \mathcal{N}(0, \sigma_c^2)$ is observation i's normally distributed deviation from the mean. Interval regression estimates $\hat{\mu}_c$ and $\hat{\sigma}_c^2$. The imputed outcomes can then be obtained as the conditional expectation of the transformed y_{ic}, given $\hat{\mu}_c$ and $\hat{\sigma}_c^2$ and the lower and upper bounds $\underline{y}_i$and $\overline{y}_i$ pertaining to each survey interval response i for the outcome:

$$\hat{y}_{ic} = f^{-1}\left\{\mathbb{E}\left[f(y_{ic})|\hat{\mu}_c, \hat{\sigma}_c^2, \underline{y}_i \leq y_{ic} < \overline{y}_i\right]\right\}$$

$$f(y_{ic}) = \mu_c + \epsilon_{ic}\hat{y}_{ic} = f^{-1}\left\{\mathbb{E}\left[f(y_{ic})|\hat{\mu}_c, \hat{\sigma}_c^2, \underline{y}_i \leq y_{ic} < \overline{y}_i\right]\right\}$$

[23] More information on the design, implementation and representativeness of the OECD EPIC Survey is provided in OECD (2023).

[24] The general heteroskedastic fixed effects regression model of the dependent variable y_{ic} on the explanatory variables $\boldsymbol{X}_{ic}$ for observation i in country c takes the form $y_{ic} = \boldsymbol{\beta}\boldsymbol{X}_{ic} + \alpha_c + \sigma_c\epsilon_i$, where $\boldsymbol{\beta}$ are the regression coefficients, α_c are country fixed effects, ϵ_i is a standard normal regression error, and σ_c are country-specific variances. Maximum likelihood estimation is used in Stata via the *hetregress* command, which also provides test statistics for whether there are significant differences between the country-level variances σ_c.

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Supplementary material for Section 3

Table A A.2. Fractional logit regression estimates of determinants of percent of recyclable material separated, by material

Marginal effect of variables on percent of material separated

Variable	Glass	Plastic containers	Plastic packaging	Metal	Batteries	Food waste	Paper/cardboard	Paper (Israel)
Charging scheme (base = no)	0.00556	0.00679	0.00964	0.0191*	0.0228**	0.0140	0.00672	-0.00148
Separation service (base = drop-off)								
Kerbside	-0.0352***	0.00358	0.0191*	0.0116	-0.0643***	0.0151	0.0177**	-0.117***
Bring to store	-0.0342**	-0.0105	-0.0128	0.0125	0.0196	-0.00427	-0.0467*	0.0887*
Age	0.00516**	0.00601***	0.00523**	0.00951***	0.00921***	0.00140	0.00687***	0.00245
Age2	-3.89e-05*	-5.16e-05**	-4.14e-05*	-8.36e-05***	-6.98e-05***	-5.08e-06	-5.73e-05**	-2.86e-05
Gender (Base = male)								
Female	-0.0224**	-0.00983	-0.00924	-0.0219**	-0.0448***	0.00547	-0.00649	-0.00417
Other / Prefer not to say	-0.0377	-0.0366	-0.0919**	0.0208	0.0149	0.0151	-0.0225	
Log(income)	0.00648	-0.00114	0.00926	0.000154	0.00229	0.00408	0.0108	0.00739
Log(household size)	0.0255***	0.0180*	0.0190**	0.0235**	0.00877	0.0227*	0.0149	-0.0472***
Children in the household (Base = no)	-0.0520***	-0.0437***	-0.0332***	-0.0371***	-0.0229	-0.0222	-0.0294**	-0.00661
Log(home size)	0.0288***	0.0385***	0.0231**	0.0238**	0.0190*	0.0256**	0.0211**	0.0711
Renter (Base = no)	-0.0238***	-0.0182**	-0.0270***	-0.0217***	-0.0354***	-0.0285**	-0.0244***	0.00109
Higher education (Base = no)	0.0167**	0.0114	0.0157*	0.0288***	0.0300***	0.00150	0.0180**	0.0124
Residential location type (Base = no)								
Suburban	0.0502	0.0688	0.104**	0.0926*	0.0333	-0.0236	0.142***	-0.193
Town/village	0.103*	0.122**	0.137***	0.126***	0.111**	0.0791	0.154***	-0.316**
Rural	0.0120	-0.0527	-0.00563	0.0861	-0.0584	-0.0739	0.00363	-0.293**
Employment status (Base = employed)								
Homemaker/retired	-0.0410***	-0.0339***	-0.0207*	-0.0257**	-0.0380**	-0.0149	-0.0316***	0.0195
Unemployed	-0.0140	0.000490	-0.00695	-0.0123	-0.00347	-0.0332	-0.00101	-0.0588
Student	0.0173	0.0279	0.00538	0.0395**	0.0592**	0.0206	0.0181	-0.0817
Other (e.g. disability)	0.0116	0.0220	0.0196	0.00909	0.00120	-0.0208	0.00276	-0.0424

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Environmental attitude profile (Base = environmentally neutral)								
Environmental prioritiser	0.0916***	0.0815***	0.0750***	0.0840***	0.0729***	0.0458**	0.0784***	0.0682
Technological optimist	-0.0404**	-0.0550***	-0.0329**	-0.0576***	-0.0450**	0.00168	-0.0544***	-0.0416
Economic prioritiser	0.00623	-0.000312	-0.00488	0.00236	-0.0114	-0.0503**	-0.00244	0.00274

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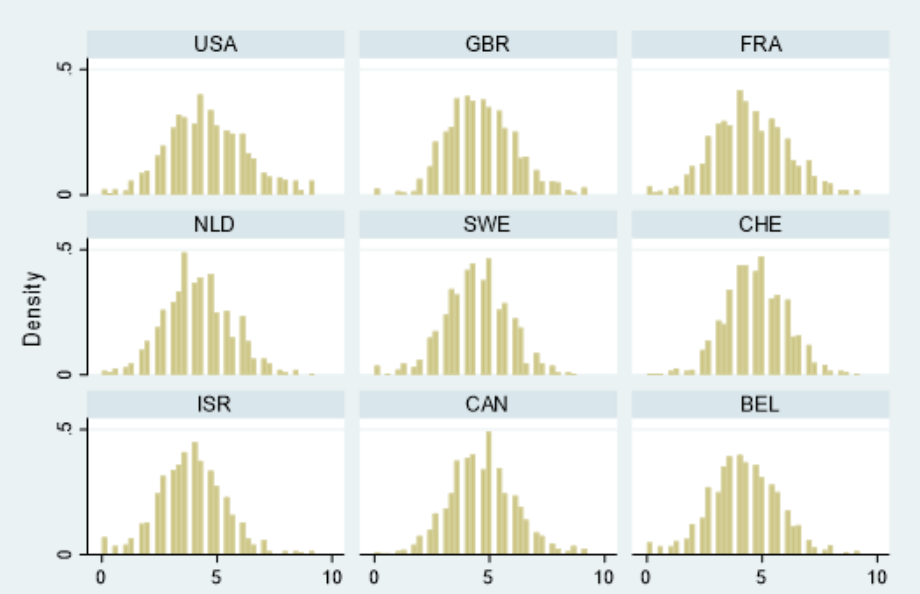
Supplementary material for Section 4

Figure A A.1. Country-level histograms of waste prevention index



Supplementary material for Section 5

Figure A A.2. Country-level histograms of food waste scores



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Supplementary material for Section 6

Table A A.3. Determinants of factors reported as most important in encouraging recycling and composting

Predictors	More money	More space	Simpler sorting	Service accessibility	Service frequency	Benefits evidence	Home collection	Cleaner containers
Charging scheme in place	0.0247	0.0642	-0.0563	0.0466	0.0667	0.184**	0.165**	0.126*
Separation service level								
Low	0.138	-0.0373	0.173	0.0531	0.128	0.124	-0.119	0.222
Medium	0.167	0.197**	0.194	-0.0800	0.226	0.219*	-0.0999	0.295**
High	0.230**	0.115	0.176	-0.425***	0.252*	0.132	-0.181	0.0757
Gender (Base = no)								
Female	-0.190***	0.248***	-0.102	0.00380	0.0383	-0.108	0.0919	-0.0152
Other / Prefer not to say	-0.353	0.0770	0.0476	0.0444	-0.300	-0.383	-0.0392	-0.237
Age	0.0130	0.00957	-0.00133	-0.00218	-0.00845	-0.0187	0.00629	0.00282
Age2	-0.000139	-9.68e-05	7.04e-05	7.08e-05	0.000157	0.000197	-5.52e-05	-1.72e-05
Log(income)	-0.139**	-0.0336	-0.0211	-0.0377	0.0310	-0.0390	-0.0441	-0.00696
Log(household size)	-0.0813	-0.115	-0.131*	-0.175**	-0.106	-0.107	-0.197**	-0.104
Children in the household (Base = no)	0.0281	0.191**	0.218**	0.133	0.227**	0.198**	0.168*	0.165*
Log(home size)	0.0824	-0.152**	0.0955	-0.0329	0.0103	0.0889	0.0806	0.00647
Renter (Base = no)	-0.00807	0.173**	0.0228	0.225***	0.135*	0.000424	0.0961*	0.179**
Higher education (Base = no)	0.0580	-0.0268	-0.0158	0.0432	-0.0577	-0.0796	0.0242	-0.125*
Residential location type (Base = urban)								
Suburban	0.116	-0.132	0.159**	-0.0859	0.00144	-0.0657	0.0134	0.0223
Town/village	0.291***	0.0810	0.179**	0.240***	0.124	0.124	0.238***	0.0934
Rural	0.279	-0.114	0.251	0.252	-0.208	0.0577	0.0148	-0.207
Employment status (Base = employed)								
Homemaker/retired	-0.149*	-0.246**	0.00902	-0.125	-0.175*	-0.0730	-0.0298	-0.0555
Unemployed	-0.209	-0.0819	-0.105	-0.0384	0.0115	-0.173	-0.105	-0.0948
Student	-0.0644	-0.211	-0.0228	-0.184	-0.382**	-0.279*	-0.249*	-0.129
Other (e.g. disability)	-0.0712	0.118	-0.0486	0.0965	0.124	-0.158	0.142	0.0929
Environmental attitude profile (Base = environmentally neutral)								

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Environmental prioritiser	-0.188*	0.0117	-0.183*	0.0478	-0.130	-0.211**	0.104	-0.299***
Technological optimist	-0.259**	-0.144	-0.166	-0.135	-0.0599	0.174	0.00126	0.172
Economic prioritiser	0.662***	0.281*	0.612***	0.124	0.326**	0.485***	0.390***	0.254

Note: Rank-ordered logit model with country fixed effects, within-country generalized (Cox and Snell) R^2 = 0.09. Base item is 'more information'; estimates are log-odds of being ranked more important.

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Supplementary material for Section 7

Overview of the discrete choice model

In this analysis, household i's utility from product j is given by:

$$U_{ij} = \alpha_j - \eta \ln p_j + \epsilon_{ij}$$

where α_i is the mean utility benefits that household i receives from the product, with the normalisation that utility for the base alternative (the disposable package) is set to zero ($\alpha_1 = 0$), η is the utility effect of the log of price (after converting prices to a common currency, USD), and ϵ_{ij} is a random utility component. A conventional conditional logit specification is used for the random utility component, assuming that it follows an Extreme Value Type I distribution. The predicted probability of choosing any package j on choice occasion t is then given by:

$$P_{jt} = \frac{\exp\{\alpha_j - \eta \ln p_j\}}{\sum_{j \in t} \exp\{\alpha_j - \eta \ln p_j\}}$$

By including the log of price in the above model, WTP is estimated as the percentage markup/markdown that the recyclable/reusable containers are worth to the consumer relative to the disposable package. This specification better harmonises WTP estimates when pooling DCE data from multiple countries. This percent WTP relative to the disposable package is given by:

$$\theta_j^{WTP} = \exp\left\{\frac{\alpha_j}{\eta}\right\} - 1$$

The quantity θ_j^{WTP} can be interpreted as the proportional markup ($\alpha_j > 0, \theta_j^{WTP} > 0$) or discount ($\alpha_j < 0, \theta_j^{WTP} < 0$) that makes the individual equally likely to purchase alternative j or the disposable package.[25] The above conditional logit specification assumes that preferences are homogeneous across households, other than random utility components ϵ_{ij}. An array of RUMs relax this assumption.

For the purposes of this report - in particular to investigate how household characteristics attitudes are related to their WTP for more sustainable packaging - a latent class choice model (LCCM) is used for identifying attitudinal classes. In contrast to LCA, preferences in the LCCM are estimated jointly with class membership determinants, namely all of the policy, socioeconomic, and attitudinal variables used in the above analyses. Four classes are allowed for in the estimation here, indexed by A, B, C and D. Given a household's set of determinants $\boldsymbol{X}_i$, the model specifies the probability of the household belonging to each class m as:

$$\Pr[m|\boldsymbol{X}_i, c] = \frac{\exp\{\boldsymbol{\beta}_m \boldsymbol{X}_i + \kappa_{cm}\}}{\sum_m \exp\{\boldsymbol{\beta}_m \boldsymbol{X}_i + \kappa_{cm}\}}$$

where $\boldsymbol{\beta}_m$ is the vector of class membership coefficients associated with the determinants and κ_{cm} are country-level fixed effects (with $\boldsymbol{\beta}_m$ and $\boldsymbol{\kappa}_m$ set to zero for an arbitrary class to identify the model).

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[25] This formula is obtained by defining θ_j^{WTP} as the price markup/discount that equates the expected utilities between package j and the disposable package, i.e. $\alpha_j - \eta \ln\left(\theta_j^{WTP} p_1\right) = \alpha_1 - \eta \ln p_1$. Solving this equation for θ_j^{WTP} and noting that $\alpha_1 = 0$ by assumption yields $\theta_j^{WTP} = \exp\{\alpha_j/\eta\} - 1$. The inclusion of prices as logs in the RUM is not ideal theoretically, as it implies a diminishing marginal effect of increasing the price of a given alternative on the probability of selecting that alternative. However, this specification facilitates joint estimation and interpretation of WTPs between countries, controlling for currency and purchasing power differences and allowing for preference heterogeneity. Linear and log-price models are estimated with the same qualitative results and similar quantitative WTP estimates.

Example choice set (United States)

Please imagine that you are purchasing laundry detergent. The detergent can be bought in either a non-recyclable container that you can dispose of after use, a recyclable container that you can recycle after use, or a refillable container that you can re-use. You pay a one-time deposit of USD 2 for the refillable container and for subsequent purchases you only pay for the detergent that you fill it with. Please keep in mind that using a refillable container requires bringing the empty container to the store and cleaning it after each use. Apart from the characteristics described below, the detergents are the same in all ways (e.g. effectiveness, ingredients, smell). The detergent can be either in liquid form or in solid form.

Given the options in the following scenarios, please select which product you would buy:

	Detergent 1	**Detergent 2**	**Detergent 3**
Price	USD 6	USD 4	USD 5
Package type	Plastic (recyclable)	Reusable container	Disposable container

Which detergent would you choose?

1. Detergent 1
2. Detergent 2
3. Detergent 3

Full regression results

Table A A.4. Marginal effects of policies and household characteristics on choice experiment latent class membership probabilities

	Avoids sustainable packaging	Prefers recyclable paper & plastic	Prefers reusable	Price indifferent
Charging scheme pricing	0.0133	0.0879***	-0.101***	-0.000621
Separation service level (base = none)				
Low	-0.0594**	0.0283	0.0254	0.00563
Medium	-0.102***	0.0531***	0.0314	0.0177**
High	-0.129***	0.0156	0.0875***	0.0263***
Gender (Base = male)				
Female	-0.00331	0.00960	-0.00301	-0.00328
Other / Prefer not to say	0.0650	-0.0470	-0.00464	-0.0134
Age	-0.00249	-0.00331	0.00633*	-0.000527
Age^2	3.01e-05	1.68e-05	-6.06e-05*	1.37e-05
Log(income)	-0.00446	0.0273***	-0.0258*	0.00297
Log(household size)	-0.00103	0.0485***	-0.0422**	-0.00529
Children in the household (Base = no)	0.0389**	0.0166	-0.0470**	-0.00846
Log(home size)	0.0106	-0.0292**	0.0212	-0.00257
Renter (Base = no)	-0.00460	0.0205*	-0.00713	-0.00881
Higher education (Base = no)	-0.0151	0.0243**	-0.00296	-0.00626
Residential location type (Base = urban)				
Suburban	-0.0306**	-0.0158	0.0379**	0.00846
Town/village	-0.0357**	-0.0152	0.0401**	0.0108*
Rural	-0.0265	-0.0272	0.0608*	-0.00707
Employment status (Base = no)				

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Homemaker/retired	0.0204	-0.00851	-0.0209	0.00897
Unemployed	0.00959	0.00336	-0.0226	0.00969
Student	0.0488	-0.0829***	0.0562	-0.0221**
Other (e.g. disability)	-0.0465**	0.0293	0.00235	0.0149
Environmental attitude profile (Base = no)				
Environmental Prioritisers	-0.239***	0.0377**	0.194***	0.00643
Technological Optimist	-0.0208	0.129***	-0.0996***	-0.00834
Economic Prioritisers.	0.0617***	-0.0142	-0.0379	-0.00966

Note: Fractional multinomial logit regression model estimated jointly with the latent class conditional logit RUM (see Table 7.1). Country fixed effects included in class membership model but not shown. Statistical significance levels: *** < 1%, ** < 5%, * < 10%.

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