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# The effect of environmental policies on environmental behaviors and intrinsic motivation: evidence from the European Union [1]

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**Abstract**

This is the first paper to study simultaneously the effect of environmental policies on individual pro-environmental behaviors and on pro-environmental preferences. Using a novel dataset that matches data on waste policies with data on behaviors and preferences, we find that environmental policies (1) decrease the amount of waste produced and (2) impact positively the pro-environmental attitudes of individuals.

**Keywords**

environmental policy, waste policy, crowding intrinsic motivation

**JEL Classification**

D02, D04, H41, Q53, Q58.

# 1 Introduction

A traditional view in economics is that the main effect of a policy is through the economic incentives that it imposes on an individual who acts in self-interest.[1] In this view, more of a certain economic incentive can achieve a higher behavioral response in the intended direction. As an example, traditional economic logic postulates that household waste generation (a negative environmental externality of private consumption) can be reduced by imposing a fee per unit of waste sufficiently high. To design an efficient policy, the policy maker's task is then to estimate the households waste "demand" curve and set the right fee, see e.g. Valente (2021) for a recent study estimating such a demand curve.

Yet, the psychology literature has increasingly paid attention to an alternative channel through which a policy may impact behavior. In particular, a policy may impact (negatively or positively) *the intrinsic motivation* to perform a task. "Intrinsic motivation" means here the internal willingness to perform a task for itself, for example due to nature relatedness, altruism, reciprocity or warm glow, and not due to any economic incentive. The psychology literature has named this phenomenon "crowding (out or in) of intrinsic motivation", Deci (1975), and has provided evidence for it in a large number of lab experiments, Deci et al. (1999) and Bowles and Polania-Reyes (2012).[2] In environmental economics, evidence for crowding effects has been provided mainly in the context of the so-called Payments for Environmental Services[3], see e.g. Agrawal et al. (2015) and the literature reviews by Rode

[1] This view has been first expressed by John Stuart Mill in his famous essay "Principles of political economy": *There is [...] one large class of social phenomena in which the immediately determining causes are principally those which act through the desire of wealth, and in which the psychological law mainly concerned is the familiar one that a greater gain preferred to a smaller. [...] By reasoning from that one law of human nature, [...] we may be enabled to explain and predict this portion of the phenomena of society.*

[2] Most commonly discussed reasons for crowding are (1) economic incentives such as fines and monitoring reduce individuals' sense of autonomy ("control aversion") and (2) economic incentives lead to market mentality and reduce the moral obligation to act pro-socially ("moral disengagement"), Bowles and Polania-Reyes (2012). Benabou and Tirole (2003), Bénabou and Tirole (2006) discuss reasons based on incomplete information and sorting. Benabou and Tirole (2003) describe a process, by which an economic incentive reveals to the agent possibly adverse intentions of the principal. Bénabou and Tirole (2006) develop a model, in which an economic reward for pro-social behavior makes it impossible (in equilibrium) to distinguish between pro-social and egoistic behavior, which leads to crowding out of intrinsically motivated individuals.

[3] Payments for Environmental Services represent programs that provide small payments or other rewards to farmers in exchange for a biding promise by the farmers to adopt nature and resource conservation

et al. (2015) and Ezzine-de Blas et al. (2019).

There are three major challenges in evaluating the effect of environmental policies on intrinsic motivation. First, when evaluating a real-world policy, there are typically no direct measures of motivation. Thus, the effect of the policy on motivation must be inferred from changes in observed behavior. However, this is impossible in many cases. As an example, consider a policy such as a tax increase on gasoline. On the one hand, it may induce a decrease in gasoline consumption because of the economic incentive (gasoline becomes more expensive). On the other hand, the tax may also positively affect the individual's perception of the policy maker: "the policy maker has pro-environmental intentions!" This may have a positive effect on the intrinsic pro-environmental motivation of the individual to consume less gasoline. If we observe only a reduction in the gasoline consumption, we cannot distinguish between these two effects. Put differently, we cannot distinguish between the direct economic effect and the effect through intrinsic motivation based only on data on the targeted behavior. To solve this problem, it is necessary to measure intrinsic motivation in a way other than through targeted behavior.

Second, the overwhelming majority of studies on the effect of environmental policies on intrinsic motivation have been carried out either as lab experiments, or as framed field experiments which are simulated games with artificial treatments, see e.g. Cardenas (2004), Rodriguez-Sickert et al. (2008), Jack (2009), Kaczan et al. (2019) and Handberg and Angelsen (2019), among others.[4] The results from such experiments, while still very important, have two major drawbacks. First, the artificial treatments typically do not provide incentives comparable to those in a real-world policy setting. Second, the experimental setup often provides cues for proper behavior ("social desirability bias"), see Bowles and Polania-Reyes (2012) for a discussion. Therefore, most experiments are associated with a substantial lack of external validity.

techniques.

[4]Agrawal et al. (2015) is a notable exception. Their method, however, does not allow to measure actual crowding effects but rather a reversal of preferences.

A third challenge consists of measuring the *total effect* of an environmental policy. In particular, an effect on intrinsic motivation might impact not only the behavior targeted by the policy, but also other behaviors (henceforth referred to as nontargeted behaviors). As an example, an individual whose intrinsic pro-environmental motivation has been crowded out by the introduction of a fine for improper sorting of waste might, as an act of reactance, stop participating in voluntary community cleaning activities. Taking the effect of a policy on nontargeted activities into account is particularly important in environmental context, where a variety of behaviors contribute to the individual's environmental footprint, Alacevich et al. (2021).

In this paper, we propose a novel strategy to measure the effect of *real-world* environmental policies on targeted behavior, nontargeted behaviors and environmental preferences *simultaneously*. In particular, we suggest to use repeated surveys on environmental behaviors and preferences and link the changes over time to policies that are implemented between the different waves of the survey. The main advantage of this strategy is that surveys often contain a variety of questions both on behaviors and on preferences. If the surveys are administered for purposes unrelated to the studied policies, then changes in answers over time are not impacted by strategic behavior directly linked to the policies.

In our paper, we study the effect of real-world waste-related policies on targeted waste behaviors such as food waste production, on nontargeted environmental behaviors such as purchasing second hand clothing and on environmental preferences. To obtain information on these variables, we use the Waste Eurobarometer survey, which was administered in 2011 and 2013 in all 28 members of the European Union. Alongside with socio-demographic characteristics such as gender, education and occupation, it collects detailed information on all of the aforementioned dimensions. We measure environmental preferences and intrinsic motivation with the answers given to questions such as "Is the environmental impact of a product important for your purchase decision?" and "Would you like stricter enforcement of existing waste-related laws?"

We match this survey data with data on waste related policies that are specific to each EU member state. We obtain the latter from the FAOLEX database which is run by the Food and Agriculture Organization of the United Nations.[5] This is a database on "national legislation, policies and bilateral agreements on food, agriculture and natural resources management". It is constantly updated and contains more than 8000 national and regional policies. The database contains more than 750 national and regional waste-related policies such as introducing curbside collection for organic waste, recycling policies and others.

Using this matched dataset, we estimate the effects of the waste policies using a difference-in-differences approach. In particular, we compare changes in answers between the two survey waves of participants who have been subject to a waste policy between 2011 and 2013 and compare these changes to changes of matched controls.

To the best of our knowledge, this is the first paper to use an integrated approach that *simultaneously* measures the effects of actual world policies on targeted and nontargeted behaviors, on intrinsic motivation and on acceptance of environmental policies. We find that waste-related policies affect positively waste-related behaviors, enhance acceptance of second hand clothing and lead to crowding in of intrinsic motivation. We also find, however, a substantial treatment heterogeneity and related effect heterogeneity. While general policies such as laws for waste separation have in general a positive effect, policies that introduce negative monetary incentives such as fines tend to crowd out intrinsic motivation and have a negative effect on nontargeted behaviors.

The paper is structured as follows. In Section 2, we describe our dataset. In Section 3, we describe our empirical strategy. Section 4 presents the empirical results. In Section 5, we discuss at length the pitfalls of our approach and suggest a research agenda that addresses these pitfalls.

[5] https://www.fao.org/faolex/en/

# 2 Data and descriptive statistics

## 2.1 The Eurobarometer surveys

The first data source for our dataset are the so called Eurobarometer surveys. There are two types of Eurobarometer surveys. The standard Eurobarometer survey asks EU citizens about their values and attitudes regarding European institutions. The survey has been conducted annually since 1973. The so called "special editions" investigate the attitudes of EU citizens towards a variety of topics such as agriculture, biotechnology, elderly people, energy, environment, family, gender issues, immigration, and so forth. Each of these topics is surveyed irregularly and at most twice. Both the standard and the special editions are commissioned by the European Union and administered in all EU member countries. Importantly, each edition asks exactly the same question in each country, translated in the country-specific language.

We use the special editions that focus on waste behaviors. There were two such surveys: the first conducted in January 2011 ( EC 2011, Flash Eurobarometer 316) and the second one in December 2013 (EC 2013, Flash Eurobarometer 388). Both surveys are carried out as telephone surveys. In each of the 27 countries where the surveys were conducted,[6] a representative sample of 1000 participants was interviewed. Representation here is defined in terms of matching basic demographic and socio-economic characteristics of the hosting country. Our total dataset consists in total of 43 341 observations, of which 21 113 belong to 2011 survey, and 22 228 to the 2013 one. The exact distribution of observations per country and year is presented in table 7 in appendix A.1. The survey asks several categories of questions, of which not all overlap. For the purpose of our study, we focus on the overlapping questions which are enlisted in table 8 in appendix A.1. We discuss them now in detail.

**Waste-related behaviors.** The first category of questions concerns waste-related behaviors. In our paper, we focus on the question "Can you estimate what percentage of the food

[6]Croatia is excluded from the sample as it was a member of the EU only in 2013.

you buy goes to waste?" (possible answers: 1 = 0%, 2 = less than 15%, 3 = less than 30%, 4 = less than 50% and 5 = more than 50%). This question corresponds to questions Q5 and Q9 from the 2011 and 2013 survey, respectively (henceforth, we use as a reference the question number from the 2011 survey).[7] Descriptive statistics for this variable are presented in panel A of table 1 for each survey separately. Each row corresponds to one question. The first column contains the number of the question. The second column contains the mean and the standard deviation (in parenthesis) of the respective variable for the full dataset, while columns 3 and 4 contain the mean (standard deviation) for the 2011 and 2013 survey, respectively. Relative frequencies for each of the 5 possible categories of food waste are presented in figure 1.

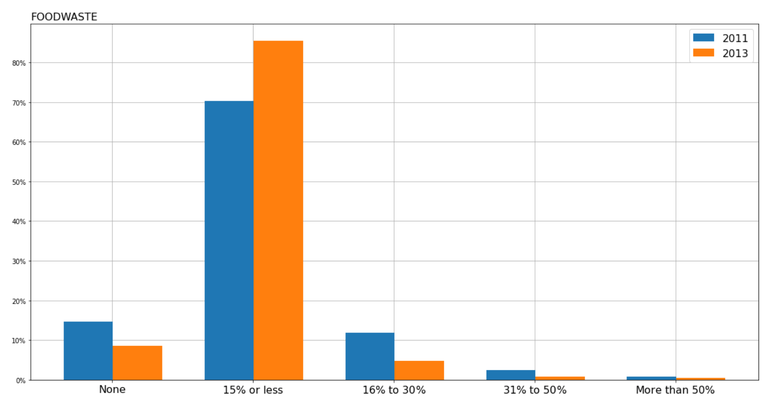



Figure 1: Distribution of the food waste variable in 2011 and 2013.

**Non-waste behaviors.** The second category consists of questions related to non-waste environmental behaviors. In particular, individuals are asked "Would you buy the following products second hand?", with one question for textiles (Q4a), electronic equipment (Q4b) and furniture (Q4c). In addition, individuals are asked what would convince them to buy more of these products (Q5). Descriptive statistics for these questions are provided in panel B of table 1. Roughly one third of the sample states that it would buy second hand clothing and this share is constant over time. The willingness to buy second hand electronics exhibits

[7]There are further waste-behavior questions in the surveys, such as "Do you think that your household is producing too much waste or not?" and "Do you separate at least some of your waste for recycling or composting?"

Table 1: Descriptive statistics

| | Mean | | | Std | | |
|---|---|---|---|---|---|---|
| | Full | 2011 | 2013 | Full | 2011 | 2013 |
| **PANEL A** | | | | | | |
| FOODWASTE (Q5) | 2.02 | 2.04 | 1.99 | 0.56 | 0.65 | 0.46 |
| **PANEL B** | | | | | | |
| SH.T (Q8,a) | 0.35 | 0.35 | 0.35 | 0.48 | 0.48 | 0.48 |
| SH.E (Q8,b) | 0.36 | 0.37 | 0.34 | 0.48 | 0.48 | 0.47 |
| SH.F (Q8,c) | 0.50 | 0.50 | 0.49 | 0.50 | 0.50 | 0.50 |
| **PANEL C** | | | | | | |
| LAW (Q4) | 0.50 | 0.68 | 0.33 | 0.50 | 0.47 | 0.47 |
| ENVIMP (Q7) | 0.56 | 0.80 | 0.33 | 0.50 | 0.40 | 0.47 |
| **PANEL D** | | | | | | |
| Male | 0.41 | 0.40 | 0.41 | 0.49 | 0.49 | 0.49 |
| Age | 52.76 | 52.35 | 53.14 | 15.67 | 15.51 | 15.81 |
| Self_employed | 0.10 | 0.10 | 0.09 | 0.29 | 0.30 | 0.29 |
| Employee | 0.35 | 0.37 | 0.34 | 0.48 | 0.48 | 0.47 |
| Manual_worker | 0.07 | 0.07 | 0.08 | 0.26 | 0.25 | 0.27 |
| Unemployed | 0.26 | 0.46 | 0.08 | 0.44 | 0.50 | 0.27 |
| Student | 0.18 | 0.01 | 0.35 | 0.38 | 0.08 | 0.48 |
| Metrop | 0.24 | 0.19 | 0.29 | 0.43 | 0.39 | 0.45 |
| Urban | 0.41 | 0.45 | 0.37 | 0.49 | 0.50 | 0.48 |
| Rural | 0.35 | 0.36 | 0.34 | 0.48 | 0.48 | 0.47 |

Notes: descriptive statistics (mean and standard deviation) for the pooled sample of the two surveys. Based on 43 341 observations.

similar shares, and the willingness to buy second hand furniture is substantially higher.

**Environmental and regulation preferences.** The next category of variables contains two questions that aim to understand citizens' environmental and regulation preferences. In particular, respondents are asked (Q6) "How important for you is a product's environmental impact - e.g. whether the product is reusable or recyclable - when making a decision on what products to buy?" (1= very important, 0= not so important), and (Q7) "What do you think needs to be done to improve waste management in your community?", with options "Stronger law enforcement of existing laws", "better waste collection services" and "make producers (households) pay for the waste they produce". We have coded the first option as 1 and all other options as 0. With this coding, we focus on whether individuals have (relative) preferences for stricter environmental regulation. Means and standard deviations of these variables can be found in panel C of table 1. The preference for stricter law enforcement exhibits a sharp drop from 68% in 2011 to 33% in 2013. Even more dramatic is the drop in having a preference for environmentally friendly products.

**Demographic and socioeconomic characteristics.** Finally, the survey asks a variety of questions related to the demographic and socioeconomic status of the individuals. Descriptive statistics of these variables are summarized in panel D of table 1. Since the samples match the demographics and socioeconomic distribution of the underlying populations, these distributions remain very stable over time.

## 2.2 Data on waste-related policies.

Our main treatment variable is whether an individual has been exposed to a (national) waste related policy in the period between the two surveys. To construct the treatment variable, we use the FAOLEX Database, a database run by the Food and Agriculture Organization (FAO) of the UN.[8]. This is a "comprehensive and up-to-date legislative and policy database, one of the world's largest online repositories of national laws, regulations and policies on food, agriculture and natural resources management." It is constantly updated and, as of January 2022, it contains detailed information on more than 5000 policies worldwide. The database is divided into several domains such as food and nutrition, agricultural and rural development, fisheries and aquaculture, environment, forestry, water, mineral resources and energy and so forth. Alongside a description of each policy, the database contains also a link to the national legislation which gave rise to the respective policy.

Using this database, we identified 28 waste-related national policies as relevant to our study. All of these policies were implemented in the period between the two surveys, see appendix A.2 for a description of our search procedure. All of these policies are related to household waste generation, recycling and management issues, and that were implemented

[8] https://www.fao.org/faolex/en/

on a national level in one of the EU members. Table 9 in appendix contains the database-names of these policies.[9]

Among these 28 waste policies, there is a substantial heterogeneity concerning the content. In more than 50% of the cases (16 case), the policy aimed at harmonizing national rules such as waste categorization (necessary for waste separation) and waste management practices (such as providing recycling centers) with the European waste directive (EC 2008/98). Furthermore, many of the policies consist of more than one component, which additionally complicates the comparison. In order to improve the interpretation of the policy (and thus the interpretation of the treatment), we identified all policies that focus on a monetary aspect such as taxes, fines and subsidies. Of all 28 policies, 9 contain a fine component (for improper waste sorting), 2 contain a tax increase and 1 contains a subsidy component. We use these policies as an alternative definition of the treatment in the robustness checks section.

### 2.3 Further variables.

For better understanding the mechanisms behind the studied effects, we collected two further country-level variables. The first one is the so called Index of Environmental Policy Stringency (EPS), developed by the OECD.[10] As the name suggests, this index aims at describing the level of environmental stringency in a given country. The first one describes the baseline (i.e. pre-treatment, pre-2011) environmental policy stringency in a given country. The index aggregates a variety of policies within a certain country, weighted by their hypothesized importance, see figure 2. In particular, policies are divided into market- and non-market based, and each of these categories receives a weight of one half. The market-based policies consist among others of taxes and feed-in tariffs, while non-market policies include e.g. government R&D expenditure on renewable energies. The added value of the EPS index from 2010 as a pretreatment characteristic is to account for the possibility that the effects of environmental policies might depend on the baseline level of environmental policy stringency.

[9] Web links to these policies can be obtained by the authors upon request.
[10] http://oe.cd/eps

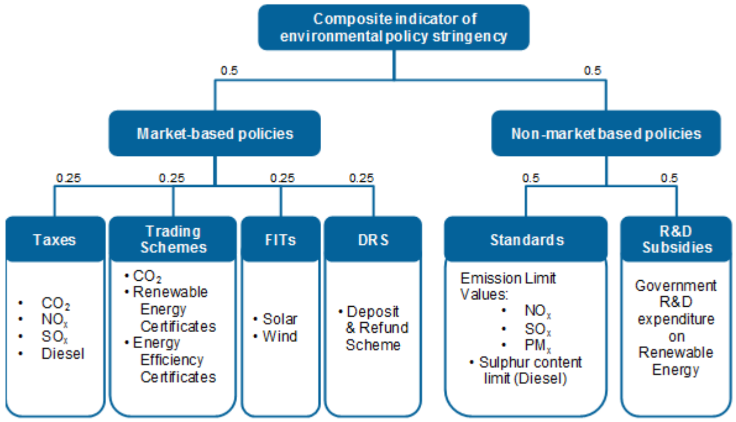



Figure 2: An index for Environmental Policy Stringency (EPS).

Finally, we also gather data on GDP per capita for 2010 for each of the countries in the sample.

# 3 Empirical framework

**Notation and treatment effects of interest.** Let $D_i \in \{0, 1\}$ be a random variable that indicates whether individual $i$ is treated ($D_i = 1$) or not ($D_i = 0$). In our main specifications, an individual is considered treated if she has been exposed to a waste policy between January 2011 and December 2013. Because we only consider policies that are enacted on a national level, $D_i$ is equal to 1 whenever individual $i$ is a citizen of a country that implemented a waste policy in the aforementioned period. We address pitfalls related to this definition of the treatment in the robustness section 4.2.1.[11]

Next, let for $d = 0, 1$, $Y_i(d)$ denote the potential outcome of individual $i$ had she been exposed to treatment arm $d$. We consider as outcomes all waste and non-waste related behaviors, as well as the environmental and regulation preferences. In other words, all variables from panels A, B and C from table 1 are used as outcome variables. With the exception of the food waste variable (Q5), all variables represent binary variables. The

[11]In particular, the above definition possibly leads to multiple versions of the treatment.

food waste variable represents a categorical variable with 5 categories. Since averages of the different categories have no meaningful interpretation, we transform this variable into 4 binary variables, each indicating a certain range of waste. As an example, the first category is the binary variable which is equal to 1 when an individual produces no food waste. Category 2 variable is a binary variable that is equal to 1 if an individual produces 15% *or less* food waste, Category 3 = 1 if an individual produces 30% or less and Category 4 - 50% or less.

Finally, let $X_i$ represent individual specific pre-treatment characteristics. In the analysis below, we split $X$ into two parts, $X = (X_1, X_2)$. $X_2$ represents demographic and socioeconomic characteristics of the particular individual, while $X_1$ denotes the baseline GDP per capita and the baseline EPS index of the country in which the individual resides.

With this notation, we define the treatment effect of interest as the average additive treatment effect on potential outcomes in 2013 for the treated,

$$\mathbb{E}[Y_{2013}(1) - Y_{2013}(0)|D = 1]. \tag{1}$$

The interpretation of ATET (1) depends on which outcome (and which definition of the treatment) we choose. For variables from panel A, ATET represents a treatment effect on behaviors targeted by waste policies. For panel B variables, ATET represents an effect on nontargeted behaviors and for panel C variables - an effect on preferences.

**Empirical strategy.** We estimate (1) with two different Difference-in-Differences (DiD) approaches. The first one is a standard linear DiD estimator with country fixed effects. Because of the binary nature of the dependent variable, in addition to the simple linear estimator, we also estimate logit DiD models which we discuss in the robustness checks section.

The second approach is a nonparametric DiD estimator that incorporates a doubly-robust machine learning estimation technique. This estimator can be described in the following way. In a first step, countries are grouped in clusters based on the country-specific characteristics $X_1$ using a standard cluster analysis algorithm. The resulting clusters are depicted in figure 3. The x-axis measures baseline GDP per capita and the y-axis the baseline index of environmental policy stringency. The cluster analysis step identified four clusters, each depicted with a different color. As an example, the blue country in the low left corner of the figure (in the following referred to as Cluster 1) consists of countries with low GDP per capita and low baseline environmental policy stringency. The cluster consists of East European countries (Bulgaria, Romania, Hungary, Estonia), as well as of some South European countries (Malta, Cyprus, Portugal). The values of GDP per capita and EPS index for each of the countries are shown in figure 7 in appendix B.1. The red cluster ("Cluster 2") has a high GDP and middle high EPS index. The green cluster ("Cluster 3") has high scores on both dimensions. It consists predominantly of Benelux and large West European countries. Cluster 4, which consists predominantly of Baltic countries, has a high environmental policy stringency and lower GDP per capita. In a second step, we estimate cluster-specific ATETs

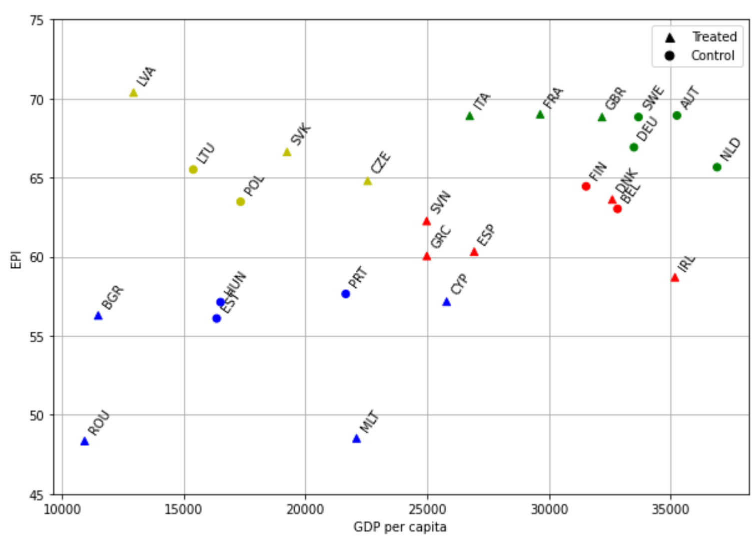



Figure 3: Cluster of countries based on GDP per capita and environmental policy stringency.

with a nonparametric DiD estimator with all individual specific characteristics $X_2$. In our main specification, we use the doubly robust machine learning (DML) approach by Chang (2020) combined with an Enseble learner approach based on LASSO and Random Forests suggested by Zimmert (2020), see appendix B.2 for a detailed description. Results obtained with alternative estimators are discussed in the robustness checks section.

The two approaches have different and complementary advantages and disadvantages. The advantage of the linear DiD estimator is the efficient way to deal with time-constant country-specific unobserved factors. The advantages of the two-step DML approach is that (i) it does not rely on restrictive functional form assumptions and (ii) it allows to study treatment effect heterogeneity along two important dimensions (GDP and environmental stringency).

# 4 Empirical results

## 4.1 Main results

**Effect of waste policies on targeted behaviors.** We start our discussion with the estimates of the effects of waste policies on food waste. Table 2 contains the estimates obtained with a linear DiD specification with country fixed effects (approach 1).[12] Each column corresponds to one dummy variable. Standard errors, which we cluster at the country level, are displayed in parenthesis. All four regressions yield a positive estimate for the treatment effect with the first estimate being significant at the 0.01 significance level and the other three have p values close to the 0.1 threshold. The coefficients range between 3% and 5.7%. According to these results, the probability that an individual produces less than a given amount of waste is positively impacted by the waste-related policies. The effect is stronger for smaller amounts of waste so that one interpretation of our results is that waste policies had on average a beneficial environmental effect.

However, there are two competing interpretations of our results. The first one is that individuals producing smaller amounts of waste potentially better estimate the proportion

[12]Results obtained with our second approach are very similar. To avoid an overflow of results (4 clusters $\times$ 4 dependent variables = 16 regressions, these results are omitted

Table 2: Linear DiD results, Food Waste

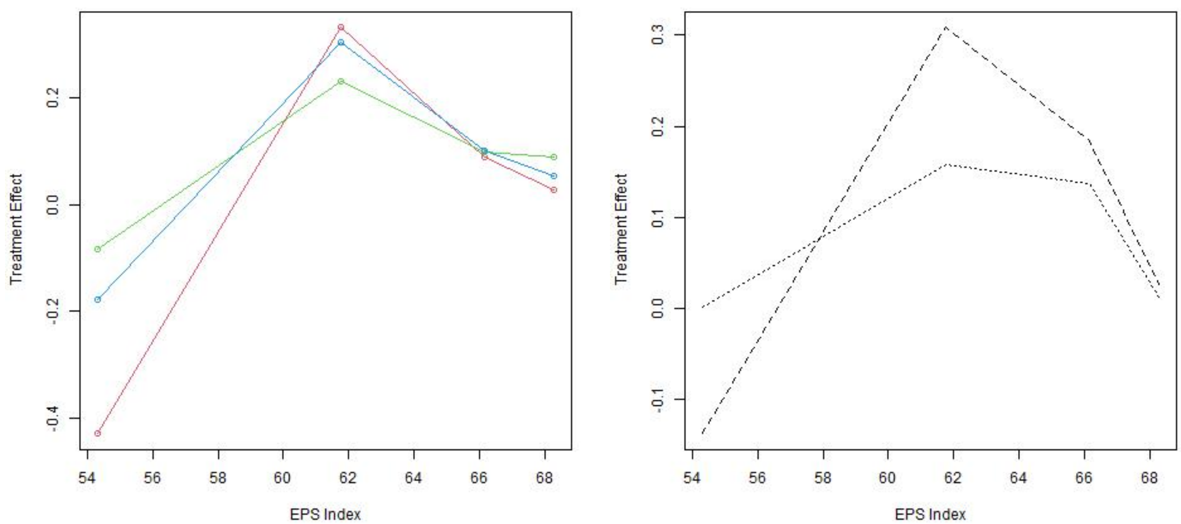
| | None | 15% or less | 30% or less | 50% or less |
|---|---|---|---|---|
| Time | 0.115*** | 0.058*** | 0.047*** | 0.046*** |
| | (0.008) | (0.007) | (0.008) | (0.009) |
| Policy | -0.028** | -0.042*** | -0.027** | -0.017 |
| | (0.011) | (0.012) | (0.013) | (0.014) |
| Policy ×Time | 0.057*** | 0.038 | 0.033 | 0.030 |
| | (0.021) | (0.024) | (0.025) | (0.026) |
| Male | 0.016*** | 0.022*** | 0.020*** | 0.019*** |
| | (0.005) | (0.003) | (0.003) | (0.003) |
| Age | 0.00004 | -0.002*** | -0.003*** | -0.003*** |
| | (0.0004) | (0.0003) | (0.0003) | (0.0003) |
| Self_employed | 0.030*** | 0.028*** | 0.027*** | 0.024*** |
| | (0.009) | (0.007) | (0.007) | (0.007) |
| Employee | 0.044*** | 0.045*** | 0.041*** | 0.038*** |
| | (0.008) | (0.006) | (0.006) | (0.006) |
| Manual_worker | 0.019* | 0.020* | 0.019* | 0.019* |
| | (0.011) | (0.012) | (0.011) | (0.012) |
| Student | -0.005 | -0.006 | 0.002 | 0.005 |
| | (0.024) | (0.018) | (0.011) | (0.011) |
| Rural | -0.024*** | -0.040*** | -0.041*** | -0.041*** |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| Urban | -0.013** | -0.017*** | -0.012** | -0.012** |
| | (0.006) | (0.005) | (0.005) | (0.005) |
| Constant | 1.780 | 2.046 | 2.091 | 2.106 |
| | (0.021) | (0.016) | (0.018) | (0.020) |
| Country Fixed effects | Yes | Yes | Yes | Yes |

Notes: estimates obtained with a linear DiD regression. Dependent variable is food waste. Country fixed effects are included. The standard errors are indicated in brackets and are clustered at the country level. Statistical significance: *p<0.1; **p<0.05; ***p<0.01.

of their household waste (e.g. because they pay more attention to waste in the first place), meaning that changes in their waste levels is associated with less uncertainty. This interpretation is supported by the monotonically increasing relationship between waste categories and uncertainty - standard errors are higher for higher categories of waste. Another possible reason is that individuals at higher quantiles of the waste distribution are less susceptible to environmental policies. Note that regressions with dependent variables indicating waste range share a similarity with quantile regression. In particular, due to possible shifts in the distribution of waste, the estimated effects cannot be interpreted as treatment effects on the same group of individuals.

Based only on the regression estimates from table 2, it is difficult to infer which explanation is most likely. In fact, the three competing mechanisms could be complementary explanations of the results. Thus, it is necessary to study effects on further outcomes.

**Effect of waste policies on nontargeted behaviors.** Consider next the estimates obtained with linear DiD regressions with nontargeted behaviors as outcome variables (variables from panel B from table 1). These estimates are presented in columns 2-4 in table 3. All three estimated effects are positive and the first two are also significant. These results suggest that on average, waste related policies increase the likelihood that individuals purchase second hand goods. The effects vary between 2.4% and 10%. To put these estimates into perspective, the predicted increase for purchasing second hand clothing amounts to almost 30% compared to the baseline average, while for electronics and furniture the respective relative magnitudes are 6.6% and 4.8%. Thus, these effects are also economically significant. We also estimate the three effects for all 4 clusters using the 2-step doubly robust machine learning estimator (approach 2). The results are presented in columns 2-4 in table 4. Each row contains the estimated effects for a given cluster. The estimates for cluster one are negative and significant and equal to -4.3%, -8.3% and -17.8%. Thus, for this group of individuals, waste-related policies caused a drop in the share of people willing to purchase second hand products. For all other clusters and, the three effect estimates for all three outcomes are positive and significant. Figure 4a contains a plot of the estimated effects within each cluster (y-axis) against the average EPS index within the corresponding cluster. Excluding cluster one, the figure reveals a monotonically decreasing relationship: the higher the baseline environmental policy stringency, the lower the effect. One possible interpretation of this finding is that citizens in countries with higher baseline environmental policy stringency are less susceptible to additional policy changes because they have reached a high level of pro-environmental behavior which is difficult to improve. An alternative explanation is that environmental policies might interact with the intrinsic motivation of individuals to behave pro-environmentally, which could depend negatively on the environmental policy stringency. We discuss this possibility in the next section.




(a) Effect size vs EPS index for Second Hand behaviors. Red= Textile, Green= Electronics, Blue=Furniture.

(b) Effect size vs EPS index for Preferences. Dashed= preference for positive env. impact of purchased goods, Dotted= preference for stricter law enforcement.

Figure 4: Effect size vs EPS Index.

**Effect of waste policies on environmental and regulation preferences.** Last but not least, we estimate also the effect of waste policies on environmental and law preferences (variables from panel C in table 1). The results obtained with approach 1 are presented in columns 5-6 in table 3, while the results obtained with approach 2 are presented in columns 5-6 in table 4. Both sets of results indicate, that on average, waste policies impact positively the preferences for environmental impact in consumption behavior as well as for stricter enforcement of waste-related rules. Moreover, except for cluster 1, the relationships environmental policy stringency and the effects on both types of preferences follow a monotonically decreasing pattern, just as in the case of nontargeted behaviors, see figure 4b.

**Interpretation of main empirical results.** One of the main findings of this section is that pro-environmental policies impact nontargeted behaviors. The literature discusses several channels for such an effect. The standard economic argument is that a policy that targets one activity changes the relative "prices" of other activities as well. This would be particularly the case with goods/behaviors that represent either substitutes or complements. The link between wearing second hand and waste disposal, however, seem to be particularly weak.

An alternative explanation offered by the psychology literature is that a change in one behavior might lead to a change in another behavior. A behavioral spillover might be triggered by mental accounting or by the attempt of an individual to behave consistently in different dimensions, Alacevich et al. (2021). Behavioral spillovers have a particular importance in environmental economics, where different actions contribute to the environmental footprint of an individual.

Yet another explanation could be that environmental policies affect the intrinsic motivation of an individual to undertake a pro-environmental action for the sake of it. Such an effect is referred to as motivation crowding (in or out), Deci et al. (1999). However, the literature has typically focused on the crowding effects of economic incentives on the *targeted behavior.* The evidence presented above suggests that motivation crowding can affect nontargeted behaviors as well. This conjecture is supported by the positive effects on the willingness to purchase goods with a positive environmental impact.

In general, it is very hard to distinguish between behavioral spillovers and effects through motivation crowding. The reason is that we estimate a total effect of a policy on a given nontargeted activity, which is hard to dissect into a direct effect (through motivation) and indirect effect (through waste behaviors).

## 4.2 Robustness checks

In this subsection, we address two important aspects of our empirical strategy. The first one is heterogeneity of the treatment across countries. The second one is the validity of the parallel trends assumption.

### 4.2.1 Heterogeneity in the treatment.

One concern with our empirical strategy is that there is heterogeneity in the treatment definition. In particular, as described in section 2.2, different countries implemented different waste policies. Thus, the "no versions of the treatment" assumption, which is a component of the Stable Treatment Unit Assumption (SUTVA), is violated. This violation has two consequences. First, the interpretation of the causal effects is not straightforward (effect of what type of policy?). Second, if the treatment variation is correlated with characteristics of the treated population, interpretation of the effect heterogeneity will be biased.

For this reason, we perform two robustness checks with restricted samples. In the first sample, the treatment is a waste policy that has a fine as a major component. In almost all of the implemented policies, the fine targets either incorrectly separated or illegally dumped waste. In the second sample, the major component of the treatment is a subsidy for "measures and initiatives [...] to promote waste prevention, reuse and consumption more efficient and causing less environmental damage". In both samples, the controls are the controls from the cluster, to which the treated individuals belong. All other observations - treated with a different treatment and controls belonging to a different cluster - are removed. These restrictions dramatically reduce the heterogeneity of the treatment.

Table 5 shows the estimation results for the fines-treatment. Fines were introduced in countries belonging to either cluster 1 or 3, and each of the two halves of the table displays a regression within a certain cluster. In both clusters, a similar pattern emerges. First, the waste policy has a negative and significant effect on the amount of food waste.[13]

[13]For compactness, we show results with a categorical variable as an outcome.

Second, however, the effect of the fine on the nontargeted activities (Second hand variables) is negative and in some cases statistically significant. Third, the effect on preferences for stricter law enforcement and environmental impact of purchased goods is also negative, and for law enforcement preferences it is also significant. Taken together, these estimates suggest that policies that introduce fines lead to crowding out effects on other environmental behaviors and on intrinsic motivation.

Next, table 6 shows the estimation results for the subsidy-treatment. While it appears to lead to an increase in food waste, the subsidy has a positive and significant effect on both nontargeted activities and preferences.

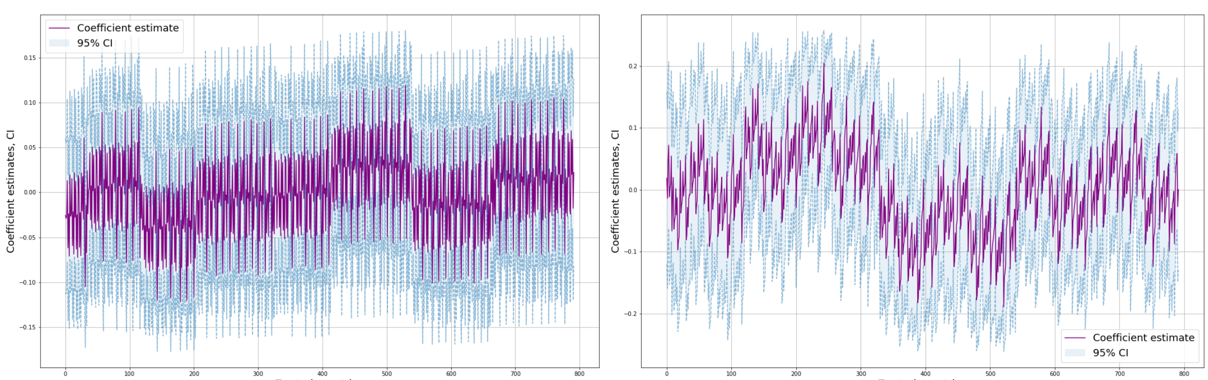
Our results thus reveal that heterogeneity in the treatment is indeed a concern for the empirical evaluation of waste policies, and that while fine-related treatments potentially crowd out intrinsic motivation and other environmental behaviors, a subsidy is associated with crowding in effects. One potential explanation with the negative effects of fines is that they compromise the individuals sense of autonomy, Deci et al. (1999). The introduction of a fine can be interpreted as an element of stricter control by the principal (the government, the municipal waste management, etc.), which then affects the overall disposition of an individual to behave pro-socially. A subsidy, on the contrary, might be used as a signal to behave pro-socially, Bowles and Polania-Reyes (2012). However, this is not the only possible explanation, and related literature finds that subsidies might lead to a counterproductive behavior, Rode et al. (2015).

#### 4.2.2 Placebo testing of the Parallel Trends assumption

The Parallel Trends assumption, which is central to the DiD approach, cannot be tested. The typical way to provide evidence for its validity is through a so-called placebo test, in which the researcher pretends that the treatment has been assigned to the treated a given number of time periods prior to the actual treatment. A nonsignificant placebo effect means that the researcher failed to detect a difference in pre-treatment trends, which is then, by way of extrapolation, interpreted as evidence for the validity of the Parallel Trends assumption. This method, however, is not feasible in our setup as it requires at least one more period of pretreatment data (i.e. another wave of the Eurobarometer survey that tool place before the 2011 wave).

To compensate for this drawback, we perform a different type of a placebo test, which tests for parallel trends inside each treatment arm $D = 0, 1$. In particular, within treatment arm $D = d$, observations are randomly split into two groups, say $d_1$ and $d_2$. Then, in a second step, a test for equality of time trends performed. This is equivalent to DiD estimator using observations only from treatment arm $d$ and with a placebo treatment indicator $\tilde{D}$ that assigns randomly 0 and 1 to the observations from that group. In order to eliminate the role of the random selection of "pseudo-treated", the procedure is repeated for different generated samples of $\tilde{D}$. This test is related to the so-called "Permutation Tests" in the Machine Learning literature, Ojala and Garriga (2010). An insignificant effect is (again by way of extrapolation) interpreted as indirect evidence for the validity of the Parallel Trends assumption.

We perform this test for a variety of samples of $\tilde{D}$ for both treated and nontreated and for all outcome variables. As an example, consider figure 5a. It displays the permutation test




(a) Permutation test for the environmental preferences variable.

(b) Permutation test for the preferences for stricter law enforcement.

Figure 5: Permutation tests.

results for the nontreated for the variable environmental preferences for the case, in which 5 countries are randomly selected to be placebo-treated. Each point on the x-axis corresponds to one choice of 5 countries. The y-axis measures the estimated effect (dark violet) and the 95% confidence bound (light blue). The figure shows that we find an insignificant effect for nearly 800 permutations (random selections of the treated). Figure 5b displays a similar pattern for the preferences for stricter law enforcement. In appendix C, we present evidence for the other outcome variables, each time with 5 countries in the pseudo-treatment group. The results are consistently insignificant throughout. Similar results are obtained with different numbers of pseudo-treated countries and are available upon request. Thus, our results support the validity of the Parallel Trends assumption.

# 5 Limitations and research agenda

There are two major limitations of our study. The first one is the definition of the treatment variable. As pointed out, the waste policies considered in this paper are constituted of a variety of legal components which makes it hard to compare them. Restricting the type of policy improves comparability. However, due to variation in the size of the fine across the remaining countries, treatments are still different.

The second limitation of our study is that there are only two waves of the study. This makes it impossible to implement a test of pre-treatment parallel trends, as it is typical in the empirical literature that uses a DiD estimation approach (even though the permutation test that we implement is similar in spirit to a pre-treatment parallel trends). The permutation test above partially addresses this drawback, using a different type of indirect evidence.

Despite these drawbacks, our study demonstrates that repeated surveys, when combined with policies occurring between different ways, are an attractive empirical approach to study environmental policies. The major advantage of surveys is that they often contain a battery of questions about behaviors and preferences which are otherwise difficult to measure.

The above considerations suggest a research agenda that keeps the advantages but avoids the disadvantages of our study. First (and trivially), surveys should be used that have more than two waves. One example for such surveys is *The International Social Survey Programme (ISSP)*. The ISSP is an international survey organized and financed by research institutions in 48 countries. It surveys attitudes towards several categories such as environment, health care and others. The Environment survey was conducted four times: in 1993, 2000, 2010 and 2020. It contains 22 questions on different environmental dimensions. General questions towards the environment include "Generally speaking, how concerned are you about environmental issues?". More specific questions target attitudes towards waste generation and separation, meat consumption, transportation and beliefs regarding climate change. The survey contains a limited number of questions on personality traits such as "Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people?". Finally, the survey includes questions on the attitudes towards regulation and the role of the state in dealing with the environment. Thus, the main advantages of this survey are the repeated survey waves (four waves compared to only two of the Eurobarometer survey), as well as the detail account on behaviors and regulation preferences.

Second, note that the source of the first drawback is that the policies considered here are national policies. National environmental policies are rarely comparable to each other, which easily leads to a violation of SUTVA. Therefore, one approach would be to focus on setups with regional variation of a policy within one country. The Eurobarometer survey contains national region identifiers, so in principle restricting attention to a single country and linking regional policies within this country to survey answers is possible. However, since the sample for each country contains at most 1000 observations, such an approach is hard to be implemented due to lack of statistical power. One survey that could be used instead is the so-called *socio-ecological panel survey ("Green-SOEP")*. The Green-SOEP is a panel survey conducted in Germany each year between 2012 and 2016. The survey collects data from more than 6000 households on attitudes toward and willingness to pay for green energy, on leisure activities in the context of their environmental footprint, on political preferences and on attitudes towards climate change, among others. It also surveys household on their housing properties with focus on energy efficiency. There are three main advantages of this survey: the very detailed account of socioeconomic characteristics, the panel structure (the same households are surveyed each year) and the information on the location of the households. The last point is particularly important when trying to relate survey answers to regional policies.

As a conclusion, using repeated surveys to learn about environmental policy effects is yet to be fully explored as an empirical approach, and future research using regional policies and surveys with more than two waves is a promising way to do that.

Table 3: Linear DiD results, nontargeted behaviors and preferences

| | SH T | SH E | SH F | ENV | LAW |
|---|---|---|---|---|---|
| Time | -0.027** | -0.057 *** | -0.025 *** | -0.491*** | -0.346*** |
| | (0.012) | (0.015) | (0.008) | (0.022) | (0.036) |
| Policy | -0.097*** | -0.067*** | -0.149*** | -0.102 *** | 0.129*** |
| | (0.008) | (0.012) | (0.009) | (0.020) | (0.026) |
| Policy $\times$Time | 0.024* | 0.041* | 0.024 | 0.042 | 0.003 |
| | (0.014) | (0.022) | (0.018) | (0.039) | (0.049) |
| Male | -0.103*** | 0.034*** | -0.039*** | -0.064*** | -0.001 |
| | (0.010) | (0.006) | (0.007) | (0.007) | (0.006) |
| Age | -0.005 *** | -0.009*** | -0.008*** | 0.0001 | -0.001** |
| | (0.0004) | (0.0003) | (0.0003) | (0.0002) | (0.0003) |
| Self_employed | -0.018 | 0.011 | 0.026** | 0.011 | -0.038*** |
| | (0.011) | (0.009) | (0.011) | (0.009) | (0.009) |
| Employee | -0.017* | 0.012 | 0.022** | 0.017*** | -0.004 |
| | (0.009) | (0.008) | (0.009) | (0.005) | (0.008) |
| Manual_worker | 0.002 | -0.001 | 0.016* | 0.019** | 0.004 |
| | (0.010) | (0.012) | (0.009) | (0.009) | (0.011) |
| Student | -0.058* | -0.004 | -0.043 | 0.108*** | 0.043 |
| | (0.035) | (0.023) | (0.034) | (0.025) | (0.028) |
| Rural | 0.008 | -0.022*** | 0.008 | 0.010 | 0.001 |
| | (0.009) | (0.007) | (0.009) | (0.008) | (0.009) |
| Urban | 0.002 | -0.017*** | -0.011* | 0.010* | -0.002 |
| | (0.007) | (0.006) | (0.006) | (0.005) | (0.008) |
| Constant | 0.830 *** | 0.947*** | 1.207*** | 0.868*** | 0.617*** |
| | (0.028) | (0.019) | (0.020) | (0.019) | (0.032) |
| Country FE | Yes | Yes | Yes | Yes | Yes |

Notes: estimates obtained with a linear DiD regression. Dependent variables: SH stands for second hand, T for textile, E for electronics, F for furniture, ENV for environmental preferences, LAW for stricter law enforcement. The standard errors are clustered at the country level. Statistical significance: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

Table 4: Nonparametric doubly robust Machine Learning DiD results, nontargeted behaviors and preferences

| | SH T | SH E | SH F | ENV | LAW |
|---|---|---|---|---|---|
| Cluster 1 | -0.043*** | -0.083*** | -0.178*** | -0.137*** | 0.001 |
| | (0.014) | (0.013) | (0.016) | (0.014) | (0.014) |
| Cluster 2 | 0.332*** | 0.231*** | 0.305*** | 0.308*** | 0.137*** |
| | (0.02) | (0.018) | (0.023) | (0.024) | (0.021) |
| Cluster 3 | 0.028** | 0.108*** | 0.054*** | 0.027* | 0.013 |
| | (0.011) | (0.013) | (0.015) | (0.014) | (0.012) |
| Cluster 4 | 0.09*** | 0.093*** | 0.101*** | 0.184*** | 0.158*** |
| | (0.016) | (0.016) | (0.016) | (0.016) | (0.015) |

Notes: estimates obtained with a nonparametric doubly robust Machine Learning DiD regression. Dependent variables: SH stands for second hand, T for textile, E for electronics, F for furniture, ENV for environmental preferences, LAW for stricter law enforcement. Each raw represents one cluster. The standard errors are clustered at the country level. Statistical significance: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

Table 5: Nonparametric Double Machine Learning Difference-in-Differences estimates of the effect of a fine on behaviors and preferences.

| Variable | **Cluster 1** | **Cluster 3** |
|---|---|---|
| FW | -0.816*** | -0.356*** |
| SH.T | 0.009 | 0.01 |
| | (0.084) | (0.085) |
| | (0.019) | (0.021) |
| SH.E | -0.05** | 0.035 |
| | (0.02) | (0.023) |
| SH.F | -0.144*** | -0.018 |
| | (0.016) | (0.025) |
| LAW | -0.172*** | -0.088*** |
| | (0.037) | (0.026) |
| ENVIMP | -0.03 | -0.005 |
| | (0.031) | (0.028) |

Standard errors are shown in brackets. Significance level: $^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$

Table 6: Nonparametric Double Machine Learning Difference-in-Differences estimates of the effect of a subsidy on behaviors and preferences.

| | Variable | |
|---|---|---|
| **Cluster 2** | FW | 0.439*** |
| | | ( (0.061) |
| | SH.T | 0.051*** |
| | | (0.017) |
| | SH.E | 0.083*** |
| | | (0.017) |
| | SH.F | 0.141*** |
| | | (0.019) |
| | LAW | 0.280*** |
| | | (0.022) |
| | ENVIMP | 0.135*** |
| | | (0.031) |

Standard errors are shown in brackets. Significance level: $^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$

# A Appendix to section data and descriptives

## A.1 Eurobarometer surveys

| Country | 2011 | 2013 | Total |
|---|---|---|---|
| Austria | 818 | 939 | 1 757 |
| Belgium | 785 | 906 | 1 691 |
| Bulgaria | 858 | 918 | 1 776 |
| Cyprus | 774 | 450 | 1 224 |
| Czech Republic | 849 | 918 | 1 767 |
| Denmark | 724 | 893 | 1 617 |
| Estonia | 771 | 917 | 1 688 |
| Finland | 830 | 865 | 1 695 |
| France | 839 | 912 | 1 751 |
| Germany | 793 | 921 | 1 714 |
| Greece | 830 | 871 | 1 701 |
| Hungary | 806 | 939 | 1 745 |
| Ireland | 834 | 904 | 1 738 |
| Italy | 746 | 883 | 1 629 |
| Latvia | 784 | 896 | 1 680 |
| Lithuania | 630 | 857 | 1 487 |
| Luxembourg | 857 | 467 | 1 324 |
| Malta | 814 | 438 | 1 252 |
| Netherlands | 773 | 949 | 1 722 |
| Poland | 839 | 888 | 1 727 |
| Portugal | 683 | 803 | 1 486 |
| Romania | 815 | 890 | 1 705 |
| Slovakia | 846 | 903 | 1 749 |

| | | | |
|---|---|---|---|
| Slovenia | 847 | 953 | 1 800 |
| Spain | 810 | 892 | 1 702 |
| Sweden | 734 | 917 | 1 651 |
| United Kingdom | 838 | 920 | 1 758 |

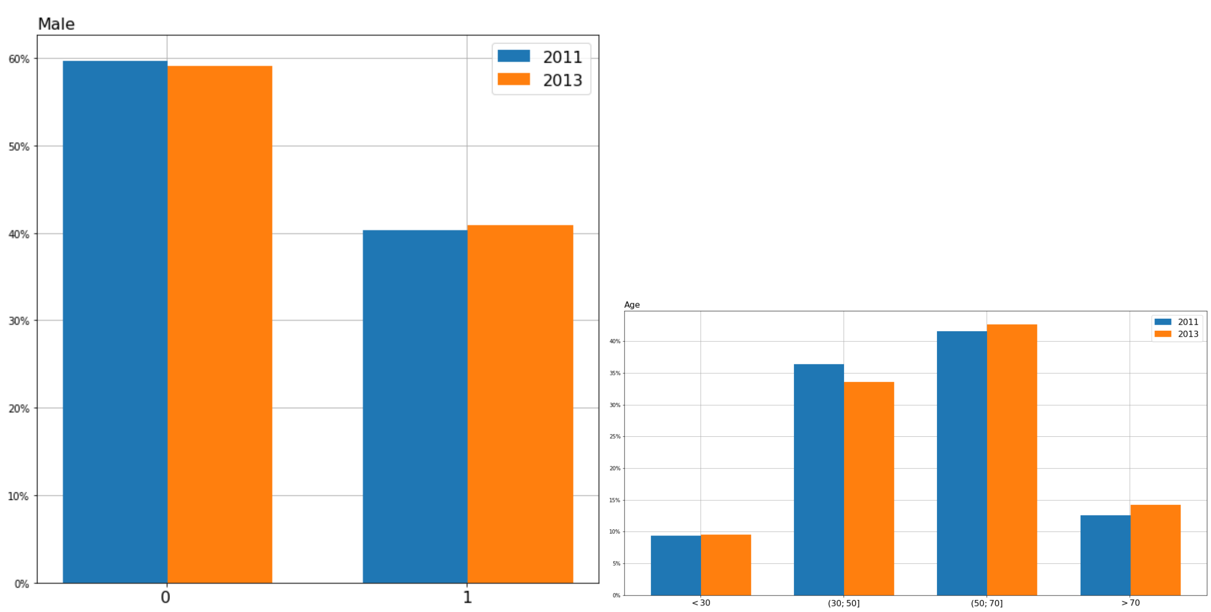
Table 7: Distribution of observations per country per time period

| 2011 | | 2013 | |
|---|---|---|---|
| **Survey questions** | | | |
| Q4(a). | What do you think needs to be done to improve waste management in your community? (Stronger law enforcement on waste management) | Q19(2). | In your opinion, which of the following actions would be the most efficient in reducing littering? (Better enforcement of existing anti-litter laws) |
| Q5. | Can you estimate what percentage of the food you buy goes to waste? | Q9. | Can you estimate what percentage of the food you buy goes to waste? |
| Q7. | How important for you is a product's environmental impact – e.g. whether the product is reusable or recyclable – when making a decision on what products to buy? | Q11. | Which of the following aspects do you consider most important when buying a durable product, like a washing machine or a fridge? (The product is environmentally-friendly) |
| Q8. | Would you buy the following products second hand? | Q12. | Would you buy the following products second hand? |
| | (a). Textiles (clothing, bedding, curtains etc.) | | 1. Textiles (clothing, bedding, curtains, etc.) |
| | (b). Electronic equipment | | 2. Electronic equipment (TV, computer, etc.) |
| | (c). Furniture | | 3. Furniture (couch, table, chairs, etc.) |
| **Demographical questions** | | | |
| D1. | Gender | D2. | Gender |
| D2. | How old are you? | D1. | How old are you? |
| D3. | How old were you when you stopped full-time education? | D4. | How old were you when you stopped full-time education? |
| D4. | As far as your current occupation is concerned, would you say you are | D5a. | As far as your current occupation is concerned, would you say you are self-employed, an |

| | | | |
|---|---|---|---|
| | self-employed, an employee, a manual worker or would you say that you are without a professional activity? | | employee, a manual worker or would you say that you are without a professional activity? |
| D6. | Would you say you live in a ...?<br>1. Metropolitan zone<br>2. Other town/urban centre<br>3. Rural zone | D13. | Would you say you live in a...?<br>3. Large town/city<br>2. Small or medium-sized town<br>1. Rural area or village |

Table 8: Common questions for 2011 and 2013 surveys.

*Note:* the table shows correspondence of questions from the 2011 Flash Eurobarometer 316 survey to questions from the 2013 Flash Eurobarometer 388 survey. We have displayed only the common questions we have used in the paper. In the main text all the variables are addressed by their number in the 2011 survey. Variable D3 was excluded from the analysis since its values available from the 2013 survey were not reliable. In particular, its distribution did not correspond to the expected one, and a big part of values did not comply with values of other variables for the same individual. A potential cause of this issue could be official variable description not corresponding to its actual encoding.




(a) Consensus-based treatment definition $D$.

(b) Distribution of gender..

Figure 6: Distribution of demographic variables.

## A.2 Waste policies

We identified the waste related policies by a "brute force" search approach. In particular, in a first step, we searched the keyword waste and identified all database domains in which waste-related policy information is contained. In a second step, we screened all policies in these domains and identified 636 policies related to waste in the 27 EU countries. The time period for the search was set to 1st January 2011 to 30th June 2013, allowing six months before the second survey for the policy effect lag. From these 636 policies, by reading the information on each and every one of them, we excluded all industry waste policies, as well as all other policies that contained no particular implications for household waste. Regional policies, i.e. policies that affect only a given region in a given country, were also excluded. Thus, in our sample, we retained only waste policies that were related to household waste, and in particular to household waste generation, recycling and management issues, and that were implemented on a national level in one of the EU members. The final list of selected policies is presented in table 9.

| Country | Date | Title |
|---|---|---|
| Austria (Tirol)* | 29.03.2011 | Ordinance by the regional government amending the Waste Management Plan. |
| Belgium (Vlaamse Gewest) | 23.11.2011 | Decree on the sustainable management of material and waste cycles. |
| Belgium (Vlaamse Gewest) | 17.02.2012 | Decree of the Flemish Government laying down the Flemish regulations on the sustainable management of material and waste cycles. |
| Bulgaria | 13.07.2012 | Law on waste management. |
| Cyprus | 23.12.2011 | Waste Law (Law No. 185(I)/2011). |
| Czech Republic | 09.01.2013 | State Environmental Policy of the Czech Republic 2012–2020. |
| Denmark | 25.03.2011 | Order No. 224 on Waste. |
| Denmark | 01.01.2013 | Order No. 1309 on Waste. |

| | | |
|---|---|---|
| France | 01.02.2011 | National Food Program (PNA) 2011 |
| France | 11.07.2011 | Decree No. 2011-828 of 11 July 2011 laying down various provisions relating to the prevention and management of waste. |
| Greece | 13.02.2012 | Law No. 4042 on the protection of the environment through criminal law, on waste management and other provisions, in compliance with EU Directives 2008/99/EC and 2008/98/EC. |
| Ireland | 31.03.2011 | European Communities (Waste Directive) Regulations 2011 (S.I. No. 126 of 2011). |
| Italy (Friuli-Venezia Giulia) | 31.12.2012 | Decree of the president of the Region No. 0278 approving the Regional Urban Waste Management Plan. |
| Italy (Lazio) | 18.01.2012 | Regional Waste Management Plan. |
| Italy (Puglia) | 13.05.2013 | Regional Urban Waste Management Plan 2013. |
| Italy (Sardegna) | 21.12.2012 | Regional Special Waste Management Plan. |
| Italy (Sicilia) | 01.01.2012 | Solid Urban Waste Management Plan. |
| Latvia | 12.07.2011 | Cabinet Regulation No. 564 of 2011 on State and Regional Waste Management Plans and State Waste Prevention Programme. |
| Latvia | 02.04.2013 | Cabinet Regulation No. 184 of 2013 on Separate Waste Collection, Preparation for Re-use, Recycling and Material Recovery |
| Malta | 01.01.2011 | Waste Regulations, 2011 (L.N. 184 of 2011). |
| Romania | 15.11.2011 | Law no. 211 of 15 November 2011 on the waste regime. |
| Slovakia | 01.01.2013 | Act amending and supplementing the Act on waste. |
| Slovenia | 31.12.2011 | Decree on waste. |
| Spain | 28.07.2011 | Law No. 22/2011 - Law on waste and contaminated soils. |

| | | |
|---|---|---|
| Spain | 01.01.2013 | Strategy "More food, less waste". Program for the reduction of food losses and waste and the recovery of discarded food. |
| United Kingdom (England; Wales) | 28.03.2011 | Waste (England and Wales) Regulations 2011 (S.I. No. 988 of 2011). |
| United Kingdom (Northern Ireland) | 16.03.2011 | Waste Regulations (Northern Ireland) 2011 (S.R. No. 127 of 2011). |
| United Kingdom (Scotland) | 16.05.2012 | Waste (Scotland) Regulations 2012 (S.S.I. No. 148 of 2012). |

Table 9: Laws

*Note:* the table shows all the laws chose as relevant that were implemented in the period from 1st January 2011 to 30th June 2013 in the EU countries. Law marked with a star was not used in the analysis since it was implemented only in one region of Austria, and it's unlikely that legislative change in one region would significantly influence outcome on the country level.

# B Appendix for the empirical framework section

## B.1 Additional figures

## B.2 Description of the DML DiD estimator

In our main results, we use the Double/Debiased Machine Learning Difference-in-Differences estimator (DMLDiD) estimator proposed by Chang (2020), which is an orthogonal extension of the semiparametric Difference-in-Differences estimator introduced by Abadie (2005). The motivation behind this approach is the following. Define $T_i$ to be a time indicator that is equal to 1 when the observation $i$ is from the post-treatment period. This time indicator is

| | GDP per capita | EPI | Policy |
|---|---|---|---|
| **Cluster 1** | | | |
| Bulgaria | 11 486.36 | 56.28 | 1 |
| Cyprus | 25 803.9 | 57.15 | 1 |
| Estonia | 16 353.21 | 56.09 | 0 |
| Hungary | 16 514.33 | 57.12 | 0 |
| Malta | 22 102.13 | 48.51 | 1 |
| Portugal | 21 658.22 | 57.64 | 0 |
| Romania | 10 929.43 | 48.34 | 1 |
| **Cluster 2** | | | |
| Belgium | 32 824.83 | 63.02 | 0 |
| Denmark | 32 608.2 | 63.61 | 1 |
| Finland | 31 532.55 | 64.44 | 0 |
| Greece | 24 990.04 | 60.04 | 1 |
| Ireland | 35 183.75 | 58.69 | 1 |
| Slovenia | 24 982.47 | 62.25 | 1 |
| Spain | 26 934.43 | 60.31 | 1 |
| **Cluster 3** | | | |
| Austria | 35 266.12 | 68.92 | 0 |
| France | 29 647.91 | 69 | 1 |
| Germany | 33 498.88 | 66.91 | 0 |
| Italy | 26 753.31 | 68.9 | 1 |
| Luxembourg* | 71 161.79 | 69.20 | |
| Netherlands | 36 915.25 | 65.65 | 0 |
| Sweden | 33 686.25 | 68.82 | 0 |
| United Kingdom | 32 187.05 | 68.82 | 1 |
| **Cluster 4** | | | |
| Czech Republic | 22 557.46 | 64.79 | 1 |
| Latvia | 12 938.02 | 70.37 | 1 |
| Lithuania | 15 390.82 | 65.5 | 0 |
| Poland | 17 336.67 | 63.47 | 0 |
| Slovakia | 19 244.15 | 66.62 | 1 |

Figure 7: GDP and EPS index for the four clusters.

handled as if it is a random variable. Then, the DML DiD estimator is defined as

$$A\hat{T}ET = \frac{1}{N}\sum_{i=1}^{N}\frac{T_i - \hat{\lambda}_i}{\hat{\lambda}_i(1-\hat{\lambda}_i)}\frac{Y_i}{\hat{\pi}}\frac{D_i - \hat{p}(X_i)}{1-\hat{p}(X_i)} \tag{2}$$

where $\hat{\lambda}_i$ is the estimator of $\mathbb{P}(T_i = 1)$, $\hat{\pi}$ is the estimator of $\mathbb{P}(D = 1)$ and $\hat{p}(X_i)$ is the estimator of propensity score $\mathbb{P}(D = 1|X = x)$.

The exact procedure of constructing this estimator is as follows: first, the whole sample is split into $K$ sub-samples of the equal size $n$. Here we split the sample into two sub-samples following Chang (2020). The final ATET estimator is equal to the average of $K$ sub-sample ATET estimators, where observations from the initial sample are assigned randomly into each sub-sample $I_k$. Each of those sub-sample estimators is defined as:

$$\widetilde{ATET}_k = \frac{1}{n}\sum_{i\in I_k}\frac{D_i - \hat{p}_k\left(X_i\right)}{\hat{\pi}_k\hat{\lambda}_k\left(1-\hat{\lambda}_k\right)\left(1-\hat{p}_k\left(X_i\right)\right)} \times \left(\left(T_i - \hat{\lambda}_k\right)Y_i - \hat{l}_{2k}(X_i)\right) \tag{3}$$

where:

- $\hat{p}_k(X_i)$ is a propensity score estimator which can be estimated using any machine learning method, for which the training set is the auxiliary sub-sample $I_k^c$ that includes all the other sub-samples of the initial sample apart from $k$;

- $\hat{\pi}_k = \frac{1}{n}\sum_{i\in I_k^c} D_i$ is the estimator of the probability of treatment $\mathbb{P}(D=1)$;

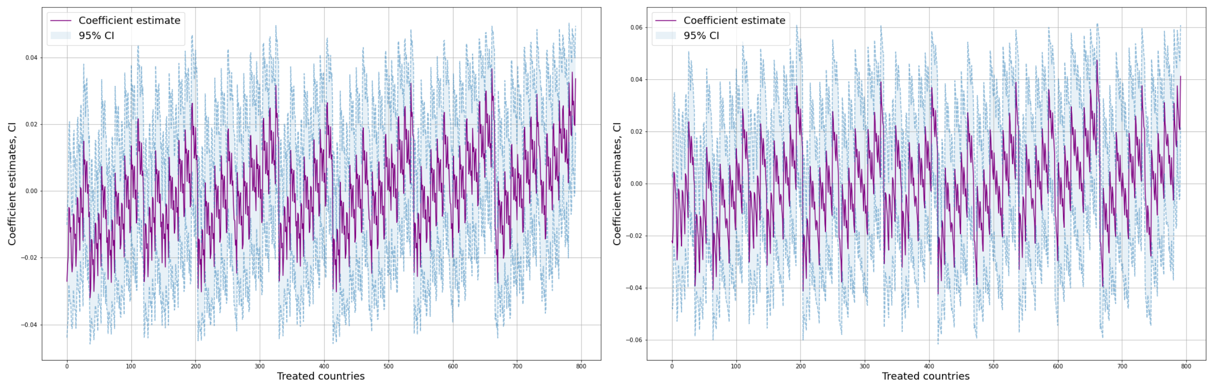
- $\hat{\lambda}_k = \frac{1}{n}\sum_{i\in I_k^c} T_i$ is the estimator of $\mathbb{P}(T=1)$;

- $\hat{l}_{2k}(X_i)$ is the estimator of the expected weighted outcomes $l_{20} = \mathbb{E}\left[(T-\lambda)\,Y|X, D=0\right]$. Similarly to $\hat{p_k}(X_i)$, it can be estimated with any machine learning method, using $I_k^c$ for training.

For each sub-sample $I_k$, the auxiliary subsample $I_k^c$ is used for calculation of $\hat{\pi}_k$ and $\hat{\lambda}_k$.

We an Ensemble Learner for estimation of the propensity scores $\hat{p_k}(X_i)$ and the function $\hat{l}_{2k}(X_i)$. An Ensemble Learner is a combination of multiple different machine learning methods, results of which are weighted in a certain way to produce the final estimation. In our analysis, the Ensemble Learner is a combination of Random Forest and Logistic LASSO models. Such a choice follows the paper of Zimmert (2020) who pointed out that ability of Random Forest to account for strong non-linearities together with smoothing properties of a LASSO can produce good estimates.

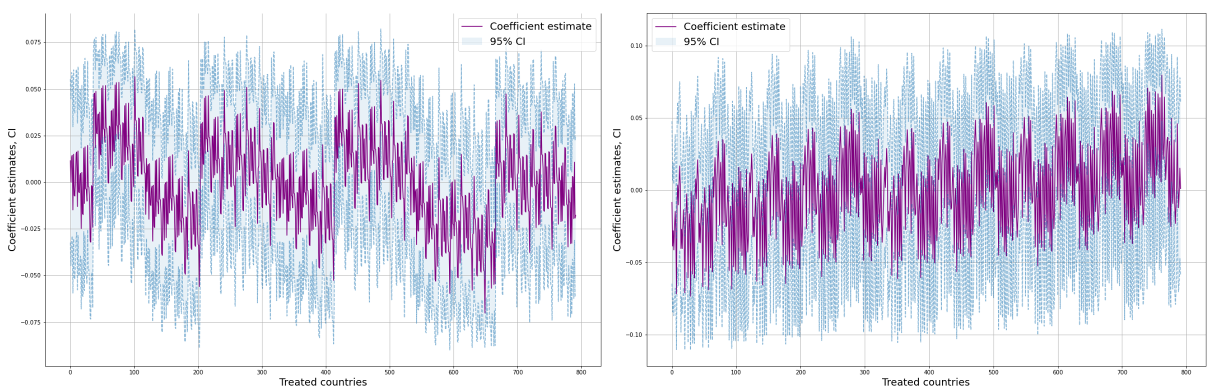
# C Appendix robustness checks




(a) Permutation test for food waste $\leq 15\%$.

(b) Permutation test forfood waste $\leq 30\%$.

Figure 8: Permutation tests.




(a) Permutation test for second hand textile.

(b) Permutation test for second hand electronics.

Figure 9: Permutation tests.

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