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# The effect of environmental policies on intrinsic motivation: evidence from the Eurobarometer surveys

\*Petyo Bonev<sup>†</sup>, Liudmila Gorkun-Voevoda<sup>‡</sup>, Michael Knaus

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## Abstract

We study the effect of environmental policies on (1) individual pro-environmental behaviors and (2) on the individual pro-environmental preferences. We obtain information on (1) and (2) from two large surveys with identical questions on waste behaviors and pro-environmental preferences commissioned by the European Commission in 2011 and 2014. Using a difference-in-differences design, we compare the outcome changes over time for those individuals who were subject to more stringent waste policies implemented between 2011 and 2014 to the outcomes of individuals who were not subject to such changes. We find that (1) effect of environmental policies on the amount of waste produced and the pro-environmental attitudes of individuals is heterogeneous across different clusters of countries and (2) introduction of monetary incentives increases efficiency of environmental policies.

**Keywords:** environmental policy evaluation, intrinsic motivation, crowding out

**JEL Codes:** D83, E61, H41, Q52, Q53, Q57, Z13.

## 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.<sup>1</sup> In this view, more of a certain economic

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<sup>1</sup>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.*

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. [31] for a recent study.

A consequence of that view is that if a policy affects a behavior not intentionally targeted by policy (henceforth a nontargeted behavior), then it must be also directly through the economic incentive provided by the policy. As an example, a subsidy for green electricity impacts the consumption of household room heating through the change in relative prices.<sup>2</sup> This is depicted in figure 1a. An environmental policy (the upper vertex in the graph) impacts a targeted activity (lower left vertex) and a nontargeted activity (lower right vertex) through the economic incentive. Recent advancements in behavioral economics have therefore focused on designing better economic incentives by circumventing or even utilizing cognitive limitations (such as inattention, anchoring and present biases), [12]. These approaches, however, although painting a richer picture of human behavior, have not significantly changed the dogma that economic policies affect behavior mainly through the explicit economic incentive, see e.g. [28] for a discussion of the standard approach in behavioral environmental economics.

Yet, parallel to the advancements in behavioral economics, 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. This is depicted in figure 1b where crowding effects are represented by a separate causal path. The effect of the policy affects the behavior both through the economic incentive (path (1)) as well as through its impact on intrinsic motivation (path (2)). The psychology literature has named this phenomenon “crowding (out or in) of intrinsic motivation”, [16], and has provided evidence for it in a large number of lab experiments, [17] and [7]. 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”), [7]. [5], [6] discuss reasons based on incomplete information and sorting. [5] describe a process, by which an economic incentive reveals to the agent possibly adverse intentions of the principal. [6] 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. In environmental economics, evidence for crowding effects has been provided mainly in the context of the so-called Payments for Environmental Services<sup>3</sup>, see e.g. [2] and the literature reviews by [25] and [18].

Evaluating the effects of policies on intrinsic motivation is a difficult econometric task. The major problem is that in the context of actual (i.e. real-world) policies, there is typically no direct

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<sup>2</sup>The relative price of a good is its value in terms of some other good, service, or bundle of goods. Changing it potentially leads to adjustments in consumption in all other goods.

<sup>3</sup>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 techniques.

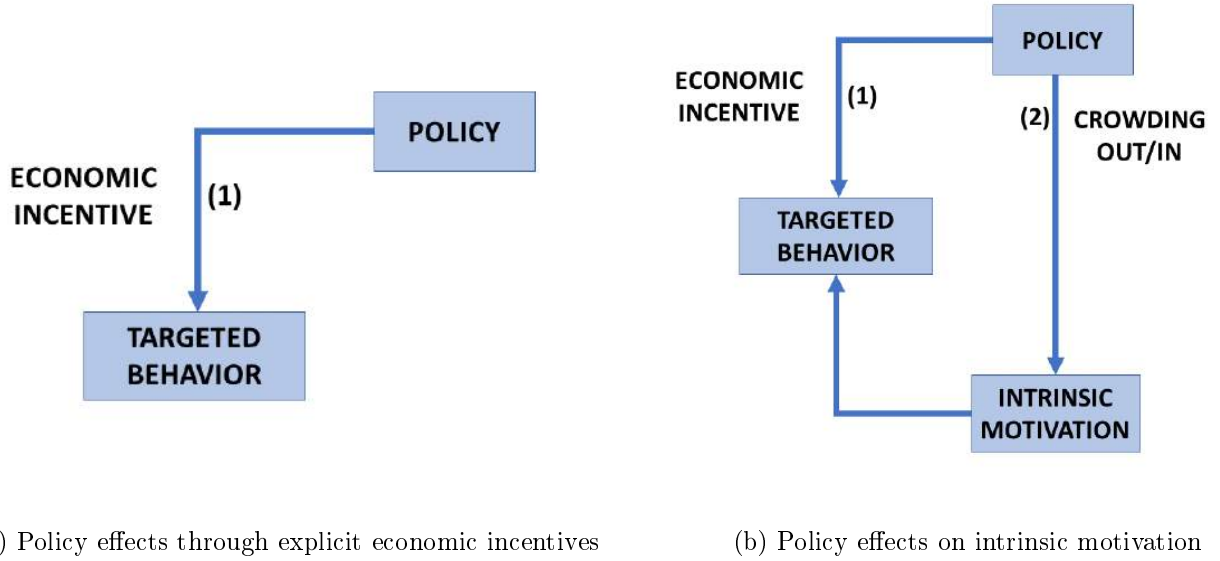


Figure 1

measure of motivation. The literature has followed two approaches to overcome this problem. The first one is to infer the effect on motivation from changes in observed behavior. With this approach, however, only the compound effect of the policy, i.e. the sum of the direct effect through the economic incentive and the indirect effect through motivation, can be identified. The second approach has been to use randomized control trials in which the outcomes are answers to survey questions. The overwhelming majority of these studies have been carried out either as lab experiments or as framed field experiments, which are simulated games with artificial treatments, see e.g. [8], [26], [22], [23] and [20], among others.<sup>4</sup> 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 [7] for a discussion. Therefore, most experiments are associated with a substantial lack of external validity.

The main objective of this paper is to evaluate the effects of real-world waste policies on actual behaviors and intrinsic motivation, as well as on attitudes towards environmental regulation. To do so, we use an innovative approach that combines large standardized surveys with data on actual policies. On the survey side, 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 information on four dimensions. The first one considers waste-related behaviors, which in the context of waste policies represent targeted behaviors. The survey includes positive questions such as “Can you estimate what percentage of the food you buy goes to waste?” and “Do you separate at least some of your waste for recycling or composting?”, as well as normative questions such as “Do you think that your household is producing too much waste or not?”. The second dimension contains questions on activities not targeted by waste policies such as “Would

<sup>4</sup>[2] is a notable exception. Their method, however, does not allow to measure actual crowding effects but rather a reversal of preferences.

you buy the following products [...] second hand?" (henceforth referred to as nontargeted behaviors). Importantly, the economic relationship between household waste behaviors and wearing second hand clothes can be considered rather weak: economic incentives that target waste behaviors neither change the relative cost of the nontargeted behaviors nor provide an unrelated economic incentive to change these behaviors. This is particularly useful for the empirical evaluation since any change in the tendency to wear second hand clothes due to the policy must be driven largely by a change in intrinsic motivation. The third dimension of questions asks about environmental attitudes in questions such as "Is the environmental impact of a product important for your purchase decision?". These questions represent our direct proxies for intrinsic motivation. Comparing the effects on nontargeted behaviors (wearing second hand) and intrinsic motivation is informative about the extent to which a change in motivation causes changes in behavior. Finally, the fourth dimension concerns attitudes towards regulation and includes questions such as "Would you like stricter enforcement of existing laws?". Changes in the answers in these questions over time are informative about the impact of policies on the general acceptance of environmental policies.

We match the survey data to 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.<sup>5</sup> 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 measures the effects of actual world policies on targeted and nontargeted behaviors, on intrinsic motivation and on acceptance of environmental policies. We find that the direction of the effect of legislation on food waste is heterogeneous across different sets of countries, which could potentially be explained by variation in baseline environmental policy stringency level. Effects on non-targeted activities examined in most of significant cases appear to be opposite of that on targeted activities. Finally, we find that introduction of monetary incentives such as fines or taxes tends to make a policy more efficient in achieving its target.

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<sup>5</sup><https://www.fao.org/faolex/en/>

## 2 Data

The data used for the main analysis is obtained from two surveys on attitudes of Europeans towards waste management and resource efficiency conducted by the European Commission in January 2011[13] and December 2013[14]. Each survey was conducted among countries which were members of the European Union at the time of surveying, leading to the final dataset consisting of 27 EU member states (Croatia is excluded from the results of the second survey because it joined the EU in July 2013 and is therefore not present in the first survey). Contents of the two surveys are not fully identical, however they share 17 common questions (12 content questions (environmental variables hereafter) and 5 demographic questions), on which the analysis is built. The full list of questions can be found in Table A.1. Questions with same formulation but different answer options were brought to the same format for consistency. The final dataset consists in total of 43 341 observations, of which 21 113 belong to 2011 survey, and 22 228 to the 2013 one. Distribution of observations per country can be found in Table A.2.

Information on environmental legislation changes which is used in the analysis was obtained from the portal of Food and Agriculture Organization of the United Nations[19]. In particular, we were interested in laws listed under the "Policy" and "Environment" sections which came into force in the period from 1<sup>st</sup> January 2011 to 30<sup>th</sup> June 2013, allowing six months before the second survey for the law effect lag. Out of those, we have selected ones that are directly related to household waste production, recycling and waste management issues. Therefore, for the 27 countries in the dataset, we have scraped total of 636 laws implemented in the aforementioned period, and have selected as relevant 28 of them. The final list of selected laws is presented in Table A.3.

Table 1: Descriptive statistics

	Mean			Std		
	Full	2011	2013	Full	2011	2013
<b>Content Questions</b>						
FOODWASTE (q5)	2.02	2.04	1.99	0.56	0.65	0.46
Too-much-waste (q1)	0.41	0.40	0.42	0.49	0.49	0.49
SEP (q2)	0.93	0.88	0.97	0.26	0.32	0.17
CONV(a) (q3_a)	0.58	0.67	0.49	0.49	0.47	0.50
CONV(b) (q3_b)	0.66	0.77	0.56	0.47	0.42	0.50
CONV(c) (q3_c)	0.55	0.65	0.45	0.50	0.48	0.50
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
FIN(a) (q12_1)	0.25	0.33	0.19	0.44	0.47	0.39
FIN(b) (q12_2)	0.59	0.77	0.43	0.49	0.42	0.50
FIN(c) (q13_2)	0.44	0.59	0.30	0.50	0.49	0.46
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
<b>Demographic Questions</b>						
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

The main explanatory variable is the variable FOODWASTE (FW) which indicates the percentage of food bought by a household that goes to waste. The variable takes integer values from 1 (no food wasted) to 5 (more than 50% of purchased food goes to waste). Variable Too-much-waste is a binary variable reflecting whether a person believes that her household is producing too much waste. Variable SEP is a binary variable showing if a person is separating at least some of her waste for recycling or composting. Variables CONV(a), CONV(b) and CONV(c) are binary variables reflecting opinion on effectiveness of measures that would convince the interviewee to separate more (or at least

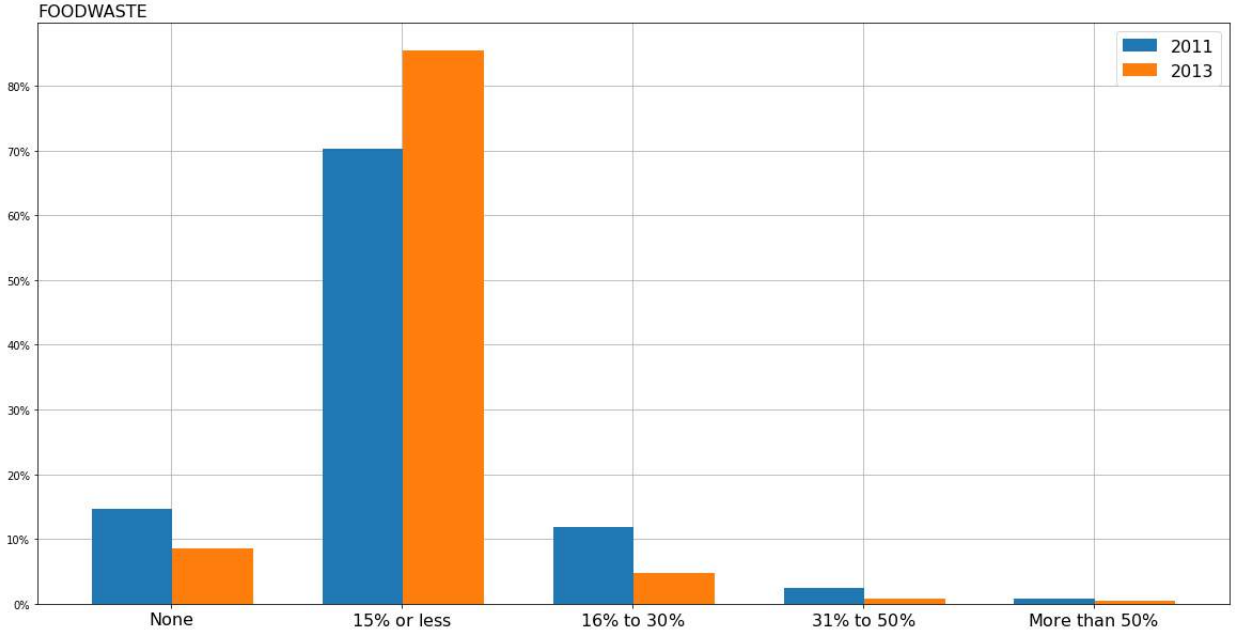


Figure 2: Distribution of the outcome variable Foodwaste.

some) of their waste. The measures are, respectively, improved waste collection at home, more and better drop-off points for recyclable and compostable waste and more information on how and where to separate waste. Variables SH.T, SH.E and SH.F are indicator variables for whether a person would buy textiles, electronics or furniture second hand. Variables FIN(a), FIN(b) and FIN(c) represent person's preferences regarding financing household waste management. The options, respectively, are: to pay taxes for waste management, to pay proportionally to the quantity of waste generated or to include cost of waste management in the price of products. LAW is a binary variable equal to 1 if a person believes that stronger law enforcement is needed to improve waste management in their community. Variable ENVIMP shows whether a product's environmental impact is important for the individual's purchase decision.

Variables Self\_employed, Employee, Manual\_worker, Unemployed and Student are binary variables representing the interviewee's employment status. Variables Metrop, Urban and Rural describe area where the person lives.

## 2.1 Correlations

Figure 3 shows correlation heatmaps of common environmental variables in the 2011 and 2013 surveys. Most variables are not highly correlated with each other, having mutual correlations below  $|0.15|$ , however there are three clusters of variables, which are more highly correlated. Composition of the clusters is almost the same in the two datasets. The first cluster consists of questions on factors that would convince the person to separate more (or at least some) of his or her waste. In the 2011 survey, question Q4 on whether the interviewee believes that stronger law enforcement on waste management is needed to improve waste management in his or her community. In both years, questions Q3(a), Q3(b) and Q3(c) have approximately the same mutual correlations. Those questions are represented in the dataset as dummy variables reflecting an interviewee's opinion on what would convince him or her to separate more (or at least some) of his or her waste - improved separate waste collection at



home; more and better drop-off points for recyclable and compostable waste or more information on how and where to separate waste, respectively. The second cluster consists of questions on whether the person would consider buying textiles, electronic equipment or furniture second-hand. In both years opinion on buying furniture second-hand has a higher correlation (approximately 0.13 higher) with the opinion on the other two categories, compared to correlation between buying textiles and electronics second hand. The third cluster consists of questions representing interviewee's opinion on financing household waste management. However, in 2013 survey all the three answer options are mutually exclusive, therefore the correlations are not meaningful.

### 3 Theoretical Framework

In this section, we present notation, the causal effect of interest and the three models for estimation of the effect of change in environmental legislation on percentage of food wasted.

We start by introducing the general setting. There is an outcome variable of interest  $Y$ , which is influenced by some treatment  $D$ . Therefore, the main objective of the causal analysis is to identify the effect which treatment  $D$  has on the outcome variable  $Y$ . In the current setting,  $D$  is set to be binary, therefore indicating whether a given unit has received the treatment (then the unit is said to be treated) or not (then the unit is said to be control).

Estimation is based on the counterfactual framework developed by Rubin[27], the so-called Rubin Causal Model. The Model assumes that for each individual in the sample there exist two potential outcomes - one with the treatment and one without. The outcome under the treatment is denoted as  $Y^1$  and the outcome if the individual was not treated is denoted as  $Y^0$ . Given those two outcomes, we would be interested in comparing them to see the effect which treatment had on the characteristic of interest of the given individual. However, in a real-world setting those two outcomes are never observed together, as an individual always either receives a treatment or not. Therefore, such an estimation of the causal effect is not possible due to missing data. Since not all the information needed for the estimation of causal effect is available in data, certain identifying assumptions are needed that make the estimation possible.

The first assumption that is needed is the Stable Unit Treatment Value Assumption (SUTVA). This assumption has two components - firstly, it assumes that units do not interfere with each other and, secondly, that each unit can only receive one version of the same treatment. The first component implies that potential outcomes of some unit are not affected by treatment assigned to other units. In other words, this means that treatment of unit  $i$  only affects the outcome of this unit  $i$  and not any other unit. The second component of SUTVA ensures that a unit that is assigned some level of treatment (basically, treatment or no treatment), can not receive some different version of the same level of treatment. If SUTVA holds, then the realized outcome  $Y$  can be represented as a combination of observed and unobserved potential outcomes.

$$Y = DY^1 + (1 - D)Y^0$$

This assumption cannot be proven from the observed data, but can only be assumed based on some background knowledge. we assume that the SUTVA assumption holds because, firstly, we assume that

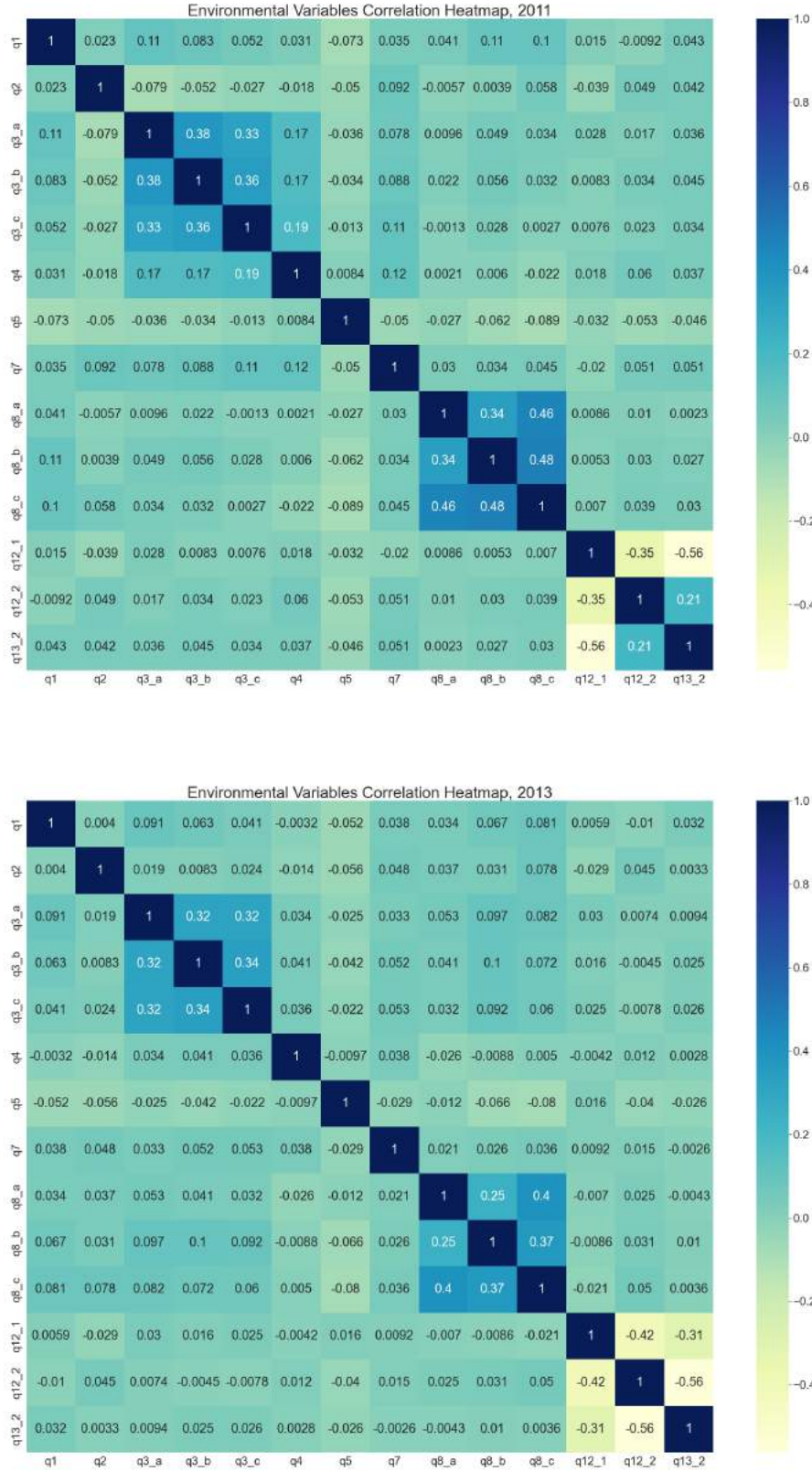


Figure 3: Correlation heatmaps of environmental variables.

the amount of food wasted in a given country is not influenced by an introduction or amendment of an environmental law in any other country and, secondly, because all the laws considered in this analysis are of the same nature - all of them target household waste reduction, separation and recycling.

The other three identifying assumptions are:

1. Conditional Independence Assumption (CIA), also sometimes referred to as unconfoundedness assumption. Potential outcomes  $Y^0$  and  $Y^1$  are independent of treatment status, conditioning on confounding variables.

$$Y^0, Y^1 \perp\!\!\!\perp D | X = x; \forall x \in \chi,$$

where  $\chi$  is the sample. The CIA assumption would be violated if there any variables that influence both potential outcomes and treatment are not observed. In the current setting, the number of variables available in the dataset is limited, therefore it is hard to assess validity of CIA.

2. Common Support. Ensures that for every set of covariates, a unit with treatment and without treatment could be observed. This makes estimation of the causal effect plausible, since it ensures that there are units with the same covariates but different treatment status, for which the outcomes could be compared.

$$0 < P(D = 1 | X = x) < 1; \forall x \in \chi$$

The Common Support assumption can be verified by a visual check of distributions of important covariates for the treated and control groups. Overlap of all the dummy demographical variables can be checked on Figures A.7, A.8, A.9 and A.10. Distribution of the only continuous variable Age is presented in Figures A.4 and A.5. After examining those figures, it can be safely assumed that the Common Support assumption holds in the current setting.

3. Exogeneity of confounders. Treatment does not influence confounders in a way that is associated with the outcome.

$$X^1 = X^0$$

For all the models presented here, we assume SUTVA, CIA, Common Support and Exogeneity on confounders assumptions to hold.

We are interested in estimating the Average Treatment Effect on the Treated (ATET) on the percentage of food being wasted. ATET shows the expected causal effect of a binary treatment (in the current setting - presence or absence of new laws in a certain time frame) on those individuals that did receive the treatment (in the current setting - those that lived in the countries where those laws were introduced/amended) and is defined as

$$ATET = \mathbb{E}[Y^1 - Y^0 | D = 1] \tag{1}$$

As was mentioned above,  $Y^1$  and  $Y^0$  for one unit are never observed together, therefore estimation of ATET is impossible in the form presented in equation (1). If all the identifying assumptions hold, then missing parameters can be expressed in terms of random variables that are observed from

data and ATET can be rewritten as

$$\begin{aligned}
ATE_T &= \mathbb{E} [Y^1 - Y^0 | D = 1] \stackrel{\text{LIE}}{=} \mathbb{E}_X [\mathbb{E} (Y^1 - Y^0 | D = 1, X)] = \\
&= \mathbb{E}_X [\mathbb{E} (Y^1 | D = 1, X) - \mathbb{E} (Y^0 | D = 1, X)] \stackrel{\text{CIA}}{=} \\
&= \mathbb{E}_X \left[ \mathbb{E} \left( \frac{Y - (1 - D)Y^0}{D} \middle| D = 1, X \right) - \mathbb{E} (Y^0 | D = 0, X) \right] = \\
&= \mathbb{E}_X \left[ \mathbb{E} (Y | D = 1, X) - \mathbb{E} \left( \frac{Y - DY^1}{1 - D} \middle| D = 0, X \right) \right] = \\
&= \mathbb{E}_X [\mathbb{E} (Y | D = 1, X) - \mathbb{E} (Y | D = 0, X)] \tag{2}
\end{aligned}$$

It can be seen from (2) that now ATET is identified, since the conditional expectations are estimable from data. Note, that in such setting ATE is identical to ATET.

### 3.1 Difference-in-Differences

The first model that is used for estimation of ATET is the Difference-in-Differences (DiD) model, which is one of the classical models for estimating causal effects in the setting in which data from multiple time periods is observed (panel data or repeated cross-sections, as in the current case). The DiD setting requires data to be observed at at least two time points, one before the treatment and one after the treatment, in each of which the sample includes treated and control units.

The model is often used in natural experiment settings. One of the most famous examples is a natural experiment performed by John Snow (1855)[29], during which he studied the difference in death rates between two districts of London. The two districts were getting water supply from two different companies. Before 1852 both companies were getting the water from Thames in the central part of London, while later one of them moved their water intake to a cleaner part of the river. By comparing the death rates in the two districts before and after the move, Snow showed that dirty water is the real cause of cholera outbreaks.

As its name suggests, the idea of DiD method is to compare the difference in means of outcomes between treated and control groups after the treatment and compare it to the difference in outcome means between the groups that was present before the treatment.

The four assumptions discussed in Section 3 are needed for identification of the DiD model. The Common Support assumption, in particular, now is required to hold for the four subsamples - pre-treatment treatment group, pre-treatment control group, post-treatment treatment group and post-treatment control group, implying that individuals with the same covariates should exist in all the four subsamples. In addition, there are two DiD-specific identifying assumptions that are necessary for the estimation:

1. No effect of treatment on the pre-treatment time period (NEPT). This assumption implies that  $ATE_{t=0} = 0$ . We assume that there is no effect of anticipation of new laws being implemented or amended on the amounts of food waste produced reported in the first survey.
2. Common Trend Assumption (CTA). This assumption is a key identifying assumption for the DiD model, and it implies that in the case no treatment was applied, the outcome variable in

the current treatment and control groups would have changed in the same way. Validity of this assumption in the current setting is discussed in Section 3.1.1.

Therefore, if NEPT, CTA and the assumptions discussed in Section 3 hold, then comparison of the differences in means would produce a valid average causal effect.

To estimate the effect, we run a regression of the form

$$Y_i = \beta_0 + \sum_{k=1}^8 \beta_k X_{ik} + \beta_9 T_i + \beta_{10} D_i + \beta_{11} T_i D_i + \epsilon_i \quad (3)$$

where  $T$  is a dummy variable representing time period, which is equal to 0 if the year of the observation is 2011 (pre-treatment period) and is equal to 1 if the year is 2013 (post-treatment period);  $D$  is a dummy variable for law implementation (treatment), that is equal to 1 if in the country which an observation comes from changes in environmental legislation took place in the period from January 2011 to July 2013, and is equal to 0 otherwise (this variable is time-constant).  $X$  is a set of demographic variables (sex, age, occupation and area of living) of the individual  $i$ . As a result, the coefficient  $\beta_9$  shows the change in the outcome variable due to time (time trend), coefficient  $\beta_{10}$  shows the difference in the outcome variable between the treatment group (countries with a change in environmental legislation) and control group (countries without such a change) in the pre-treatment period (in the year 2011). Coefficient of the interaction term between time and treatment,  $\beta_{11}$ , shows the difference in change of the outcome variable between the treatment and control groups, which represents the value of interest.

Such a model could be estimated via Ordinary Least Squares method, if the outcome variable was continuous. However, in the current setting we do not observe the actual percentage of food wasted  $FW^*$  but only its discretized version  $FW$ , which is an ordinal variable taking integer values from 1 to 5. Therefore, using OLS would not be most appropriate. Instead, we use an Ordinal Logistic Regression, which is designed for estimating models with discrete ordinal outcome variables. Therefore, the categorization of each individual into one of the observed levels of  $FW$  is implicitly based on the unobserved continuous  $FW^*$ . Likelihood of getting outcomes as in the observed sample is given by

$$\mathbb{L} = \prod_{j=1}^5 [P(FW_i = j)]^{N_j} \quad (4)$$

where  $N_j$  is the number of people observed in each category. In order to estimate the unknown  $\beta_k, k \in \{1, \dots, 11\}$  in the Equation (3), they should be chosen so as to maximize the likelihood in Equation (4). For that the probability distribution of the error term  $\epsilon_i$  needs to be known or assumed. As follows from its name, Ordinal Logistic Regression assumes that the error terms follow logistic distribution. This allows to get the probabilities for calculation of likelihood in 4, since under logistic distribution

$$P(X \leq x) = \frac{1}{1 + \exp(-x)} \quad (5)$$

There is one potential drawback of the Ordinal Logistic Regression model. It assumes that the effect is the same for all categories. The model considers an odds ratio showing the probability of belonging to a category  $j$  or lower and defined as

$$\frac{P(FW \leq j)}{P(FW > j)}, j \in \{1, \dots, 4\} \quad (6)$$

which is constant for all  $j$  (group 5 is excluded since  $P(FW > 5) = 0$ ). In our case that implies that the change in environmental legislation would have the same effect on people who wasted only little food before the change and those people who wasted over a half of it. This implication is arguable from the practical point of view, since if a person is already not wasting much food, then there is not as much room for waste reduction as for those who waste a lot.

Therefore, Ordinal Logistic Regression model can be written as

$$\log \left[ \frac{P(FW \leq j)}{P(FW > j)} \right] = \beta_{0j} + \sum_{k=1}^8 \beta_k X_k + \beta_9 T + \beta_{10} D + \beta_{11} TD \quad (7)$$

Note that only the intercept is specific to each category  $j$ , while slope coefficients are the same due to the property described above.

Therefore, the coefficients  $\beta_k, k \in \{1, \dots, 11\}$  show the expected change in logged odds ratio when the value of the corresponding explanatory variable changes. A useful value to describe the results would also be the

### 3.1.1 Common Trend Assumption

As stated in Section 3, a key assumption ensuring identification of the Difference-in-Differences model is the Common Trend Assumption. It can be written as

$$\begin{aligned} & \mathbb{E}(Y_{t=1}^0 | X = x, D = 1) - \mathbb{E}(Y_{t=0}^0 | X = x, D = 1) = \\ & = \mathbb{E}(Y_{t=1}^0 | X = x, D = 0) - \mathbb{E}(Y_{t=0}^0 | X = x, D = 0) = \\ & = \mathbb{E}(Y_{t=1}^0 | X = x) - \mathbb{E}(Y_{t=0}^0 | X = x); \forall x \in \chi \end{aligned}$$

The usual check for this assumption is a visual verification of the outcome variable trends in treatment and control groups before the treatment date. However, obviously such a check requires availability of data at several pre-treatment time points, which is not available from the datasets used in this paper.

Therefore, other assumptions need to be imposed under which the Common Trend Assumption can be assumed to hold. For example, Cecere et. al. (2014)[9] divided observations into groups based on the geographical position of a country they belong to. Namely, they have divided the 27 countries into four groups - Western Europe, Eastern Europe, Southern Europe and Northern Europe. The authors have assumed that inside those geographical clusters the Common Trend Assumption holds.

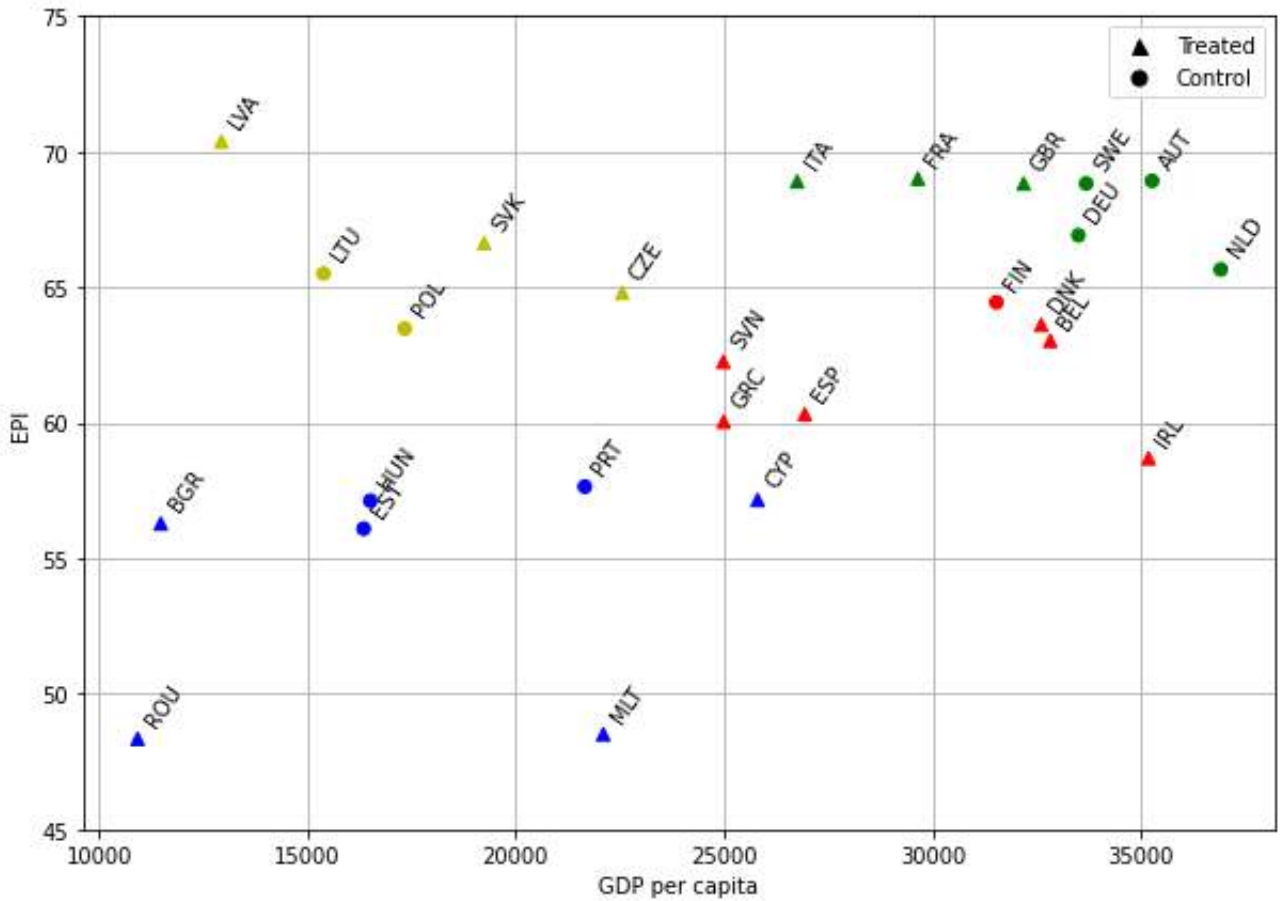
We have decided to search for an alternative partition of countries into groups as purely cardinal directions-based separation does not necessarily imply common trends in waste behaviour. Alternatively, we propose an assumption that countries which are similar in terms of their GDP per capita as well as strictness of their current environmental legislation are likely to have a common trend in waste behaviour. As a measure of strictness of environmental legislation we are using the Environmental Performance Index[15] (EPI). To measure the similarity in terms of GDP per capita and EPI and to allocate countries into appropriate groups, we have implemented k-Means clustering algorithm.

The k-Means algorithm is based on an idea to determine the initial approximation of the centres of potential clusters and assign all data points in the sample to one of those clusters, minimizing

the in-cluster sum of squared Euclidean distances from each point to the cluster centre (inertia). Given the initial approximation, each object is assigned to a cluster which centre is the closest to it. After that a new centre of each cluster is computed as the average of feature vectors. The above procedure is repeated until the centres do not change their position after recomputing.

Figure 4 depicts a scatterplot of countries with GDP per capita on the x-axis and Environmental Performance Index on the y-axis. The points are coloured according to their resulting cluster assignment from the k-Means algorithm. Countries, which experienced environmental legislation changes are plotted with triangles, those which did not - with circles. More detailed information on the resulting cluster composition is presented in Table 2. In the end, there are four resulting clusters, and all the further analysis will be performed inside each cluster separately. Descriptive statistics individually for each of the four clusters are presented in Tables A.4, A.5, A.6 and A.7. Note that Luxembourg is not presented on the scatterplot for visibility reason, because its GDP per capita is far above GDP per capita of any other country in the sample, and therefore including it on the plot would distort the scale.

Figure 4: Clustering results from k-Means.



*Note:* The figure shows clustering of countries based on their GDP per capita and EPI. There are four clusters, each of which are indicated by a distinct color. Treated countries have triangle-shaped markers, control countries have round markers. Luxembourg was cut off the plot for better visual clarity; it belongs to cluster 3 (marked with green on the plot).

Table 2: Clusters composition obtained from k-Means clustering

GDP per capita		EPI	Policy	GDP per capita		EPI	Policy
Cluster 1				Cluster 3			
Bulgaria	11 486.36	56.28	1	Austria	35 266.12	68.92	0
Cyprus	25 803.9	57.15	1	France	29 647.91	69	1
Estonia	16 353.21	56.09	0	Germany	33 498.88	66.91	0
Hungary	16 514.33	57.12	0	Italy	26 753.31	68.9	1
Malta	22 102.13	48.51	1	Luxembourg	71 161.79	69.2	0
Portugal	21 658.22	57.64	0	Netherlands	36 915.25	65.65	0
Romania	10 929.43	48.34	1	Sweden	33 686.25	68.82	0
				United Kingdom	32 187.05	68.82	1
Cluster 2				Cluster 4			
Belgium	32 824.83	63.02	1	Czech Republic	22 557.46	64.79	1
Denmark	32 608.2	63.61	1	Latvia	12 938.02	70.37	1
Finland	31 532.55	64.44	0	Lithuania	15 390.82	65.5	0
Greece	24 990.04	60.04	1	Poland	17 336.67	63.47	0
Ireland	35 183.75	58.69	1	Slovakia	19 244.15	66.62	1
Slovenia	24 982.47	62.25	1				
Spain	26 934.43	60.31	1				

*Note:* column "Policy" of the table takes value 1 if there were any environmental policy changes in the respective country, and 0 otherwise.

Table 3: EPI and GDP per capita among the treated and non-treated country groups.

	EPI		GDP per capita	
	Mean	Std	Mean	Std
Treated	61.579	6.994	23 889.907	7 547.055
Control (without Luxembourg)	63.416	4.571	26 452.466	8 858.602
Control (with Luxembourg)	63.898	4.667	30 178.243	15 424.582



### 3.2 Difference-in-Differences with Propensity Scores Weighting

An alternative approach to estimating  $ATE$  is to model the propensity score, which is the probability of treatment given the covariates

$$p(x) = \mathbb{P}(D = 1|X = x) \quad (8)$$

Propensity score methods are good for minimization of selection bias in selection on observables setting, where the treatment and control groups composition could potentially change over time. In this work, we are using the propensity scores weighting strategy for estimating the ATET with the Difference-in-Differences model. The problem of changed group composition is not the main concern of the current dataset since by construction of the surveys representative samples are obtained. However, we can still face the problem of different groups compositions of treatment and control, because a representative sample for each country could vary. Propensity score weighting allows to overcome that by making observations in all the four groups similar. Another advantage of weighting over propensity scores matching is that it allows to use all the observations in the sample, whereas matching would omit those not matched.

The strategy consists of two steps: firstly, propensity scores are estimated and, secondly, a Difference-in-Differences model discussed in Section 3.1 is run using the estimated propensity scores as weights for observations. The first step involves weighting observations in the four groups (pre-treatment treated, pre-treatment control, post-treatment treated and post-treatment control) in order to make them similar in covariates. Since we are interested in estimating the effect of policy changes on the group that was not treated in the first time period but will become treated in the second time period (denoted as group 1), we weigh each of the other three groups to match the distribution of covariates in this group 1 (following Stuart et al. (2014)[30]). Therefore, in this setting we define propensity score as the probability of an individual to belong to the group 1.

Estimation of propensity scores is performed via a multinomial logistic regression using group number as an outcome variable (1 for pre-treatment treated, 2 for post-treatment treated, 3 for pre-treatment control and 4 for post-treatment control). The model is similar to ordered logistic regression discussed in Section 3.1 in the sense that it is designed for the cases of discrete outcome variable, however it does not imply any ordering in categories, which is the case in the current setting. On the other hand, in Section 3.1 some ordering of the outcome categories was present, since intuitively the lower the category, the "better" is the outcome. After fitting the multinomial logistic regression, we use it to obtain predicted probabilities of each observation to belong into one of the four groups  $p_k$ ,  $k \in \{1, \dots, 4\}$ . Using those probabilities, weighting for an individual  $i$  is constructed as

$$w_i = \frac{p_1(x_i)}{p_g(x_i)} \quad (9)$$

where  $p_g$  is the estimated probability to belong to the group to which this individual actually belongs (therefore, for all individuals in group 1  $w_i = 1$ ). Consequently, the final estimator can be obtained by estimating the Difference-in-Differences model from Equation 7, with the only difference that the observations are now weighted by the weights calculated in Equation 9.

### 3.3 Double/Debiased Machine Learning Difference-in-Differences

The third estimator we are using is the Double/Debiased Machine Learning Difference-in-Differences estimator (DMLDiD) estimator proposed by Chang (2020)[10], which is an orthogonal extension of the Abadie's[1] semiparametric Difference-in-Differences estimator of ATET. Particularly, in the case of repeated cross-sections, under the assumptions presented in Section 3 the ATET estimator can be calculated as

$$ATET = \frac{1}{N} \sum_{i=1}^N \frac{T_i - \hat{\lambda}_i}{\hat{\lambda}_i(1 - \hat{\lambda}_i)} \frac{Y_i D_i - \hat{p}(X_i)}{\hat{\pi} (1 - \hat{p}(X_i))} \quad (10)$$

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  $\mathbb{P}(D = 1|X = x)$ . This estimator of ATET is constructed for the case when  $\hat{p}(X_i)$  is estimated with classical non-parametric estimation techniques (such as kernel estimation). However, if machine learning methods are used for the first stage estimation, this estimator may lose its convenient properties of being  $\sqrt{N}$ -consistent and asymptotically normal, therefore producing a bias in the final estimation. There are two reasons for such behaviour. Firstly, a score function based on Abadie's estimator has a non-zero directional derivative with respect to the propensity score. Using estimators for which this derivative would be equal to zero (the Neyman orthogonality condition[11]) is important to obtain valid estimators of ATET when machine learning methods are used for estimation of the nuisance parameters. Secondly, generally machine learning estimators in such a setting will not be  $\sqrt{N}$ -consistent since they often have a slower convergence rate due to regularization bias. Therefore, if machine learning estimates are directly used in (10), then the estimators will not be  $\sqrt{N}$ -consistent. The DMLDiD estimator is able to correct bias obtained from machine learning-based first stage estimation by introducing zero-mean adjustment terms to the second stage estimator, which make the Neyman orthogonality condition hold. Author combines the new adjusted scores with the cross-fitting algorithm developed by Chernozhukov et al. (2018)[11] to construct the DMLDiD estimator.

Therefore, the procedure is as follows: firstly, the whole sample is split into  $K$  sub-samples of the equal size  $n$ . Here we are splitting the sample into two sub-samples following Chang (2020)[10]. 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:

$$\widetilde{ATET}_k = \frac{1}{n} \sum_{i \in I_k} \frac{D_i - \hat{p}_k(X_i)}{\hat{\pi}_k \hat{\lambda}_k (1 - \hat{\lambda}_k) (1 - \hat{p}_k(X_i))} \times \left( (T_i - \hat{\lambda}_k) Y_i - \hat{l}_{2k}(X_i) \right) \quad (11)$$

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  $l_{20} = \mathbb{E}[(T - \lambda)Y|X, D = 0]$ . 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 are using an Ensemble Learner for estimation of the propensity scores  $\hat{p}_k(X_i)$  and the function  $\hat{b}_k(X_i)$ . 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 my analysis, the Ensemble Learner is represented by a combination of Random Forest and Logistic LASSO models. Such a choice follows a paper of Zimmert (2020)[34] 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.

## 4 Empirical Results

### 4.1 Difference-in-Differences

Table 4 shows results of the Difference-in-Differences model estimation using an Ordered Logistic Regression, separately for each cluster. Recaping from Section 3.1, equation of the estimated regression looks as

$$\log \left[ \frac{P(FW \leq j)}{P(FW > j)} \right] = \beta_{0j} + \sum_{k=1}^8 \beta_k X_k + \beta_9 Date + \beta_{10} Policy + \beta_{11} PolicyTime$$

The first two columns of Table 4 report the estimated regression coefficients  $\beta_k, k \in \{1, \dots, 11\}$  and their standard errors. The third column reports values of the logged odds ratio (log-odds); columns four and five report 2.5% and 97.5% bounds of log-odds confidence interval.

The main estimate of interest is the coefficient  $\beta_{11}$  of the interaction term between policy and time period dummies. As can be seen from the table, in clusters 1 and 2 the coefficient is negative and is significant on 0.1% confidence level, which means that policy changes are associated with decrease of food waste. In cluster 3 the coefficient is positive but is only significant on 15% confidence level. In cluster 4 it is as well positive and also significant on 0.1% confidence level.

Interpreting the coefficient values, let's examine the values of regression coefficients and the log-odds. For cluster 1 they imply that in the countries, in which change of environmental legislation did not take place, the odds of wasting less food (reporting a lower category of FW) compared to wasting more food (reporting a higher category) are 32.6% lower than in the countries, in which the change did take place. As stated in Section 3.1, these odds are constant for every level of comparison. For cluster 2, in control countries the odds of wasting less food versus wasting more food are 30.5% lower than in treated countries. Similarly, for clusters 3 and 4 odds for the control group are, respectively, 16.5% and 131.7% higher than for treated group. The strongest effect is observed in cluster 4, which is, interestingly, positive, implying that policy changes are associated with increase of food waste. Possible reason for this result is a policy crowding-out effect, which is discussed in more detail in Section 5.

Looking at other coefficients, it is interesting to note that age has a significant negative effect on food waste in all the four clusters. The size of the effect is also very similar, and is equal to 3.2% lower odds of wasting less for a person of one year of age less in clusters 1 and 3; 3.2% lower odds

in cluster 2 and 4.1% in cluster 4. This result suggests that younger people tend to waste more food than older people.

The dummy variable Rural, which indicates whether a person lives in the rural area, is significant and negative for all the four clusters. Size of the effect is also larger than that for age. In Cluster 4 it is the largest, and is equal to 51.3% lower odds of wasting less food for those who live in a non-rural area. This cluster is also the only one where the dummy variable Urban from the same category is significant. In clusters 1, 2 and 3 the effect of Rural is equal to, respectively, 30.7%, 35.2% and 11.7% lower odds of wasting less food. This result is intuitive, since people who live in the rural area are more likely to have more opportunities to use surpluses of food that would have otherwise been sent to waste (for example, as a fertilizer for plants or to feed animals).

Table 4: DiD via ordered logistic regression model results.

	Regr. coef	Regr. s.e.	Log-odds coef.	Log-odds 2.5%	Log-odds 97.5%
<b>Cluster 1</b>					
policy.time	-0.395***	(0.088)	0.674	0.567	0.800
Date	-0.058	(0.064)	0.943	0.832	1.069
policy	0.468***	(0.063)	1.597	1.412	1.807
Male	0.111**	(0.045)	1.117	1.022	1.221
Age	-0.033***	(0.002)	0.968	0.965	0.971
Self_employed	0.386***	(0.085)	1.471	1.246	1.738
Employee	0.316***	(0.057)	1.371	1.227	1.533
Manual_worker	0.095	(0.092)	1.100	0.919	1.318
Student	0.258	(0.230)	1.295	0.820	2.017
Rural	-0.366***	(0.059)	0.693	0.618	0.778
Urban	-0.071	(0.054)	0.931	0.837	1.036
<b>Cluster 2</b>					
policy.time	-0.363***	(0.136)	0.695	0.532	0.908
Date	0.060	(0.127)	1.061	0.828	1.360
policy	0.448***	(0.097)	1.566	1.294	1.895
Male	0.138***	(0.049)	1.148	1.043	1.263
Age	-0.032***	(0.002)	0.968	0.965	0.972
Self_employed	0.226**	(0.092)	1.254	1.046	1.501
Employee	0.339***	(0.063)	1.404	1.242	1.587
Manual_worker	0.194*	(0.105)	1.214	0.988	1.489
Student	-0.183	(0.270)	0.833	0.486	1.398
Rural	-0.449***	(0.063)	0.639	0.565	0.722
Urban	-0.051	(0.061)	0.950	0.843	1.071
<b>Cluster 3</b>					
policy.time	0.153	(0.100)	1.165	0.958	1.419
Date	-0.268***	(0.062)	0.765	0.678	0.864
policy	-0.332***	(0.073)	0.717	0.622	0.827
Male	0.103**	(0.050)	1.109	1.006	1.222

Age	-0.032***	(0.002)	0.968	0.964	0.972
Self_employed	-0.057	(0.094)	0.944	0.785	1.136
Employee	0.120*	(0.066)	1.127	0.990	1.284
Manual_worker	0.314***	(0.109)	1.369	1.104	1.692
Student	-0.128	(0.284)	0.880	0.495	1.511
Rural	-0.124*	(0.065)	0.883	0.777	1.003
Urban	0.057	(0.065)	1.059	0.933	1.202
<b>Cluster 4</b>					
policy.time	0.840***	(0.105)	2.317	1.886	2.847
Date	-0.195**	(0.083)	0.823	0.699	0.969
policy	-0.542***	(0.078)	0.582	0.499	0.677
Male	0.041	(0.053)	1.042	0.940	1.155
Age	-0.041***	(0.002)	0.959	0.956	0.963
Self_employed	0.087	(0.091)	1.091	0.913	1.304
Employee	0.093	(0.068)	1.097	0.960	1.255
Manual_worker	-0.170*	(0.098)	0.844	0.697	1.023
Student	0.337	(0.281)	1.400	0.800	2.405
Rural	-0.720***	(0.070)	0.487	0.425	0.558
Urban	-0.384***	(0.064)	0.681	0.600	0.772

*Note:* the table shows estimated effects of environmental legislation changes produced by Difference-in-Differences model. Standard errors are shown in brackets. Stars indicate significance level: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

## 4.2 Difference-in-Differences with Propensity Scores Weighting

Table 5 shows results of estimation of Difference-in-Differences model with propensity scores weighting, separately for each cluster. Similarly to results in Section 4.1, the coefficient of interest is the one that correspond to the interaction term between Date and Policy dummies. As can be seen from the table, directions of the effect are similar to those with the non-weighted DiD. In clusters 1 and 2 the effect is negative, suggesting that change of environmental policy is associated with the decrease in food waste. Both estimates are significant on 0.1% significance level. In clusters 3 and 4 the effect is, as well like in the previous model, positive. However, effect in cluster 3 is again non-significant, and effect in cluster 4 is significant on 0.1% significance level.

Looking at the other variables, it can be noticed that, similarly to the previous model, higher age and living in the rural area are associated with less food waste.

## 4.3 Double/Debiased Machine Learning Difference-in-Differences

Results of the estimation is presented in Table 6, which shows the mean, standard deviation, upper confidence bound (0.975<sup>th</sup> quantile of the sample distribution) and the lower confidence bound (0.025<sup>th</sup> quantile) from the sampling distribution obtained from 1000 iterations.

Table 5: Results of DiD model with propensity scores weighting.

	<b>Cluster 1</b>	<b>Cluster 2</b>	<b>Cluster 3</b>	<b>Cluster 4</b>
Date	-0.030*	0.012	-0.059***	-0.049***
	(0.017)	(0.012)	(0.012)	(0.017)
policy	0.152***	0.114***	-0.038***	-0.115***
	(0.017)	(0.012)	(0.012)	(0.017)
policy.time	-0.129***	-0.087***	0.018	0.172***
	(0.024)	(0.017)	(0.017)	(0.025)
Male	0.020	0.010	0.015	0.004
	(0.013)	(0.009)	(0.009)	(0.013)
Age	-0.009***	-0.006***	-0.005***	-0.011***
	(0.0005)	(0.0003)	(0.0004)	(0.0005)
Self_employed	0.078***	0.023	-0.020	0.007
	(0.023)	(0.016)	(0.016)	(0.022)
Employee	0.053***	0.054***	0.011	0.012
	(0.016)	(0.011)	(0.012)	(0.016)
Manual_worker	-0.005	0.053**	0.057***	-0.044*
	(0.024)	(0.022)	(0.020)	(0.026)
Student	0.089	0.075	-0.004	0.153
	(0.061)	(0.069)	(0.072)	(0.098)
Rural	-0.072***	-0.086***	-0.018	-0.169***
	(0.021)	(0.012)	(0.013)	(0.017)
Urban	-0.014	-0.025**	0.016	-0.088***
	(0.020)	(0.012)	(0.012)	(0.016)
Constant	2.398***	2.310***	2.390***	2.575***
	(0.035)	(0.025)	(0.026)	(0.035)

*Note:* the table shows estimated effects of environmental legislation changes produced by Difference-in-Differences model with propensity scores weighting. Standard errors are shown in brackets. Stars indicate significance level: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

It can be seen that effect in cluster 1 is negative and significant, which implies that changes in environmental legislation are associated with decrease in percentage of food wasted. On the contrary, the effects in clusters 2, 3 and 4 is positive, indicating that new environmental laws cause an increase in food waste.

## 4.4 Comparison

Table 7 shows comparison of the estimated ATET from all the three models - ordinary Difference-in-Differences (DiD), Difference-in-Differences with propensity scores weighting (wDiD) and Double/De-biased Machine Learning Difference-in-Differences (DML DiD).

Table 6: ATET estimators obtained from the DMLDiD estimation technique.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mean	-0.478	0.639	0.305	0.195
s.e.	(0.040)	(0.067)	(0.036)	(0.048)
LCB	-0.560	0.520	0.236	0.106
UCB	-0.402	0.743	0.377	0.290

Table 7: Comparison of DiD, wDiD and DML DiD models results.

	DiD	wDiD	DMLDiD
Cluster 1	-0.395*** (0.088)	-0.129*** (0.024)	-0.478*** (0.04)
Cluster 2	-0.363*** (0.136)	-0.087*** (0.017)	0.639*** (0.067)
Cluster 3	0.153 (0.100)	0.018 (0.017)	0.305*** (0.036)
Cluster 4	0.840*** (0.105)	0.172*** (0.025)	0.195*** (0.048)

*Note:* the table shows estimated effects of environmental legislation changes on food waste produced by standard Difference-in-Differences model (DiD), Difference-in-Differences model with propensity scores weighting (wDiD) and Double/Debiased Machine Learning Difference-in-Differences model (DML DiD). Standard errors are shown in brackets. Stars indicate significance level:  $*p < 0.1$ ;  $**p < 0.05$ ;  $***p < 0.01$

As can be seen from the table, in clusters 1 and 4 the estimated effect is significant in all the three models, being negative in the first one and positive in the fourth. While a negative effect is somewhat intuitive, since it suggests that the environmental policies are achieving their target of reducing food waste, a positive effect can be a sign of crowding-out, which will be discussed in more detail in Section 5.

For cluster 3, the effect is positive for all the three models, however it is only significant in DML DiD model. For cluster 2, the effect is significant and negative for the DiD and wDiD models, however the DML DiD model produces a positive effect. Such a difference in results could potentially be caused by the nature of true underlying relation between policy changes and food waste. It is possible that in this cluster this relation differs significantly from its linear form assumed by the specification of DiD and wDiD models.

## 5 Economic Interpretation

As was presented in Section 4.4, the effects of environmental policy changes differ in direction for different countries clusters. As discussed before, this could be an indicator of poorly designed policies that lead to crowding out of incentives for various reasons. However, the policies were chosen in such a way that they target the same objectives. Moreover, in many countries the policies implemented were based on the same European Union directives. For example, Cyprus, Greece, Ireland, Latvia, Romania, Slovakia, Slovenia and the UK were all following the EU Directives 2008/99/EC or 2008/98/EC. Therefore, it is of use to investigate some cluster-specific differences that could have potentially led to the opposite effects.

For example, such potential difference could be in the base level of the EPI. Such a difference implies that the same policy implemented in countries with different base level of environmental policy stringency could lead to crowding-in in some cases and to crowding-out in the others. Figure 5 shows scatterplots of EPI levels plotted against the ATETs estimated by the DiD, wDiD and DML DiD models. Even though the estimates are not the same across the three models, the trend is always the same - a higher value of EPI as associated with the higher value of estimated ATET. This implies that the clusters, in which the average value of EPI is higher, are associated with the crowding-out of incentives. The effect could be caused by the so-called separability assumption not holding. This assumption implies that role of social preferences can be separated from the role of incentives in an agent's behaviour, meaning that a person's response to a certain policy is independent of their pre-existing level of social preferences (Bowles and Polanía-Reyes 2012)[7]. Therefore, environmental policy stringency level could be a proxy for the level of people's social preferences, which would explain the difference in effect directions.

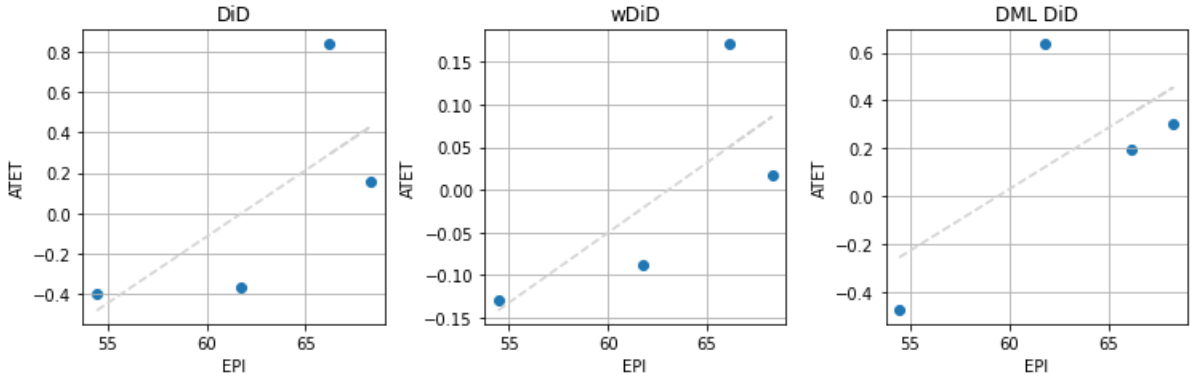


Figure 5: Relation between the estimated ATETs and EPI for different models.

Another potential reason for such a difference could be presence of different motivational mechanisms that incentivize people to comply with the introduced laws. Even though most of the laws are formulated in a similar way, some of them introduce fines, taxes or even subsidies as incentives, while others make use of educational activities to raise awareness among citizens. Differences in effect of policy change among such laws is studied in Section 6.2.



## 6 Further Analysis

As further analysis, we study two matters - effect of environmental policy changes on various non-targeted activities and effect of adoption of different types of monetary incentives to ensure compliance with the newly introduced laws.

### 6.1 Non-targeted activities

As was discussed before, policies often affect not only the activities that they are designed for but also other activities which are implicitly connected with the targeted ones. It is important for policy-makers to anticipate the potential policy spillovers in order to achieve the expected effect. However, the connections between targeted and non-targeted activities and the resulting outcome is often not straightforward. To test for the potential effect of legislation changes on non-targeted activities, we have chosen eight behavioural aspects addressed in the surveys used in this work which are not directly related to waste reduction and separation - LAW, ENVIMP, SH.T, SH.E, SH.F, FIN(a), FIN(b) and FIN(c).

Table 8 shows comparison of estimated ATETs on those non-targeted activities produced by DiD, wDiD and DML DiD models. Figure 6 presents comparison of the estimated effects across clusters for those activities, estimates of which are significant in all the three models. It can be seen, that there is only one case where direction of the effect differs across models - preference to include the cost of waste management in the price of products in cluster 3. It is interesting to note that in clusters 1 and 4, which are also associated with more consistent significant policy effects on food waste, direction of the effect is the same for all inspected non-targeted activities. Moreover, the direction of those effects is opposite of the effect on the targeted variable FW. In cluster 1, effect on variables ENVIMP and SH.F is negative, which implies that change in environmental policies is associated with decreased importance of products' environmental impact and lower willing to buy second-hand furniture. On the contrary, in cluster 4 effect on those variables (and, additionally, on willingness to buy second-hand textiles and electronic equipment) is positive. Therefore, this observation suggests that behaviour associated with wasting food is inversely related to the behaviour associated with such non-targeted activities as paying attention to products' environmental impact when making a purchase decision and eagerness to buy second-hand products. Same logic is also applicable to cluster 2, where effects on SH.T, SH.E and SH.F are positive, while the effect on FW is significantly negative in two out of three cases.

Additionally, there is a positive effect on belief that stronger law enforcement is needed for improvement of waste management in cluster 4. This is a remarkable result, since this is the only cluster in which the effect on this opinion is significant. Additionally, the direction of the effect is of interest, since it implies that introduction of new laws (all of which are only increasing the overall environmental policy stringency) makes people believe that even stricter legislation is needed. On the other hand, the effect on food waste in the cluster was all crowded out, increasing the amount of food waste produced, which is not intuitive together with the previous result. Relation between those activities is an important topic for further research.

Table 8: Comparison of estimated effects of policy changes on non-targeted activities.

Activity	LAW			ENVIMP			SH.T			SH.E		
Model	DiD	wDiD	DML DiD	DiD	wDiD	DML DiD	DiD	wDiD	DML DiD	DiD	wDiD	DML DiD
Cluster 1	0.382*** (0.090)	0.107*** (0.017)	0.001 (0.014)	-0.241*** (0.093)	-0.053*** (0.017)	-0.137*** (0.014)	-0.013 (0.088)	0.023 (0.018)	-0.043*** (0.014)	-0.046 (0.090)	-0.024 (0.017)	-0.083*** (0.013)
Cluster 2	0.140 (0.121)	0.002 (0.017)	0.137*** (0.021)	0.694*** (0.133)	0.128*** (0.016)	0.308*** (0.024)	0.509*** (0.111)	0.106*** (0.017)	0.332*** (0.02)	0.223* (0.118)	0.036** (0.017)	0.231*** (0.018)
Cluster 3	-0.234*** (0.076)	-0.054*** (0.017)	0.013 (0.012)	-0.090 (0.088)	-0.044*** (0.015)	0.027* (0.014)	-0.104 (0.078)	-0.022 (0.016)	0.028** (0.011)	0.245*** (0.078)	0.047*** (0.016)	0.108*** (0.013)
Cluster 4	0.726*** (0.102)	0.150*** (0.020)	0.158*** (0.015)	1.018*** (0.107)	0.199*** (0.019)	0.184*** (0.016)	0.394*** (0.095)	0.090*** (0.021)	0.09*** (0.016)	0.488*** (0.102)	0.090*** (0.020)	0.093*** (0.016)

Activity	SH.F			FIN(a)			FIN(b)			FIN(c)		
Model	DiD	wDiD	DML DiD	DiD	wDiD	DML DiD	DiD	wDiD	DML DiD	DiD	wDiD	DML DiD
Cluster 1	-0.133 (0.086)	-0.050*** (0.018)	-0.178*** (0.016)	-0.285*** (0.095)	-0.065*** (0.017)	-0.114*** (0.009)	-0.327*** (0.086)	-0.088*** (0.018)	-0.161*** (0.015)	-0.043 (0.085)	-0.007 (0.018)	-0.14*** (0.012)
Cluster 2	0.199* (0.120)	0.031* (0.017)	0.305*** (0.023)	0.859*** (0.148)	0.119*** (0.015)	0.206*** (0.018)	-0.383*** (0.122)	-0.137*** (0.016)	0.107*** (0.025)	0.049 (0.115)	0.035** (0.017)	0.182*** (0.022)
Cluster 3	-0.060 (0.075)	-0.003 (0.017)	0.054*** (0.015)	0.394*** (0.088)	0.059*** (0.015)	0.098*** (0.008)	0.165** (0.082)	0.016 (0.016)	0.118*** (0.015)	-0.199** (0.077)	-0.031* (0.016)	0.053*** (0.014)
Cluster 4	0.533*** (0.098)	0.111*** (0.021)	0.101*** (0.016)	-0.006 (0.100)	0.016 (0.020)	0.044** (0.018)	0.322*** (0.100)	0.078*** (0.021)	0.071*** (0.017)	0.023 (0.099)	-0.017 (0.021)	-0.027* (0.016)

*Note:* the table shows estimated effects produced by standard Difference-in-Differences model (DiD), Difference-in-Differences model with propensity scores weighting (wDiD) and Double/Debiased Machine Learning Difference-in-Differences model (DML DiD). Standard errors are shown in brackets. Stars indicate significance level: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

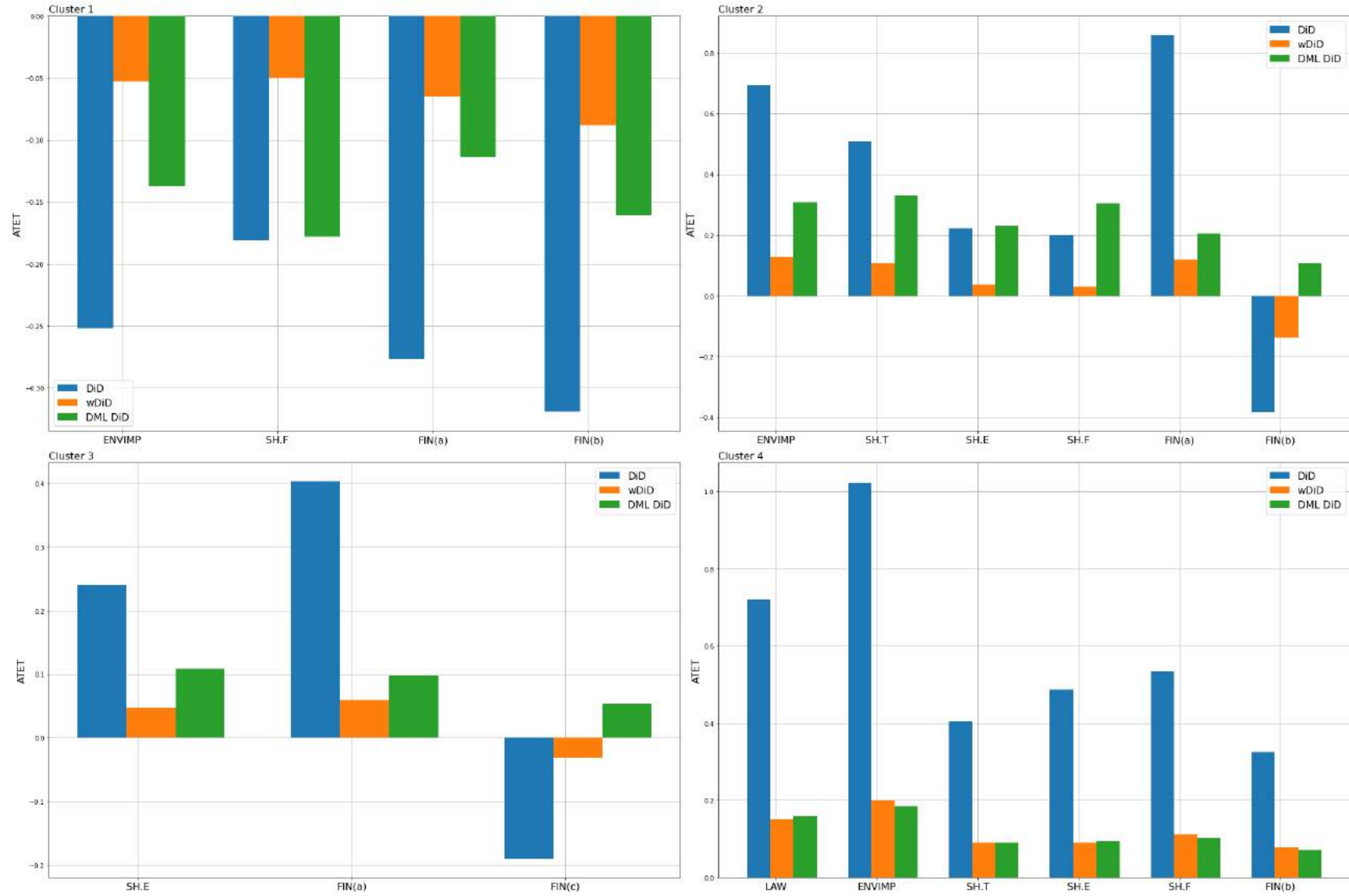


Figure 6: Comparison of significant ATET estimates for non-targeted activities for the four clusters.

*Note:* the figure only includes those estimates that were significant on at least 10% significance level in all the three models.

## 6.2 Monetary incentives

In the analysis performed in the previous sections, the laws were chosen to be similar based on the activities which they were targeting, however no attention was paid to the incentives implied by them which would encourage citizens to comply with those laws. This section is devoted to studying those incentives in order to compare the effect of differences in the actual measures that are implied by the introduction of the new (or change of existing) environmental legislation, in particular, the effect of monetary incentives such as fines or taxes.

In Cluster 1, Bulgaria, Cyprus and Malta have all introduced fines for non-compliance with the introduced laws (for example, for disposing waste in unauthorised places). On the contrary, Romania in its Law on the Waste Regime establishes measures to be taken for informing people about reusable and recyclable nature of products and raising awareness, but does not introduce any monetary incentives for motivation of citizens. In Cluster 2, the Flemish region of Belgium has introduced a law that establishes adoption of subsidies for individuals promoting waste prevention, separation, reuse and more efficient consumption. Policies in all the other treated countries in cluster 2 introduce fines for non-compliance. Therefore, we compare the effect of introduction of a subsidy to the effect of introduction of a fine. In Cluster 3, England, Wales and the Northern Ireland have introduced fines for persons which fail to comply with the regulations, on the contrast to France and Italy which focused on raising awareness and promoting waste-reducing behaviour. In Cluster 4, Latvia and Slovakia, unlike Czech Republic, have introduced a tax-like mandatory payment for packaging or some elements of it, which was free of charge beforehand. Overlap plots for visual check of Common Support assumption in this setting are presented in Figures A.11, A.12, A.13, A.14 and A.15.

Tables 9 and 11 show results of the DiD, wDiD and DML DiD models used to estimate the effects of introduction of legislation that implies new monetary incentives relative to introduction of legislation not containing new fines or taxes, respectively, on the percentage of food wasted and on non-targeted activities discussed in Section 6.1. As can be seen from the tables, in all the three clusters discussed above introduction of monetary incentives lead to decrease in the explanatory variable FOODWASTE, both in the cases of introduction of fines and taxes. This result implies that introducing a monetary incentive is likely to make the law more efficient compared to introducing the same law but without such incentive, which is an important implication for policy-makers.

Interestingly, in cluster 4, where monetary incentives were introduced in the form of taxes, the effect of this introduction on variable FIN(a) is significantly positive according to all the three models. This effect implies that introduction of taxes increased people's willingness to pay taxes for waste management.

Table 10 show estimated effects of introduction of a subsidy for pro-environmental behaviour relative to introduction of a fine for non-compliance with the policy. It can be seen from the table that all the three models report a significant increase in food waste under a subsidy compared to fine. Therefore, a conclusion could be made that introduction of subsidies for pro-environmental activities is associated with worse effects on amounts of food waste than introduction of fines for absence of prescribed pro-environmental behaviour.

As an additional point of view, Table A.9 in the Appendix compares the effects of policy

Table 9: Comparison of effects of introduction of fines in comparison with introduction of new laws without fines from DiD, weighted DiD and DML DiD models.

	Variable	DiD	wDiD	DMLDiD		DiD	wDiD	DMLDiD
<b>Cluster 1</b>	FW	-0.320** (0.125)	-0.131*** (0.035)	-0.816*** (0.084)	<b>Cluster 3</b>	-0.587*** (0.159)	-0.113*** (0.029)	-0.356*** (0.085)
	LAW	0.692*** (0.152)	0.056** (0.023)	-0.172*** (0.037)		0.644*** (0.125)	0.136*** (0.027)	0.088*** (0.026)
	ENVIMP	-0.417*** (0.115)	0.128*** (0.022)	-0.03 (0.031)		0.308** (0.143)	0.030 (0.024)	-0.005 (0.028)
	SH.T	0.523*** (0.140)	0.101*** (0.022)	0.009 (0.019)		0.232* (0.127)	0.032 (0.026)	0.01 (0.021)
	SH.E	0.138 (0.141)	0.025 (0.022)	-0.05** (0.02)		0.355*** (0.129)	0.081*** (0.026)	0.035 (0.023)
	SH.F	-0.140 (0.134)	-0.057** (0.023)	-0.144*** (0.016)		0.161 (0.126)	0.025 (0.027)	-0.018 (0.025)
	FIN(a)	-0.402*** (0.135)	-0.087*** (0.023)	-0.198*** (0.018)		0.381*** (0.140)	0.063*** (0.024)	0.036* (0.021)
	FIN(b)	0.360*** (0.131)	0.051** (0.024)	-0.102*** (0.024)		-0.076 (0.133)	-0.088*** (0.025)	-0.143*** (0.028)
	FIN(c)	0.024 (0.123)	0.035 (0.025)	-0.154*** (0.028)		0.073 (0.129)	0.019 (0.026)	-0.054** (0.025)

*Note:* the table shows estimated effects produced by standard Difference-in-Differences model (DiD), Difference-in-Differences model with propensity scores weighting (wDiD) and Double/Debiased Machine Learning Difference-in-Differences model (DML DiD). Standard errors are shown in brackets. Stars indicate significance level: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

changes which introduce monetary incentives (fines or taxes) on food waste to the effects of policy changes which did not introduce any monetary incentives. Instead of comparing the effects to each other, the table compares both effects to countries from the control groups. Cluster 2 is omitted because all of the policy changes that took place in this cluster involved introduction of monetary incentives. It can be seen that introduction of monetary incentives such as fines is associated with decrease in food waste according to all the three models (effect of adoption of taxes is also negative but not statistically significant on any reasonable significance level). At the same time, introduction of environmental laws which do not imply any monetary motivation, is associated with the increase of food waste in all the three clusters examined.

## 7 Conclusion

We have studied the causal effect of change in legislation addressing household waste in the European Union in the period from 2011 to 2013 on its targeted activity (food waste), non-targeted activities

Table 10: Comparison of effects of introduction of a subsidy in comparison with introduction of a fine, from DiD, weighted DiD and DML DiD models.

	Variable	DiD	wDiD	DMLDiD
<b>Cluster 2</b>	FW	1.054*** (0.138)	0.167*** (0.020)	0.439*** (0.061)
	LAW	0.865*** (0.112)	-0.104*** (0.013)	0.280*** (0.022)
	ENVIMP	0.385*** (0.126)	0.062*** (0.018)	0.135*** (0.031)
	SH.T	0.021 (0.116)	-0.001 (0.018)	0.051*** (0.017)
	SH.E	0.117 (0.127)	0.037** (0.017)	0.083*** (0.017)
	SH.F	0.337*** (0.112)	0.064*** (0.019)	0.141*** (0.019)
	FIN(a)	0.066 (0.136)	0.018 (0.017)	0.052*** (0.016)
	FIN(b)	0.386*** (0.125)	0.101*** (0.018)	0.189*** (0.023)
	FIN(c)	-0.287** (0.118)	-0.054*** (0.018)	-0.001 (0.021)

*Note:* the table shows estimated effects produced by standard Difference-in-Differences model (DiD), Difference-in-Differences model with propensity scores weighting (wDiD) and Double/Debiased Machine Learning Difference-in-Differences model (DML DiD). Standard errors are shown in brackets. Stars indicate significance level: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

Table 11: Comparison of effects of introduction of taxes included in the price of products in comparison with introduction of new laws without such taxes from DiD, weighted DiD and DML DiD models.

	Variable	DiD	wDiD	DMLDiD
<b>Cluster 4</b>	FW	-1.104*** (0.136)	-0.234*** (0.030)	-0.119* (0.068)
	LAW	-0.999*** (0.126)	-0.220*** (0.027)	-0.184*** (0.031)
	ENVIMP	0.046 (0.130)	0.015 (0.026)	0.045 (0.028)
	SH.T	-0.126 (0.127)	-0.046* (0.027)	-0.008 (0.023)
	SH.E	-0.109 (0.141)	-0.027 (0.024)	0.001 (0.021)
	SH.F	-0.369*** (0.133)	-0.083*** (0.026)	-0.035 (0.032)
	FIN(a)	0.437*** (0.142)	0.063*** (0.024)	0.082*** (0.02)
	FIN(b)	0.056 (0.129)	0.011 (0.026)	0.082*** (0.028)
	FIN(c)	0.024 (0.126)	0.038 (0.027)	0.06*** (0.022)

*Note:* the table shows estimated effects produced by standard Difference-in-Differences model (DiD), Difference-in-Differences model with propensity scores weighting (wDiD) and Double/Debiased Machine Learning Difference-in-Differences model (DML DiD). Standard errors are shown in brackets. Stars indicate significance level: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

(willingness to use second-hand products and purchase decisions based on environmental impact assessment), preferences and beliefs (waste management financing preferences and opinion on the need of stricter policies). The analysis was based on 25 environmental laws introduced or amended in 15 EU countries from 2011 to 2013 and on two surveys performed by European Commission on attitudes of Europeans towards resource efficiency. For modelling the effect we have used a standard logistic regression-based Difference-in-Differences model, a Difference-in-Differences model with propensity scores weighting and a Double/Debiased Machine Learning Difference-in-Differences model with ensemble learner. We have discovered that direction of the effect on food waste differs across different country-clusters, which could potentially be explained by variation in baseline environmental policy stringency level. Effect on non-targeted activities examined in most of significant cases appear to be opposite of that on targeted activities. Finally, we discovered that introduction of monetary incentives such as fines or taxes tends to make a policy more efficient in achieving its target.

There are still several questions remaining open for further research. This paper focused only on food waste as a targeted aspect, however it would be interesting to study the effect of the same laws on other targeted activities, such as waste separation. Additionally, interrelation between the targeted and non-targeted activities requires further investigation to understand the underlying mechanism and the causes of the negative correlation between them observed in the paper. A more detailed examination of the effect of monetary incentives on non-targeted activities and preferences is as well a topic for further exploration.



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# A Appendices

## Common questions

2011	2013
<b>Content questions</b>	
Q1. Do you think that your household is producing too much waste or not?	Q4(2). For each of the following statements, please tell me whether you totally agree, tend to agree, tend to disagree or totally disagree. (Your household is generating too much waste)
Q2. Do you separate at least some of your waste for recycling or composting?	Q6. Do you sort the following types of waste, at least occasionally?
Q3a. What would convince you to separate more of your waste?	Q7a. What would convince you to separate more of your waste?
Q3b. What would convince you to separate at least some of your waste?	Q7b. What would convince you to separate at least some of your waste?
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?
Q6. What would help you to waste less food?	Q10. Amongst the following elements, which would help you to waste less food?
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? (a). Textiles (clothing, bedding, curtains etc.) (b). Electronic equipment (c). Furniture	Q12. Would you buy the following products second hand? 1. Textiles (clothing, bedding, curtains, etc.) 2. Electronic equipment (TV, computer, etc.) 3. Furniture (couch, table, chairs, etc.)
Q9. What prevents you from buying these products second hand?	Q13. What prevents you from buying second hand products?
Q12. Which one would you prefer: to pay taxes for waste management or to pay an amount related to the quantity of waste each household generates?	Q8. Managing household waste has a cost. I am going to read out three possible ways of financing this management (there are others as well): through a flat rate, a contribution relative to your waste production, or more producer responsibility. Please indicate which
Q13. Which one would you prefer: to pay taxes for waste management or to	

include the cost of waste management  
in the price of the products you buy?

you would prefer?

### 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 self-employed, an employee, a manual worker or would you say that you are without a professional activity?	D5a. As far as your current occupation is concerned, would you say you are self-employed, an employee, a manual worker or would you say that you are without a professional activity?
D6. Would you say you live in a ...? 1. Metropolitan zone 2. Other town/urban centre 3. Rural zone	D13. Would you say you live in a ...? 3. Large town/city 2. Small or medium-sized town 1. Rural area or village

Table A.1: 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. 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.

## Distribution of observations per country per time period

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 A.2: Distribution of observations per country per time period

## Laws

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).

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Table A.3: Laws

*Note:* the table shows all the laws chose as relevant that were implemented in the period from 1<sup>st</sup> January 2011 to 30<sup>th</sup> 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.



Table A.4: Descriptive statistics for Cluster 1

	Mean				Std			
	2011		2013		2011		2013	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control
<b>Content Q-ns</b>								
FOODWASTE (q5)	2.10	1.94	1.95	1.91	0.80	0.64	0.56	0.52
Too-much-waste (q1)	0.36	0.37	0.37	0.36	0.48	0.48	0.48	0.48
SEP (q2)	0.73	0.86	0.85	0.98	0.44	0.34	0.36	0.14
CONV(a) (q3_a)	0.81	0.71	0.51	0.47	0.39	0.46	0.50	0.50
CONV(b) (q3_b)	0.87	0.81	0.67	0.51	0.34	0.39	0.47	0.50
CONV(c) (q3_c)	0.77	0.66	0.54	0.41	0.42	0.47	0.50	0.49
SH.T (q8_a)	0.22	0.46	0.23	0.46	0.42	0.50	0.42	0.50
SH.E (q8_b)	0.28	0.37	0.26	0.36	0.45	0.48	0.44	0.48
SH.F (q8_c)	0.32	0.54	0.28	0.53	0.47	0.50	0.45	0.50
FIN(a) (q12_1)	0.35	0.25	0.21	0.18	0.48	0.44	0.41	0.38
FIN(b) (q12_2)	0.72	0.71	0.34	0.40	0.45	0.46	0.47	0.49
FIN(c) (q13_2)	0.55	0.48	0.32	0.27	0.50	0.50	0.47	0.45
LAW (q4)	0.81	0.68	0.48	0.23	0.39	0.47	0.50	0.42
ENVIMP (q7)	0.81	0.78	0.29	0.30	0.39	0.41	0.46	0.46
<b>Demographic Q-ns</b>								
Male	0.41	0.37	0.39	0.37	0.49	0.48	0.49	0.48
Age	50.23	51.64	50.40	52.12	15.87	15.86	15.84	16.07
Self_employed	0.09	0.10	0.09	0.07	0.29	0.31	0.28	0.26
Employee	0.34	0.34	0.34	0.40	0.48	0.47	0.47	0.49
Manual_worker	0.08	0.12	0.06	0.04	0.27	0.33	0.24	0.19
Unemployed	0.47	0.43	0.08	0.09	0.50	0.50	0.28	0.29
Student	0.01	0.01	0.30	0.35	0.10	0.08	0.46	0.48
Metrop	0.11	0.24	0.41	0.33	0.32	0.43	0.49	0.47
Urban	0.59	0.46	0.32	0.36	0.49	0.50	0.47	0.48
Rural	0.30	0.30	0.27	0.30	0.46	0.46	0.44	0.46

Table A.5: Descriptive statistics for Cluster 2

	Mean				Std			
	2011		2013		2011		2013	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control
<b>Content Q-ns</b>								
FOODWASTE (q5)	2.12	2.01	2.04	1.99	0.64	0.46	0.43	0.35
Too-much-waste (q1)	0.46	0.47	0.49	0.38	0.50	0.50	0.50	0.48
SEP (q2)	0.92	0.96	0.99	1.00	0.28	0.19	0.11	0.06
CONV(a) (q3_a)	0.74	0.53	0.50	0.47	0.44	0.50	0.50	0.50
CONV(b) (q3_b)	0.80	0.74	0.58	0.67	0.40	0.44	0.49	0.47
CONV(c) (q3_c)	0.69	0.59	0.47	0.46	0.46	0.49	0.50	0.50
SH.T (q8_a)	0.31	0.59	0.31	0.48	0.46	0.49	0.46	0.50
SH.E (q8_b)	0.41	0.44	0.36	0.33	0.49	0.50	0.48	0.47
SH.F (q8_c)	0.55	0.74	0.53	0.68	0.50	0.44	0.50	0.47
FIN(a) (q12_1)	0.33	0.35	0.18	0.10	0.47	0.48	0.39	0.29
FIN(b) (q12_2)	0.80	0.80	0.44	0.54	0.40	0.40	0.50	0.50
FIN(c) (q13_2)	0.63	0.68	0.29	0.32	0.48	0.47	0.46	0.47
LAW (q4)	0.68	0.58	0.30	0.20	0.47	0.49	0.46	0.40
ENVIMP (q7)	0.84	0.77	0.40	0.19	0.37	0.42	0.49	0.39
<b>Demographic Q-ns</b>								
Male	0.40	0.50	0.41	0.49	0.49	0.50	0.49	0.50
Age	52.39	54.82	53.31	57.99	15.18	15.36	15.19	15.88
Self_employed	0.10	0.08	0.08	0.08	0.30	0.27	0.28	0.27
Employee	0.38	0.44	0.32	0.17	0.49	0.50	0.47	0.37
Manual_worker	0.04	0.03	0.07	0.22	0.20	0.18	0.26	0.41
Unemployed	0.47	0.44	0.51	0.53	0.50	0.50	0.50	0.50
Student	0.00	0.00	0.01	0.00	0.07	0.07	0.11	0.05
Metrop	0.18	0.31	0.29	0.25	0.38	0.46	0.45	0.43
Urban	0.42	0.40	0.34	0.44	0.49	0.49	0.47	0.50
Rural	0.40	0.29	0.37	0.31	0.49	0.45	0.48	0.46

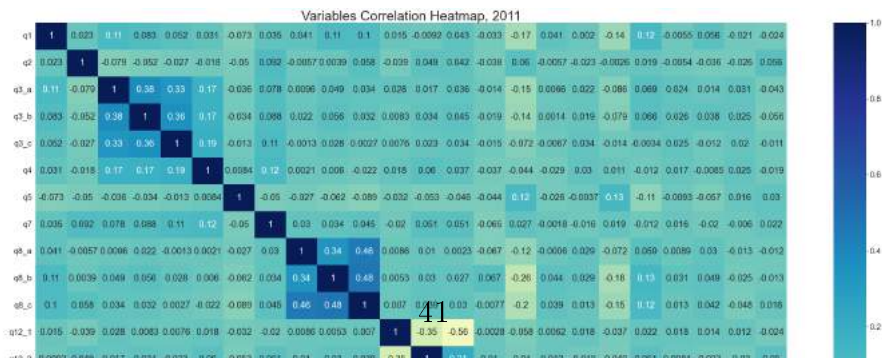


Table A.6: Descriptive statistics for Cluster 3

	Mean				Std			
	2011		2013		2011		2013	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control
<b>Content Q-ns</b>								
FOODWASTE (q5)	2.08	2.13	2.04	2.04	0.62	0.54	0.40	0.38
Too-much-waste (q1)	0.41	0.43	0.43	0.44	0.49	0.50	0.50	0.50
SEP (q2)	0.94	0.97	0.99	1.00	0.23	0.17	0.12	0.04
CONV(a) (q3_a)	0.73	0.46	0.53	0.35	0.44	0.50	0.50	0.48
CONV(b) (q3_b)	0.74	0.62	0.58	0.43	0.44	0.48	0.49	0.50
CONV(c) (q3_c)	0.68	0.50	0.48	0.33	0.46	0.50	0.50	0.47
SH.T (q8_a)	0.36	0.36	0.33	0.34	0.48	0.48	0.47	0.47
SH.E (q8_b)	0.40	0.43	0.40	0.34	0.49	0.50	0.49	0.47
SH.F (q8_c)	0.59	0.55	0.58	0.53	0.49	0.50	0.49	0.50
FIN(a) (q12_1)	0.30	0.31	0.18	0.14	0.46	0.46	0.39	0.34
FIN(b) (q12_2)	0.78	0.82	0.47	0.49	0.42	0.38	0.50	0.50
FIN(c) (q13_2)	0.62	0.64	0.27	0.32	0.48	0.48	0.44	0.47
LAW (q4)	0.68	0.58	0.39	0.33	0.46	0.49	0.49	0.47
ENVIMP (q7)	0.83	0.86	0.33	0.37	0.38	0.35	0.47	0.48
<b>Demographic Q-ns</b>								
Male	0.39	0.43	0.42	0.44	0.49	0.50	0.49	0.50
Age	53.97	54.21	53.18	56.65	15.45	15.03	15.57	15.45
Self_employed	0.10	0.10	0.10	0.08	0.29	0.30	0.30	0.27
Employee	0.34	0.38	0.37	0.31	0.47	0.49	0.48	0.46
Manual_worker	0.06	0.06	0.05	0.09	0.24	0.23	0.23	0.29
Unemployed	0.50	0.46	0.07	0.04	0.50	0.50	0.26	0.19
Student	0.00	0.01	0.32	0.42	0.06	0.08	0.47	0.49
Metrop	0.17	0.19	0.27	0.25	0.37	0.39	0.44	0.43
Urban	0.44	0.33	0.46	0.36	0.50	0.47	0.50	0.48
Rural	0.39	0.48	0.28	0.39	0.49	0.50	0.45	0.49

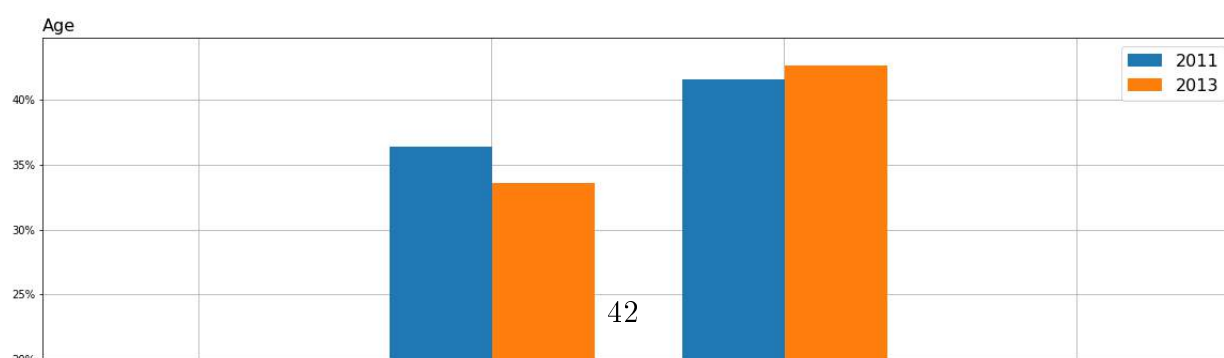
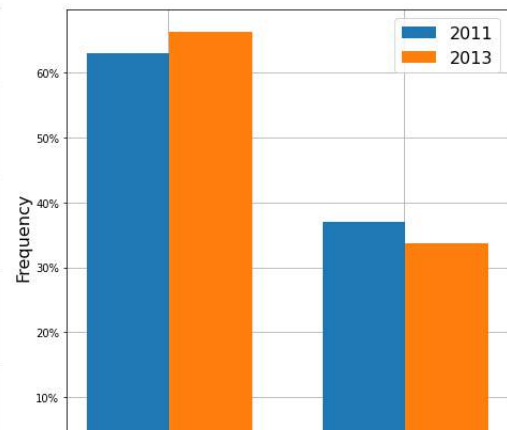
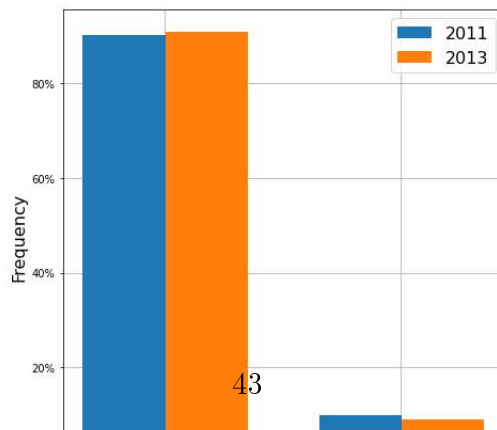
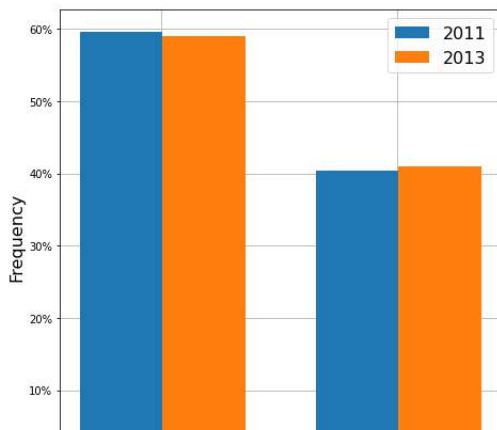


Table A.7: Descriptive statistics for Cluster 4

	Mean				Std			
	2011		2013		2011		2013	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control
<b>Content Q-ns</b>								
FOODWASTE (q5)	1.82	1.98	1.95	1.90	0.66	0.68	0.49	0.49
Too-much-waste (q1)	0.28	0.41	0.30	0.40	0.45	0.49	0.46	0.49
SEP (q2)	0.84	0.79	0.98	0.95	0.37	0.41	0.16	0.21
CONV(a) (q3_a)	0.54	0.81	0.53	0.57	0.50	0.39	0.50	0.50
CONV(b) (q3_b)	0.74	0.83	0.63	0.46	0.44	0.37	0.48	0.50
CONV(c) (q3_c)	0.57	0.74	0.49	0.42	0.49	0.44	0.50	0.49
SH.T (q8_a)	0.36	0.47	0.40	0.40	0.48	0.50	0.49	0.49
SH.E (q8_b)	0.26	0.44	0.32	0.38	0.44	0.50	0.47	0.49
SH.F (q8_c)	0.31	0.52	0.39	0.47	0.46	0.50	0.49	0.50
FIN(a) (q12_1)	0.32	0.45	0.20	0.30	0.47	0.50	0.40	0.46
FIN(b) (q12_2)	0.72	0.75	0.42	0.37	0.45	0.43	0.49	0.48
FIN(c) (q13_2)	0.57	0.48	0.31	0.23	0.50	0.50	0.46	0.42
LAW (q4)	0.63	0.76	0.31	0.29	0.48	0.43	0.46	0.45
ENVIMP (q7)	0.66	0.79	0.30	0.23	0.47	0.41	0.46	0.42
<b>Demographic Q-ns</b>								
Male	0.38	0.39	0.40	0.38	0.48	0.49	0.49	0.49
Age	51.59	48.88	50.75	50.67	15.92	15.30	16.46	15.76
Self_employed	0.11	0.12	0.12	0.11	0.31	0.32	0.33	0.32
Employee	0.37	0.35	0.34	0.34	0.48	0.48	0.47	0.48
Manual_worker	0.07	0.12	0.10	0.11	0.26	0.33	0.30	0.32
Unemployed	0.44	0.40	0.06	0.07	0.50	0.49	0.24	0.26
Student	0.00	0.01	0.33	0.30	0.06	0.09	0.47	0.46
Metrop	0.22	0.24	0.20	0.36	0.42	0.43	0.40	0.48
Urban	0.47	0.50	0.44	0.37	0.50	0.50	0.50	0.48
Rural	0.30	0.26	0.37	0.27	0.46	0.44	0.48	0.44



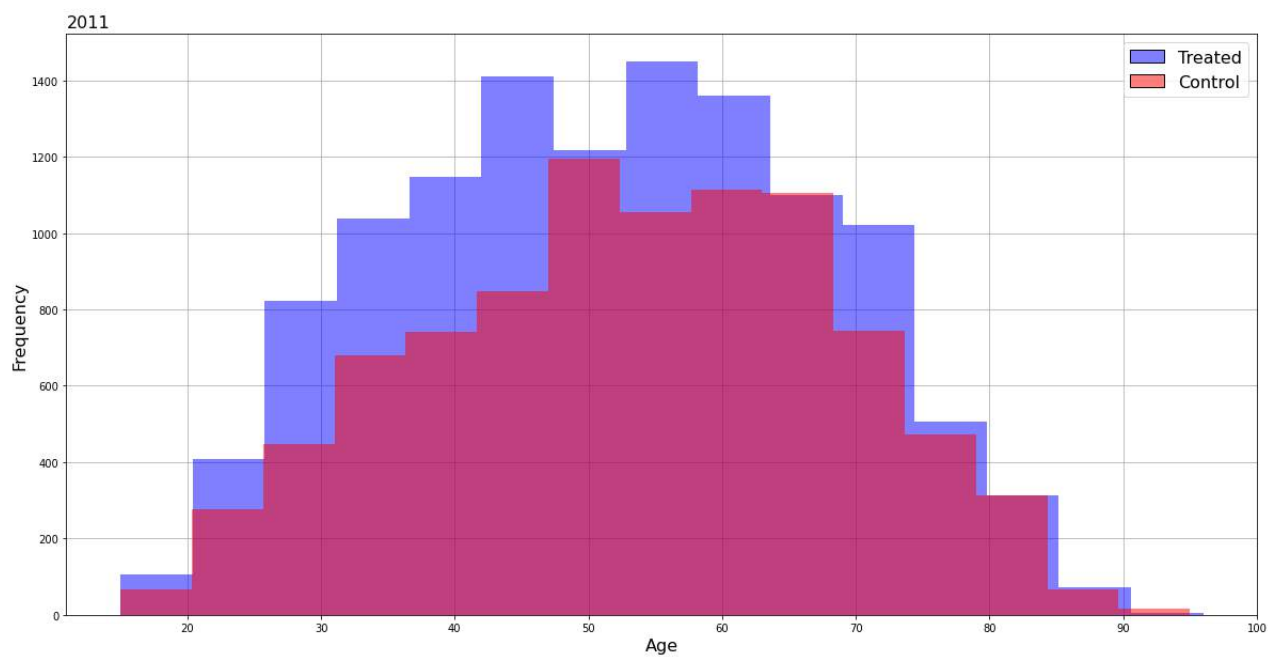


Figure A.4: Overlap histogram for variable Age in 2011.

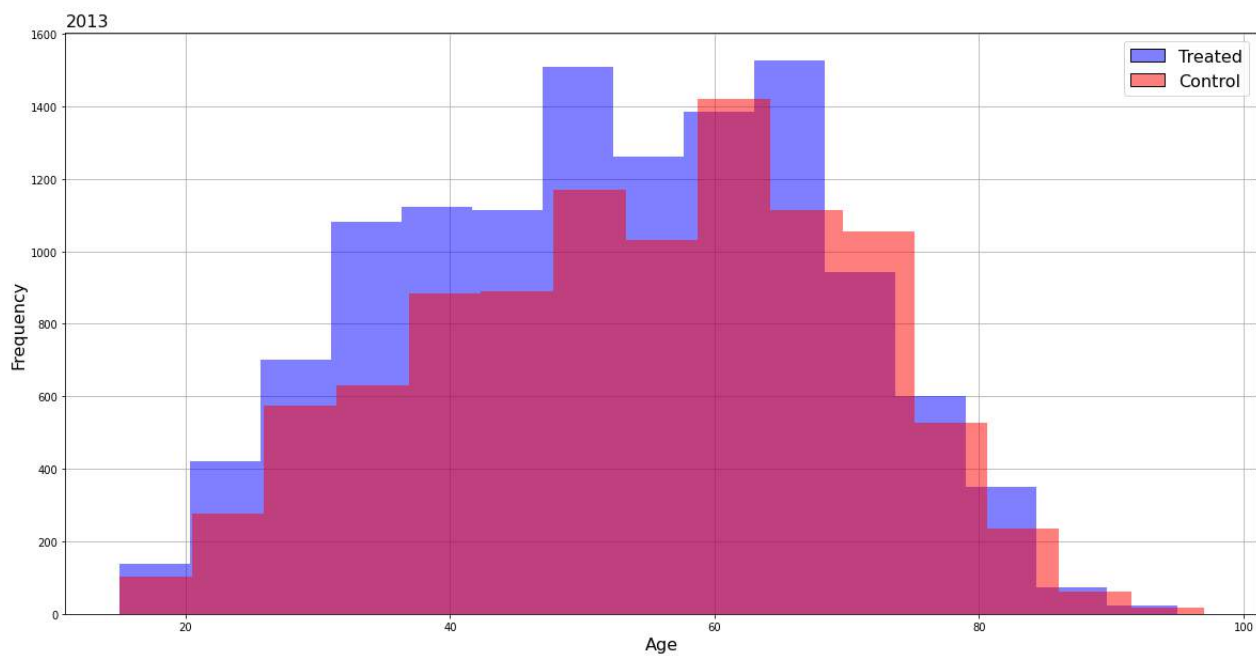


Figure A.5: Overlap histogram for variable Age in 2013.

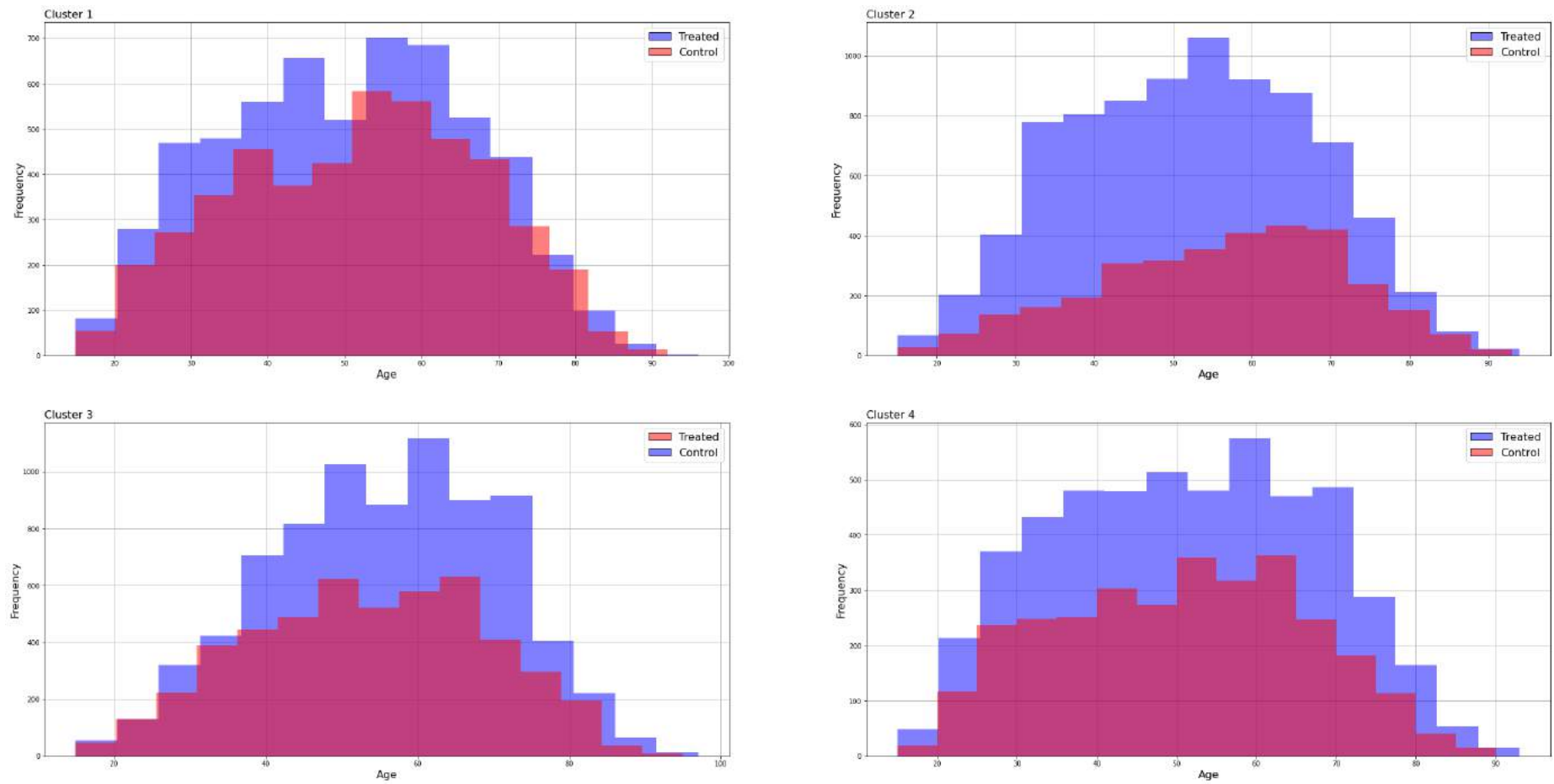


Figure A.6: Overlap histograms for variable Age in each cluster.

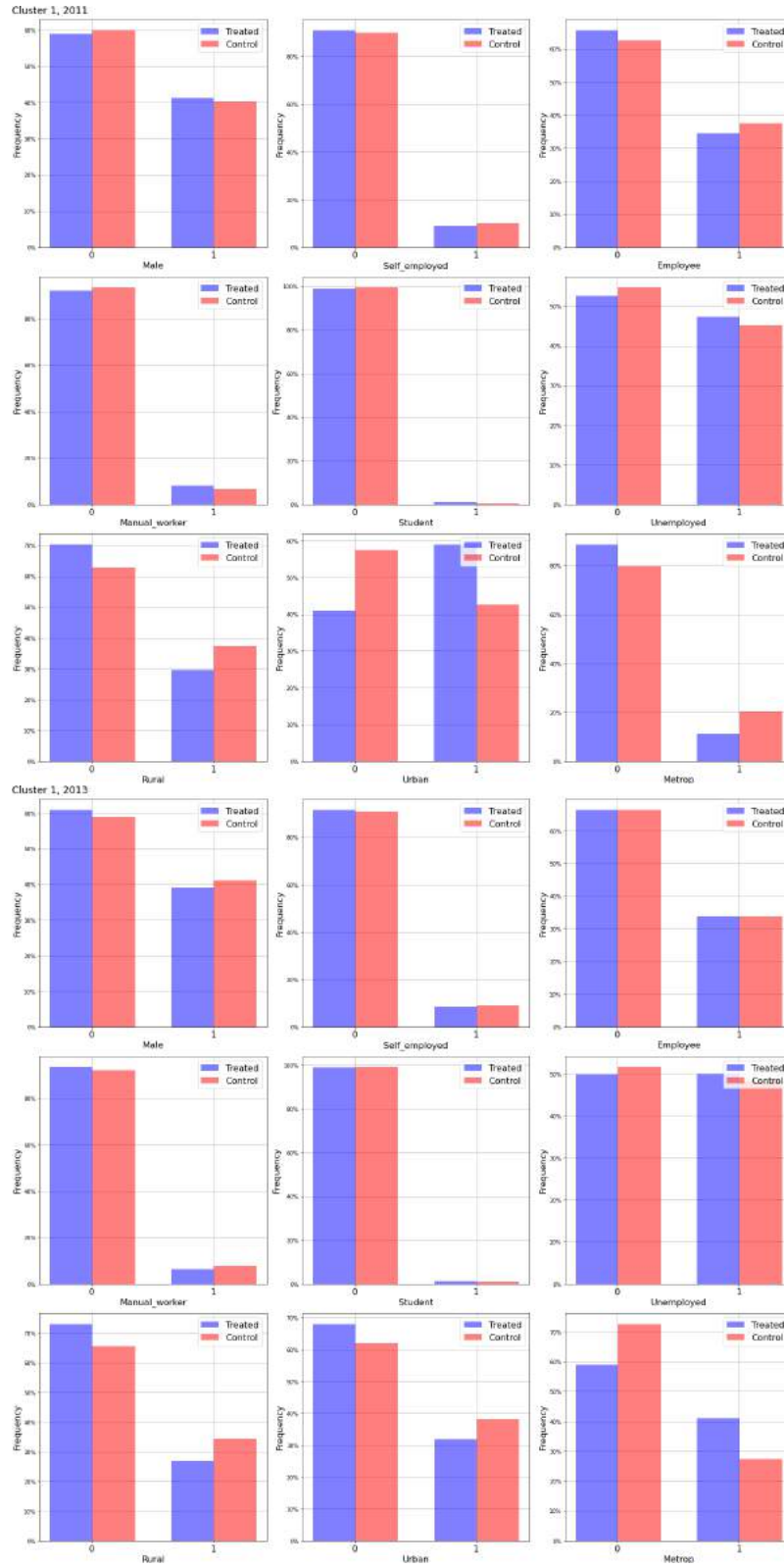


Figure A.7: Overlap histograms for binary demographic variables for cluster 1.  
*Note:* the bins are plotted side-by-side instead of on top of each other for visual clarity.

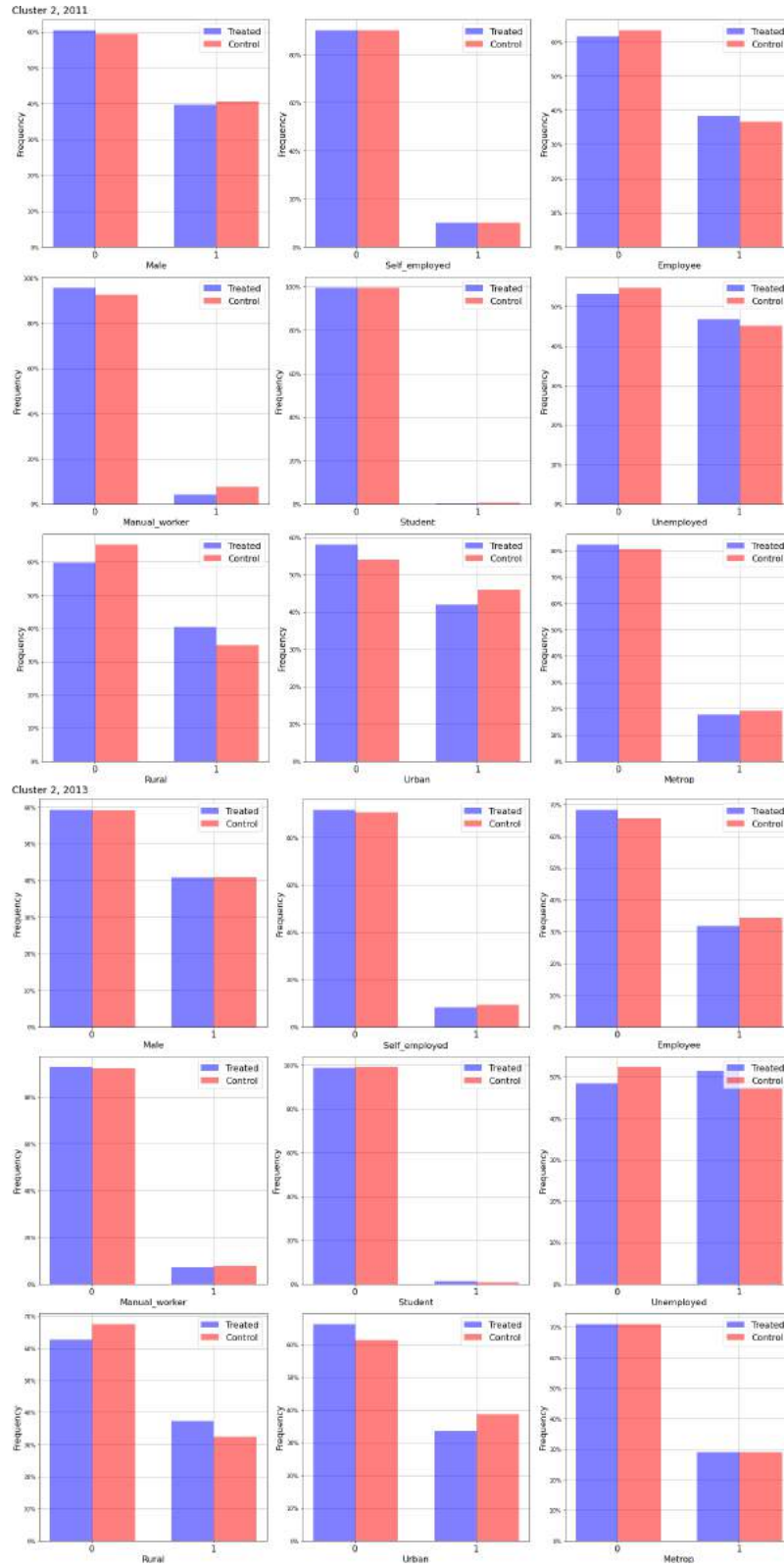


Figure A.8: Overlap histograms for binary demographic variables for cluster 2.

*Note:* the bins are plotted side-by-side instead of on top of each other for visual clarity.



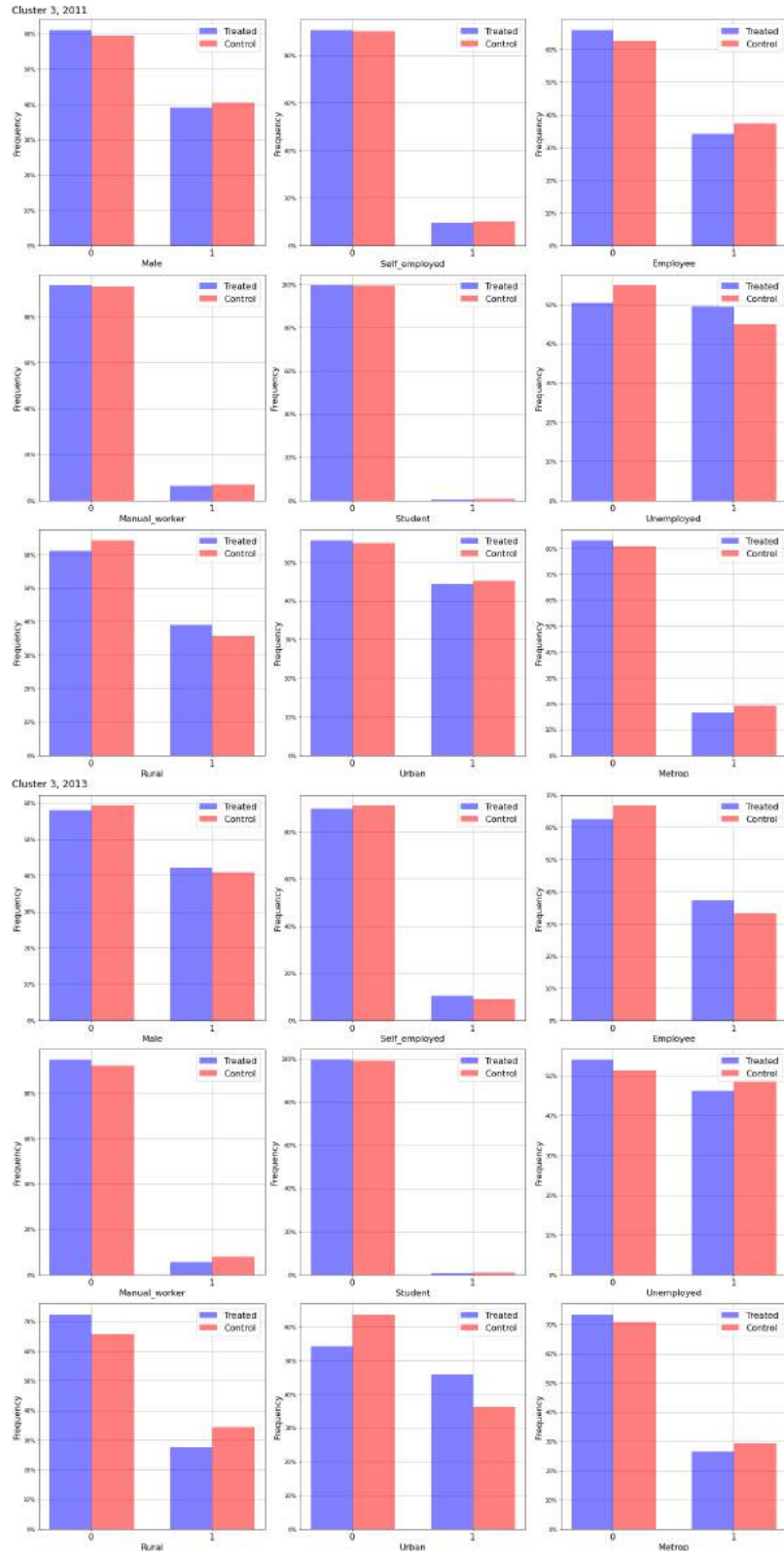


Figure A.9: Overlap histograms for binary demographic variables for cluster 3.  
*Note:* the bins are plotted side-by-side instead of on top of each other for visual clarity.

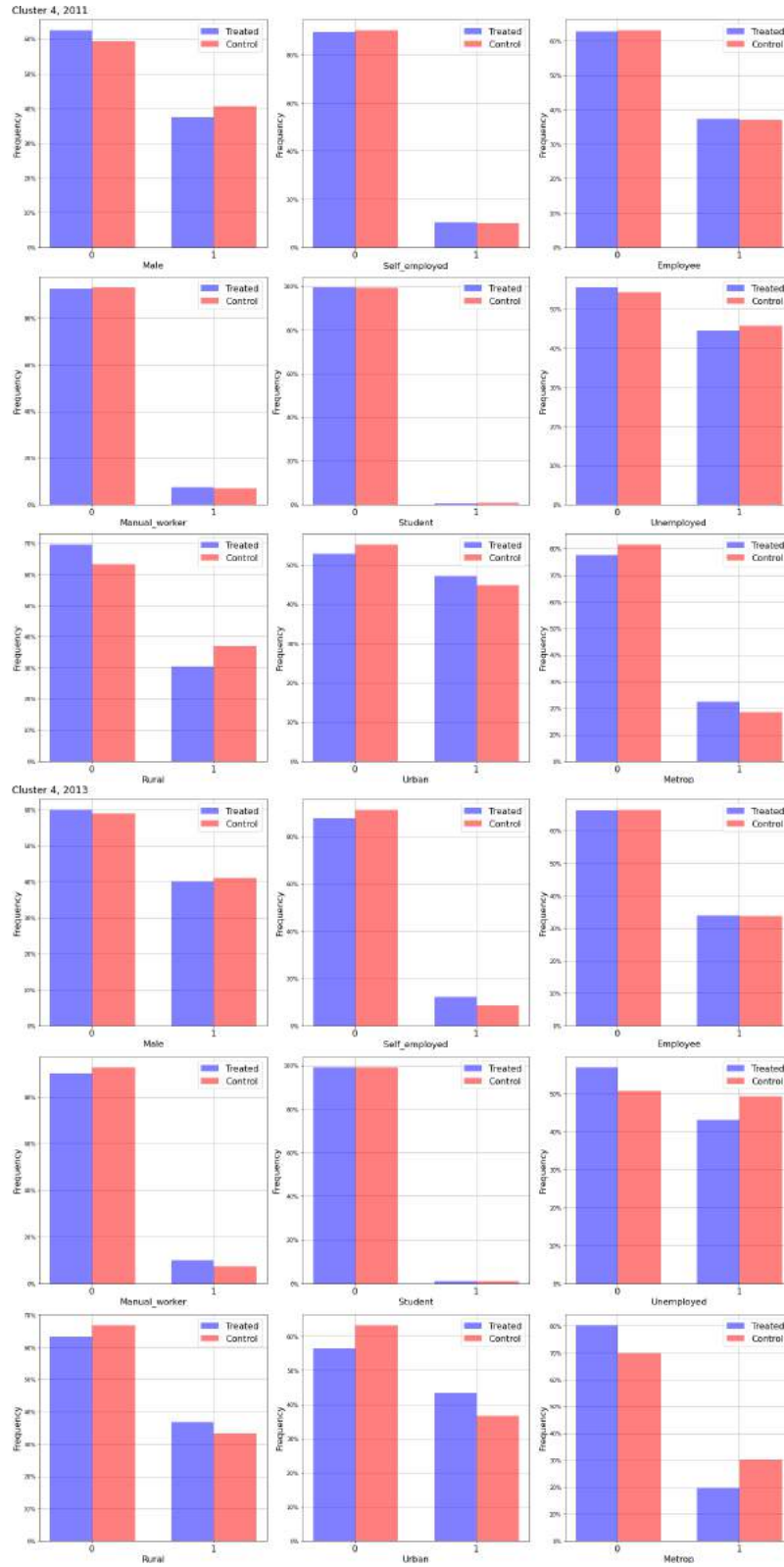


Figure A.10: Overlap histograms for binary demographic variables for cluster 4.  
*Note:* the bins are plotted side-by-side instead of on top of each other for visual clarity.

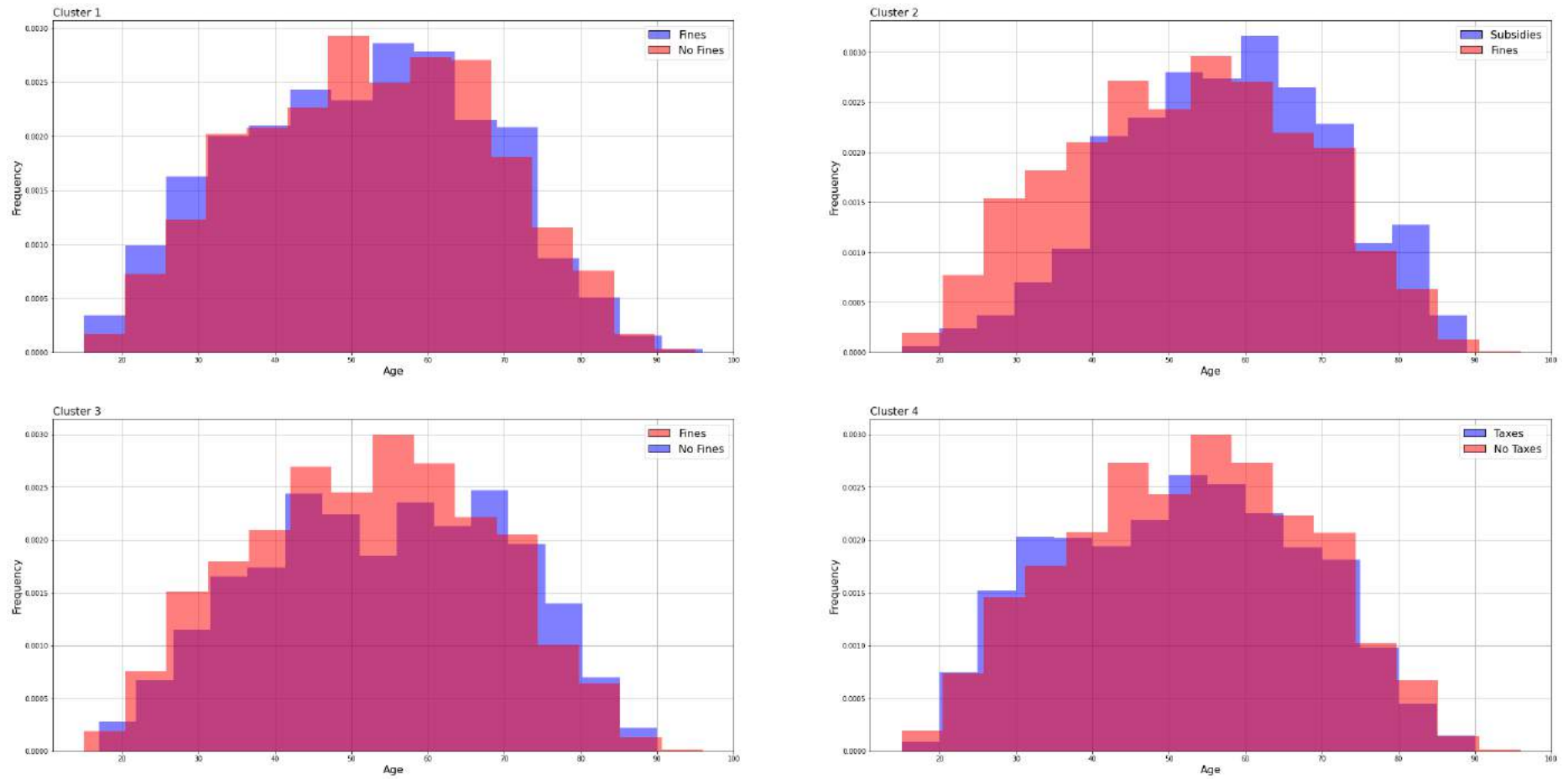


Figure A.11: Overlap histograms for variable Age in each cluster for the monetary incentives analysis.

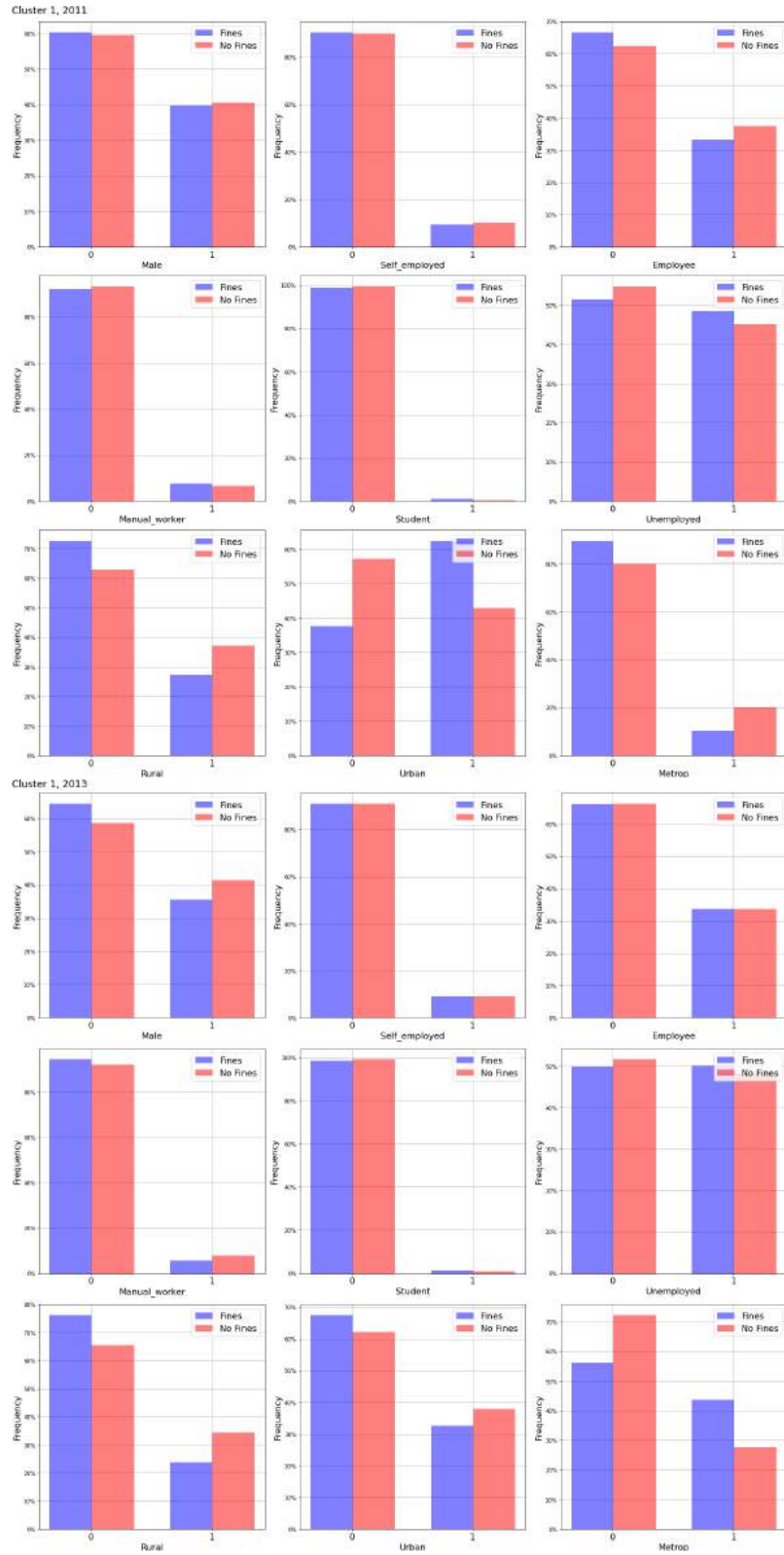


Figure A.12: Overlap histograms for binary demographic variables in cluster 1 in 2011 and 2013 for the monetary incentives analysis.

*Note:* the bins are plotted side-by-side instead of on top of each other for visual clarity.

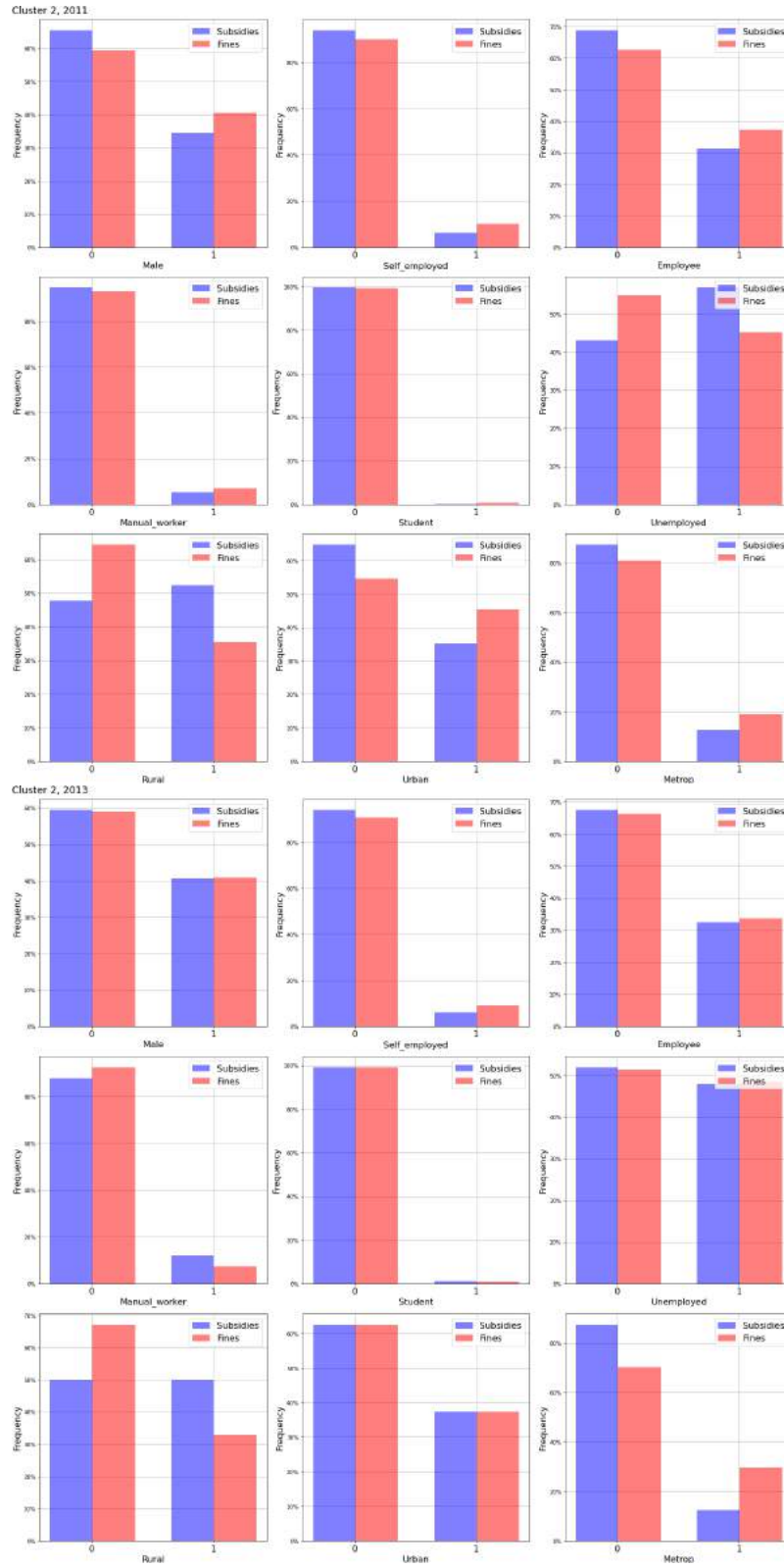


Figure A.13: Overlap histograms for binary demographic variables in cluster 2 in 2011 and 2013 for the monetary incentives analysis.

*Note:* the bins are plotted side-by-side instead of on top of each other for visual clarity.

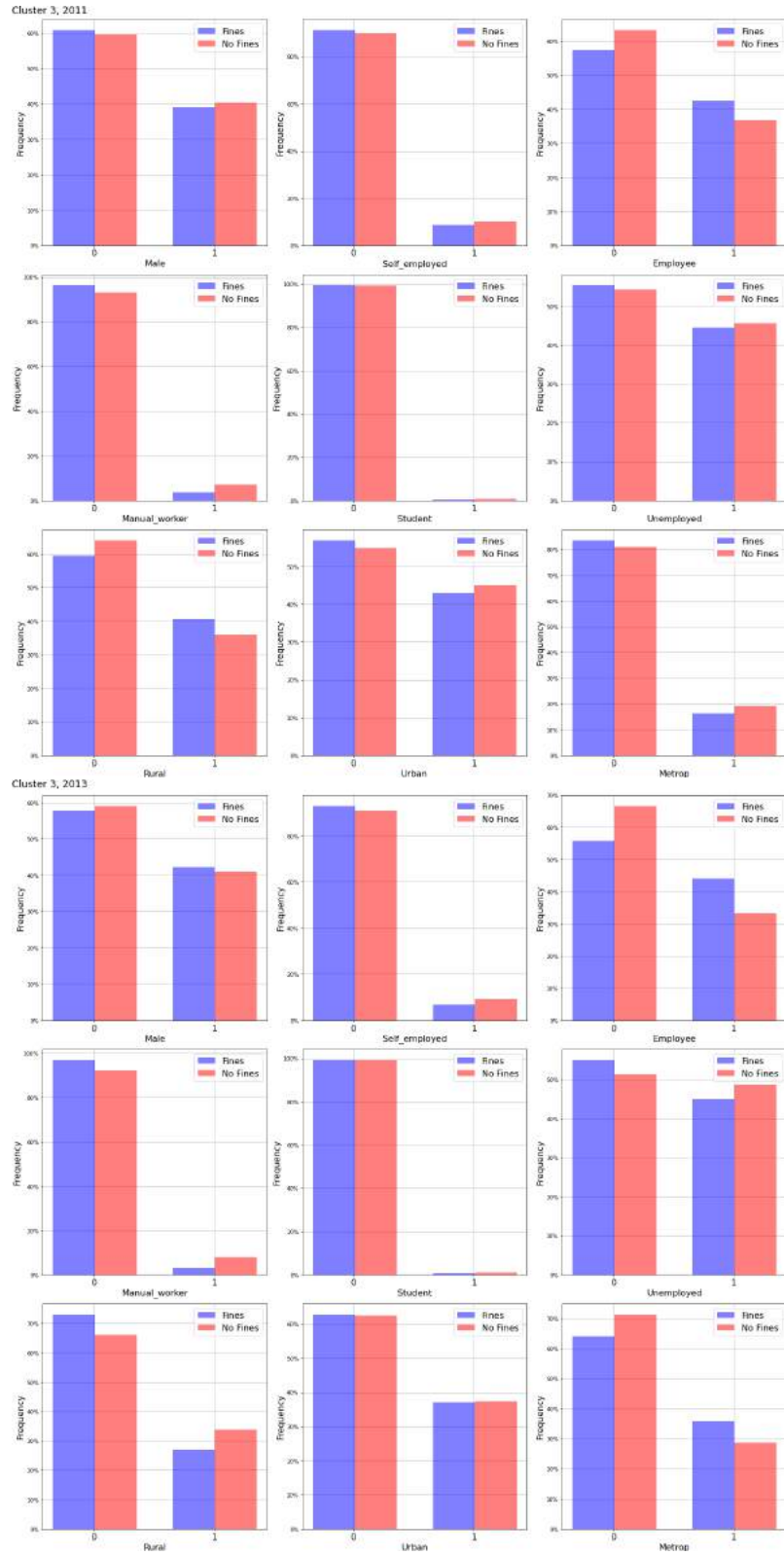


Figure A.14: Overlap histograms for binary demographic variables in cluster 3 in 2011 and 2013 for the monetary incentives analysis.

*Note:* the bins are plotted side-by-side instead of on top of each other for visual clarity.

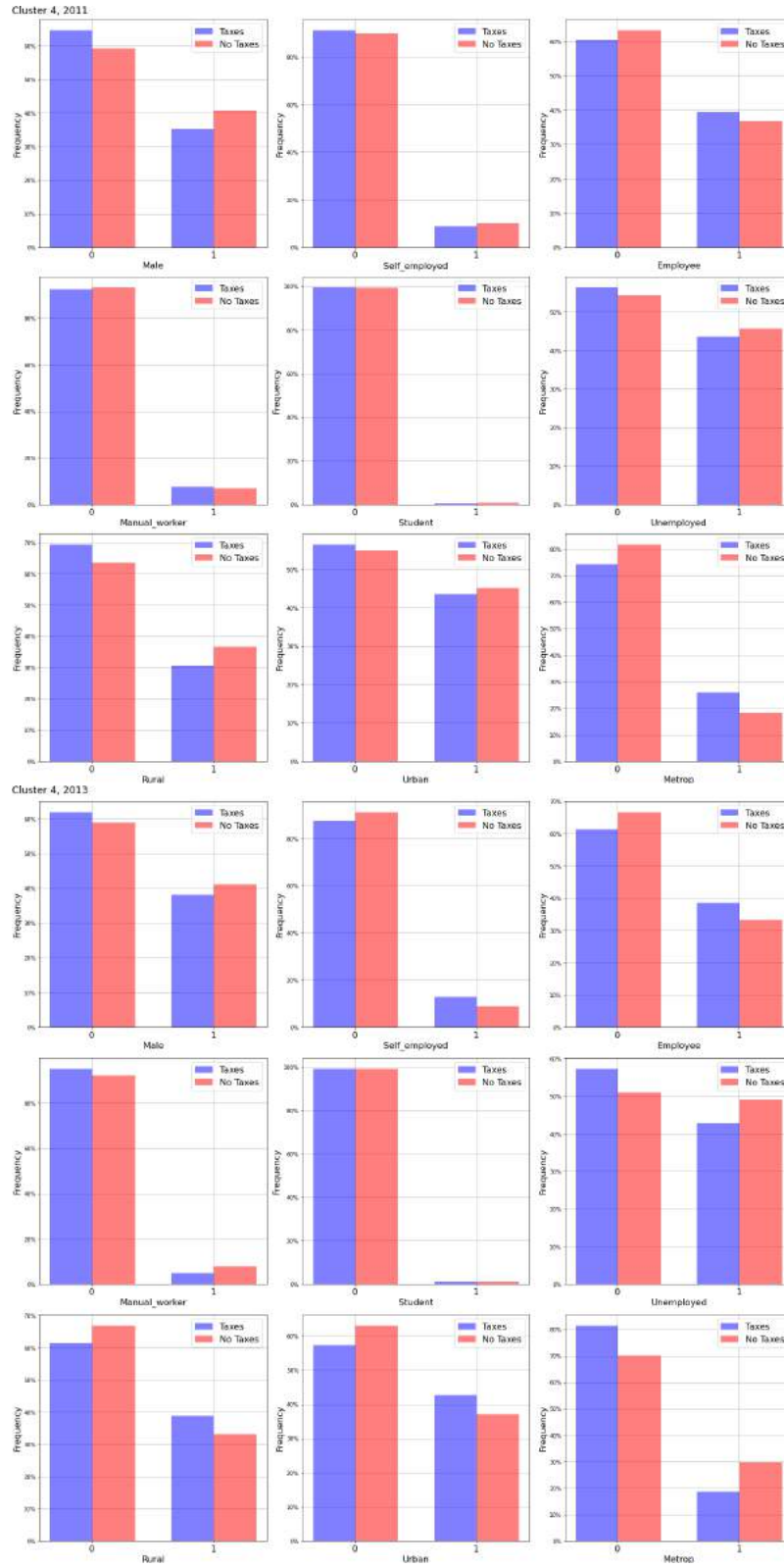


Figure A.15: Overlap histograms for binary demographic variables in cluster 4 in 2011 and 2013 for the monetary incentives analysis.

*Note:* the bins are plotted side-by-side instead of on top of each other for visual clarity.

Table A.8: Summary of types of monetary incentives introduced by different countries.

Country	Incentive type
<b>Cluster 1</b>	
Bulgaria	Fines
Cyprus	Fines
Malta	Fines
<b>Cluster 2</b>	
Belgium	Subsidies
Denmark	Fines
Greece	Fines
Ireland	Fines
Slovenia	Fines
Spain	Fines
<b>Cluster 3</b>	
United Kingdom	Fines
<b>Cluster 4</b>	
Latvia	Taxes
Slovakia	Taxes



Table A.9: Comparison of effects of introduction of monetary incentives on food waste from DiD, weighted DiD and DML DiD models.

	DiD	wDiD	DMLDiD
<b>Cluster 1</b>			
Fines	-0.438*** (0.090)	-0.151*** (0.025)	-0.932*** (0.039)
No Fines	0.138 (0.119)	0.055** (0.025)	0.321*** (0.068)
<b>Cluster 3</b>			
Fines	-0.252* (0.141)	-0.049*** (0.019)	-0.030 (0.069)
No Fines	0.552*** (0.117)	0.083*** (0.019)	0.351*** (0.040)
<b>Cluster 4</b>			
Taxes	-0.136 (0.102)	-0.023 (0.025)	-0.072 (0.048)
No Taxes	1.288*** (0.121)	0.284*** (0.023)	0.278*** (0.054)

*Note:* the table shows estimated effects of changes in environmental legislation with and without monetary incentives, compared to absence of changes, on percentage of food wasted. Standard errors are shown in brackets. Stars indicate significance level:

\* $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$ . It can be seen that introduction of monetary incentives such as fines is associates with decrease in food waste according to all the three models (effect of adoption of taxes is also negative but not statistically significant on any reasonable significance level). At the same time, introduction of environmental laws which do not imply any monetary motivation, is associated with the increase of food waste in all the three clusters examined. As a topic for further research, it would be interesting to study the analogous effect on non-targeted activities and preferences.