

SHOULD CHARITABLE AND POLITICAL DONATIONS BENEFIT FROM SIMILAR TAX TREATMENTS? EVIDENCE FROM A SURVEY EXPERIMENT

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WORKING PAPER N°2026/05

MARCH 2026

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Should Charitable and Political Donations Benefit from Similar Tax Treatments? Evidence from a Survey Experiment*

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January 29, 2026

Abstract

In many countries, both charitable and political donations benefit from generous – and often similar – tax incentives. While a large literature has studied the tax-price elasticity of charitable giving, little is known about political donations. Using a large-scale survey experiment ($N = 12,600$), we investigate the relative efficiency of different tax schemes in fostering political and charitable donations. We document that repealing the existing non-refundable income-tax credit decreases charitable donations but not political donations, pointing toward greater fiscal incentives behind charitable giving. We next show that, conditional on giving, matching – where the government matches individual donations at a fixed rate – increases both political and charitable giving, but that it decreases the probability of giving to charities at the extensive margin. Finally, using a Principal Component Analysis (PCA) and generic machine learning, we document important dimensions of heterogeneity, and discuss the policy implications of our findings.

Keywords: charitable giving, political donations, tax incentives, matching subsidies, rebate subsidies, survey experiment, heterogeneous treatment effects.

JEL No: H24, H31, L38.

*We are particularly grateful to Pierre-Henri Bono and Martial Foucault from the CEVIPOF (Sciences Po Paris) thanks to whom we were able to carry our survey experiment as part of the 9th wave of the “*French Electoral Survey*.” We gratefully acknowledge the many helpful comments and suggestions from Mirko Draca, Antoine Ferey, Stefano Fiorin, Moritz Hengel, and Stefan Pollinger. We are also grateful to seminar participants at Bocconi University and the Paris School of Economics, and to conference participants at the BSE Summer Forum and at the CAGE Summer School. The experiment was pre-registered at the AER RCT Registry: AEARCTR-0009023. The research leading to this project has received funding from the European Research Council under the European Union’s Horizon 2020 research and innovation programme (Grant Agreement no. 948516). All errors remain our own.

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1 Introduction

Both charitable giving and political giving have reached new highs in recent years. As increases in donations coincided with the introduction of tax incentives in some countries, a growing literature estimates the effects of such incentives on charitable contributions (e.g. [Karlan and List, 2007](#); [Almunia et al., 2020](#)). However, little is known on political donations, although they benefit from similar tax treatments in many countries such as France, Germany, Italy and Spain (see e.g. [Cagé, 2018](#)). Other countries, such as Belgium and the United States, have historically introduced tax deductions for political donations, before abolishing them. From a tax policy perspective, it remains an open question whether the price elasticity of political and charitable donations is the same.

To tackle this question, this paper uses a large pre-registered survey experiment and investigates the relative effectiveness of three different forms of tax reliefs – non-refundable tax credit, direct reimbursement, and matching subsidy – in fostering political and charitable donations. The survey was performed in 2022, with a sample representative of the French population (12,600 surveyed individuals). All surveyed individuals were randomly assigned to one of eight groups (approximately 1,575 individuals by group) designed to explore the effect of different tax relief schemes on charitable and political giving. More precisely, we first provided all surveyed individuals with an information sheet explaining the existing French non-refundable income-tax credit system – under which donations to charities, political parties and electoral campaigns are eligible to a 66% tax credit – using a 50/50 randomization allocating them either to the political giving group or to the charitable giving group. Second, we further randomized each sub-sample into four equally sized groups: (i) the control group, (ii) the immediate reimbursement treatment group (T1), (iii) the matching treatment group (T2), and (iv) the repeal of the tax credit treatment group (T3). We measure the effect of the different treatments by asking respondents the following question: would you consider making a donation in the next 12 months (extensive margin), and if so, how much would you consider giving (intensive margin)?

At baseline, around 42% of the respondents declare that they are willing to make a charitable donation, and less than 6% a political one. Conditional on giving, charitable donors plan to contribute around €285. We find that political and charitable donations do not react similarly to the different treatments. First, while repealing the existing income tax credit decreases charitable giving at both the extensive and the intensive margin (we observe an overall drop corresponding to around one third of the mean), it does not affect political donations. Second, the probability of donating to charities is lower under matching than in the current tax credit system. However, conditional on giving, people report that they would contribute more to both charities and political parties with matching.

Finally, using both a Principal Component Analysis (PCA) and a generic machine learning

approach (Chernozhukov et al., 2023), we document large heterogeneity in treatment effects for charitable giving. We obtain three main dimensions – defined with respect to income, education, profession, age and political preferences – that capture the largest variations in the data. Following the categorization of Cagé and Piketty (2023), we interpret them as: (i) the social-ecological left (Left bloc), (ii) the progressive liberal center (Center-right bloc), and (iii) the patriotic national right (Far-right bloc). We find that, at the extensive margin, repealing the existing income tax credit (T3) would mostly negatively affect far-right voters. By contrast, we document a negative effect of both T1 (direct reimbursement) and T2 (matching) for center-right voters (who tend to be high-income), probably reflecting the use of charitable giving as a way to avoid paying the income tax. There is no heterogeneity in treatment effects for political donations.

Finally, we discuss the policy implications of our findings. Regarding political donations, we argue that the existing tax credit should be repealed given that doing so would not affect respondents' willingness to donate or the amount they would donate conditional on giving. Yet it would save resources for the State by reducing its fiscal expenditures. Regarding charitable donations, repealing the existing tax credit would lead to a drop in both the number of donors and the amounts contributed by donors, and so might not be desirable if preserving the size of the charitable sector is a priority. However, the observed price elasticity of charitable donations is relatively low.¹ Besides, if policymakers are willing to further incentivize charitable giving, then a preferable policy would consist in replacing the existing tax credit with a matching system, but doing so would increase the fiscal expenditures of the State, lead to a higher concentration of charitable giving, and subsidize the preferences of the richest and oldest citizens (given that, at the intensive margin, the center-right bloc voters are those whose donations increase the most under the matching treatment).

Literature review Our article first contributes to the very large literature on giving and tax incentives. A first strand of this literature has investigated the tax-price elasticity of charitable donations in the United States (Randolph, 1995; Auten et al., 2002; Bakija and Heim, 2011) or other empirical contexts (Fack and Landais, 2010; Bönke et al., 2013; Bönke and Werdt, 2015; Cagé and Guillot, 2022).² We contribute to this literature by estimating the elasticity of both charitable and political donations, in a context where both kinds of giving benefit from a similar tax treatment.

The second strand of the literature has focused on the rebate-match gap, i.e. the fact that, while a 50% rebate should in practice be equivalent to a 1:1 match, people seem more likely

¹As shown in Section 5 below, the price elasticity in the repeal treatment is equal to -0.18 .

²See List (2011) for a literature review, and Meer (2014) for additional evidence on the effects of the price of giving.

to donate under matching than rebating (Eckel and Grossman, 2003, 2008, 2017).³ While this literature mostly relies on lab and field experiments, Scharf and Smith (2015) survey taxpayers who have previously donated in UK’s Gift Aid system, to compare the effects of a tax rebate and of a matched payment. Building on their work, we contribute to the literature by considering individuals regardless of whether they are liable to the income tax (and thus independently of whether they can actually benefit from existing tax credits) and independently of their past giving behavior. More generally, while the match-rebate literature tends to focus only on the intensive margin of donations, we consider the effectiveness of different tax relief schemes both at the intensive and at the extensive margin. This is particularly important given that – according to our findings – matching has a positive impact at the intensive margin but a negative impact on the probability of giving to charities. Additionally, we go one step further than the match-rebate literature by also considering the effect of a direct reimbursement, and by showing that the effectiveness of the different forms of tax relief varies with the nature of the donations (political versus charitable giving), which has important policy implications.

Our paper contributes more broadly to the literature on the cost effectiveness of matching (see Epperson and Reif, 2019, for a recent literature review). Karlan and List (2007) use a natural field experiment and show that matching grants on charitable giving increase both the revenue per solicitation and the response rate (see also Meier, 2007). Karlan et al. (2011) document important heterogeneity in treatment effects where matching significantly increases donations by recent donors. In the context of the French tax credit system, we further show that switching to a matching system would allow the youngest and most precarious citizens who have not previously donated to become donors. However, among established donors, doing so would overwhelmingly subsidize the preferences of the oldest and richest donors who would give more conditional on giving.

Finally, our paper contributes to the literature on the determinants of political donations. While the literature identifies two broad sets of motives underpinning individuals’ donations to political parties and electoral campaigns – contributions as a strategic investment and contributions as a consumption good (Gordon et al., 2007; Bouton et al., 2022) – it mostly overlooks the role played by tax credits. Boatright et al. (2006) is one exception, but they focus on whether the awareness of existing tax credits for electoral campaigns increases public participation; similarly, Green et al. (2015) consider the role played by matching funds on small donor contributions and show that emphasizing them seems to have little effect (see also Schwam-Baird et al., 2016). By contrast, our results show that – even for political donations – substituting existing tax credit schemes with matching funds would increase the amount received by parties and campaigns.

The rest of the paper is organized as follows. In Section 2 below, we briefly describe

³See also Eckel and Grossman (2006) and Davis et al. (2005) for further evidence.

the institutional context for charitable and political giving in France and present our survey experiment. Section 3 presents our empirical strategy and reports the results. Section 4 investigates the heterogeneity of the effects. Finally, Section 5 discusses the policy implications of our findings and concludes.

2 Institutional context and experimental design

In this section, we begin by providing an overview of the regulatory framework in France pertaining to charitable and political contributions. We then describe our experimental design.

2.1 Tax deduction for donations in France

In France, households can donate to charities and political parties. Both types of donations are eligible for a 66% non-refundable income tax credit (Fack and Landais, 2010; Cagé and Guillot, 2022). Donors can deduct 66% of the donated amount from their income tax bill, up to a ceiling capped at 20% of their taxable income.

In contrast to charitable donations, political donations are capped by law in France (Cagé, 2024). These contributions encompass both campaign donations and donations to political parties. An individual is permitted to contribute a maximum of €4,600 to each political campaign and up to €7,500 per year to political parties.

2.2 Experimental design

Survey The survey experiment was pre-registered at *AER RCT Registry: AEARCTR-0009023*. The survey took place between April 2 and April 4, 2022, as part of the 9th wave of the “French Electoral Survey”.⁴ It samples 12,600 individuals representative of the French voting-age population, and contains comprehensive information on individual socio-economic characteristics (see online Appendix Table B.1 for baseline descriptive statistics).

Experiment Figure 1 summarizes the design of the experiment. First, we collect baseline information on whether the individuals have made a charitable and/or a political donation over the last 12 months, and if so, the amount of the donation(s), as well as on whether the

⁴The “French Electoral Survey” is a monthly panel jointly conducted by Ipsos, the CEVIPOF and *Le Monde* before the French presidential elections. It is run online by the “Access Panel Online” from IPSOS. See Cagé et al. (2023) for a description. While one might be concerned that the timing of the survey – conducted just a few days before the Presidential election – could affect the external validity of our findings, we do not believe this to be the case. First, charitable donations do not spike in election years (Cagé et al., 2023; Cagé and Guillot, 2022). Second, although political donations do increase during election years (in particular due to campaign contributions), it is difficult to believe that a lack of response to different tax schemes in such years would turn into a response in non-election years, when political salience is lower.

individuals were aware of the existing tax credit scheme.⁵

Second, we randomly assigned the 12,600 surveyed individuals to one of eight groups (approximately 1,575 individuals by group) designed to explore the effect of donation incentive schemes on charitable and political giving. To do so, we proceed in three steps. First, we provide all the surveyed individuals with the following information sheet, randomly assigning them to either the charitable giving group (donations to non-profit organizations or foundations) or the political giving group (donations to political parties or electoral campaigns).

- *Currently, if you make a donation to [a non-profit organization or a foundation] / [a political party or electoral campaign] and you are subject to the income tax, you benefit from a non-refundable income tax credit equal to 66% of the total amount of the payment from the moment you report the donation. However, this reduction is not valid if you are not subject to the income tax.*
- *Example: if you donate €100 this year to [a non-profit organization or a foundation] / [a political party or electoral campaign], the amount of taxes you will have to pay next year will be automatically reduced by €66 (i.e. 66% of the amount donated).*

Second, we further randomized each group into four equally sized sub-groups⁶.

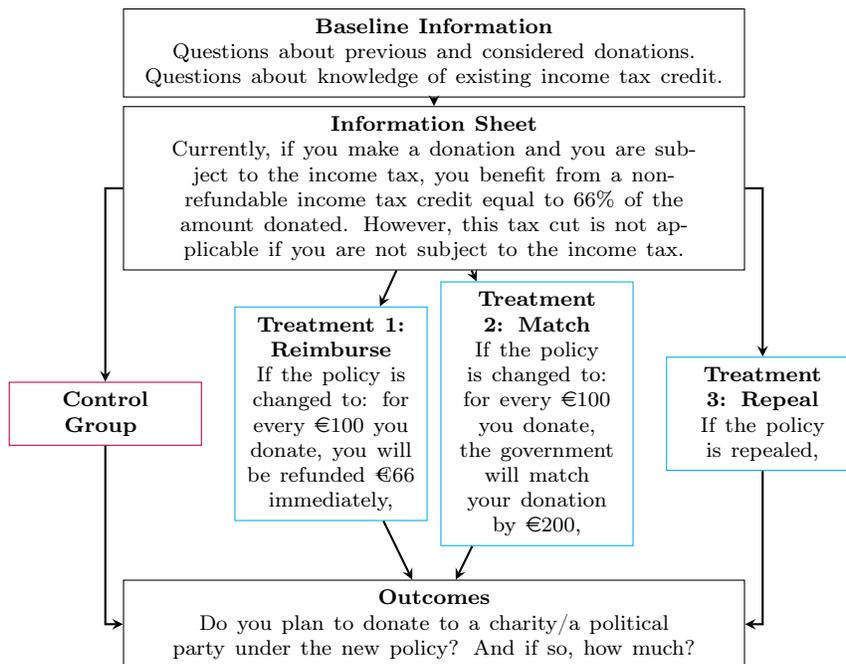
1. **Control group.**
2. **Treatment 1 – Direct reimbursement:** *If the tax reduction system were modified as follows: if you make a donation to [a non-profit organization or a foundation] / [a political party or electoral campaign], the government immediately refunds 66% of the amount of your donation.*
3. **Treatment 2 – Matching:** *If the tax reduction system were modified as follows: if you make a donation, for every euro donated to [a non-profit organization or a foundation] / [a political party or electoral campaign] the government will donate €2 to that [non-profit organization or foundation] / [political party or electoral campaign].*
4. **Treatment 3 – Repeal of the tax credit system:** *If the tax reduction system were repealed.*

Third, we collect our outcomes of interest with the following question: *Would you consider making a donation to [a non-profit organization or a foundation] / [a political party or electoral campaign] in the next 12 months? If so, how much would you consider giving?*

⁵We did not have to collect the socio-demographic characteristics of the respondents or their political preferences given that this was already done in the Electoral Survey.

⁶Randomization was stratified based on (i) gender interacted with age, (ii) the socio-professional category, (iii) the region where the respondent lives, and (iv) the size of the city.

Figure 1: Experiment design



Notes: The figure summarizes the main steps of our surveyed experiment. The survey took place between April 2 and April 4, 2022, as part of the 9th wave of the “French Electoral Survey” ($N = 12,600$).

2.3 Balancing tests

Before turning to the effects of the treatments, we provide the results of our balancing checks. Online Appendix Table [B.2](#) shows that surveyed individuals do not widely differ across our four treatment and control groups (sub-Table [B.2a](#) reports the results for the charitable giving group and sub-Table [B.2b](#) for the political giving group). Of the 150 tests performed (25 variables \times 3 pairwise comparisons \times 2 subgroups), only 8 show statistically significant differences at the 5% level (4 in each of the two sub-groups). This is in line with what we would expect by chance (given that 5% of 150 is equal to 7.5). In other words, the balancing tests validate the randomization procedure as no systematic differences are found across the treatment and control groups. In addition, to further ensure that our results are not driven by the small imbalances we observe, we control for this rich set of individual characteristics in all our regressions.

3 Empirical strategy and results

3.1 Specification

We estimate the following model:

$$Donation_i = \pi_0 + \pi_1 Treatment_i + \mathbf{X}'_i \pi_2 + u_i \quad (1)$$

where i index the individuals. Our dependent variable, $Donation_i$, is either (i) an indicator variable equal to one if the individual reports that she would consider a donation and to zero otherwise (extensive margin), (ii) the amount they reported that they would give (intensive margin), or (iii) the unconditional amount they reported that they would give (i.e. including the zeros; both margins). We perform the analysis separately for the charitable donations group and for the political donations group.

Our main independent variable of interest, $Treatment_i$, is a categorical variable for the different treatment groups, and we use the control group as the omitted category. \mathbf{X}'_i is a vector of individual-level controls including demographics (gender, age, marital status, residential area), income brackets, religion, life satisfaction, trust in political actors, trust in various members of the society, knowledge of the existing tax scheme (measured before the experiment), and previous (charitable and political) donations. We include these controls one at a time.

3.2 Results

We investigate the effect of the treatments for both political and charitable giving. Figure 2 shows the average outcome for the control group and each treatment group. First note that the giving probability in the control group is seven times higher for charitable donations (42%) than for political donations (6%); political giving is indeed a relatively rare event in France (see e.g. Cagé, 2018). This remains true for our three treatment groups. The average amount donated is also higher for charitable giving than for political donations.

Figure 3 reports the treatment effects (estimation of equation (1)) at the extensive margin (sub-Figure 3a), the intensive margin (sub-Figure 3b), and when we consider both margins simultaneously (sub-Figure 3c).⁷ We first report the results absent any controls, and then introduce the controls gradually.

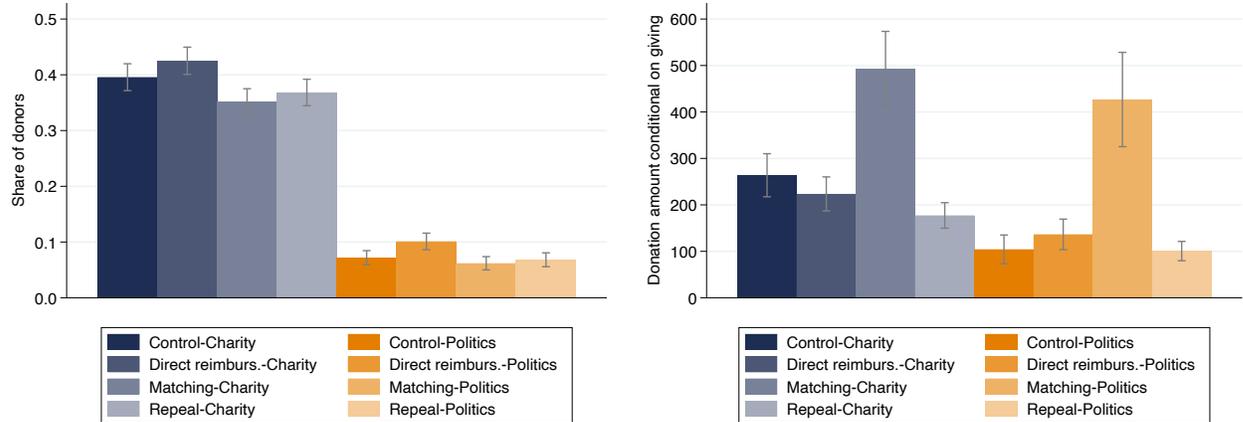
Charitable donations In the case of charitable donations, the individuals in the **direct reimbursement** treatment group (T1) do not behave significantly differently from those in the control group. We observe a higher probability of giving at the extensive margin (around 2 percentage points) but the difference is not statistically significant. This is a somewhat surprising result because it implies that people do anticipate the income tax credit they will benefit from with a delay, and seem not to value negatively the price of time (or uncertainty).

Regarding the **matching** treatment (T2), we find that it decreases significantly the probability of making a donation compared to the control group, with a 5 to 6 percentage-point

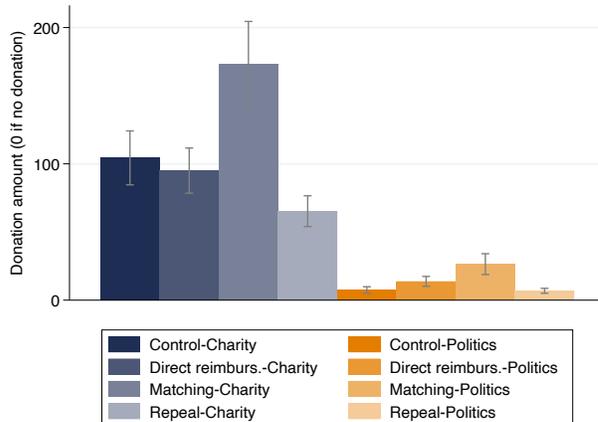
⁷See online Appendix Tables B.3 to B.5 for the corresponding regression results.

Figure 2: Average outcomes depending on the treatment status

(a) **Extensive margin** (willingness to make a donation) (b) **Intensive margin** (amount given cond. on giving)



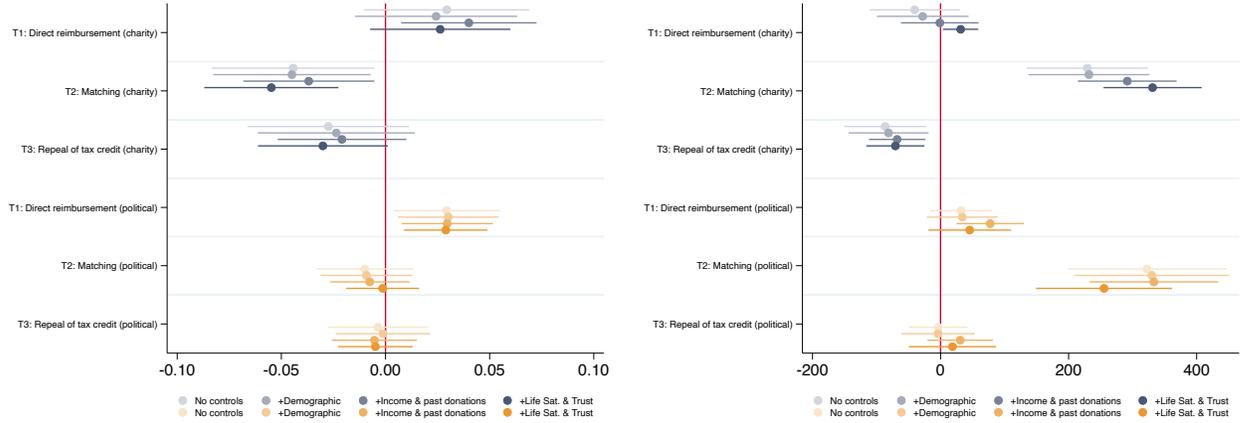
(c) **Both margins** (amount given includ. the zeros)



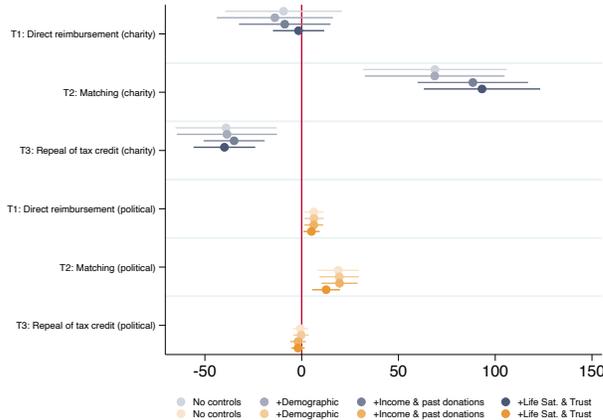
Notes: The figure shows the average outcome by treatment status, at the extensive margin (sub-Figure 2a), the intensive margin (sub-Figure 2b) and when we consider both margins simultaneously (sub-Figure 2c). The extensive margin is defined as the probability that the individual declares that they are willing to make a donation. For the subset of respondents who are willing to give, the intensive margin is defined as the amount they declare they are willing to give. Both margins is defined as the amount respondents are willing to give, including the zeros (i.e. the individuals who declare that they are not willing to make a donation). The four groups correspond to (i) the control group (Control-), (ii) the Direct reimbursement treatment group (Direct reimburs.-), (iii) the Matching treatment group (Matching-), and (iv) the Repeal of the tax credit system treatment group (Repeal-). The sample includes all the individuals in the experiment. We consider separately the individuals who were shown the charitable giving information sheet (shades of blue) and the individuals who were shown the political giving information sheet (shades of orange). The error bars represent 95% confidence intervals.

Figure 3: Treatment effects for charitable and political donations

(a) **Extensive margin** (willingness to make a donation) (b) **Intensive margin** (amount given cond. on giving)



(c) **Both margins** (amount given includ. the zeros)



Notes: The figure shows the average treatment effects estimated using OLS (equation (1)), at the extensive margin (sub-Figure 3a), the intensive margin (sub-Figure 3b), and when we consider both margins simultaneously (sub-Figure 3c) (see online Appendix Tables B.3 to B.5 for the corresponding regression tables). An observation is an individual. The extensive margin is defined as the probability that the individual declares that they are willing to make a donation. For the subset of respondents who are willing to give, the intensive margin is defined as the amount they declare they are willing to give. Both margins is defined as the amount respondents are willing to give, including the zeros (i.e. the individuals who declare that they are not willing to make a donation). The three treatment groups correspond to (i) the Direct reimbursement treatment group (T1), (ii) the Matching treatment group (T2), and (iii) the Repeal of the tax credit system treatment group (T3). The sample includes all the individuals in the experiment in sub-Figures 3a and 3c and the subset of those who declare that they are willing to make a donation in sub-Figure 3b. We consider separately the individuals who were shown the charitable giving information sheet (shades of blue) and the individuals who were shown the political giving information sheet (shades of orange). “Demographic controls” include: categorical variables for age, gender, socio-economic status, unemployment, marital status, city size and region of residence. “Income and past donations” controls include: income brackets, knowledge of existing tax credit for charity and political giving, an indicator variable equal to one if the respondent reports that they made a donation during the past 12 months, and the amount donated. “Life satisfaction and trust controls” include: continuous measures of life satisfaction, trust in politics (i.e. the president, members of parliament, the city mayor), in the media, and in society (i.e. family, acquaintances, and strangers). The error bars represent 95% confidence intervals.

drop, corresponding to around 13% of the mean. This is an interesting finding compared to the rebate-match literature that mostly focuses on the intensive margin of donations. It is also consistent with what is found in the literature using in-lab dictator games on smaller samples (e.g. [Diederich et al., 2022](#), have 613 participants): at the extensive margin, matching grants negatively impact giving while at the intensive margin, they have positive effects. Perhaps because the matching system is more complicated to understand (in particular for French citizens where it does not exist) and somehow less transparent for the donors, it decreases the observed willingness to contribute.⁸ By contrast, at the intensive margin (i.e. conditional on giving), we observe a positive effect consistent with the existing literature: compared to the existing tax credit, matching increases the amount received by charities by between €229 and €331 depending on the specifications (i.e. around 100% of the mean). Overall (when considering both margins simultaneously), we observe a €69-93 increase in the amount citizens are willing to give (around 63-83% of the mean).⁹

Finally, the **repeal of the existing tax credit** would reduce charitable giving both at the extensive and at the intensive margin. At the extensive margin, we observe a 3 percentage-point drop in the probability of giving (around 10% of the mean) and, conditional on giving, a drop in the amount donated between €68 and €87 (around 24-31% of the mean). Overall, we observe a €35-40 drop in the amount individuals are willing to contribute, corresponding to 32-36% of the mean.

Political donations Political donations seem less responsive to the treatments, both at the extensive and the intensive margin. The only statistically significant treatment effect at the extensive margin is for the **direct reimbursement**, which increases the probability of giving by 3% relative to the control group. As a result, it also increases the overall amount individuals are willing to contribute when we consider both margins jointly.

At the intensive margin, the **matching treatment** significantly increases the amount received by political parties by between €255 and €333 depending on the specifications (i.e. over 150% of the mean). This is a large effect, whose magnitude is stronger relative to the mean than the one we obtain for charitable donations. Note however that only a few respondents are willing to make a political donation, so the intensive margin for political giving is computed for a relatively low number of observations.

⁸Another possible explanation is that donors contribute to avoid paying income tax – because they are opposed to the tax per se – and so no longer do so absent the tax credit (even for an unchanged donation cost for them). We come back to this point in Section [4](#) below when discussing the heterogeneity results.

⁹While the magnitude of this effect might seem large, it should be remembered that we consider the checkbook donations plus the match in the matching case, i.e. the amount received by the charity, similarly to what is done in the literature (see for example [Scharf and Smith, 2015](#)). In this paper, the authors find that a match increases the amount received by charities by between 5.4 to 27.4% depending on the implied price of giving (the lower the price, the higher the effect). In our case, the implied price of giving is approximately twice as low (0.34 versus 0.6) but the effect we find is approximately twice as high. Indeed, for both margins (see online Appendix Table [B.5](#)), the effect corresponds to a 60% increase in the amount received by charities.

Importantly, we observe no effect of the **repeal of the tax credit** for political donations. Note that this is not due to small statistical power. Indeed, our design has 80% power at the 5% significance level to detect treatment effects at the extensive margin of about 2.7 percentage points for political donations (5.2 percentage points for charitable donations), and at the intensive margin of approximately €16 (0.11 sd) for political donations (€64 for charitable donations). In other words, even though they benefit from similar tax treatments, political giving seems to be much less price elastic than charitable giving. We will come back to this point when discussing the policy implications of our findings in Section 5 below. Furthermore, our findings also illustrate the fact that the purpose of the donation (in our context political vs. charitable) plays an important role in the price elasticity of giving. This heterogeneity can help to rationalize largely different estimates found in the literature.

Robustness checks The above results are robust to the use of different specifications. First, as appears clearly in Figure 3, the magnitude of the estimates is nearly unchanged independently of the set of controls included. Second, we show in the online Appendix that the results are robust to estimating equation (1) in logarithm rather than in level (Table B.6). They are also robust to using logit rather than an OLS specification (Table B.7).

4 Heterogeneity of the treatment effects

We are interested in the heterogeneity of the treatment effects. As there are many dimensions of heterogeneity to be explored and that they are often strongly correlated – e.g. life satisfaction, political preference and income – we first employ a Principal Component Analysis (PCA) to reduce the covariates’ dimension and to avoid cherry-picking variables of interest (Section 4.1). We then confirm our findings with the generic machine learning approach of Chernozhukov et al. (2023) (Section 4.2).

4.1 Principal Component Analysis

We first perform a Principal Component Analysis (PCA) using all the independent variables considered in the estimation of equation (1). PCA is a common dimension reduction technique in computer science and social sciences, particularly with socio-economic survey data (Vyas and Kumaranayake, 2006).¹⁰ Online Appendix Table B.8 provides the list of the variables used in the analysis. In a nutshell, PCA reduces the dimensionality of the data by finding axes, known as components, that capture the largest variations in the dataset. Those components can be cautiously interpreted by checking the variables with the highest loadings, which indicate the

¹⁰See also Chan and Kwok (2022) who use principal components in a Difference-in-Differences framework to control for unobserved trends.

variables most correlated with the components¹¹ Online Appendix Figure A.1 reports the eigenvalues of the principal components, which represent the degree of explained variance. We retain the first three principal components for parsimony following the scree test.¹²

Interestingly, as appears in online Appendix Table B.8, these three components reflect the tripartite political cleavage in France (Cagé and Piketty, 2023). The first component loads strongly and positively age and retirement status, and then Catholicism, life satisfaction and voting for Emmanuel Macron in the first round of the 2022 Presidential elections. It also loads moderately reported past charitable giving, right-wing self-reported political preferences, the fact of being married, of earning a high income, and of being trustful (both in political actors and in other members of society). This axis calls on to the image of the moderate, establishment center-right represented by the Macron camp. Following (Cagé and Piketty 2023), we call it the “progressive liberal center.”

The second component loads most strongly education, being a senior executive or professional, and income. Contrarily to the first component, it loads negatively religion and age, and positively voting for Jean-Luc Mélenchon in the first round of the 2022 Presidential elections, as well as city size. This component represents the educated urban elite who identifies with the left – the “Brahmin Left” as per (Piketty (2018) and (Gethin et al. (2022)). We call it the “social-ecological left.”

Finally, the third component loads very strongly right-wing self-reported political preferences, voting for Marine Le Pen in the first round of the elections, and Catholicism. It loads age negatively. This dimension captures the far-right political supporters. It is interesting to see that it loads negatively trust, as well as reported past charitable donations, in line with previous findings on the far-right donation gap (Cagé et al., 2023). We call it the “patriotic national right.”

Specification To study heterogeneity, we estimate the following model:

$$Y_i = \pi_0 + \pi_1 Treatment_i + \pi_2 Treatment_i \times Comp_{ji} + \mathbf{Comp}'_i \boldsymbol{\pi}_3 + \mathbf{X}'_i \pi_4 + u_i \quad (2)$$

where $Treatment_i$ is, as before, an indicator variable for the treatments. $Comp_{ji}$ is the (continuous) predicted value of component j of respondent i , \mathbf{Comp}'_i is a vector of the three predicted components per respondent. \mathbf{X}'_i is a vector of individual-level controls (defined as in equation (I)). We run a separate regression for each treatment arms ($T = 1, 2, 3$), as well as for each of the three principal components ($j = 1, 2, 3$). We standardize each component to

¹¹Note that the components’ signs are arbitrary: loadings only indicate that some variables correlate strongly with the components in two opposite directions, and may be flipped for interpretability. For the sake of transparency, we retain here the signs as they are produced by Stata’s *pca* command.

¹²The three components together explain 28.5% of the total variance, which falls within the range of PCA applied in socio-economic survey data (Vyas and Kumaranayake, 2006).

mean 0 and standard deviation 1. Y_i , the dependent variable, is alternatively the willingness to give (extensive margin) and the amount given depending on giving (intensive margin).

Results Figure 4 reports the results. We first plot the average treatment effects (ATEs) and then, for each component, the conditional average treatment effects (CATE) for the individuals who score one standard deviation higher than the component average (keeping the other two components at their mean values).¹³ Left-hand side figures show the results for charitable giving (shades of blue) and right-hand side figures for political giving (shades of orange).

Almost all statistically significant HTEs are found at the extensive margin (sub-Figure 4a), particularly for charitable giving. Both the direct reimbursement treatment (T1) and the matching treatment (T2) are strongly divided across the “progressive liberal center” component. Both treatments seem to discourage people who score high in this component from donating and encourage those who score low. For the former, the reason could be that high-income individuals may donate to charities to avoid paying income tax because they oppose it. Hence, if the tax relief schemes no longer lower their income tax, even with the price of giving unchanged, they may choose to stop donating. As for the latter, those scoring low in this component are most likely to earn a relatively low income and thus be ineligible for the existing tax credit (given that their marginal income tax rate is equal to zero). Contrariwise, they would benefit from the direct reimbursement – as well as indirectly from the matching – thus encouraging them to become donors.

As for the repeal of the tax credit treatment (T3), we see a different picture where those who score high in the “patriotic national right” component are the most negatively affected. This may be because those who identify with the far-right place little value on charitable giving¹⁴, such that repealing the tax credit would discourage them more than other groups. Conversely, those who score lower on the far-right component are less affected by the treatment.

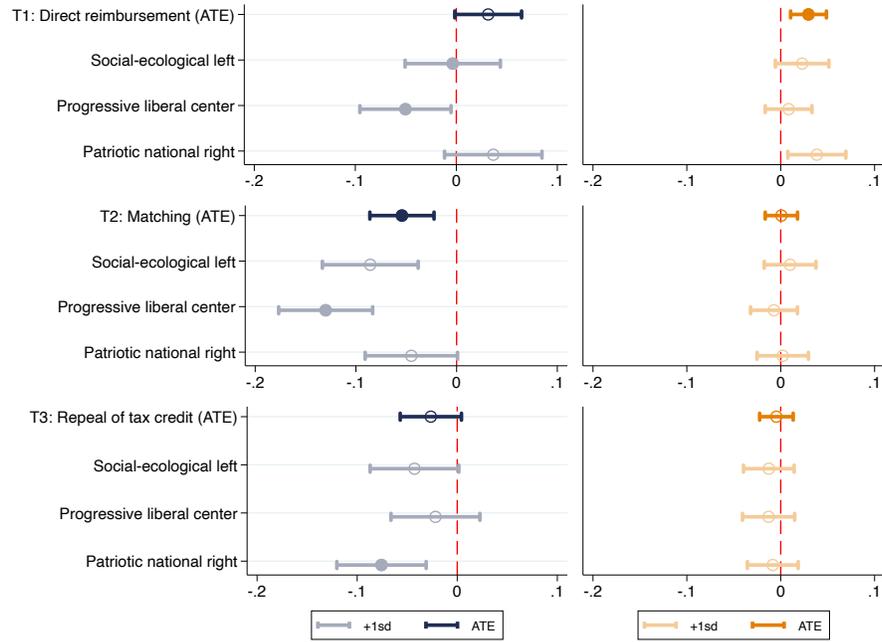
Finally, at the intensive margin (i.e. when we consider the amount individuals report they are willing to contribute conditional on giving), we observe much less heterogeneity in treatment effects, both for charitable giving and for political giving. The only exception is for the matching treatment (T2) whose positive impact on charitable giving is larger for progressive liberal center individuals than for the others.

¹³In other words, we report the treatment effects for hypothetical individuals that score (1, 0, 0) in the three components. The components are not categorizations but rather three “cardinal directions” or axes of a coordinate system; an individual can score high or low in all three components. Here, for each of the components considered separately, we are interested in the size of the treatment effect for an individual who scores one standard deviation higher than the component average.

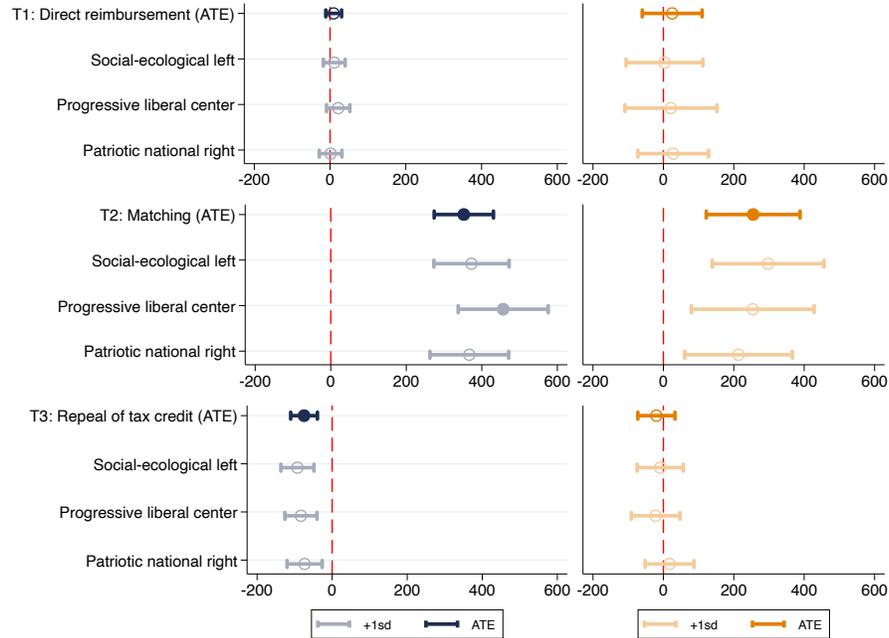
¹⁴For example, Cagé et al. (2023) shows that far-right voters are significantly less likely to donate, taking into account other observables such as income, life satisfaction or local charity supply.

Figure 4: Heterogeneous treatment effects: Principal Component Analysis

(a) Extensive margin: Willingness to make a donation



(b) Intensive Margin: Amount willing to donate conditionally on giving



Notes: The figures report the size and 95% confidence intervals of the average treatment effects (ATEs), and the conditional average treatment effects (CATEs) for the individuals who score one standard deviation higher than the component average (keeping the other two components at their mean values) (estimation of equation (2)). Standard errors are calculated with the delta method, using Stata's *lincom* command. In sub-Figure 4a (extensive margin), the dependent variable is an indicator variable equal to one if the individual declares that they are willing to make a donation, and to zero otherwise. In sub-Figure 4b (intensive margin), for the subset of respondents who declare that they are willing to make a donation, the dependent variable is the amount received by the charity or political party. Each sub-figure represents one treatment branch. The left-hand side figures (shades of blue) report the estimations for charitable giving, and the right-hand side figures (shades of orange) report political giving.

4.2 Generic Machine Learning

Finally, we follow Chernozhukov et al. (2023) and perform a generic machine learning approach. This method predicts the conditional average treatment effects (CATE) in a non-parametric way with machine learning algorithms, then retroactively examines the characteristics of the most positively affected and most negatively affected groups (see online Appendix Section C for details). Tables C.1 and C.2 report the results, which are consistent with those obtained with the PCA approach. However, as highlighted in Chernozhukov et al. (2023), this machine learning approach comes at the cost of a loss of statistical power, mainly due to sample splitting and its non-parametric nature.¹⁵

According to our estimates, there are HTEs both at the extensive margin (Table C.1) and at the intensive margin (Table C.2) for the direct reimbursement (T1) and the repeal of the tax credit (T3) treatments for charitable giving. We do not find heterogeneity regarding the matching treatment (T2), or for political giving.

Regarding the characteristics of the group most affected by the treatments, we see that the probability of giving (extensive margin, Table C.1) is higher under T1 for the low-income individuals, who also have a higher probability of being unemployed and of voting for Mélenchon in the first round of the 2022 Presidential elections (roughly corresponding to the social-ecological left voters described in the PCA above). By contrast, the progressive liberal center voters – who tend to be older and earn a higher income – appear to be much less affected by the different treatments.

5 Discussion, Policy implications and Conclusion

One might be worried that our survey elicits hypothetical choices rather than close to real monetary decisions relying on incentivization. However, non-incentivized survey responses often provide reliable measures of preferences and beliefs, especially in large, representative samples like ours (Grewenig et al., 2022; Hufe and Weishaar, 2025). Indeed, the absence of financial incentives allowed us to field a large, nationally representative sample (with more than 12,000 surveyed individuals), which enhances external validity and statistical power compared to smaller incentivized experiments.

Overall, using the results of our experiment, we calculate that the elasticity of charitable donations to the existing tax credit is equal to -0.18 .¹⁶ While this estimated elasticity lies

¹⁵Sample splitting in the cross validation process means that only part (usually half) of the sample was used to train the predicting algorithm, as opposed to 100% in standard regression techniques. Not imposing any parametric form means forgoing all the structural assumptions in prediction, and treating all variables as ranks. Both compromise the statistical power and require a larger sample size to achieve the same significance.

¹⁶The average charitable donation for the control group is equal to €112.5. It decreases by €41 when the tax price increases from 34% to 100% (with the repeal of the existing income tax credit), hence an elasticity of -0.18 .

at the smaller end of the (absolute value) estimates in the existing literature, it lies precisely in the middle of the elasticity range estimated by [Fack and Landais \(2010\)](#). Our paper goes one step further by also showing that – contrarily to charitable donations – political donations seem to be inelastic to the repeal of the tax credit.

Yet in many countries – including France, Germany, Italy and Spain – both charitable donations and political donations benefit from a favorable tax treatment. In other words, the non-refundable income tax credit for political donations seems to act as a windfall for political donors in France, and charitable and political donations should not benefit from the same tax relief scheme.

Next, we compare three different alternative schemes and outline the trade-off between fiscal spending and encouraging charitable giving. Under a direct reimbursement scheme, the overall donation level does not change much, but younger and lower-income citizens become donors. If the tax relief scheme is repealed, the donation level decreases slightly but large fiscal savings can be made as the tax elasticity is not high. If a matching scheme replaces a tax credit system, donation levels increase dramatically because the donors do not fully internalize the matching price, which entails a substantial fiscal subsidy.

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Online Appendix to the paper:
Should Charitable and Political Donations Benefit from Similar
Tax Treatments? Evidence from a Survey Experiment

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January 29, 2026

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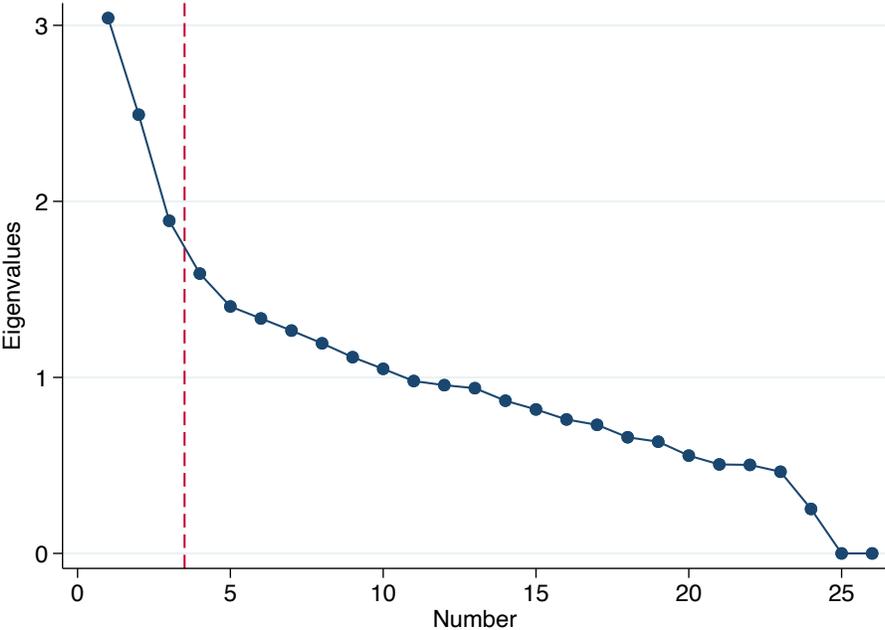
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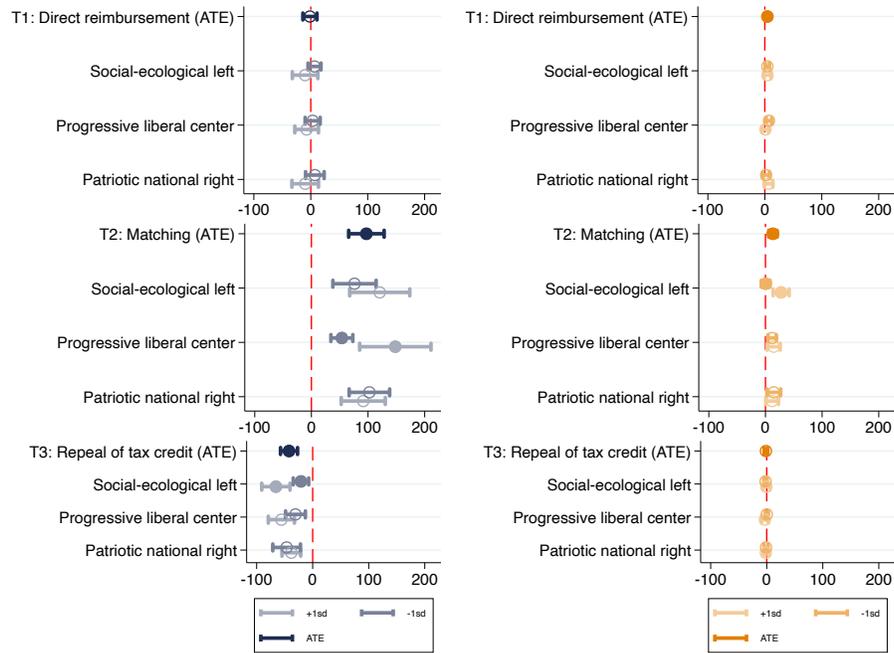
A Additional figures

Figure A.1: Scree Plot of the PCA Decomposition: Eigenvalues depending on the number of components



Notes: The Figure plots the eigenvalues of the top 25 principal components of the principal component analysis. The vertical line represents the adopted cut (top 3 principal components).

Figure A.2: Heterogeneous treatment effects: Principal Component Analysis, Both Margins



Notes: The figures report the size and 95% confidence intervals of the average treatment effects (ATEs), and the conditional average treatment effects (CATEs) for the individuals who score one standard deviation higher and for those who score one standard deviation lower than the average of the component (keeping the other two components at average) (estimation of equation (2)). Standard errors are calculated with the delta method, using Stata's *lincom* command. The dependent variable is the amount received by the charity or political party, where no donation is recorded as zero. Each sub-figure represents one treatment branch. The left-hand side figures (shades of blue) report the estimations for charitable giving, and the right-hand side figures (shades of orange) for political giving.

B Additional tables

Table B.1: Descriptive statistics: Respondents to the 9th wave of the “French Electoral Survey”

	Mean	Median	St. Dev
<i>Demographics</i>			
=1 if woman	0.52	1	0.5
Age	50.11	50	17.7
=1 if married/civ. union	0.50	0	0.5
=1 if unemployed	0.06	0	0.2
=1 if farmer, craftsman, shopkeeper or company manager	0.05	0	0.2
=1 if managers and professionals or intermediate professions	0.26	0	0.4
=1 if employee	0.17	0	0.4
=1 if worker	0.24	0	0.4
=1 if retired or inactive	0.29	0	0.5
Size of the city where the respondent lives			
Fewer than 2,000 inhabitants	0.23	0	0.4
2,000-9,999 inhabitants	0.13	0	0.3
10,000-49,999 inhabitants	0.12	0	0.3
50,000-199,999 inhabitants	0.12	0	0.3
More than 200,000 inhabitants	0.40	0	0.5
Religion			
=1 if Catholic	0.51	1	0.5
=1 if Other Religion	0.07	0	0.3
=1 if No Religion	0.42	0	0.5
Household Income			
Below €1,250	0.10	0	0.3
€1,250-€1,999	0.20	0	0.4
€2,000-€2,499	0.14	0	0.3
€2,500-€3,499	0.22	0	0.4
€3,500-€4,999	0.18	0	0.4
Above €5,000	0.08	0	0.3
Life Satisfaction			
Overall life satisfaction (0-10)	5.84	6	2.1
Political Preference			
Self-reported political preference (0 (left) to 10 (right))	5.63	5	2.5
=1 if intended vote E. Macron 2022, 1st round	0.23	0	0.4
=1 if intended vote M. Le Pen 2022, 1st round	0.20	0	0.4
=1 if intended vote JL. Melenchon 2022, 1st round	0.15	0	0.4
Observations	12600		

Notes: The table reports descriptive statistics for the 12,600 survey respondents in our sample. An observation is an individual.

Table B.2: Balancing test

(a) Charitable giving

Variable	(1) Control Mean/(SE)	(2) Direct Reimbursement Mean/(SE)	(3) Match Mean/(SE)	(4) Repeal Mean/(SE)	(2)-(1) Mean difference	(3)-(1) Pairwise t-test Mean difference	(4)-(1) Mean difference
Demographics							
Age	50.883 (0.636)	50.549 (0.612)	50.279 (0.647)	49.886 (0.620)	-0.333	-0.604	-0.997
=1 if woman	0.494 (0.016)	0.481 (0.016)	0.515 (0.016)	0.495 (0.016)	-0.013	0.021	0.000
=1 if Independent worker	0.042 (0.008)	0.051 (0.008)	0.041 (0.007)	0.042 (0.007)	0.009	-0.001	-0.000
=1 if Managers and professionals	0.259 (0.014)	0.280 (0.014)	0.266 (0.014)	0.274 (0.014)	0.021	0.007	0.014
=1 if Employee	0.176 (0.012)	0.175 (0.012)	0.146 (0.011)	0.173 (0.011)	-0.002	-0.030*	-0.004
=1 if Worker	0.202 (0.014)	0.206 (0.014)	0.240 (0.016)	0.233 (0.015)	0.004	0.038*	0.031
=1 if Retired or Inactive	0.321 (0.014)	0.288 (0.013)	0.307 (0.014)	0.279 (0.013)	-0.033*	-0.014	-0.042**
=1 if Rural	0.230 (0.014)	0.243 (0.014)	0.243 (0.014)	0.217 (0.013)	0.013	0.012	-0.014
Size of the city where the respondent lives							
=1 if 2 000 to 9 999 inhab.	0.131 (0.011)	0.118 (0.010)	0.137 (0.011)	0.126 (0.010)	-0.013	0.006	-0.005
=1 if 10 000 to 49 999 inhab.	0.117 (0.010)	0.113 (0.010)	0.104 (0.009)	0.115 (0.010)	-0.004	-0.013	-0.002
=1 if 50 000 to 199 999 inhab.	0.119 (0.010)	0.119 (0.010)	0.137 (0.011)	0.136 (0.011)	-0.000	0.018	0.017
=1 if More than 200 000 inhab. + Paris	0.402 (0.016)	0.407 (0.015)	0.379 (0.015)	0.407 (0.015)	0.005	-0.023	0.005
Region where the respondent lives							
=1 if Auvergne-Rhône-Alpes	0.119 (0.011)	0.112 (0.010)	0.117 (0.010)	0.125 (0.010)	-0.007	-0.002	0.006
=1 if Bourgogne-Franche-Comté	0.042 (0.007)	0.048 (0.006)	0.043 (0.006)	0.049 (0.007)	0.005	0.001	0.006
=1 if Bretagne	0.051 (0.006)	0.057 (0.007)	0.064 (0.008)	0.052 (0.006)	0.006	0.013	0.002
=1 if Centre-Val de Loire	0.041 (0.006)	0.055 (0.007)	0.043 (0.006)	0.033 (0.005)	0.013	0.002	-0.008
=1 if Corse	0.003 (0.002)	0.002 (0.001)	0.001 (0.001)	0.004 (0.002)	-0.001	-0.002	0.001
=1 if Grand Est	0.074 (0.008)	0.098 (0.010)	0.080 (0.008)	0.076 (0.008)	0.025**	0.006	0.003
=1 if Hauts-de-France	0.093 (0.010)	0.085 (0.008)	0.095 (0.010)	0.098 (0.010)	-0.008	0.002	0.005
=1 if Normandie	0.069 (0.008)	0.041 (0.006)	0.068 (0.008)	0.055 (0.007)	-0.028***	-0.001	-0.014
=1 if Nouvelle-Aquitaine	0.092 (0.009)	0.099 (0.010)	0.113 (0.011)	0.090 (0.009)	0.007	0.021	-0.003
=1 if Occitanie	0.096 (0.009)	0.092 (0.009)	0.087 (0.009)	0.088 (0.009)	-0.004	-0.009	-0.008
=1 if Pays de la Loire	0.058 (0.007)	0.053 (0.007)	0.052 (0.007)	0.060 (0.008)	-0.005	-0.006	0.003
=1 if Provence-Alpes-Côte d'Azur	0.099 (0.010)	0.089 (0.010)	0.067 (0.008)	0.089 (0.009)	-0.010	-0.032**	-0.010
=1 if Île-de-France	0.164 (0.012)	0.172 (0.012)	0.170 (0.012)	0.182 (0.013)	0.008	0.007	0.018
Number of observations	1348	1350	1336	1357	2698	2684	2705

(b) Political giving

Variable	(1) Control Mean/(SE)	(2) Direct Reimbursement Mean/(SE)	(3) Match Mean/(SE)	(4) Repeal Mean/(SE)	(2)-(1) Mean difference	(3)-(1) Pairwise t-test Mean difference	(4)-(1) Mean difference
Demographics							
Age	50.955 (0.613)	49.623 (0.616)	50.372 (0.611)	50.779 (0.604)	-1.332	-0.583	-0.176
=1 if woman	0.511 (0.016)	0.510 (0.016)	0.522 (0.016)	0.494 (0.016)	-0.002	0.011	-0.017
=1 if Independent worker	0.065 (0.010)	0.047 (0.008)	0.051 (0.009)	0.043 (0.008)	-0.018	-0.014	-0.022*
=1 if Managers and professionals	0.266 (0.014)	0.280 (0.014)	0.261 (0.014)	0.266 (0.014)	0.014	-0.005	-0.000
=1 if Employee	0.182 (0.012)	0.175 (0.012)	0.174 (0.012)	0.177 (0.012)	-0.007	-0.007	-0.005
=1 if Worker	0.199 (0.014)	0.222 (0.015)	0.230 (0.015)	0.213 (0.015)	0.023	0.030	0.014
=1 if Retired or Inactive	0.288 (0.013)	0.276 (0.013)	0.284 (0.013)	0.301 (0.013)	-0.012	-0.004	0.013
=1 if Rural	0.220 (0.014)	0.226 (0.014)	0.240 (0.014)	0.225 (0.014)	0.006	0.020	0.005
Size of the city where the respondent lives							
=1 if 2 000 to 9 999 inhab.	0.132 (0.011)	0.130 (0.010)	0.124 (0.010)	0.126 (0.011)	-0.002	-0.008	-0.006
=1 if 10 000 to 49 999 inhab.	0.107 (0.009)	0.129 (0.010)	0.127 (0.010)	0.125 (0.010)	0.022	0.020	0.019
=1 if 50 000 to 199 999 inhab.	0.111 (0.009)	0.118 (0.010)	0.136 (0.011)	0.124 (0.010)	0.007	0.025*	0.014
=1 if More than 200 000 inhab. + Paris	0.431 (0.016)	0.397 (0.015)	0.374 (0.015)	0.399 (0.015)	-0.033	-0.057**	-0.031
Region where the respondent lives							
=1 if Auvergne-Rhône-Alpes	0.127 (0.011)	0.125 (0.010)	0.122 (0.011)	0.142 (0.011)	-0.002	-0.005	0.015
=1 if Bourgogne-Franche-Comté	0.037 (0.005)	0.049 (0.007)	0.047 (0.007)	0.039 (0.006)	0.012	0.009	0.002
=1 if Bretagne	0.054 (0.006)	0.054 (0.007)	0.055 (0.007)	0.048 (0.007)	0.001	0.002	-0.005
=1 if Centre-Val de Loire	0.027 (0.004)	0.037 (0.007)	0.040 (0.006)	0.046 (0.006)	0.011	0.013*	0.019***
=1 if Corse	0.001 (0.001)	0.002 (0.001)	0.005 (0.002)	0.001 (0.001)	0.001	0.003	-0.000
=1 if Grand Est	0.075 (0.009)	0.093 (0.009)	0.091 (0.009)	0.102 (0.009)	0.018	0.015	0.027**
=1 if Hauts-de-France	0.094 (0.009)	0.109 (0.011)	0.103 (0.010)	0.079 (0.008)	0.015	0.009	-0.015
=1 if Normandie	0.053 (0.007)	0.048 (0.007)	0.047 (0.007)	0.050 (0.007)	-0.005	-0.006	-0.003
=1 if Nouvelle-Aquitaine	0.100 (0.010)	0.092 (0.009)	0.093 (0.009)	0.095 (0.009)	-0.009	-0.007	-0.005
=1 if Occitanie	0.100 (0.009)	0.086 (0.009)	0.098 (0.010)	0.101 (0.009)	-0.014	-0.002	0.002
=1 if Pays de la Loire	0.057 (0.008)	0.060 (0.007)	0.069 (0.009)	0.058 (0.007)	0.003	0.012	0.001
=1 if Provence-Alpes-Côte d'Azur	0.084 (0.009)	0.081 (0.009)	0.082 (0.008)	0.076 (0.008)	-0.003	-0.003	-0.008
=1 if Île-de-France	0.191 (0.013)	0.164 (0.012)	0.151 (0.012)	0.161 (0.012)	-0.027	-0.040**	-0.030*
Number of observations	1325	1343	1306	1350	2668	2631	2675

Notes: The table presents balancing tests for the variables used for the stratified randomization. Sub-table [B.2a](#) presents the results for the charitable giving group. Sub-table [B.2b](#) presents the results for the political giving group. The value displayed for t-tests are the differences in the means across the groups. Standard errors are robust. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table B.3: Treatment effects for charitable and political donations: Extensive margin (willingness to make a donation)

	Charitable donations				Political donations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Direct reimbursement	0.03 (0.02)	0.02 (0.02)	0.04** (0.02)	0.03 (0.02)				
Matching	-0.04** (0.02)	-0.04** (0.02)	-0.04** (0.02)	-0.05*** (0.02)				
Repeal of tax credit	-0.03 (0.02)	-0.02 (0.02)	-0.02 (0.02)	-0.03* (0.02)				
Direct reimbursement					0.03** (0.01)	0.03** (0.01)	0.03*** (0.01)	0.03*** (0.01)
Matching					-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.00 (0.01)
Repeal of tax credit					-0.00 (0.01)	-0.00 (0.01)	-0.01 (0.01)	-0.00 (0.01)
Demographic controls		✓	✓	✓		✓	✓	✓
Income and past donations			✓	✓			✓	✓
Life satisfaction and trust controls				✓				✓
Observations	6,312	6,308	6,308	5,411	6,288	6,282	6,282	5,354
Mean DepVar	0.39	0.38	0.38	0.39	0.08	0.08	0.08	0.06
Sd DepVar	0.49	0.49	0.49	0.49	0.26	0.26	0.26	0.24

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table shows the treatment effects estimated using OLS (equation [1](#)) at the extensive margin. An observation is an individual. Columns (1) to (4) report the results for the charitable donations group, and Columns (5) to (8) for the political donations group. The dependent variable is a binary variable equal to one if the respondent declares that they are willing to make a donation, and to zero otherwise. Columns (1) and (5) show the treatment effects with no controls, which are then progressively included in Columns (2) to (4) and (6) to (8). “Demographic controls” include: categorical variables for age, gender, socio-economic status, unemployment, marital status, city size and region of residence. “Income and past donations” controls include: income brackets, knowledge of existing tax credit for charity and political giving, an indicator variable equal to one if the respondent reports that they made a donation during the past 12 months, and the amount donated. “Life satisfaction and trust controls” include: continuous measures of life satisfaction, trust in politics (i.e. the president, members of parliament, the city mayor), in the media, and in society (i.e. family, acquaintances, and strangers).

Table B.4: Treatment effects for charitable and political donations: Intensive margin (amount willing to give conditional on giving)

	Charitable donations				Political donations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Direct reimbursement	-40 (36)	-28 (37)	-1 (31)	31** (14)				
Matching	229*** (48)	232*** (48)	292*** (39)	331*** (39)				
Repeal of tax credit	-87*** (33)	-81** (32)	-68*** (22)	-70*** (23)				
Direct reimbursement					32 (25)	34 (28)	78*** (27)	46 (33)
Matching					323*** (63)	330*** (61)	333*** (51)	255*** (54)
Repeal of tax credit					-4 (23)	-4 (29)	31 (26)	19 (35)
Demographic controls		✓	✓	✓		✓	✓	✓
Income and past donations			✓	✓			✓	✓
Life satisfaction and trust controls				✓				✓
Observations	2,537	2,535	2,535	2,212	393	393	393	288
Mean DepVar	285	286	286	284	181	181	181	161
Sd DepVar	654	654	654	661	283	283	283	232

Notes: * p<0.10, ** p<0.05, *** p<0.01. The table shows the treatment effects estimated using OLS (equation **(1)**) at the intensive margin. An observation is an individual. Columns (1) to (4) report the results for the charitable donations group, and Columns (5) to (8) for the political donations group. Only the individuals who report that they are willing to make a charitable donation (respectively a political donation) are included in Columns (1) to (4) (respectively in Columns (5) to (8)). The dependent variable is the amount the respondent reports they are willing to give (conditional on giving). Columns (1) and (5) show the treatment effects with no controls, which are then progressively included in Columns (2) to (4) and (6) to (8). "Demographic controls" include: categorical variables for age, gender, socio-economic status, unemployment, marital status, city size and region of residence. "Income and past donations" controls include: income brackets, knowledge of existing tax credit for charity and political giving, an indicator variable equal to one if the respondent reports that they made a donation during the past 12 months, and the amount donated. "Life satisfaction and trust controls" include: continuous measures of life satisfaction, trust in politics (i.e. the president, members of parliament, the city mayor), in the media, and in society (i.e. family, acquaintances, and strangers).

Table B.5: Treatment effects for charitable and political donations: Both margins (total amount willing to give, including the zeros)

	Charitable donations				Political donations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Direct reimbursement	-9 (15)	-14 (15)	-9 (12)	-2 (7)				
Matching	69*** (19)	69*** (18)	88*** (15)	93*** (15)				
Repeal of tax credit	-39*** (13)	-39*** (13)	-35*** (8)	-40*** (8)				
Direct reimbursement					6** (3)	6** (3)	6** (2)	5** (2)
Matching					19*** (5)	19*** (5)	20*** (5)	13*** (4)
Repeal of tax credit					-1 (2)	-0 (2)	-2 (2)	-2 (2)
Demographic controls		✓	✓	✓	✓	✓	✓	✓
Income and past donations			✓	✓			✓	✓
Life satisfaction and trust controls				✓				✓
Observations	6,312	6,308	6,308	5,411	6,288	6,282	6,282	5,354
Mean DepVar	110	110	110	112	14	14	14	10
Sd DepVar	429	429	429	437	91	91	91	68

Notes: * p<0.10, ** p<0.05, *** p<0.01. The table shows the treatment effects estimated using OLS (equation (1)) at the intensive margin. An observation is an individual. Columns (1) to (4) report the results for the charitable donations group, and Columns (5) to (8) for the political donations group. Only the individuals who report that they are willing to make a charitable donation (respectively a political donation) are included in Columns (1) to (4) (respectively in Columns (5) to (8)). The dependent variable is the amount the respondent reports they are willing to give (unconditional on giving, i.e. including the zeros). Columns (1) and (5) show the treatment effects with no controls, which are then progressively included in Columns (2) to (4) and (6) to (8). “Demographic controls” include: categorical variables for age, gender, socio-economic status, unemployment, marital status, city size and region of residence. “Income and past donations” controls include: income brackets, knowledge of existing tax credit for charity and political giving, an indicator variable equal to one if the respondent reports that they made a donation during the past 12 months, and the amount donated. “Life satisfaction and trust controls” include: continuous measures of life satisfaction, trust in politics (i.e. the president, members of parliament, the city mayor), in the media, and in society (i.e. family, acquaintances, and strangers).

Table B.6: Robustness check: Treatment effects for charitable and political donations: Intensive margin, *Logarithm* of the amount willing to give conditional on giving

	Charitable donations				Political donations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Direct reimbursement	0.02 (0.07)	0.07 (0.07)	0.15** (0.06)	0.16*** (0.05)				
Matching	0.85*** (0.08)	0.86*** (0.07)	0.95*** (0.06)	0.98*** (0.06)				
Repeal of tax credit	-0.27*** (0.08)	-0.24*** (0.07)	-0.20*** (0.06)	-0.19*** (0.06)				
Direct reimbursement					0.41** (0.16)	0.48*** (0.15)	0.67*** (0.14)	0.35** (0.17)
Matching					1.44*** (0.21)	1.49*** (0.20)	1.57*** (0.17)	1.21*** (0.21)
Repeal of tax credit					0.01 (0.21)	0.09 (0.17)	0.29* (0.16)	0.11 (0.19)
Demographic controls		✓	✓	✓		✓	✓	✓
Income and past donations			✓	✓			✓	✓
Life satisfaction and trust controls				✓				✓
Observations	2,537	2,535	2,535	2,212	393	393	393	288
Mean DepVar	4.82	4.82	4.82	4.82	4.50	4.50	4.50	4.47
Sd DepVar	1.20	1.20	1.20	1.19	1.17	1.17	1.17	1.07

Notes: * p<0.10, ** p<0.05, *** p<0.01. The table shows the treatment effects estimated using OLS (equation (1)) at the intensive margin. An observation is an individual. Columns (1) to (4) report the results for the charitable donations group, and Columns (5) to (8) for the political donations group. Only the individuals who report that they are willing to make a charitable donation (respectively a political donation) are included in Columns (1) to (4) (respectively in Columns (5) to (8)). The dependent variable is the *logarithm* of the amount the respondent reports it is willing to give (conditional on giving). Columns (1) and (5) show the treatment effects with no controls, which are then progressively included in Columns (2) to (4) and (6) to (8). “Demographic controls” include: categorical variables for age, gender, socio-economic status, unemployment, marital status, city size and region of residence. “Income and past donations” controls include: income brackets, knowledge of existing tax credit for charity and political giving, an indicator variable equal to one if the respondent reports that they made a donation during the past 12 months, and the amount donated. “Life satisfaction and trust controls” include: continuous measures of life satisfaction, trust in politics (i.e. the president, members of parliament, the city mayor), in the media, and in society (i.e. family, acquaintances, and strangers).

Table B.7: Robustness check: Treatment effects for charitable and political donations: Extensive margin (willingness to make a donation), Logit model

	Charitable donations				Political donations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Willing to donate								
Direct reimbursement	0.12 (0.08)	0.10 (0.09)	0.25** (0.10)	0.18 (0.11)				
Matching	-0.19** (0.09)	-0.20** (0.09)	-0.24** (0.10)	-0.37*** (0.11)				
Repeal of tax credit	-0.12 (0.08)	-0.10 (0.09)	-0.15 (0.10)	-0.20* (0.11)				
Direct reimbursement					0.37** (0.17)	0.42*** (0.16)	0.57*** (0.19)	0.70*** (0.20)
Matching					-0.16 (0.19)	-0.13 (0.18)	-0.05 (0.20)	0.00 (0.24)
Repeal of tax credit					-0.06 (0.19)	-0.04 (0.18)	-0.05 (0.21)	-0.08 (0.24)
Demographic controls		✓	✓	✓		✓	✓	✓
Income and past donations			✓	✓			✓	✓
Life satisfaction and trust controls				✓				✓
Observations	6,312	6,308	6,308	5,411	6,288	6,282	6,282	5,342
Mean DepVar	0.39	0.38	0.38	0.39	0.08	0.08	0.08	0.06
Sd DepVar	0.49	0.49	0.49	0.49	0.26	0.26	0.26	0.24

Notes: * p<0.10, ** p<0.05, *** p<0.01. The table shows the treatment effects at the extensive margin estimated using a logit model. An observation is an individual. Columns (1) to (4) report the results for the charitable donations group, and Columns (5) to (8) for the political donations group. The dependent variable is a binary variable equal to one if the respondent declares that it is willing to make a donation, and to zero otherwise. Columns (1) and (5) show the treatment effects with no controls, which are then progressively included in Columns (2) to (4) and (6) to (8). “Demographic controls” include: categorical variables for age, gender, socio-economic status, unemployment, marital status, city size and region of residence. “Income and past donations” controls include: income brackets, knowledge of existing tax credit for charity and political giving, an indicator variable equal to one if the respondent reports that they made a donation during the past 12 months, and the amount donated. “Life satisfaction and trust controls” include: continuous measures of life satisfaction, trust in politics (i.e. the president, members of parliament, the city mayor), in the media, and in society (i.e. family, acquaintances, and strangers).

Table B.8: PCA Decomposition Loadings

Variable	Social-ecological left	Progressive liberal center	Patriotic national right
Age	-0.15	0.41	-0.28
Woman	-0.10	-0.06	-0.05
Education	0.39	-0.06	0.21
Socio-Economic Category: Farmer, Artisan	0.00	-0.02	0.04
Socio-Economic Category: Senior Executives and Professionals	0.38	-0.12	0.34
Socio-Economic Category: Employee	-0.10	-0.18	0.05
Socio-Economic Category: Worker	-0.18	-0.21	-0.03
Socio-Economic Category: Retired or Inactive	-0.14	0.41	-0.34
Unemployed	-0.13	-0.19	-0.06
Married	0.07	0.20	0.10
Income Bracket	0.26	0.16	0.23
=1 if knows existing tax credit for charitable giving	-0.10	-0.03	-0.06
=1 if knows existing tax credit for political giving	-0.08	0.03	-0.11
Donated to Political Party	0.04	0.03	0.04
Donated to Charity	0.17	0.19	-0.11
Religion: Catholic	-0.23	0.33	0.31
Religion: Other Religion	0.03	-0.08	-0.02
Religion: No Religion	0.22	-0.30	-0.31
Life Satisfaction	0.28	0.21	0.06
Trust in Political Actors	0.25	0.21	-0.10
Trust in Members of Society	0.22	0.16	-0.16
City Size	0.11	-0.01	0.03
Left(0)–Right(10) Scale	-0.20	0.17	0.40
Vote Mélenchon 2022	0.10	-0.18	-0.28
Vote Macron 2022	0.20	0.21	-0.02
Vote Le Pen 2022	-0.29	-0.06	0.27

Notes: The table lists the variables used for the PCA decomposition, and their loadings (correlations) with the three main components that we label "Social-ecological left", "Progressive liberal center", and "Patriotic national right". The analysis is implemented via stata's *pca* command, taking these variables as input, without specifying any additional arguments, and choosing the top three components. The variables "Income brackets" (1-13), "Life satisfaction" (1-10), "City size" (1-5), "Left (0) - right (10) scale" (0-10), "Trust in Political Actors" (1-4), "Trust in Members of Society" (1-7), and "Education" (1-7) are continuous. The other variables are binary. All variables are standardized before the PCA decomposition. A high (absolute) value of a loading symbolizes that this covariate correlates strongly with the component.

C Heterogeneous treatment effects: Machine learning approach

C.1 Overview

We follow Chernozhukov et al. (2023) and use the generic machine learning inference method. This method allows the detection of HTEs in a non-parametric and disciplined manner, avoiding over-fitting or cherry-picking. We describe the methodology briefly below; further details are provided in the CRAN package *GenericML*'s documentation.

The core of the strategy is to split the data into a training and a predicting set, and to estimate an “individual-level” conditional average treatment effect (CATE) with standard machine learning techniques (such as random forest, GLM, etc.).¹ The individual-level estimations are biased proxies of CATE, but by repeating the procedure many times under different sample splits, we can infer their key features in an unbiased way. We are interested in three outcomes. First, we infer the Best Linear Predictor (BLP) of the CATE on machine learning proxies to test for the existence of HTEs. If HTEs are statistically significant, we are then interested in the Sorted Grouped Average Treatment Effect (GATES), or the magnitude of the average treatment effect for each quintile from the most negatively to the most positively affected. Finally, we explore the characteristics of the most or least affected groups with the Classification Analysis (CLAN), or the average features for each of the five quintiles.

We run the GenericML algorithm on all treatment branches for both charitable and political giving. As before, we consider the extensive and the intensive margins separately. In the first step, we include the following covariates in the prediction algorithm: age, gender, employment status, marital status, socio-economic category and income of the respondent, as well as the size of the city where the respondent lives.² In the last step – CLAN analysis – we further include life satisfaction, self-reported political preferences (on a left-right scale), and indicator variables for the intended vote in the first round of the 2022 French presidential election for Emmanuel Macron, Marine Le Pen and Jean-Luc Mélenchon (the three candidates who ranked first in the first round).

C.2 Existence of heterogeneous treatment effects

Tables C.1 (extensive margin) and C.2 (intensive margin) report the coefficients and p-values of the average treatment effects (ATE) and HTEs estimated using the GenericML algorithm.³

¹The predictions of ML algorithms are thus non-parametric and agnostic.

²Compared to the specification used in Section 4.1 we thus include the same set of covariates with the exception of self-reported life satisfaction, trust, and self-reported political preferences due to missing values. We also convert the income scale into larger categories to reduce the dimension of the covariate matrix and ensure enough observations for each case. Specifically, we use 3 rather than 13 income brackets: less than €1500 (corresponding roughly to minimum wage), €1500-€3000, and above €3000 per month.

³A statistically significant HTE coefficient means that the individualized treatment effect (predicted without using the individual's treatment status) is predictive of the actual outcome; in other words, that there are HTEs with respect to the set of covariates estimated in a non-parametric way.

First, note that the magnitude and significance of the ATEs for all the treatment branches are consistent with our main specification (Tables [B.3](#), [B.4](#) and [B.5](#)).

Regarding the heterogeneity of the treatments, at the extensive margin (Table [C.1](#)), we obtain statistically significant HTE for both the direct reimbursement treatment (T1) and the repeal of the existing tax credit treatment (T3) for charitable giving. Consistently with the results of Section [3.2](#), there is no HTE (nor ATE) for political giving,

Similarly, we do not find any significant HTE at the intensive margin for political giving (Table [C.2](#)).⁴ Regarding charitable giving, we document HTEs statistically significant at the 11% level for both the direct reimbursement treatment (T1) and the repeal of the existing tax credit treatment (T3). The estimated effects are not statistically significant for matching.

C.3 Sorted grouped average treatment effects (GATEs) and Classification analysis (CLAN)

We report the GATEs and CLAN in Figures [C.1](#) to [C.4](#). The figures at the top report the GATEs, which can be interpreted as the mean and 95% confidence interval of the treatment effect for each quintile. The Q1 coefficient represents the average treatment effect for the 20% of respondents who are the most negatively affected by the treatment, and the Q5 coefficient for the 20% who are the most positively affected. The ATE for the whole sample is represented by the red dashed lines.

The characteristics of the most positively (versus most negatively) affected individuals are then reported in the figures *infra* (CLAN).⁵

⁴Of course, we cannot rule out the possibility that there is simply not enough power due to sample size – less than half of the sample donate and thus are included in the intensive margin analysis, while only 5% of the respondents donate to politics on average.

⁵Note that since the CLANs are the group averages for each quintile, the estimates can be continuous even when the outcome is binary (such as the unemployment rate).

Table C.1: Average Treatment Effect (ATE) and Best Linear Prediction (BLP) of Heterogeneous Treatment Effects: Willingness to make a donation (extensive margin)

Donation Type	Treatment	ATE	P-value (ATE)	HTE	P-value (HTE)
Charitable Giving	Direct Reimbursement	0.03	0.28	0.84	0.05
	Matching	-0.05	0.09	0.65	0.15
	Repeal of tax credit	-0.03	0.36	0.13	0.09
Political Giving	Direct Reimbursement	0.03	0.10	0.29	0.27
	Matching	-0.01	0.59	-1.63	0.33
	Repeal of tax credit	-0.01	0.73	-0.06	0.30

Notes: The table reports the results of the heterogeneous treatment effects analysis estimated via the R-package GenericML (Chernozhukov et al., 2023). The dependent variable is the willingness to make a donation (extensive margin). We run the analysis for charitable and political giving separately, and each treatment group independently. The third column (ATE) reports the average treatment effects and the fourth column (P-value (ATE)) the corresponding p-values. The fifth column (HTE) reports the best linear predictor of the heterogeneous treatment effects, and the sixth column (P-value (HTE)) the corresponding p-values.

Table C.2: Average Treatment Effect (ATE) and Best Linear Prediction (BLP) of Heterogeneous Treatment Effect: Amount willing to donate conditionally on giving (intensive margin)

Donation Type	Treatment	ATE	P-value (ATE)	HTE	P-value (HTE)
Charitable Giving	Direct Reimbursement	-34.33	0.49	0.43	0.11
	Matching	236.22	0.00	0.15	0.42
	Repeal of tax credit	-78.74	0.05	0.35	0.11
Political Giving	Direct Reimbursement	28.06	0.45	0.18	0.50
	Matching	330.60	0.00	-0.18	0.86
	Repeal of tax credit	-6.56	0.85	-0.45	0.57

Notes: The table reports the results of the heterogeneous treatment effects analysis estimated via the R-package GenericML (Chernozhukov et al. 2023). For the subset of respondents who declare that they are willing to make a donation, the dependent variable is the amount that they are willing to donate (intensive margin). We run the analysis for charitable and political giving separately, and each treatment group independently. The third column (ATE) reports the average treatment effects and the fourth column (P-value (ATE)) the corresponding p-values. The fifth column (HTE) reports the best linear predictor of the heterogeneous treatment effects, and the sixth column (P-value (HTE)) the corresponding p-values.

Figure C.1: Treatment heterogeneity using machine learning: Grouped average treatment effect (GATE) and characteristics, Willingness to make a charitable donation (extensive margin)

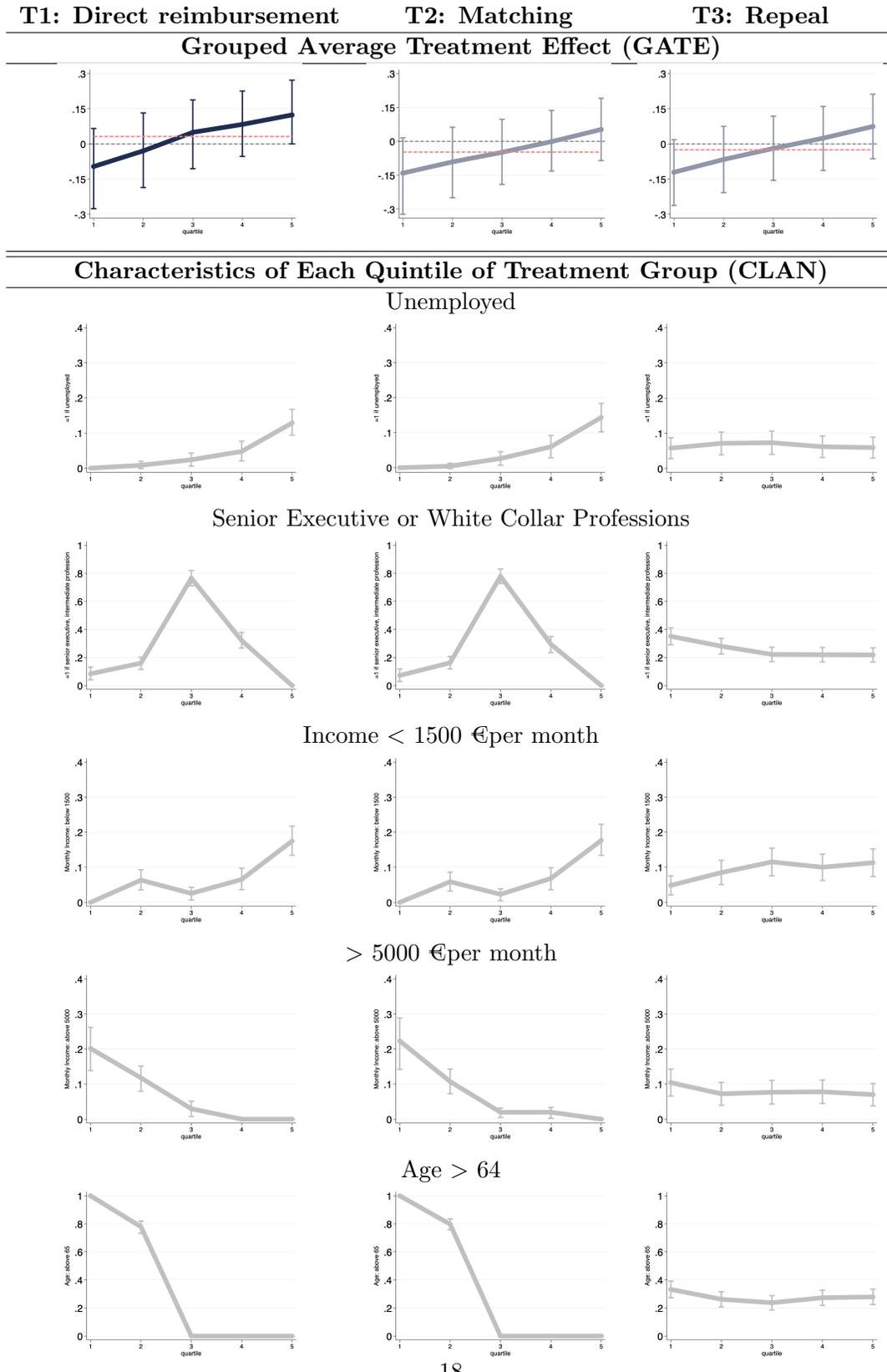
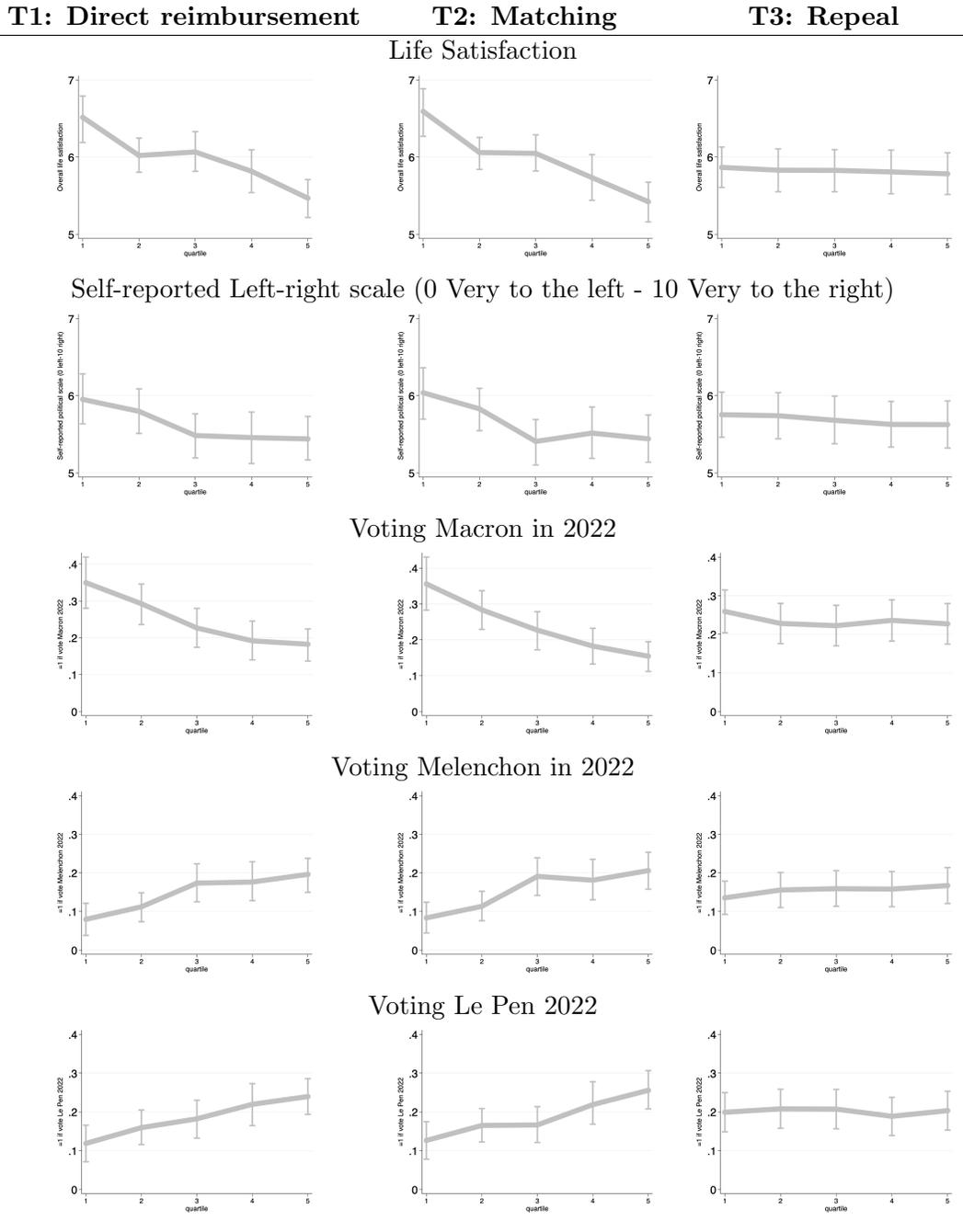


Figure C.1: (cont'd)



Notes: The figure reports the Grouped Average Treatment Effect (GATE) and the characteristics of each group (CLAN) for each of the treatments, estimated via the R-package GenericML. The dependent variable is the willingness to make a charitable donation (extensive margin). The top figure reports the GATEs and the corresponding 95% confidence intervals. Each coefficient represent the average treatment effect for a quintile, from the most negatively to the most positively affected. The red dashed line represents the ATE. The infra figures report the CLAN. Each coefficient represents the group mean for the given variable in each quintile, from the most negatively to the most positively affected. 95% confidence intervals are reported for each variable.

Figure C.2: Treatment Heterogeneity: average treatment effect and characteristics for each quintile of effects, Charitable Donation, Intensive margin

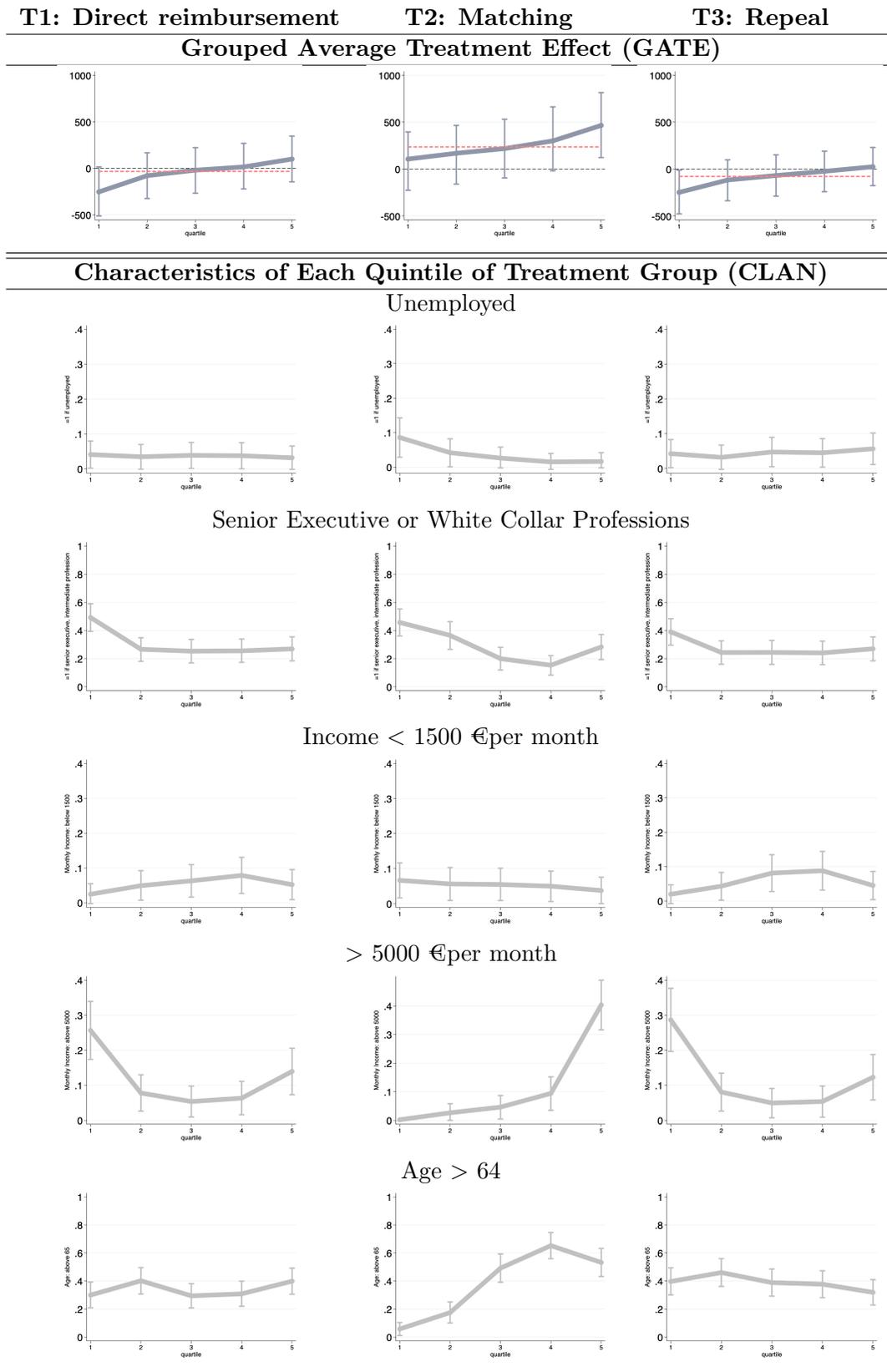


Figure C.2: Cont'd

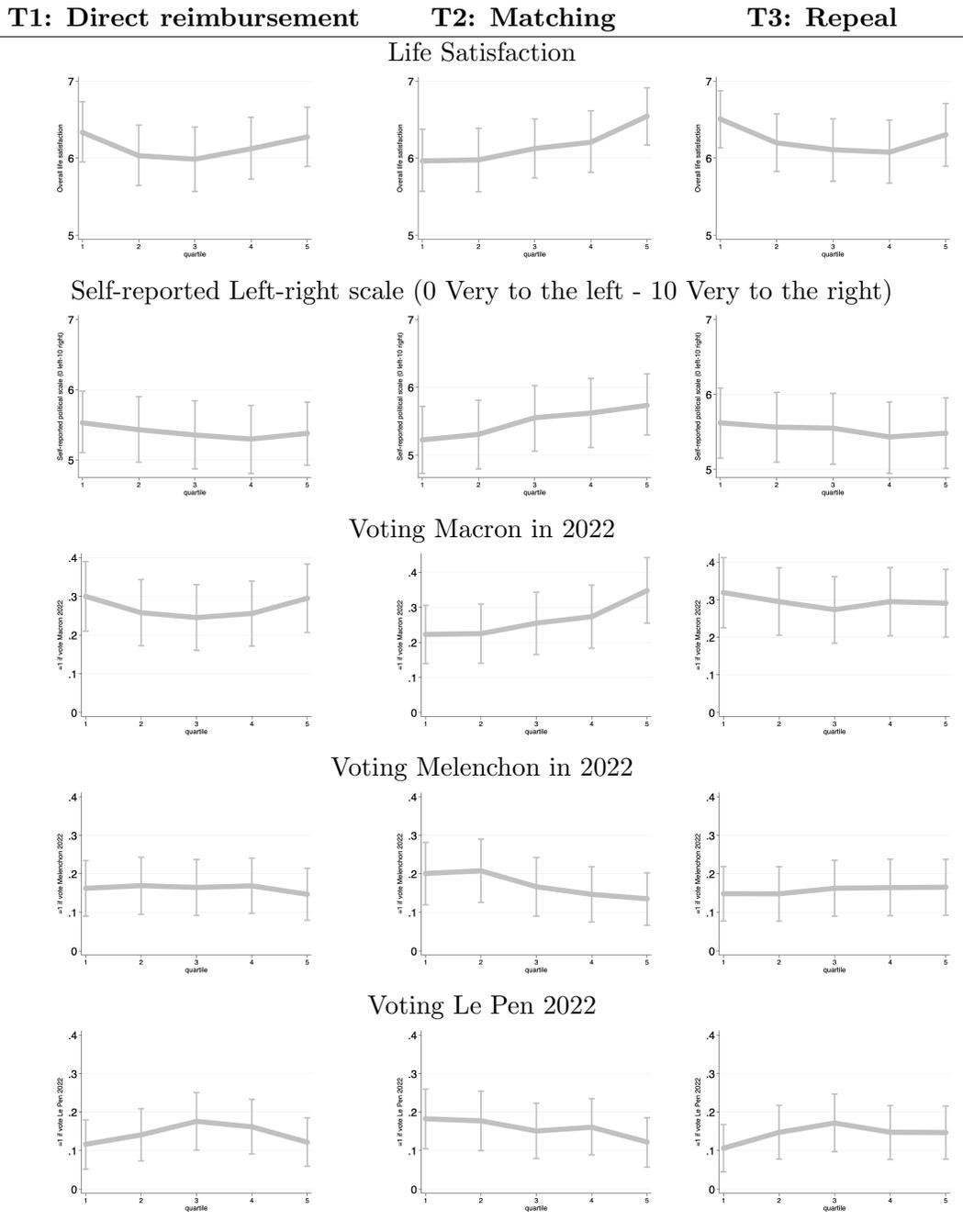


Figure C.3: Treatment Heterogeneity: average treatment effect and characteristics for each quintile of effects, Political Donation, Extensive margin

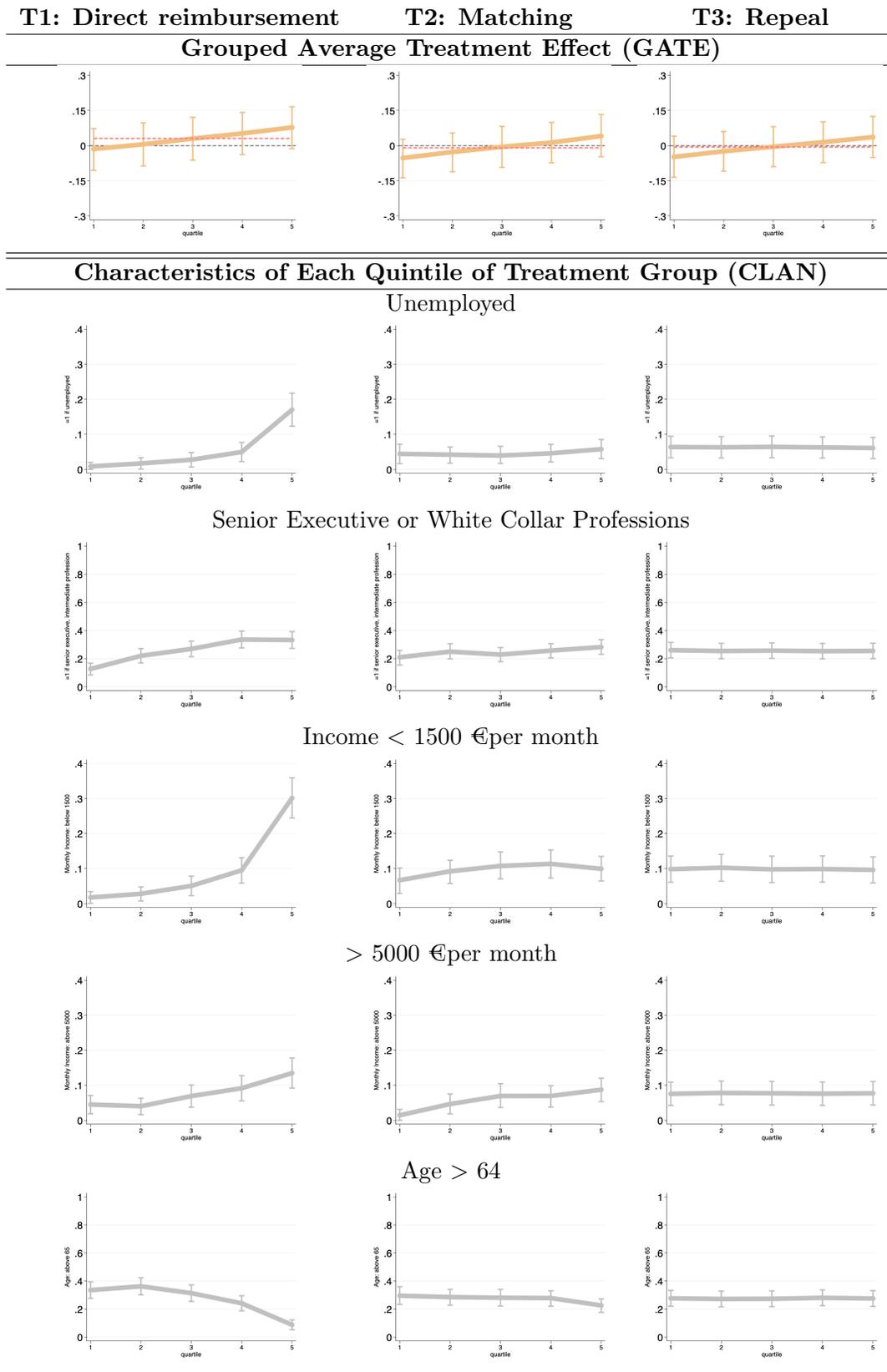


Figure C.3: Cont'd

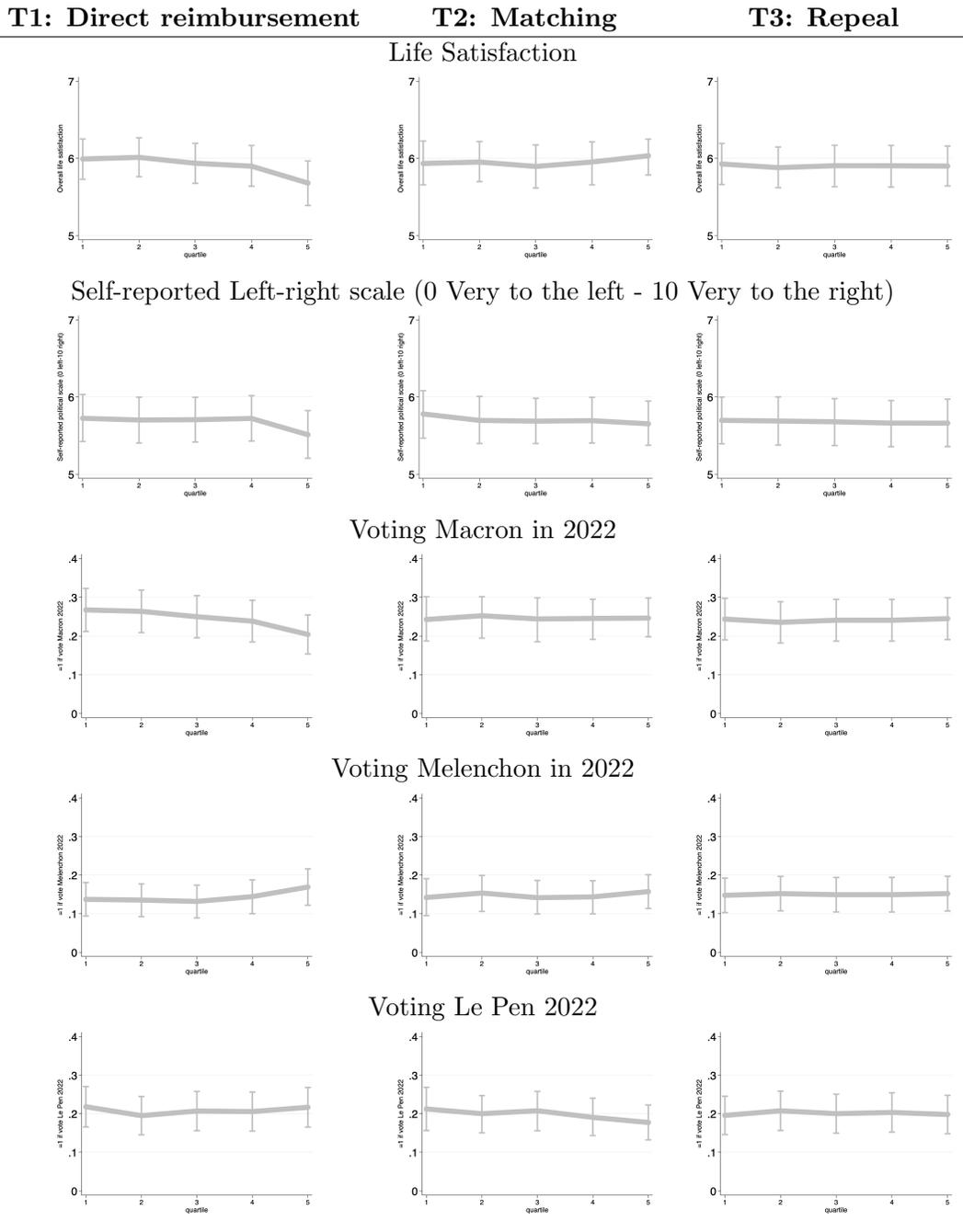


Figure C.4: Treatment Heterogeneity: average treatment effect and characteristics for each quintile of effects, Political Donation, Intensive margin

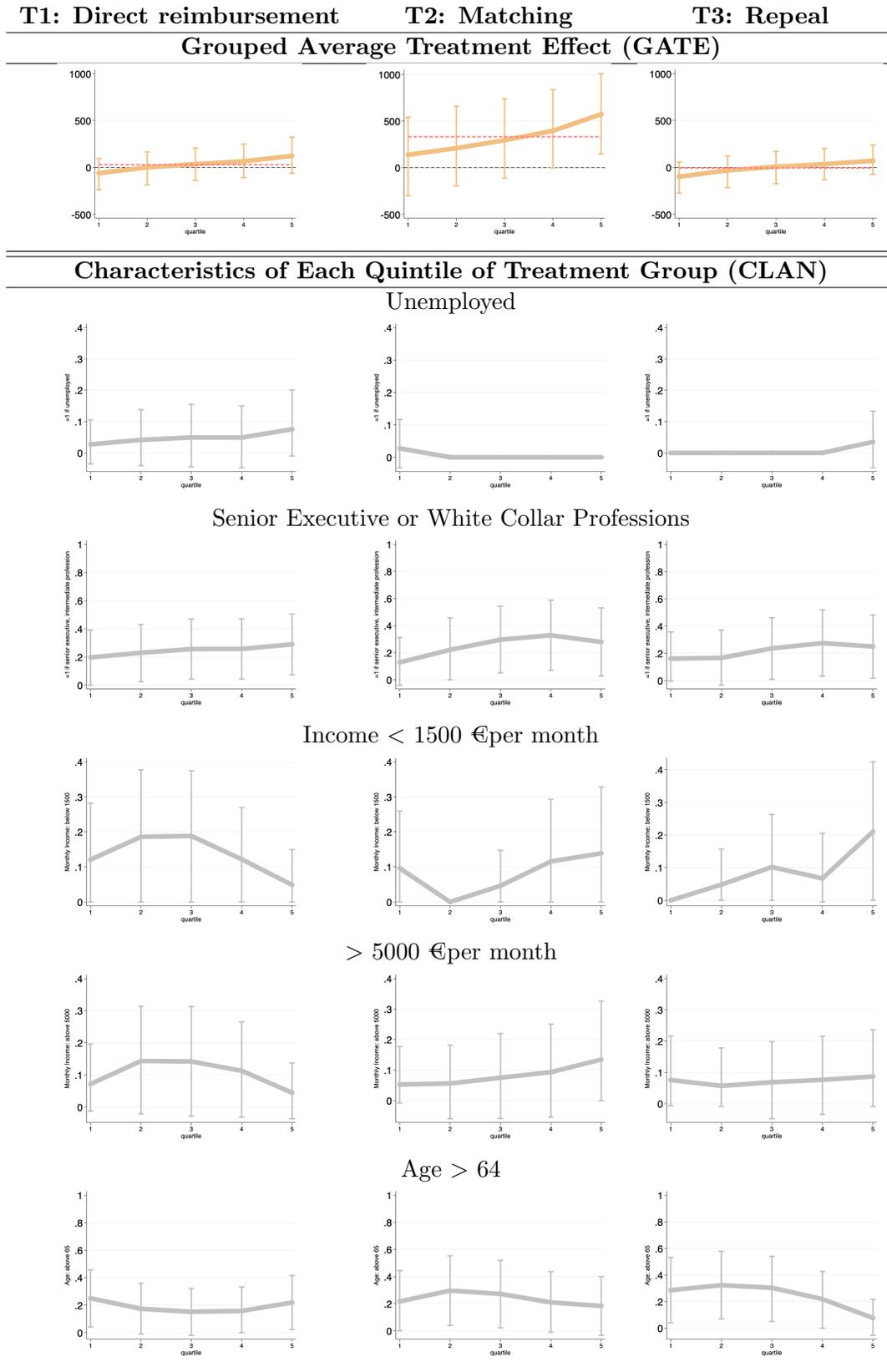


Figure C.4: Cont'd

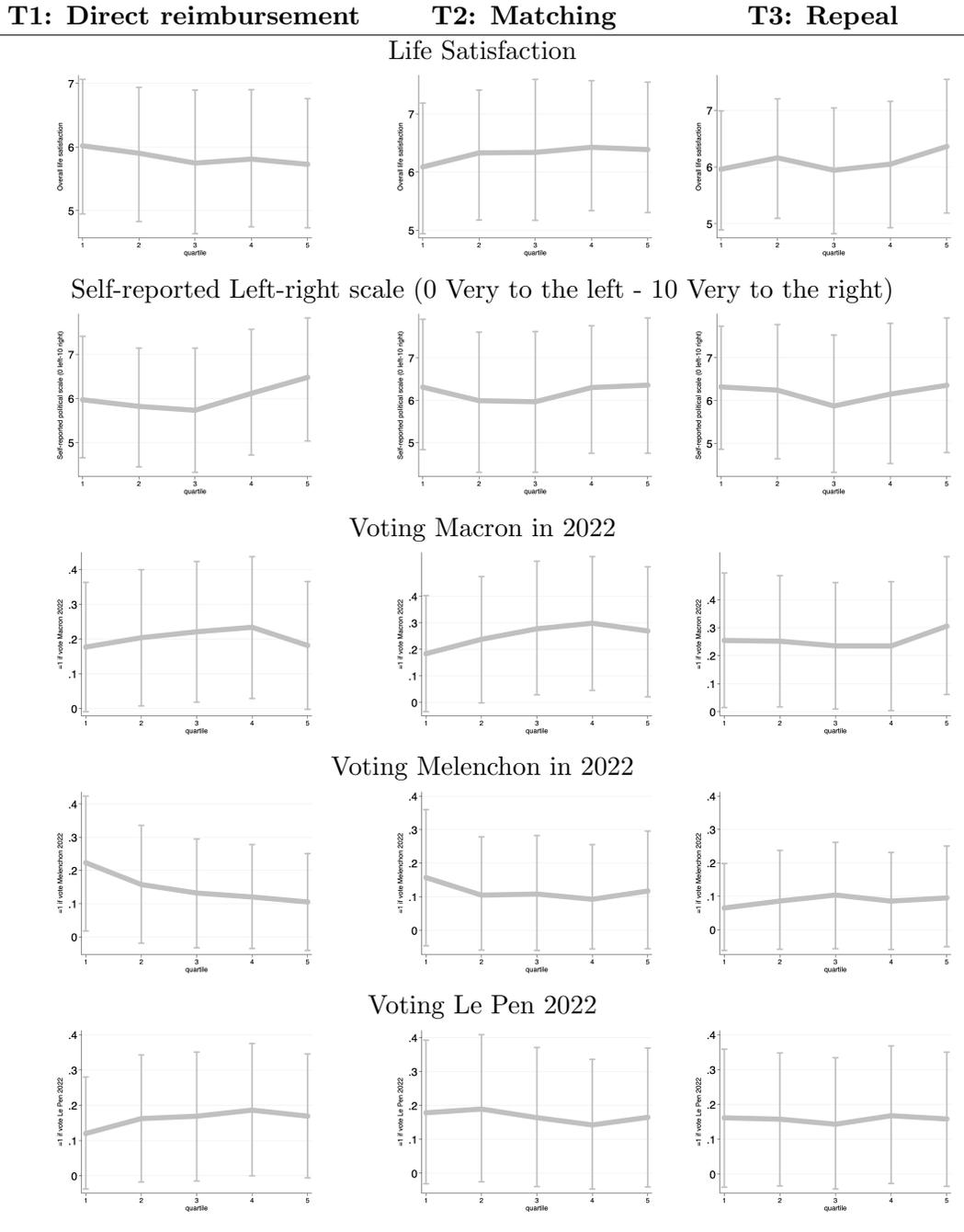


Figure C.5: Treatment Heterogeneity: average treatment effect and characteristics for each quintile of effects, Charitable Donation, Both margins

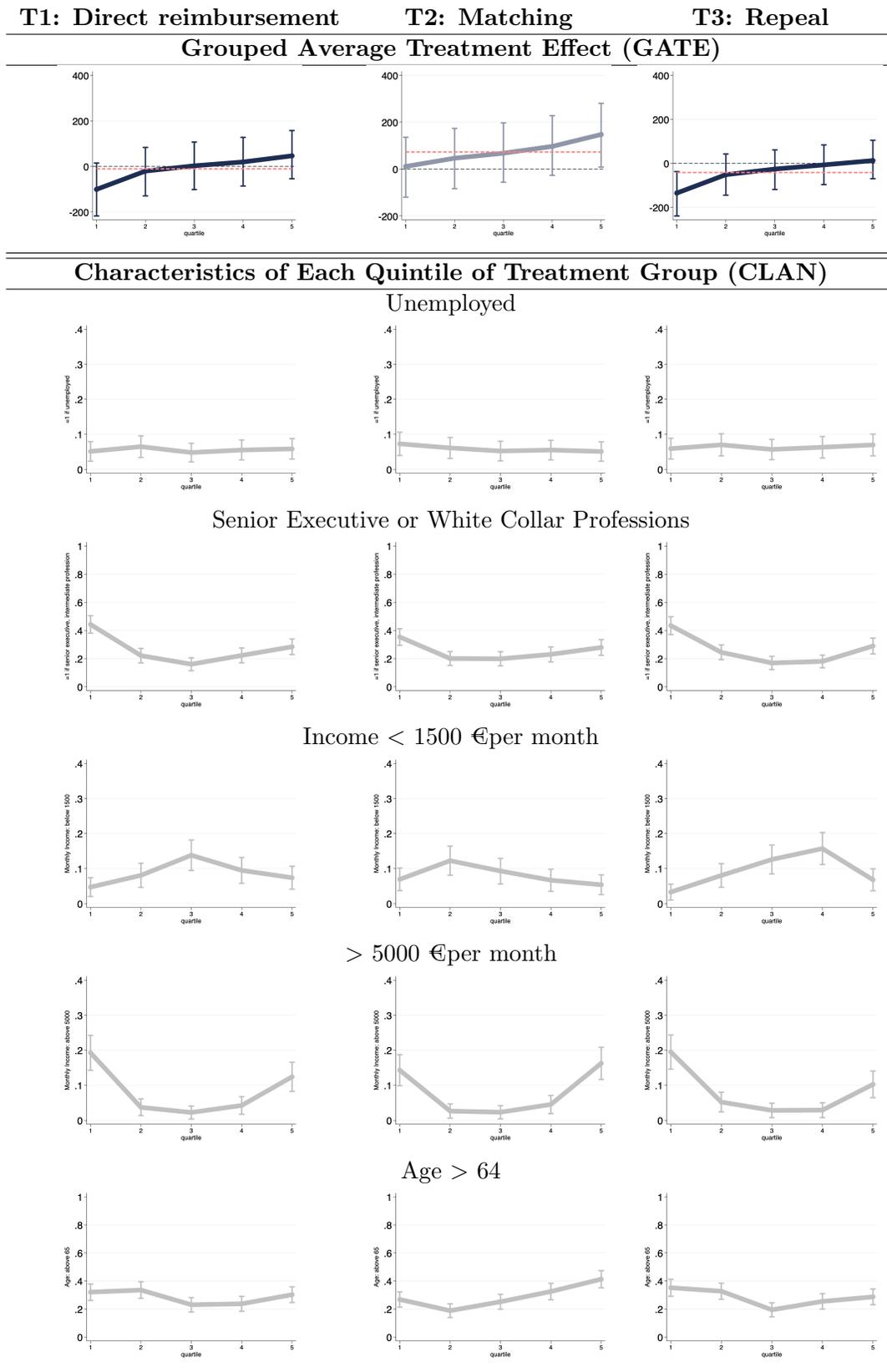


Figure C.5: Cont'd

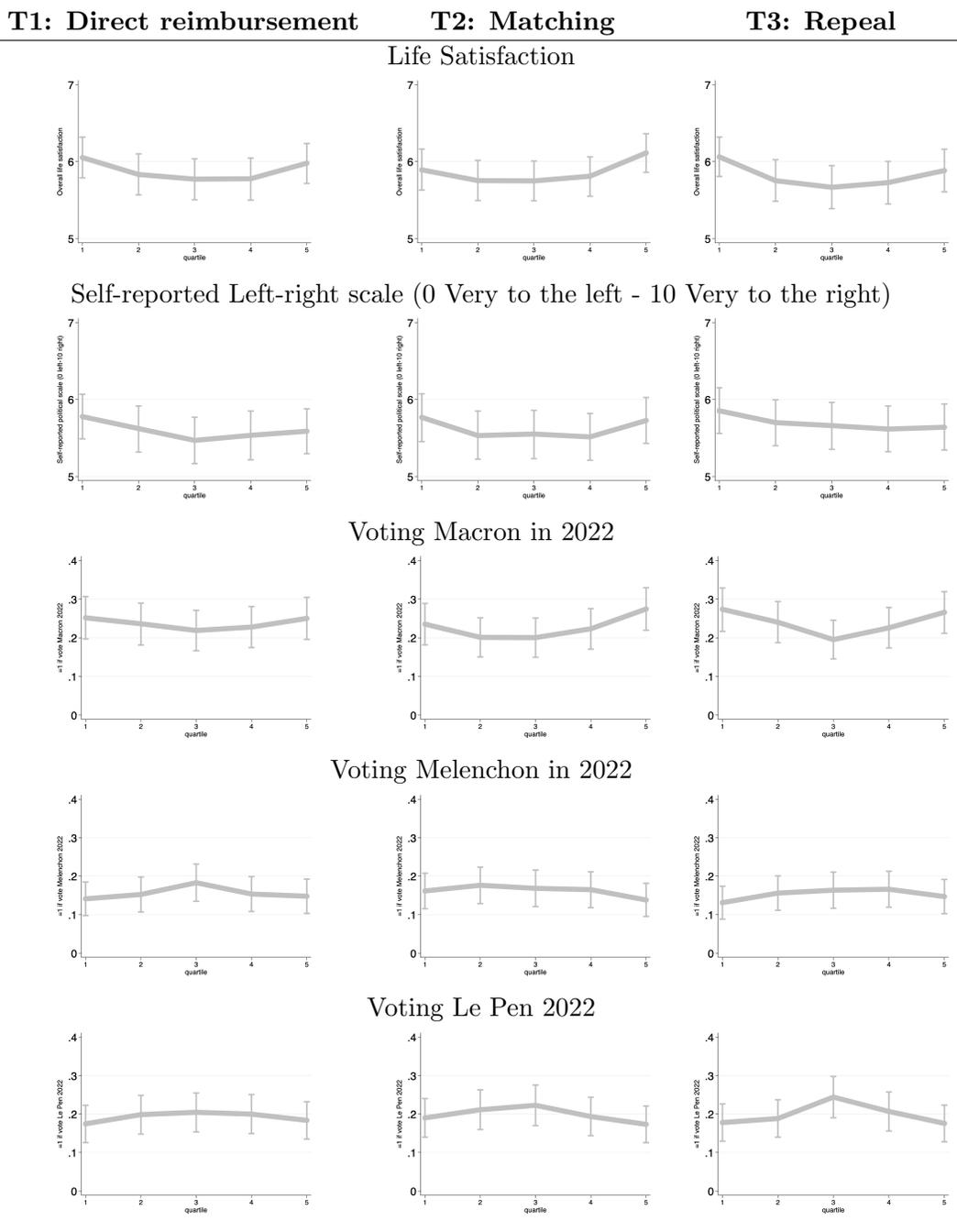


Figure C.6: Treatment Heterogeneity: average treatment effect and characteristics for each quintile of effects, Political Donation, Both margins

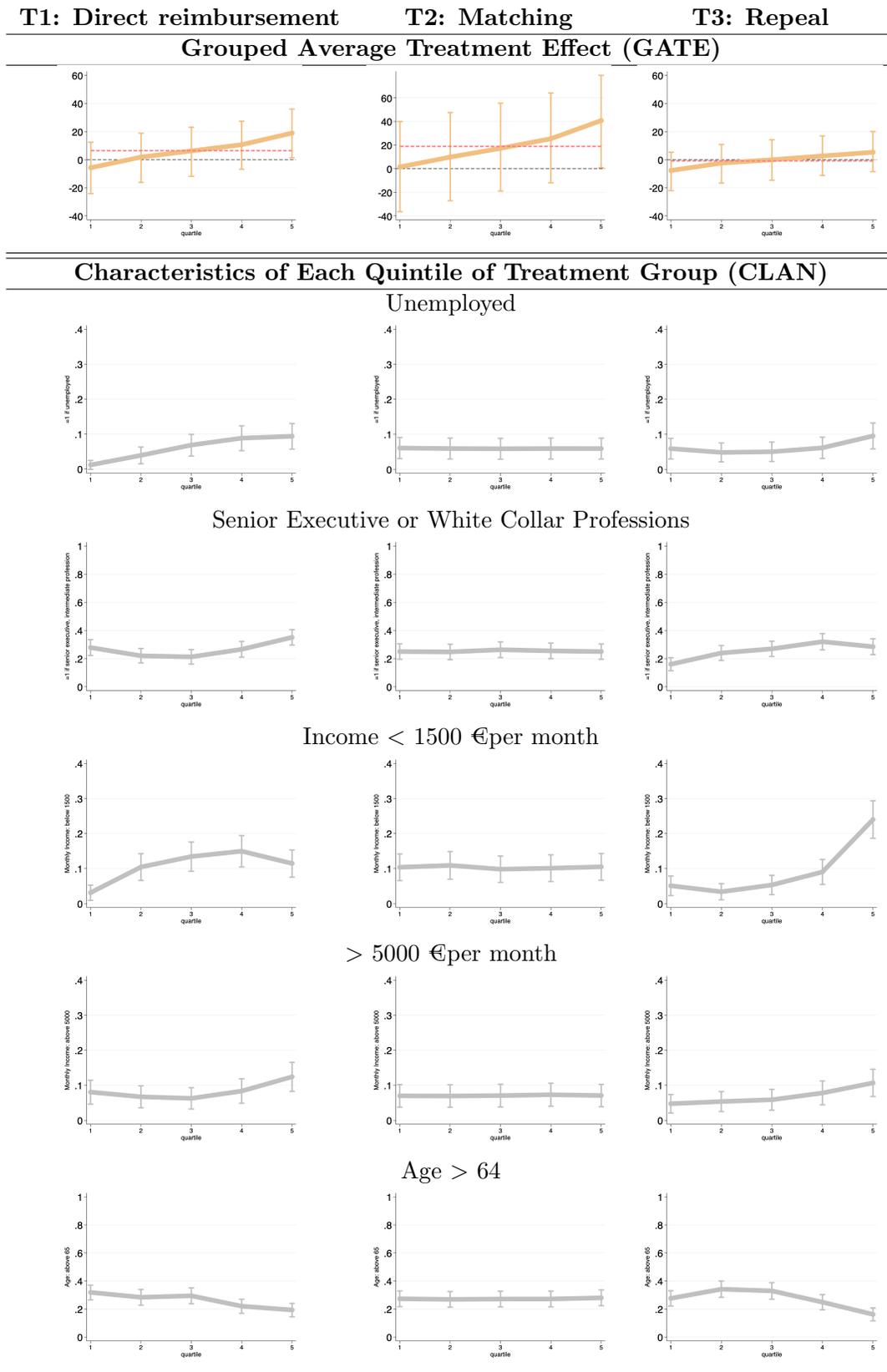
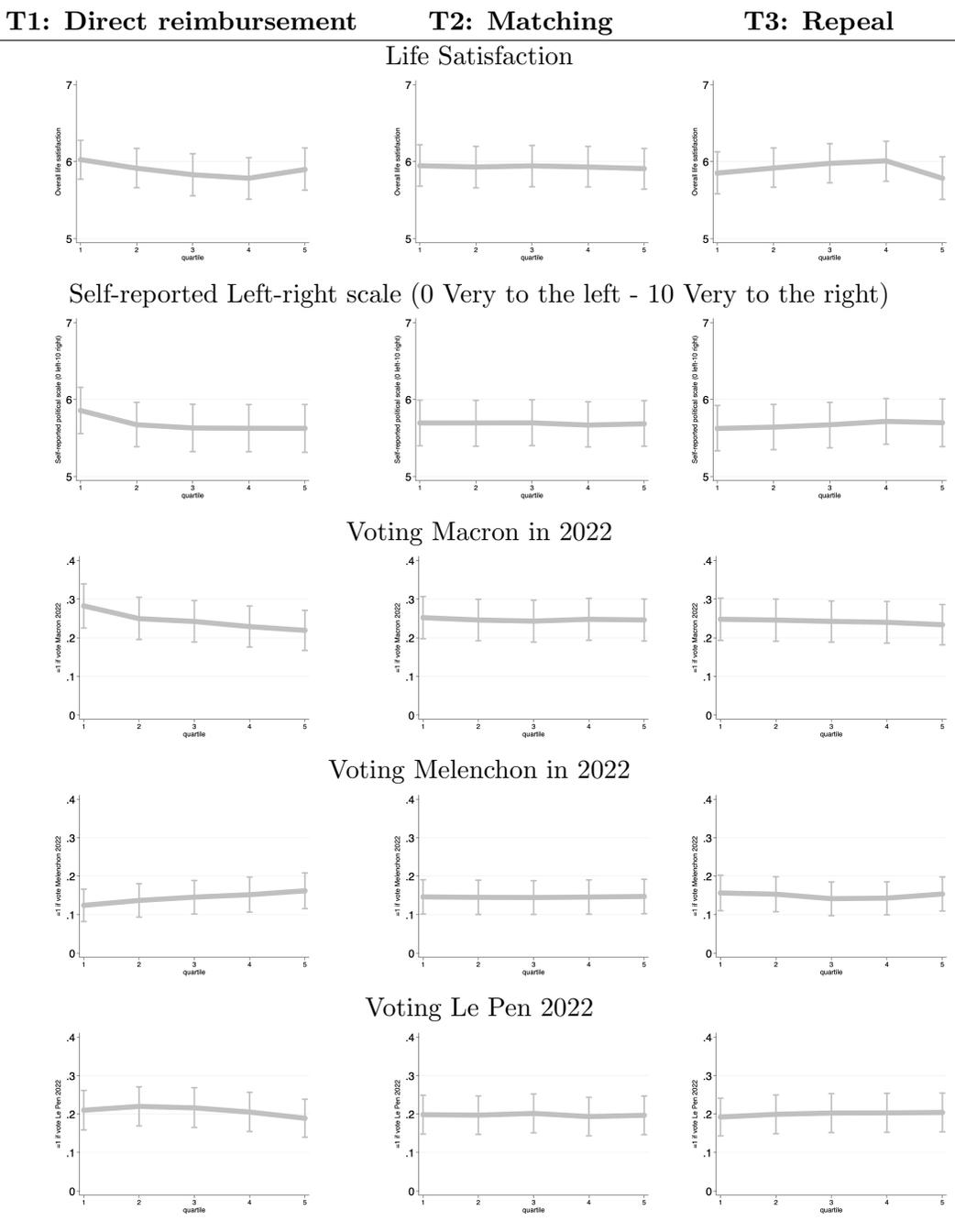


Figure C.6: Cont'd



References

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