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Abstract

We study the effect of time preference on donations relying on a panel dataset of Italian households. After developing an intertemporal model to derive theorethical implications on the relationship between impatience and altruistic donation, we address the issue empirically, relying on a quasi-experimental setting. We find that both the amount and the probability of donating (i.e. altruism) vary non linearly with impatience in intertemporal choice, eventually declining at higher level of impatience. Consistent with previous experimental evidence, these results support the view that psychological discounting matters for altruistic behaviour and, more in general, that individual parameters, often not directly observable, add up to tax policies to determine altruistic behaviours.

Keywords: Two-limit Tobit, Generalized Propensity Score, Quasi-experiment, Altruism, Discounting

JEL: C21, D03, D64

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1 Introduction

Altruism is a trait of mankind that cannot be ignored (Harman [2010], Kirchgässner [2010]). Nevertheless, for long it hardly fitted in the *homo œconomicus* scheme. In models populated by selfish individuals, altruistic donations were one of the biggest puzzles in economics (Andreoni [2006]); they could be only partly rationalized at high level of income when donations' marginal disutility become sufficiently low and when the associated tax benefits become appreciable. After Becker (1974)'s seminal contribution on social interacting agents, however, the role of altruistic preferences in accounting for individual choices has been more and more recognized, and several forms of other-regarding preferences have been put forward to cope with the economic puzzle of philanthropy (Andreoni [2006], Bénabou and Tirole [2006]). Typically, altruistic preferences are introduced in the standard model of consumer choice by adding up an altruistic term - weighted by the degree of altruism - to one's own consumption (Shapiro [2010]).

From an empirical point of view, however, the evidence on the drivers of altruism is still sparse, and mainly focused on the effect of tax system on money donations. For example, in List [2011] international differences are studied with respect to differences in tax policies and national attitude towards social needs. He shows that the likelihood of donating increases (non-linearly) with household income and education. The role of deep preferences remains much less investigated empirically as there is still no comprehensive evidence on the individual characteristics that affect altruistic behavior. In this respect, Bauer et al. [2013], while finding that highly-educated, high-income and religious individuals are most likely to contribute to any charity, point out that unobservable factors behind this correlation appear to be important in countries with low social expenditure. Individual parameters and attitudes such as risk aversion and impatience, which are generally not controlled for in these studies, may have in fact an important role in affecting individual behavior, even more so in countries where tax incentives are less important (see Cappellari et al. [2011]). Moreover, Albanese et al. [2013] show that neglecting individual deep parameters may cause serious concerns in terms of omitted variables.

Our paper contributes to this literature by studying – both theoretically and empirically – the effects of a specific preference trait, i.e. impatience (the propensity to postpone gratification in exchange of delayed rewards), on altruism. Investigating these effects is relevant in several respects. First, it has implications about the design of fund-raising and tax-deduction schemes for charity organizations and policy makers (Cappellari et al. [2011], Andreoni and Serra-Garcia [2016]). From a macroeconomic viewpoint, it helps understanding how time preference may affect a society and its growth via social capital, through the connection between altruism and social capital (Fehr [2009], Cox [2004]),[1] in combination and in addition to the effects of patience on human and physical capital accumulation (Knack and Keefer [1997], Glaeser et al. [2002], Barsky et al. [1997]). Additionally, studying the effect of time preference may also prove useful to gauge insights on the broader effects of preference-impacting shocks (Becchetti et al. [2017]). More in general, assessing the effect of time preference on altruism adds a contribution to the growing empirical literature studying how patience help shaping a large number of lifetime outcomes, such as health and labour earnings (e.g. Golsteyn et al. [2014], Sutter et al. [2013]).

However, only a few papers focus on the topic providing specific evidence. In two field experiments, Breman [2011] shows that the amount donated increases significantly when donors commit to future donations. Nevertheless, as these experiments cannot control for differences in individual time preferences, the author cannot disentangle whether this effects is due to differences in intertemporal preferences or budget constraints. Also from a theoretical viewpoint, Andreoni and Serra-Garcia [2016] show that introducing time in the process of giving can uncover important dynamics, as well as substantial heterogeneity in the motivations for giving. They put forward a model where individuals derive utility from making a giving decision, which is distinct from the utility individuals experience when paying for the gift. In line with Breman [2011], the results from their experiments suggest that donations increases when individuals are asked to donate later. They also show that individual are dynamically inconsistent (they choose to give when choice is made in advance but reverse their choices when giving occurs immediately). Dreber et al. [2016] set-up a model of dual-self: a patient self makes decisions in each period to maximize the discounted sum of utility net of a cost of self-control (i.e the temptations faced by shorter-run self who values future utility less than longer-run self does). They find that an increase in the cost of self-control will increase altruistic behaviour. The only paper providing evidence on the pure effect of time preferences is Angerer et al. [2014], who study altruism through a donation experiment relying on a sample of primary school children. They find that higher risk aversion and impatience in intertemporal choice decrease non-linearly the level of donations. They also find that altruism increases with age, and that girls are more altruistic than boys.

In the theoretical part of our work we show that non-linear effects of time preferences on altruism may arise also in a simple discounted utility model where we take into account the two typical motives for altruism, i.e.: joy of giving (Andreoni [1989, 1990]) and the so called "pure altruism" (Becker [1974]), and the willingness to preserve own consumption above a certain level (Chatterjee and Raviku-

[1]Donation has also been extensively used as a measure of social capital: e.g. blood donation in Guiso et al. [2006].

mar [1999], Alvarez-Pelaez and Diaz [2005]). The joy of giving utility derives from the very act of donating, while the pure altruism utility is the beneficial reward enjoyed for the effect of donation; therefore, they logically and practically refers to different times reflecting the inherently intertemporal dimension of donation (see Angerer et al. [2014]). Our theoretical model predicts that, at lower levels of impatience, the effect of time preference on altruism may be ambiguous and dependent on the distribution of the two motives across the population, thus being essentially an empirical issue. At higher levels of impatience, however, it becomes more and more likely that the effect of time preference on altruism is unambiguously negative.

Taking these predictions into account, in our empirical part we rely on quasi-experimental analysis adopting the generalized propensity score methodology (GPS) recently proposed by Hirano and Imbens [2004], which is an extension of the propensity score methodology for binary treatments, the well-established methodology for reducing bias caused by non-random treatment assignment in observational studies. Similarly to the binary propensity score method, the GPS approach requires that after controlling for observable characteristics, any remaining differences in treatment intensities across individuals is independent of the potential outcome (i.e. the weak unconfoundedness assumption). This implies that the GPS has a balancing property, i.e. for units belonging to the same GPS strata the level of treatment examined can be considered as random. However, differently from this approach, it will allow us estimating the so-called *dose-response* function, that is the (average) response in the probability of donating to changes in the level of a continuous treatment variable (i.e. the level of impatience). This approach has already been successfully used for causal inference in a variety of recent observational studies (see Fryges and Wagner [2008], Becker et al. [2012]).

Therefore, differently from Angerer et al. [2014], in which risk tolerance and patience are measured under experimental conditions but in a very particular setting, our research provides evidence with arguably higher external validity. Namely, we apply the GPS to a very large panel dataset of adults from the Italian Survey on Household Income and Wealth (SHIW). This surveys contains information about *whether* and *how much* individuals donate to any charity (our measure of altruism) and – in addition to a full set of economic, social and demographic variables (including individual income) – a measure of time preferences. The main advantage of our empirical strategy is that we can take advantage from a crucial asset of our dataset, i.e. the presence of a large set of relevant covariates, which are necessary for this estimation technique.

Consistently with the results from the theoretical model, our empirical results indicate that the effect of time preferences on altruism is non-linear. In particular, we find that at lower levels of impatience both the probability and the amount donated to charity are rather flat or decrease slowly with impatience, but then decline more sharply as impatience grows at higher levels. These results are robust to several controls, and support the hypothesis that – in addition to tax incentives – individual parameters and attitudes do have important impact on altruistic behaviors. Although we focus on the effect of time preference, our analysis does not imply that it is the only individual parameter affecting donations. Other factors could well matter, such as risk tolerance. Under our empirical strategy, however, we take them into account so that it is only after balancing the treatment and the control groups with respect to them that we assess the effect of time preference on donations.

The paper is organized as follows. Section 2 presents our theoretical model, while Section 3 gives details on the data and illustrates the main variables of interest. Section 4 describes the methodology to estimate a dose-response function to evaluate the effect of impatience on altruism and trust, providing details about the common support condition and the balancing of covariates. Section 5 provides the main empirical results from the GPS estimation, while Section 6 contains several robustness checks. Section 7 concludes.

2 The theoretical setting

In order to assess the relationship between time preference and donation, we develop a simple intertemporal model with two periods. We consider that altruistic behaviour can increase the donor's utility through two channels, well-known in literature (Becker [1974], Andreoni [1990]): the "good feeling" coming from the very act of donating (the so-called "joy of giving" or "warm-glow" channel), and the reward associated to the beneficial effect that the donation will bring to the receiver (the so-called "pure altruism" channel). The former brings utility as soon as donation is made (we assume it occurs at the same time as current consumption), whilst the latter channel unfolds its effect later and it materializes together with future consumption. Since the pure altruism's beneficial effect is delayed, it is related to the concept of patience (mentioned in the introduction) as the propensity to postpone gratification in exchange of delayed rewards. We also assume that a minimum level of own consumption (either present or future) has to be preserved (Chatterjee and Ravikumar [1999], Alvarez-Pelaez and Diaz [2005]).[2] This implies that donating is possible only provided that at least a certain amount is left for own consumption.

[2]For evidence of minimum consumption requirements see e.g. Rosenzweig and Wolpin [1993] who find that the minimum consumption can amount to a relevant portion of total consumption expenditure.

We formalize what described above with the agent's objective function:

$$U = (1-\alpha)u(c) + \alpha\gamma j(a) + \frac{1}{1+\rho}[(1-\alpha)u(d) + \alpha\phi v(a)] \tag{1}$$

where c is consumption in the first period, a is the donation amount, $\rho \geq 0$ is the intertemporal discount rate,[3] d is consumption in the second period. The utility from consumption, $u(\cdot)$, is strictly increasing and weakly concave in its argument. The parameter $\alpha \in [0, 1/2]$ is associated to the importance of altruism relative to selfishness.[4] The function $j(a)$ refers to the "joy of giving" effect; it is associated with the parameter $\gamma \in (0, 1)$ capturing the weight of this altruistic motive. The function $v(a)$ is the "pure altruism" effect and its weight is captured by the parameter $\phi \in (0, 1)$. The functions $j(\cdot)$ and $v(\cdot)$ are assumed weakly increasing and weakly concave in their arguments: this warrants that altruism cannot be detrimental but also cannot improve utility at increasing rates.[5]

The maximization of Eq. (1) occurs under constraints: the first one is the budget constrain stating that the income $y > 0$, which the individual is endowed with in the first period, has to be shared among consumption c, donation a and savings s. The savings, increased by the exogenous interest rate $r \geq 0$, are used to fund the second period consumption d:

$$y = c + a + s \tag{2}$$

$$d = s(1+r) \tag{3}$$

Moreover, a non negativity constraint holds for donation, i.e.: $a \geq 0$. As far as consumption is concerned, we assume that a stricter requirement holds: a minimum level of consumption $\underline{k} > 0$ has to be satisfied, i.e.: $c \geq \underline{k}$ and $d \geq \underline{k}$.

We focus on how the maximization problem's solution (c^*, d^*, a^*) varies with ρ. First, we consider the solution when the consumption constraint is not binding: it turns out that this is the case for a "sufficiently" low level of ρ : $(\rho \leq \bar{\rho})$. Then we consider the maximizing solution under the case $\rho > \bar{\rho}$ and assess the role of increasing impatience in this case as well.

[3] We model the intertemporal utility as in the standard discounted utility model Ã la Samuelson [1937]. For a critical review on models of time discounting see Frederick et al. [2002].

[4] We constrain α to be less than a half to exclude the unlikely case that donation matters more than own consumption. However, such a restriction can be removed without affecting the results.

[5] In order to keep things simple we abstract from idiosyncratic shocks and uncertainty; nonetheless, introducing them in presence of risk averse individuals would only reinforce our qualitative result making more tightening the constraint effect on donation.

Case a: minimum consumption constraint is not binding

The optimization of Eq. (1) at interior solutions has to satisfy the first order conditions:

$$\frac{\partial U}{\partial c} \quad : \quad u'(c) = \frac{1}{1+\rho} u'(d)(1+r) \tag{4}$$

$$\frac{\partial U}{\partial a} \quad : \quad \alpha\gamma j'(a) + \frac{1}{1+\rho}\alpha\phi v'(a) = \frac{1}{1+\rho}(1-\alpha)u'(d)(1+r) \tag{5}$$

where we have taken into account the budget constraint. The first order conditions hold with equality only provided that $c > \underline{k}$ and $d > \underline{k}$. In order to gain in algebraical tractability, we assume the following explicit functional forms: $u(\cdot) = \ln(\cdot)$ and $j(\cdot) = v(\cdot) = \ln(1+\cdot)$. Hence, we let the "joy of giving" and "pure altruism" effects differ only with respect to their intertemporal implications and their weights (γ and ϕ) but not as far as the functional form is concerned: this allows to make results unconfounded by any difference in the functional forms. Moreover, note that for altruism utility a simple log form, i.e. $\ln(a)$, cannot be assumed as it would prevent by construction the choice of no donation.

We now assess the role of impatience. As usual, current consumption c is increasing in the discount rate ρ whilst the opposite holds for future consumption d. As regards donation, we have the following:

Lemma 1. *When $c^* > \underline{k}$ and $d^* > \underline{k}$, the donation amount a^* is (weakly) decreasing in the discount rate ρ if and only if the joy of giving parameter γ is (weakly) lower than the pure altruism parameter ϕ:*

$$\frac{\partial a^*}{\partial \rho} \leq 0 \;\; \text{if} \;\; \gamma \leq \phi$$

Proof. The solution to the maximization problem is:

$$c^* = \min\left[\frac{(1+y)\ (1-\alpha)\ (1+\rho)}{(2+\rho)(1-\alpha)+\alpha[\gamma(1+\rho)+\phi]}; \frac{1+\rho}{2+\rho}y\right] \tag{6}$$

$$d^* = \min\left[\frac{(1+y)\ (1-\alpha)\ (1+r)}{(2+\rho)(1-\alpha)+\alpha[\gamma(1+\rho)+\phi]}; \frac{1+r}{2+\rho}y\right] \tag{7}$$

$$a^* = \max\left[\frac{\alpha[\gamma(1+\rho)+\phi]y-(1-\alpha)(2+\rho)}{\alpha[\gamma(1+\rho)+\phi]+(1-\alpha)(2+\rho)}; 0\right] \tag{8}$$

The non negativity constraint on a may be binding or not: if it is binding the solution is given by the second argument of the min and max operators above, otherwise the first term holds. Note that $a^* > 0$, as long as $y > \frac{(1-\alpha)(2+\rho)}{\alpha[\gamma(1+\rho)+\phi]}$; this condition can be seen as a non-poverty requirement for donation: since a poor agent can afford low levels of consumption and have a high consumption marginal utility, she prefers to use all her income to consume, set donation at zero and accept receiving zero utility from altruism.[6] Moreover, it can be easily checked that, as expectable, the altruism-related parameters α, γ, ϕ have a negative effect on c^* and d^* and a positive effect on a^*.

The effect of the discount factor ρ can be assessed by taking the partial derivatives. In the case $a^* = 0$, it is straightforward to see that $\partial c^*/\partial\rho > 0$ and $\partial d^*/\partial\rho < 0$ and of course $\partial a^*/\partial\rho = 0$. In the case $a^* > 0$:

$$\frac{\partial c^*}{\partial \rho} = \frac{(1+y)\,(1-\alpha)\,(1-\alpha+\alpha\phi)}{[2+\rho+\alpha\,(-2+\gamma-\rho+\gamma\rho+\phi)]^2} > 0 \tag{9}$$

$$\frac{\partial d^*}{\partial \rho} = -\frac{(1+r)(1+y)\,(1-\alpha)\,(1-\alpha+\alpha\phi)}{[2+\rho+\alpha\,(-2+\gamma-\rho+\gamma\rho+\phi)]^2} < 0 \tag{10}$$

$$\frac{\partial a^*}{\partial \rho} = \frac{(1+y)\;(1-\alpha)\;\alpha\;(\gamma-\phi)}{(2+\rho+\alpha\;(-2+\gamma-\rho+\gamma\rho+\phi))^2} \leq 0 \Leftrightarrow \phi \geq \gamma \tag{11}$$

Hence the effect of a higher impatience is unambiguously positive on current consumption, negative on future consumption, and ambiguous on donation: it is negative if pure altruism prevails. □

Lemma 1 states that the effect of impatience on donation depends on the relative importance of the two altruistic motives: if pure altruism is more important than the joy of giving, than donation decreases with impatience. Intuitively, in this case a lower impatience, by discounting the future less, implies that a higher weight in the intertemporal utility is attached to the second period, where the effect of the more important altruistic motive (pure altruism) occurs. Conversely, if it is joy of giving that matters more, then a lower impatience attenuates the beneficial effect of this altruistic motive by increasing the weight of the future. Therefore, the effect of time preference on altruism can be ambiguous: it is basically an empirical issue depending on the distribution of the altruistic motives among the population.

Case b: minimum consumption constraint is binding

As shown by Eq. (10), as impatience goes up, future consumption declines. The minimum consumption constraint becomes binding, i.e.: $d = \underline{k}$, for a sufficiently high $\rho > \bar{\rho}$. From Eq. (10), $\bar{\rho}$ is defined as:

$$\bar{\rho} = \frac{(1-\alpha)(1+r)(1+y) - \underline{k}[2(1-\alpha)+\alpha(\gamma+\phi)]}{\underline{k}(1-\alpha+\alpha\gamma)} \tag{12}$$

It can be shown that $\bar{\rho}$ is increasing in y and r and is decreasing in the altruism parameters α, γ, ϕ and in $\underline{k}$. The economic intuition are the following: $\bar{\rho}$ is higher if income relative to the minimum consumption level is higher (because it is easier to afford a consumption above the minimum level) or if the interest rate is higher so that less savings are necessary to afford the same level of consumption in the future.

[6] It can be argued to be a mild requirement as long as α is sufficiently small.

As far as the altruistic parameters are concerned, an increase in their value implies a shift toward donation in the trade-off with own consumption, but this reduction in consumption makes the minimum consumption constraint more likely to be binding.

In this case, d is fixed at $d = \underline{k}$ and the maximization problem can be written as:

$$U = (1-\alpha)\ln(c) + \alpha\gamma\ln(1+a) + \frac{1}{1+\rho}[(1-\alpha)u(\underline{k}) + \alpha\phi\ln(1+a)] \tag{13}$$

with $a = y - c - \underline{k}/(1+r)$. The following Lemma holds:

Lemma 2. *When $\rho > \bar{\rho}$ so that $d = \underline{k}$, then donation is unambiguously (weakly) decreasing in impatience: $\partial a^*/\partial\rho \leq 0$.*

Proof. By plugging $a = y - c - \frac{k}{1+r}$ into Eq. (13) and maximizing for c, we get the solution:

$$c^* = \min\left[\frac{(1-\alpha)\ (1+\rho)\left(y+1-\frac{k}{1+r}\right)}{(1+\rho)(1-\alpha)+\alpha[\gamma(1+\rho)+\phi]}; y - \frac{\underline{k}}{1+r}\right] \tag{14}$$

$$d^* = \underline{k} \tag{15}$$

$$a^* = \max\left[\frac{\alpha[\gamma(1+\rho)+\phi]\left(y-\frac{k}{1+r}\right)-(1+\rho)(1-\alpha)}{(1+\rho)(1-\alpha)+\alpha[\gamma(1+\rho)+\phi]}; 0\right] \tag{16}$$

where the first argument refers to the case where $a > 0$. As in Case (a), a donation is more likely for higher y, α, ϕ; it is less likely for higher $\underline{k}$. This is consistent with what could be intuitively expected.[7] As far as the effects of impatience are concerned, we have the following partial derivatives:

$$\frac{\partial c^*}{\partial\rho} = \frac{(1-\alpha)\,\alpha\phi\left(y+1-\frac{k}{1+r}\right)}{[(1+\rho)(1-\alpha)+\alpha\gamma(1+\rho)+\alpha\phi]^2} > 0 \tag{17}$$

$$\frac{\partial a^*}{\partial\rho} = \frac{-(1-\alpha)\,\alpha\phi\left(y+1-\frac{k}{1+r}\right)}{[(1+\rho)(1-\alpha)+\alpha\gamma(1+\rho)+\alpha\phi]^2} < 0 \tag{18}$$

□

Intuitively, since agents want to ensure themselves a sufficient level of future consumption, when they are more impatient they want to increase current consumption but cannot cut too much on fu-

[7] In Eq. (16) a donation is more likely with higher interest rates: this occurs because less savings are necessary to meet the minimum level of future consumption. However, this result is also affected by the simplifying choice of logarithmic utility functions which implies that the saved portion of income is insensitive to the interest rate. Since the responsiveness of donation to interest rate is outside the scope of this work, we do not analyze this result further.

ture consumption, so they cut on altruism and donation. Hence, when impatience is high, its effect on donation turns out to be negative.

Incidentally, let us spend few words on the situation where impatience is instead at its lower bound, i.e. $\rho = 0$: in this case $c = d$, as implied by Eq. (4). When the minimum consumption constraint is not binding, results in Lemma 1 are still valid. If the minimum consumption constraint is binding, it means that is so for both current and future consumption: $c = d = \underline{k}$; in this situation a donation is made out of the residual resources, if any: $a^* = \max[y - \underline{k}(2+r)/(1+r); 0]$ and a small increase in the discount factor has locally no effect.

The overall effect of time preference on donation

Summing up the results in Lemma 1 and Lemma 2, we have the following Proposition:

Proposition 1. *The effect of time preference on donation can be non-linear. For $\rho \leq \bar{\rho}$ the effect is ambiguous as it may be positive, negative or nihil depending on the relative weight of altruistic motives (joy of giving, pure altruism). For higher impatience, i.e.: $\rho > \bar{\rho}$, the effect of time preference on donation is negative.*

$$\frac{\partial a}{\partial \rho} \begin{cases} \leq 0 \ \text{ if } \ \phi \geq \gamma & \text{for } \rho \leq \bar{\rho} \\ < 0 & \text{for } \rho > \bar{\rho} \end{cases}$$

Proof. Proposition 1 follows from joining results from Lemma 1 and Lemma 2. □

Taking into account the model implications, we now move to the data and the empirical part. Bringing the model to data, the implication of Proposition 1 is that when discounting is not too high its effect on donation may be ambiguous as it depends on the distribution among the population of the preference parameters for the two channels of altruism. As impatience is sufficiently high and grows further, however, it can be expected that its effect on donation is most likely negative because of the greater likelihood that for someone it is above the threshold, with the associated negative effect stated in Proposition 1.

3 Data Description

We select our data from the 2008, 2010 and 2012 SHIW surveys, the years in which questions about individual discount rates were first introduced. The survey is a large representative sample of the Italian population and covers – for all three years – questions on several aspects of the individual's life, such as education, living and working conditions, as well as information on individual's attitudes toward risk and level of impatience. This survey has been extensively used in several studies to identify micro-founded effects on a great variety of topics (see for example, Battistin et al. [2009], Jappelli and Pistaferri [2000], De Blasio and Nuzzo [2010], Bottazzi et al. [2006]). The sampling unit is the household, and although the information are mainly available for the head of the household, there are also additional information both at the family level and for each component.

To keep control of the composition of our sample, we restrict our attention to those heads of household who participated in the study all three years (i.e. a balanced sample). However, we do not conduct a full panel data analysis for two reasons. Firstly, it is hard to control for time-varying factor with the GPS methodology and a non-linear model. Secondly, the measurement of discount rates (our measure of impatience) slightly changed across survey (see below). In order to check the robustness of our results over time and avoid confounding changes in impatience with changes in measurements, we replicate each year the same analysis with the same sample of individuals. Therefore, we first apply the GPS propensity score analysis to the impatience level derived from 2012 survey, using as (lagged) covariates data from 2010 survey. We then check the robustness of the results relying on impatience level from survey 2010 and (lagged) covariates from 2008 survey.

In the following sections, we first describe in detail our outcome variable (i.e. our measures of altruism) along with our measure of impatience (i.e. our "treatment measure"), while Table (1) describes and summarizes our set of control variables. In particular, we rely on lagged values (i.e. year 2010) as these variables are predetermined with respect to the current time errors (i.e. 2012). As Table (1) shows, the data contains a large number of covariates. In particular, we use information that have been identified in previous studies as determinants of donation, such as individual and family income (see for e.g. List [2011]). Moreover, we have information on individual characteristics, such as individual sex, education and age, as well as information on individual attributes, which are often unobservable characteristics, such as individual attitude towards risk (see Angerer et al. [2014], Cappellari et al. [2011]).

INSERT TABLE (1) HERE

The richness of the set of covariates makes the application of GPS methodology to this dataset appropriate. In fact, the key assumption for the GPS methodology (see below) is the weak unconfoundedness assumption, which is also known as the assumption of selection on observables: it requires that after controlling for observable characteristics, any remaining difference in treatment intensity across individuals is independent of the potential outcome of interests. As this assumption is not statistically testable, to plausibly apply this method, a large set of relevant covariates is thus required.

3.1 Measuring altruism.

We develop our measure of altruism relying on the SHIW question on donation. We can observe whether the head of the family has contributed with money to charitable but we cannot observe whether (s)he has also contributed with time. Previous research has analysed the relationship between time and money donations finding evidence that individual unobserved characteristics, such as their altruistic attitude, drive a significant and positive relationship between time and money donation (Cappellari et al. [2011], Bauer et al. [2013]). Differently from previous studies, however, we also have information on the amount of charitable contribution. More specifically, the head of the family answered the following question:

"Did you or a member of the household make donations or other contributions (e.g. to non-profit associations, voluntary organizations, charities)? (If "Yes") What was the amount of the payments?

From this question we derive a dummy variable *Donation* equal to 1 if the individual answered yes, and 0 otherwise, which we will use as dependent variable in our analysis of altruism. We also derived a variable *Donation Amount* which is equal to the amount of money individuals gave for donations. The assumption is that this measure is similar to that derived in dictator games in economic experiments (i.e. the size of donation sent as a first mover). As shown in Table 1, almost one fifth of respondents has on average made a donation in 2012 (the share was basically equal in 2010). This is in line both with the share of 17% documented by Bauer et al. [2013] using international survey data and also with the average share of money contributors reported in Cappellari et al. [2011] using Italian data.[8] Conditional on having given, the average donated amount is 322 euros, which corresponds to 1.2% of the contributors average income (1.7% of the overall average income).[9]

3.2 Measuring impatience.

The level of discount rates to measure individual impatience were elicited by asking to the head of the family the following question:

"You have won the lottery and will receive a sum equal to your household's net yearly revenue. You will receive the money in a year's time. However, if you give up part of the sum you can collect the rest of your win immediately. To obtain the money immediately would you give up 10% of your win?"

[8]Cappellari et al. [2011] using the year 2000 wave of the *Indagine Multiscopo sulle famiglie - Aspetti della vita quotidiana* by the Italian National Statistical Office (ISTAT) report an average of 19.3% for women and 21.7% for men.

[9]For the US, Andreoni (2006) documents an average share ranging between 1.5% and 2.1% between 1968 and 2001.

If the respondent's answer is "yes", the interviewer asks for a discount of 20%, whereas if the answer is "no" the interviewer asks for a discount of 4%. In this latter case, if the answer is again "no" the interviewer also asks whether the head of the family is willing to give up the money for a discount of 2%. If the respondent would also accept a discount of 20%, the interviewer asks for a discount of 30%. In 2010 this question was slightly different, allowing for a bit less of variability in discount rates (i.e. less categories) up to 20%, while in 2008 this question was only administered to a random subset of households.

To determine the level of impatience in each year (i.e. the implied discount rate), we use the midpoint of the range of two discount values. Thus, for example, if a respondent is willing to accept a reduction of 10% but will not accept a discount of 20%, the midpoint is 15%. As highlighted above, to avoid time-varying confounding factors and changes in measurement, we will focus on data derived from surveys 2012, to then check the robustness of our results in year 2010.

Several techniques are available to elicit individual discount rates and there is no consensus on best practices (Hardisty et al. [2013]). Eliciting individual discount rates as in the SHIW surveys (i.e. through multiple staircase choice-method) has advantages with respect to previous methods because it avoids answer inconsistencies and appears easier for participants to understand (Hardisty et al. [2013]). Moreover, in our case there is no need to infer ex-post the discount rates (and thus imposing a functional form for preferences) as participants are directly asked the value of their discount rates (i.e. the percentage). Differently from economic experiments, the choices are not incentivized. Nevertheless, Falk et al. [2014] have shown that these measures correlate well with experimental measures when the number of survey items increase.

4 Model Specification

In the absence of experimental data, matching methods provide an appealing alternative. The main feature that makes matching methods such an attractive empirical tool is the possibility of mimicking an experiment *ex-post*. In particular, Rosenbaum and Rubin [1983] showed that conditioning on the propensity score is sufficient to balance treatment and comparison groups. Subsequently, the literature has extended the propensity score methods to the cases of multivalued treatments (Imbens [2000], Lechner 2001) and, more recently, to continuous treatments (Hirano and Imbens [2004] and Imai and Van Dyk [2004]).

The approach developed by Hirano and Imbens [2004] is particularly suited for our paper. They proposed estimating an entire "*dose-response function*" of a continuous treatment, i.e. a relationship between the exposure to a continuous treatment and an outcome variable. In the following we briefly recall this approach. Readers already familiar with this procedure, may directly move to the next section.

We define a set of potential outcome $\{Y_i(t)\}$ for $t \epsilon T$, where T represents the continuous set of potential treatments (in this paper, the level of impatience) defined over the interval $[t_0, t_1]$, and $Y_i(t)$ is referred to as the unit-level dose-response function (in the paper, the probability of donating). For each individual $i = 1, ..., N$, we observe a $k \times 1$ vector of covariates, X_i; the level of treatment delivered, T_i; the corresponding outcome $Y_i = Y_i(T_i)$.

Hirano and Imbens [2004] generalized the concept of unconfoundedness for binary treatments to one of *weak unconfoundedness* for continuous treatments

$$Y(t) \perp T \,|X \quad for\, all\, T \tag{19}$$

Individuals differ in their characteristics X such that some are more or less likely to have higher discount rates (i.e. level of impatience) than others. Weak unconfoundedness means that, after controlling for observable characteristics X, any remaining difference in the level of impatience (i.e. T) across individuals is independent of the potential donation (i.e. $Y(t)$).

The generalized propensity score is defined as

$$R = r(T\,|X) \tag{20}$$

where $r(t, x) = f_{T|X}(t\,|x)$ is the conditional density of the treatment given the covariates. Similarly to the propensity score with binary treatments, the generalized propensity score is assumed to have a balancing property which requires that, within strata $r(t, x)$, the probability that $T = t$ does not depend on the value of X. In other words, conditional on observable characteristics X, when looking at two individuals with the same *ex-ante* probability of having a particular level of impatience (i.e. discount rate), their actual level of impatience is independent of X. That is, the propensity score summarizes all the information in a multi-dimensional vector X so that

$$X \perp 1\{T = t\}\,|r(t, X) \tag{21}$$

In combination with weak unconfoundedness, the balancing property implies that assignment to treatment is *weakly uncounfounded given the generalized propensity score.* Then, for every t

$$f_T(t|r(t,X),Y(t)) = f_T(t|r(t,x)) \tag{22}$$

Therefore the GPS can be used to eliminate any bias associated with differences in the covariates in two steps. In the first step, one has to estimate the conditional expectation of the outcome (i.e. in our case the probability of donating) as a function of two scalar variables: the treatment level T (i.e. the discount rates) and the generalized propensity score R (i.e. $\beta(t,r) = E[y\,|T = t,\ R = r]$). In the second step, one has to estimate the dose-response function at a particular level of the treatment intensity by averaging the conditional expectation estimated in the first step over the generalized propensity score at that particular level of the treatment intensity (i.e. $\mu(t) = E[\beta(t, r(t,X))]$).

4.1 Practical implementation

1) Estimation of the propensity score. Hirano and Imbens [2004] rely on a normal distribution to estimate the treatment intensity given the covariates. However, in this context, T (i.e. the level of impatience) cannot be assumed to be normally distributed as discount rates are a fractional variable bounded between [0, 0.3]. In addition, it is not possible to resort to GLM to estimate discount rates relying on a fractional logit regressions as in Papke and Wooldridge [1996], as this would not allow in the subsequent steps to fully specify the density function of the treatment estimates. It is also not possible to assume a Beta distribution as in Bia et al. [2014], as we have several observations at limits. We therefore resort to a two-limit Tobit Model assuming the following distribution for the treatment intensity given the covariates:

$$T_i|X_i \sim \Phi(L_1 - x_i\beta/\sigma)^{d_0} \cdot 1/\sigma\phi(y_i - x_i\beta/\sigma)^{d_1} \cdot \Phi(L_2 - x_i\beta/\sigma)^{d_2}$$

where $\Phi(.)$ is the standard normal cumulative distribution function, $\phi(.)$ is the standard normal probability density function, σ is the standard deviation, x_i is a row vector of covariates and β_1 a column vector. L_1 and L_2 are the lower and upper limits of the censored distribution (in our case 0 and 0.3 respectively), and y is a generic notation for observed values within the limits. For each observation, only one of the exponents d_j $(j = 0, 1, 2)$ will take the value of one, depending upon whether the observed value is either equal to or within the two limits.

2) Common support condition and balancing of covariate. Similarly to standard propensity score matching methods, we test the common support condition as follows. We divide the sample into three groups $j = 1, 2, 3$, which are defined according to the distribution of the impatience level (i.e. discount ratio). For each treatment group j, we calculate the median treatment intensity T_{Mj} and evaluate the GPS for the whole sample at median treatment intensities using the estimates for β and σ derived from the estimation of the propensity score. For each group and each observation $i = 1, .., N$ we calculate $\hat{R}(T_{Mj}, X_i)$. We then divide the GPS obtained into three blocks. We test the common-support condition by plotting the GPS values $\hat{R}(T_{Mj}, X_i)$ for each block against the GPS values the distribution of the GPS (i.e. $\hat{R}(T_{Mj}, X_i)$) for the rest of the sample, to then drop those observations that will lye outside the common support.

To test the balancing property, we apply the approach of blocking on the score suggested by Hirano and Imbens [2004]. As above, we again divide the sample into three groups according to the distribution of the impatience level (i.e. discount ratio). Within each group, we evaluate the GPS at the median values of the treatment variable (i.e. discount ratio). Then, we divide each group into five blocks by the quintiles of the GPS evaluated at the median level.[10] Within each of these blocks, we compare the mean difference of each covariates with respect to individuals who have a GPS such that they belong to that block (i.e. the same *predicted* treatment intensity) with those who are in the same block, but have a different actual treatment intensity (i.e. groups). That is, we assign each individual to the respective block according to its GPS evaluated at the median level and compare the means of covariates with individuals in a different treatment level (i.e. in the control group), but similar GPS.

3) Estimate the conditional expectation of the outcome. Using the GPS values estimated in the first stage $\hat{R}$ and the observed treatment intensities T_i we estimate the conditional expectation of the outcome Y_i as a flexible function of these two arguments:

$$\varphi E\{(Y_i \mid T_i,\ R_i)\} = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 T_i^3 + \alpha_4 \hat{R}_i + \alpha_5 \hat{R}_i^2 + \alpha_6 \hat{R}_i^3 + \alpha_7 T_i \hat{R}_i$$

where the GPS terms aim controlling for selection into treatment intensities. The estimated coefficients have not direct causal interpretation. However, if the estimated coefficients of the GPS terms are equal to zero indicate whether the covariates introduce any bias (Hirano and Imbens [2004]). More precisely, if the GPS terms are jointly significant, their introduction is indeed relevant and significantly reduces the bias of the estimated response of the probability of donating to changes in individual level of impatience.

[10] We groups are defined according to the following cutpoints: 0-0.035;0.035-0.125; 0.125-0.3. Choosing a finer or coarser specification does not change significantly the results.

4) Obtain the dose-response function. The last step consists of averaging the estimated regression function over the score function evaluated at the desired level of the treatment. Given the estimated parameters $\hat{\alpha}$, the observed level of impatience T_i and the estimated GPS $\hat{R}$, the *average* potential outcome (i.e. the average probability) is obtained as

$$E\{Y(t)\} = \frac{1}{N}\sum_{i=1}^{N}\hat{\alpha}_0 + \hat{\alpha}_1 T_i + \hat{\alpha}_2 T_i^2 + \hat{\alpha}_3 T_i^3 + \hat{\alpha}_4 \hat{r(t, X_i)} + \hat{\alpha_5} \hat{r(t, X_i)}^2 + \hat{\alpha}_6 \hat{r(t, X_i)}^3 + \hat{\alpha}_7 T_i \hat{r(t, X_i)}$$

The entire dose-response function is thus obtained by estimating this average potential outcome for each level of the treatment. In other words, for each individual we have to evaluate the GPS for each level of the treatment, so that we have as many propensity scores as there are levels of treatment. Then, for each level of the treatment, we obtain the average response by averaging over all the individual responses. In the paper, we use bootstrap methods to obtain the standard errors that take into account estimation of the GPS and the $\hat{\alpha}$-parameters. In addition to the dose–response function itself we also display its derivative with respect to impatience level —which is commonly referred to as the treatment-effect function, and it has a causal interpretation.

5 Results

Before presenting the main results of the GPS methodology, we first explore the relationship between the individual parameters and the probability of donating and giving credit to friends by using a probit model. In Table (2), we start with a basic model including only impatience, to then include their squared and cubic interactions. We report regression results for both coefficients and marginal effects.

INSERT TABLE (2) HERE

In columns *a*, we observe that impatience significantly decreases the probability of donating (-18.4%). In columns *b*, we include the squared and cubic terms for impatience. However, we refrain from interpreting the coefficient on the interactions terms as tests about partial effects and interaction terms are not necessarily informative in non-linear model. One cannot assess the statistical significance of this interaction effect with a simple t-test on the coefficient of the interaction term, and it can also be economically misleading (see Greene [2010]). We therefore directly report the overall marginal effects for each variable. The results now suggest that impatience does significantly and positively affect the probability of donating (+34%). In columns *c*, we finally include a dummy for each year, in order to account for any unobservable changing factor that may affect individual decisions. Results are substantially analogous.

While – at a first look – they might appear contradictory, these results highlight non-linear relationships between impatience and the probability of donating. However, they are not useful to assert any casual claim. We therefore turn to a more useful analysis of the dose-response function.

In Table (3) we report the results of step 1 that estimates the propensity score relying on the Tobit specification. These results suggest that better educated, risk tolerant, and richer individuals are less impatience. They also suggest that older and employed individuals are less patient.[11]

INSERT TABLE (3) HERE

In Figure (1) and Table (4) we report the results related to step 2 testing the common support and balancing property. For example, in Figure (1) - panel *a* - we plot the distribution of the GPS for group 1 (see the black bars) against the distribution of the GPS for the rest of the sample, i.e. group 2 and 3 (see the white bars). Similarly for group 2 and 3 (see Figure (1), panel *b* and *c*). By inspecting the overlap of these distributions, we find that there are 27 participants whose GPS is not among the common regions of the three groups. We thus impose the common support by dropping those participants (less than 2% of our sample), for a total of 2948 observations in 2012.

INSERT FIGURE (1) HERE

INSERT TABLE (4) HERE

Table (5) illustrates the group and block structure. For instance, we compare the covariates of 292 observations in group 1/block 1 to the observations in control 1/ block 1. Taking the sum over all blocks and adding the respective control groups yields the total number of observations (i.e. 2955) in the common support regions. If adjustment for the GPS properly balances the covariates, we would expect all differences not to be statistically significant. Table (4) reports the mean *t-statistics* for each group across all covariates. There is evidence that the balancing property is satisfied, with only 1 out 33 t-values significant after controlling for the GPS. We thus conclude that the estimated generalized propensity score perform well in reducing potential treatment bias.

INSERT TABLE (5) HERE

[11]Several studies has shown how impatience can be an important determinant of education (see for example Sutter et al. [2013]). Therefore, even though our regressors are predetermined, we check the robustness of our results by excluding the variable education. Results are analogous.

In Table (6) we report estimation of the dose response function from step 3. As highlighted above, the estimated coefficients have no direct causal interpretation. However, we note that the coefficients of the GPS are highly significant and different from zero, suggesting that the GPS procedure allows to remove potential bias introduced by the covariates.

INSERT TABLE (6) HERE

Our main results from step 4 are presented in Figure (2), where the left panel indicates that there is a non-linear relationship between the level of impatience and the probability of donating. In particular, the probability of donating is initially rather flat or mildly decreasing, to then decline more sharply at higher levels of impatience. In other terms, the marginal increase in the level of impatience significantly affects the probability of donating only at medium-high level of impatience. This can be seen from the derivative of the dose-response function with respect to impatience level in the right panel of Figure (2). The 90% confidence band of the treatment effect function always excludes the zero for level of the discount ratio between 19% and 27%. Within this range, an increase in the individual impatience will significantly reduce the probability of donating (i.e. the variation in the probability of donating is negative) around 2%. This effect is also economically significant, if we consider that the sample probability of donating is 19% (see Table (1)), corresponding to a reduction of about 10%. For values below this range the effects are any longer significant and unambiguous.[12]

INSERT FIGURE (2) HERE

The dose-response function for the amount donated in 2012 (see Figure (3)) exhibits a similar shape as for the probability of donating. Importantly, consistent with the analysis of the probability of donating, the marginal increase in the level of impatience (i.e. the pair-effect function depicted in the treatment-effect function) significantly affects the amount donated only at medium-high level of impatience, approximately between 22%-27%. Within this range, the variation in the amount donated is negative. That is, an increase in the level of impatience will reduce the amount donated up to 25 Euro. This effect is highly economically significant, considering that the sample average amount of a donation is about 61 Euro (see Table (1)), resulting in a reduction of about 41% . Below this range the effects of higher impatience tend to be small and scarcely insignificant.

[12]At the very extreme values of the (empirically) observed range of impatience the effects are somewhat irregular, mostly likely because at these corner values we have very different type of observations.

INSERT FIGURE (3) HERE

6 Robustness

We now check whether the results appear robust over different years. We thus replicate all the same steps of the previous analysis but using, as outcome variables, the probability of donating in 2010. For the sake of brevity, we now only report the main results from step 4 and for the probability of donating in Figure (4). As Figure (4) highlights, even though in 2010 the question about discount rates does not allow for the same level of variability (see Section 2.2), the results are consistent with the previous analysis: the 90% confidence band of the treatment effect function always excludes the zero for medium-high level of discount ratio, i.e. between 14% and 19%. In line with the testable prediction of our model, a marginal increase in the individual impatience, within this range, will significantly reduce the probability of donating. Below this range, the effects are any longer significant and unambiguous.[13]

INSERT FIGURE (4) HERE

7 Discussion and Conclusions

In this paper we contribute to the literature on the determinants of altruism by studying the effect that individual impatience has on the probability of donating money to charitable organizations. In order to do that, we have first derived theoretical implications from a simple intertemporal model relating individual's time preference and donation, where we have considered that donating may increase utility both through the concurrent channel coming from the joy of giving and through the delayed channel arising from the pure altruism; in addition, we have taken into account the willingness to preserve own consumption above a certain level. The model results suggest that at lower levels of impatience the effect of time preference on donation may be ambiguous, but then it is eventually negative at higher discount rates.

We then relied on quasi-experimental setting to estimate the response of the (average) probability of donating to changes in the level of individual impatience. That is, we relied on the recent generalized

[13]It is fair to recall that the weak uncounfoundness assumption cannot be tested. To generate a bias, however, such factors should not only affect donations but also vary with the intensity of impatience in a different way in the treatment and the control groups.

propensity score methodology to estimate a continuous dose-response function. To perform our analysis we relied on the SHIW panel dataset of Italian households in year 2008-2012. The use of this dataset is appropriate because it contains information on impatience, which is often an unobservable characteristic outside the laboratory, along with a full set of economic, social and demographic variables, which are necessary to plausibly implement this method.

Our results are consistent with the testable predictions derived from our model. Our first result suggest that below a certain level of impatience (less than 19%) the probability of donating is mildly decreasing or rather flat as impatience grows; instead, at higher level of impatience (between 19%-27%), an increase in the levels of impatience significantly and more sharply decreases the probability of donating. Moreover, our second result highlights that for below a certain level of impatience (less than 22%) the responsiveness of the amount donated to an increase in the level of impatience is rather flat, but at higher level of impatience (22%-27%) an increase in the level of impatience reduces the amount donated. In this latter case, the (average) amount donated can decrease of about 40% even for a smaller increase in the level of impatience. These results are robust across years.

While the results are consistent with our model, a causal interpretation of the results is subject to the main concern that the existence of an unobservable factor might render the effect of impatience spurious. However, to be relevant, this unobservable factor should be omitted from each yearly analysis of the probability of donating, as well as from each yearly analysis of the amount donated. Moreover, it would have to explain a sufficient amount of variation in the analysis of the individual level of impatience. To be that the case, it could only be an individual level factor, as our analysis is conducted in a single country. However, our analysis already controlled for many relevant individual characteristics, some of which were unobservable in previous studies due to data constraints, and results were robust to these additional controls. Finally, these results are also consistent with previous experimental research highlighting a non-linear relationship between the level of impatience and the probability of donating.

As result, our findings are thus informative regarding the hypothesis that individual parameters and attitudes have important impact, in addition to tax incentives, on altruistic behaviors. In particular, our main result that higher level of impatience may decrease the probability of donating confirms and complements previous experimental results with evidence having a greater external validity. Our analysis has focused on time preference, but the dataset and the methodology that we have used is suited to explore in further research the effects of other individual preference parameters, such as risk aversion or trust, thus enriching the empirical comprehension of donation drivers.

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Table 1: Summary statistics and Variable Description

Variable	Description	Mean	Std. Dev.	Min.	Max.	N
Donate$_{2012}$	This is a dummy variable equal to 1 if the respondent donated in 2012, and 0 otherwise.	0.189	0.392	0	1	2999
Amount Donated$_{2012}$	This variable contains the amount donated by the respondent in 2012.	60.839	322.355	0	11000	2999
Discount rates$_{2012}$	This is the treatment variable and measures the impatience level of the respondent. It is explained in detail in section 2.2.	0.082	0.094	0	0.3	2999
Risk tolerance$_{2010}$	This is categorical variable measuring the (financial) risk tolerance of the respondent.	1.74	0.789	1	4	2996
Education$_{2010}$	This is categorical variable measuring the education level of the respondent.	3.694	1.691	1	8	2996
Family Size$_{2010}$	This variable measures the total number of family component.	2.46	1.245	1	12	2996
Age$_{2010}$	This variable measures the age of the respondent (i.e. head of the household).	60.592	14.431	20	95	2996
Family Income Holders$_{2010}$	This variable measures the total number of family component earning a salary.	1.666	0.73	1	6	2996
House Property$_{2010}$	This is a dummy variable equal to one if the household own the house is living in, and 0 otherwise.	0.759	0.428	0	1	2996
Single$_{2010}$	This is a dummy variable equal to one if the head of household is single, and 0 otherwise.	0.1	0.301	0	1	2996
Divorced$_{2010}$	This is a dummy variable equal to one if the head of household is divorced, and 0 otherwise.	0.078	0.269	0	1	2996
Widow$_{2010}$	This is a dummy variable equal to one if the head of household is widow, and 0 otherwise.	0.199	0.399	0	1	2996
Log Income$_{2010}$	This variable measures the logarithm of the income of the head of household.	9.831	0.918	1.142	12.472	2978
Employed$_{2010}$	This is a dummy variable equal to one if the head of household is employed, and 0 otherwise.	0.398	0.489	0	1	2996

Table 2: BASIC PROBIT MODEL

The dependent variable is a dummy variable (i.e. *Donation*) equal to 1 if the individual donated and zero otherwise.

	Coeff	*Margins*	*Coeff*	*Margins*	*Coeff*	*Margins*
	a	*a*	*b*	*b*	*c*	*c*
Impatience	-1.229***	-0.184***	9.837***	0.345***	9.791***	0.342***
	(0.378)	(0.057)	(2.392)	(0.118)	(2.402)	(0.118)
Impatience^2			-88.164***		-86.028***	
			(22.215)		(22.550)	
Impatience^3			167.785***		159.244***	
			(53.665)		(54.941)	
Year 2010					0.129*	0.019*
					(0.068)	(0.010)
Year 2012					0.175**	0.026**
					(0.071)	(0.010)
Constant	-1.393***		-1.566***		-1.690***	
	(0.048)		(0.061)		(0.081)	
Log-likelihood	-3604	-3604	-3588	-3588	-3585	-3585
Observations	7561	7561	7561	7561	7561	7561

Table 3: Estimation of the Generalized Propensity Score (GPS)

This table reports the marginal effects of a two-limit Tobit model. The dependent variable is the discount rates in 2012. Descriptions of the regressors are available in Table(1).

Variable	*Coef.*	*Std. err*
Risk Tolerance$_{2010}$	-0.007*	(0.004)
Education$_{2010}$	-0.004*	(0.002)
Family Size$_{2010}$	0.016***	(0.004)
Female	-0.013*	(0.007)
Age$_{2010}$	0.001***	(0.000)
Family Income Holders$_{2010}$	-0.021***	(0.005)
House Property$_{2010}$	-0.014**	(0.007)
Single$_{2010}$	0.021*	(0.011)
Divorced$_{2010}$	0.023*	(0.012)
Widow$_{2010}$	0.043***	(0.010)
Log Income$_{2010}$	-0.023***	(0.004)
Employed$_{2010}$	0.017*	(0.009)
Constant	0.234***	(0.040)
Sigma	0.142***	(0.003)
Log-likelihood	-188	
Observations	2975	

Table 4: Balance of covariates for the GPS

This table illustrates the results for test of the balancing properties. Observations are first divided into three "treatment" groups according to the actual level of the discount rates: [0, 0.035], [0.035, 0.125] and [0.125, 0.3]. In addition, within each group, observations are divided into five blocks according to the estimated GPS (see Table (5)). For each variable, we then compare the equality of covariates between units who belong to the the treatment interval of the HHI, and units that are in the same GPS interval but belong to another treatment interval. The balancing property has been tested using a standard two-sided *t-test*. There is strong evidence against the balancing property when $1.96 < t < 2.576$.

	Group 1: [0,0.035]			*Group 2: [0.035,0.125]*			*Group 3: [0.125,0.3]*		
	Mean	**Std**	**t-test**	**Mean**	**Std**	**t-test**	**Mean**	**Std**	**t-test**
Risk Tolerance$_{2010}$	0.047	0.028	1.658	-0.055	0.031	**-1.767**	0.018	0.039	0.457
Education$_{2010}$	-0.023	0.053	-0.432	0.059	0.066	0.892	0.064	0.074	0.857
Family Size$_{2010}$	0.064	0.046	1.400	-0.059	0.048	-1.227	0.001	0.058	0.009
Age$_{2010}$	0.108	0.511	0.212	-0.658	0.559	-1.177	0.227	0.673	0.337
Family Income Holders$_{2010}$	0.021	0.024	0.869	0.005	0.029	0.190	-0.002	0.034	-0.072
House Property$_{2010}$	-0.004	0.015	-0.273	0.005	0.017	0.295	0.013	0.019	0.702
Single$_{2010}$	0.003	0.011	0.249	0.003	0.012	0.249	-0.004	0.015	-0.275
Divorced$_{2010}$	-0.004	0.010	-0.399	0.002	0.011	0.150	0.000	0.013	0.004
Widow$_{2010}$	-0.004	0.013	-0.314	-0.023	0.015	-1.537	0.023	0.014	1.601
Log Income$_{2010}$	-0.039	0.027	-1.446	0.030	0.033	0.919	0.096	0.035	**2.719**
Employed$_{2010}$	-0.008	0.018	-0.436	0.006	0.019	0.336	0.020	0.024	0.846

Table 5: Cell size for mean comparison of treat and control units

Block	*Group 1*	*Control 1*	*Group 2*	*Control 2*	*Group 3*	*Control 3*
1	290	543	191	440	109	885
2	290	256	191	414	109	573
3	290	289	191	381	109	458
4	290	211	191	430	109	300
5	290	200	191	328	108	188
Total	1449	1499	955	1993	544	2404

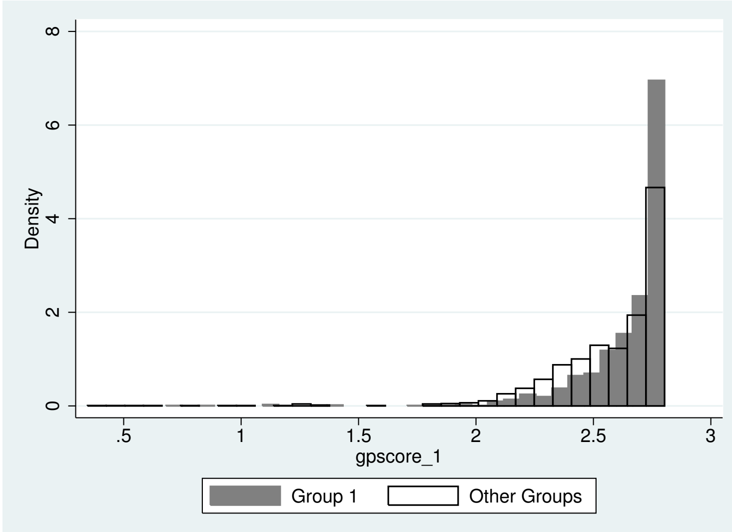
Groups are generated according to three cutpoints of discount ratio in 2012 (i.e. 0.035, 0.125 and 0.3), whereas blocks are generated according to the quintiles of the GPS evaluated at the median treatment intensity for each group. The sum of observations over blocks in a group yields the total number of observations in that group. The sum of observations in a group with observations from the respective control group yield the total number of observations in the common support region.

Table 6: ESTIMATION OF THE DOSE-RESPONSE FUNCTION FOR THE PROBABILITY OF DONATING

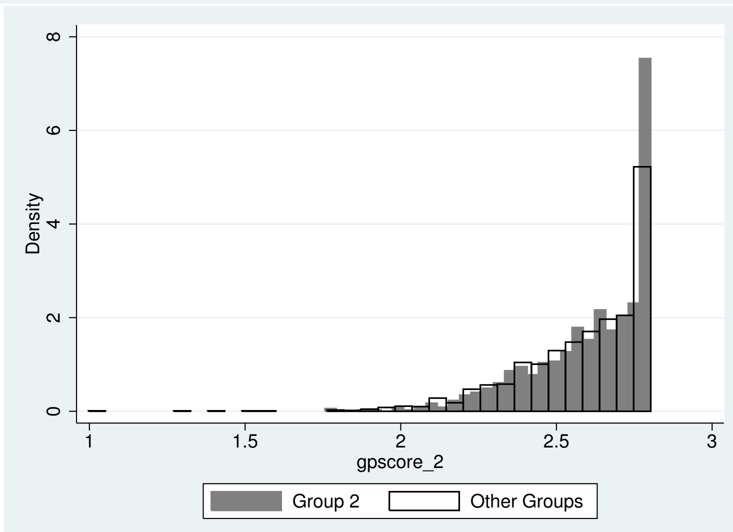
The dependent variable is a dummy variable (i.e. *Donation*) equal to 1 if the individual donated in 2012 and zero otherwise.

Variable	Coeff	Std Error
Impatience$_{2012}$	14.779	(10.322)
Impatience$^2{}_{2012}$	-192.272***	(74.364)
Impatience$^3{}_{2012}$	387.144**	(158.668)
Gps	8.628***	(1.704)
Gps^2	-4.973***	(1.182)
Gps^3	0.785***	(0.233)
Gps$\cdot$Impatience$_{2012}$	0.493	(2.042)
Constant	-4.114***	(0.517)
Log-likelihood	-1396	
Observations	2948	

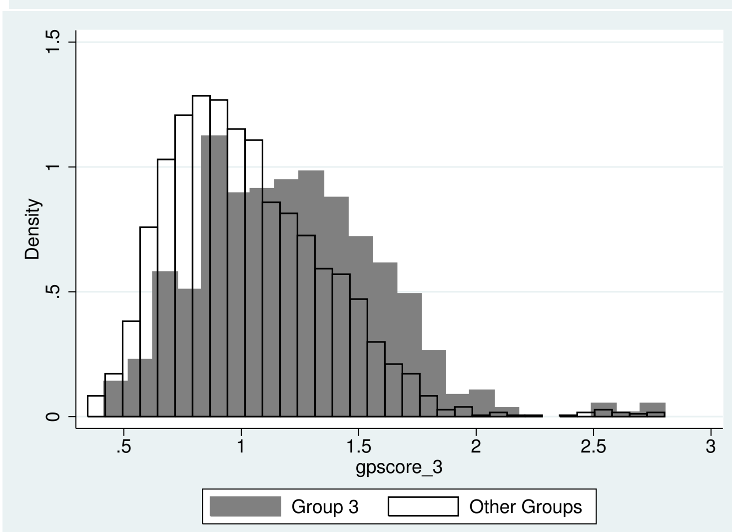
Figure 1: Common Support of the Generalized Propensity Score



a.



b.



c.

Figure 2: Dose-Response and Treatment-Effect Function for Donation

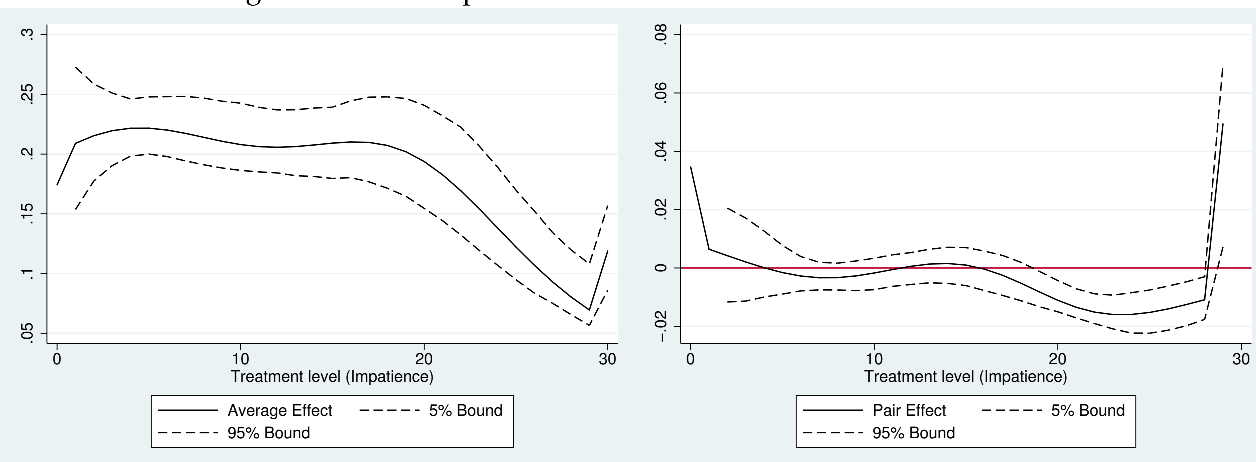


Figure 3: Dose-Response and Treatment-Effect Function for Donation Amount

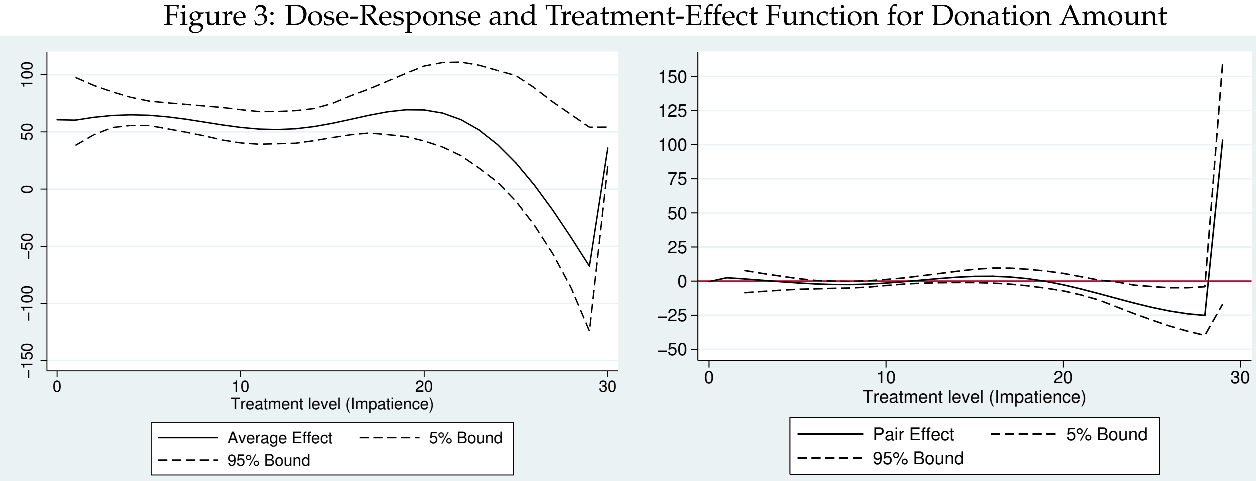


Figure 4: Dose-Response and Treatment-Effect Function for Donation (2010)