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Chapter 1

Introduction

This thesis consists of three articles analyzing government resources, such as subsidies and government grants, devoted to charitable giving. Research on charitable giving is of particular importance as the charity sector in developed countries is often sizeable and governments frequently spend substantial portions of their budgets on supporting charitable giving in the form of direct government grants and subsidies on donations. The annual report on philanthropy in the USA for the year 2012, for instance, shows that about 117 million US households donated to charitable organizations and that charitable giving accounted for more than $ 315 billion (Giving USA 2013).

Chapters 2 and 3 of this thesis investigate tax evasion in the form of subsidies received for false declarations of charitable donations. Individuals in many developed countries can deduct donations to charities from their income tax. By reporting higher donations to charities than actually made, individuals reduce their tax liabilities and thus evade income taxes. In Chapter 2, I develop a theoretical model of charitable giving and tax evasion and subsequently test in an experiment whether subjects overreport their donations. Chapter 3 analyzes the optimal subsidy rate on charitable giving considering tax evasion through subsidies for falsely reported donations. The final chapter of this thesis, Chapter 4, tests whether government grants to a private charitable organization will displace, i.e., crowd out, private donations. In particular, this study investigates how crowding out depends on the disclosure of government grants.

Tax Evasion and Charitable Giving—An Experimental Approach Chapter 2 of this thesis compares the level of tax evasion under a rebate and match subsidy, respectively, which are the two subsidy types for charitable donations commonly in place in developed countries. Under the rebate subsidy the individual receives the subsidy, while under the match subsidy the charity organization receives

the subsidy. The focus of the investigation in Chapter 2 is not whether the rebate or match subsidy induces more donations, but rather whether the rebate or match subsidy induces more overreporting of donations. If a rebate subsidy leads to more evasion than a match subsidy, the match subsidy could lead to the government's desired level of donations at a lower cost. Furthermore, I am interested whether it makes sense for governments to spend a lot of money on programs to increase the probability of detection and subsidy rate under the rebate and match subsidy, respectively. First, I develop a theoretical model of charitable giving and tax evasion. The model offers testable hypotheses for my experiment. The model predicts that an increase in either the probability of detection or the subsidy rate, has a larger effect on evasion under the match than under the rebate subsidy. Second, I test in an experiment whether subjects report higher donations than the actual donations they made, and thus evade taxes.

The experimental results show that the level of overreporting is higher under the rebate subsidy than under the match subsidy. Moreover, increases of the match subsidy rate lead to larger decreases in overreporting than increases of the rebate subsidy rate. A higher probability of an audit under the rebate subsidy has no significant effect on overreporting, whereas a higher probability under the match decreases overreporting. The results of this chapter may provide new insights for policymakers to implement effective subsidy schemes. My experiment suggests that replacing rebate schemes with match schemes may not only have the potential to increase donations, but also to decrease overreporting of donations.

The Impact of Tax Evasion on the Optimal Subsidy on Charitable Giving Chapter 3 analyzes the optimal subsidy rate on charitable giving considering tax evasion through false declarations of charitable donations. The analysis distinguishes between self-reporting and third-party reporting of donations, the two reporting schemes for charitable giving in place in developed countries. The taxpayer reports the donation and is eligible to the subsidy under self-reporting of donations (e.g. income tax deductions in the USA). In comparison, the taxpayer reports the donation and the charity is eligible to the subsidy under third-party reporting of donations (e.g. match subsidy in the UK). As governments seem to stick to a reporting scheme once chosen, for example, because of privacy concerns or bureaucratic inertia, I do not intend to find the best reporting scheme but to determine an optimal subsidy under a given reporting scheme.

The main theoretical results are the following. First, the optimal subsidy depends critically on the probability of tax evasion being detected, which differs under self-reporting and third-party reporting of

donations. As the government decides to switch from a self-reporting to a third-party reporting scheme, the optimal subsidy rate increases. Second, if an increase in the subsidy results in a decreasing level of tax evasion (e.g. in response to a tax enforcement reform), the optimal subsidy under self-reporting increases. In comparison, if an increase in the subsidy results in a decreasing level of overreporting under third-party reporting, the optimal subsidy can either decrease or increase, depending on whether the government revenues from penalty payments from tax evaders are higher than losses from overreporting. Third, an increase in the share of true donations in total reported donations, for example, in response to an information campaign about the social costs of tax evasion, leads to a higher optimal subsidy under self-reporting. In contrast, an increase in the share of true donations can also lead to a lower optimal subsidy rate under third-party reporting as this reporting scheme can generate high revenues from penalties.

Simulations additionally show that the optimal subsidy under self-reporting ranges from close to 0 % to 38 %, while the optimal subsidy under third-party reporting ranges from 20 % to 41 %. Moreover, if an increase in the subsidy results in an increasing level of overreporting under *third-party reporting*, the optimal subsidy rate increases in my calibrations. Finally, a decrease in the share of true donations leads to a lower optimal subsidy rate in my simulations.

Disclosure of Government Grants and Crowding Out Chapter 4 tests the hypothesis that government grants to charitable organizations will crowd out private donations by accessing a large database of US charities. The existing empirical literature on crowding out ignores that private donors are often not aware of government grants given to charities. As individuals can, however, only consciously adjust their donations in response to government grants if they are informed about the grants, the disclosure of government grants may have a decisive impact on the crowding out of private donations. This study is the first attempt to estimate whether crowding out depends on the disclosure of the government grants, where the study uses the availability of the Form 990 on the charity's website as a proxy for disclosure.

In my estimations I find that government grants completely crowd out private donations if the tax return Form 990 is available on the website of the charity, while there is no crowding out if the Form 990 is not available on the website. This result suggests that the disclosure of government grants through the online availability of the Form 990 may lead to unintended costs, which may be taken into consideration, for example, by policymakers when designing legal disclosure requirements. In addition, the analysis shows that one additional dollar spent on fundraising increases donations by considerably more than

one dollar. It follows that charities do not maximize net revenues, because they may instead target, for instance, higher ratings from charity rating agencies (see, for example, Andreoni and Payne 2011). Finally, I do not find evidence that reduced fundraising efforts of charities after receiving government grants is the explanation for crowding out. This finding suggests that a policy that requires charitable organizations to increase their program expenses by the full amount of the government grants may not be feasible for the organizations. The reason is that individuals decrease their donations after observing the grants and crowding out is not a consequence of a reduction in fundraising efforts by the charities.

Chapter 2

Tax Evasion and Charitable Giving—An Experimental Approach

2.1 Introduction

This study introduces an experiment that investigates tax evasion through subsidies received for false declarations of charitable donations. Taxpayers in many developed countries can deduct donations to charities from their income tax and reduce their tax liabilities by reporting higher cash or gift donations (e.g. clothes, cars) to charities than actually made, and thus evade income taxes. The study compares evasion under a rebate and match subsidy, respectively, which are the two subsidy types for charitable giving commonly in place in OECD countries. Under a rebate subsidy the taxpayer gets a tax credit at the marginal income tax rate. Under a match subsidy the charity organization gets a subsidy for the donation of the taxpayer. A match subsidy is a commitment by the government (e.g. UK, Canada) or by cooperations to match donations of others at a certain rate. This chapter asks whether a rebate subsidy to donors leads to higher degrees of overreporting of donations than a match subsidy to charities. If a rebate subsidy leads to more overreporting than a match subsidy, the match subsidy could lead to the government's desired level of donations at a lower cost. That is, the focus of the chapter is not whether the rebate or match subsidy induces more donations, but rather whether the rebate or match subsidy induces more tax evasion.

Research on charity is of particular importance since the share of charity to GDP in many OECD countries is sizable. According to Giving USA (2013), an annual report on charitable giving in the USA, in the year 2012 charity accounted for more than $ 315 billion, which was more than 2 % of GDP. In

2010, 75 % of US taxpayers listed charitable donations on their tax return, where the average deduction was more than $ 3,800. In the USA the taxpayer is frequently responsible for determining the market value of the gift donation, where there are often no fixed formulas or methods for determining the value (see Internal Revenue Service, IRS 2013). Ackerman and Auten (2011) show that a tightening of the rules for vehicle donations in the US tax reform 2004 resulted in a 66 % drop in the number of donated vehicles. The most obvious way to evade taxes through charitable giving is simply to indicate a cash donation at the income tax return. Tiehen (2001) finds donations reported to the US tax authority (IRS) are higher than reported donations on household surveys that investigate donor behavior. Fack and Landais (2013) use the French tax enforcement reform of 1983 as a natural experiment to provide evidence for tax evasion related to charitable giving. Prior to 1983, French taxpayers were only asked to *keep* a receipt of each charitable contribution they declared on their tax returns. Since 1983, French taxpayers must *enclose* receipts with their tax returns when claiming the charitable deductions. The total *reported* contributions decreased by more than 75 % in 1983 after the reform, whereas they estimate that the share of overreported donations before the reform was between 40 % and 60 %. If taxpayers want to claim donations from their income tax returns in Austria, the taxpayers are only required to produce a receipt of the donation upon request of the tax authority, while taxpayers in the USA have to provide an acknowledgment of the donation from the charity organization if the individual contribution is larger than $ 250 (IRS 2013). In short, it may not be particularly difficult to make up charitable donations in order to evade taxes.

This chapter provides a theory of tax evasion in the context of charitable giving. The theory distinguishes between the rebate and match subsidy and offers testable hypotheses for my experiment. I predict that the decision to overreport depends strongly on the probability of tax evasion being detected and on the level of the subsidy. Furthermore, I expect that an increase in the probability of detection and the level of the subsidy has a larger effect on evasion under the match than under the rebate, since the motive to evade under the rebate may differ from the motive to evade under the match. Even though both the match and rebate subsidy are based on donation reports of individuals, the charity receives the subsidy under the match, while the individual receives the subsidy under the rebate.[1] That is, individuals who face a rebate subsidy may evade for selfish reasons to benefit themselves, while individuals who face a match subsidy may evade for altruistic reasons to benefit the charity. Some individuals may only be willing to evade for the charity if it is unlikely that they have to pay a fine for evading. Thus, I am

[1]For instance, both the match and the rebate are claimed through the Gift Aid programme in the UK.

interested in the individuals' responsiveness to a change in the probability of detection and the level of subsidy.

To find out whether the rebate or match subsidy induces more tax evasion, the study makes use of a laboratory experiment for the following reasons. To my knowledge, there is no tax reform that can be used as a natural experiment to directly explore this question, since governments seem to stick to the type of subsidy once chosen.[2] To observe a natural experiment, a government would have to replace a rebate with a theoretically equivalent match scheme for exogenous reasons, or vice versa. Eckel and Grossman (2008) argue that the lab provides excellent control (e.g. no processing costs or delay with tax refunds that could lead to differences in the match and rebate subsidies) at the cost of some natural context. Furthermore, the marginal tax rate and thus the subsidy is a function of income and other policy instruments (Huck and Rasul 2011). Policymakers may expect a decrease in donations and thus introduce or increase a subsidy for donations. This endogeneity makes it difficult to properly identify the effects of a change of the subsidy on overreporting and donations in empirical work. There might also be a selection bias with respect to audited taxpayers and even if audits are random, the overall level of evasion is difficult to infer because the distribution of tax evaders is potentially skewed (Fack and Landais 2013). Alm et al. (2010) emphasize that a lab experiment allows us to observe the exact amount of misreporting, while in empirical investigations based on field data it is hard "to measure accurately – something that by its very nature people want to conceal" (Alm et al. 2010, p. 548). Finally, the lab provides the opportunity to create a very comprehensive data set such that I can control for individual and policy parameters that may have an impact on charitable donations.

In my experiment I find that the level of overreporting of donations is higher under the rebate than under the match subsidy. This finding suggests that the optimal subsidy under the rebate is generally lower than under the match, everything else equal.[3] Moreover, the probability of an audit does not have a significant influence on evasion under the rebate, while the probability is an important predictor of evasion under the match. For instance, a ten percentage point increase in the probability of an audit under the match reduces overreporting by almost ten percent. I estimate a positive price elasticity of overreported donations, which means that overreporting decreases with the subsidy rate. The elasticity is 0.66 under the match and 0.19 under the rebate in my preferred specification. If the findings are

[2] In the UK, for example, the match subsidy is offered to all taxpayers, while the rebate subsidy is only provided for high-income taxpayers. Since there has been no exogenous variation in the subsidy type, this does not suffice to identify the respective amounts of tax evasion accurately either.

[3] Chapter 3 of this thesis will show that the optimal subsidy of giving generally increases if the share of overreporting decreases.

confirmed in further studies, by knowing the elasticities of overreported donations and the shares of reported donations to actual donations, policymakers may consider adapting the level of the subsidy in place or switching to match subsidy schemes.

Related Literature My experiment combines two streams of literature that have attracted a lot of attention in public economics. First, there is a rich literature on charitable giving. Notable empirical contributions that try to estimate the price elasticity of charitable giving, which reflects the change of donations in response to an increase in the subsidy rate, have been made by Taussig (1967), Feldstein and Taylor (1976), and Clotfelter (1985). Huck and Rasul (2011) give a review of the empirical price elasticities of giving in the literature and summarize that increases in the subsidy rates generally lead to more donations.[4] In order to overcome the endogeneity concerns of empirical works, Eckel and Grossman (2003, 2006, 2008), Davis et al. (2005), Karlan and List (2007), Huck and Rasul (2011), Scharf and Smith (2015), and others use field and lab experiments to estimate the price elasticity of giving under match and rebate subsidies. These experiments show that increases in the match subsidy are a more effective tool to increase donations than theoretically equivalent increases in the rebate subsidies with the same net cost of giving. That is, both field and lab experiments indicate the price elasticity of donations is higher under the match than under an equivalent rebate. While Meier (2007) finds that donations decline after their experiment when donors no longer receive match subsidies, his field experiment does not investigate the long run impacts of rebate subsidies.

Second, there is a long history of studies on income tax evasion, which was triggered by the seminal theoretical analysis by Allingham and Sandmo (1972).[5] Slemrod (1989) and Feldman and Slemrod (2007) use data from US tax audits to estimate tax evasion through charitable donations. Both studies conclude that overreporting of charitable donation is quantitatively important. Slemrod (1989) finds that the elasticity of overreported donations is low and that overreporting of donations is less price responsive than actual donations. Fack and Landais (2013), which is the only paper besides Slemrod (1989) that aims to measure the elasticity of overreported donations, exploit variation in reporting behavior in response to a tax reform in France. Fack and Landais find the elasticity of overreported donations to be large before the tax reform (between -1.35 and -2.32) and to be small after the tax reform (between -0.19 and -0.57). Cojoc and Stoian (2014) find in their experiment that subjects cheat more on self-reported

[4]While List and Peysakhovich (2011) show that individuals are more responsive to stock market upturns than downturns, they do not investigate whether the price elasticity of giving differs under upturns and downturns.

[5]Detailed summaries of the literature on income tax evasion can be found in Andreoni et al. (1998), Slemrod (2007), and Alm (2012).

tasks in the first stage if they know that they have the opportunity to donate to a charity in a second stage. While Douoguih et al. (2014) argue that charitable donations can be used as a costly signal that a high-income taxpayer truthfully reported her income situation such that she will not be examined by an auditor, Hungerman (2014) allows individuals to hide income in a warm-glow model of charitable giving. Unlike in my study, Cojoc and Stoian (2014), Douoguih et al. (2014), and Hungerman (2014) do not consider that donations themselves can be used to evade taxes. In independent work, Blumenthal et al. (2012) test in a laboratory experiment how match and rebate subsidies can be used to overreport charitable donations.[6] In the experiment of Blumenthal et al. (2012) each subject repeatedly faces both a match and a rebate, where the match subsidy is between 0 and 100 %. In comparison to Blumenthal al. (2012), my experiment makes use of a one-shot between-subject design, where the donations of a subjects were either subject to a match or rebate subsidy to avoid income effects. Moreover, I do not restrict the match subsidy to lie between 0 and 100 %, as higher match rates are frequently used in practice (see, for example, Karlan and List 2007, and Rondeau and List 2007). In addition, Karlan et al. (2011) argues that the optimal match subsidy may be more than 100 % for certain types of donors. Finally, I provide a theory of tax evasion in the context of charitable giving that derives testable predictions for the probability of detection and subsidy rate on overreporting.

The rest of this chapter is organized as follows. I discuss the theory and derive predictions in Section 2.2. I present the experimental design in Section 2.3. The experimental results are presented in Section 2.4. Section 2.5 concludes.

2.2 Theory

In this section, I present a theory of tax evasion related to charitable giving in order to obtain testable predictions for the experiment described in Section 2.3. The model is close to standard models of charitable giving (e.g. DellaVigna et al. 2012, Onderstal et al. 2013) and to models of tax evasion (e.g. Allingham and Sandmo 1972, Kleven et al. 2011).

In case of a rebate subsidy, the decision problem of the individual becomes the following. Individual i gets utility α_i from private consumption and β_i from the charitable good. The differentiable, strictly increasing, and concave function $\alpha_i = \alpha_i\left(I_i, g_i, g_i^e, s_r, \theta\right)$ depends on income I_i, the non-negative individ-

[6] The idea of the experiment by Blumenthal et al. (2012) was first mentioned in the proceedings of the 2007 IRS research conference (Turk et al. 2007). I was unaware of the suggestion by Turk et al. (2007) and first presented the design of my experiment in May 2011 at the Vienna Graduate Seminar in Economics.

ual's true donations to the charity g_i and overreported donations g_i^e, the subsidy rate s_r ($0 \leq s_r \leq 1$), and the non-negative fine rate θ. For example, $I_i - g_i$ is equal to consumption if donations are not subsidized. If the individual receives a rebate subsidy for the donation, the subsidy is equal to the donated amount g_i times the rebate subsidy rate s_r. An increase in the subsidy rate increases the money available for consumption. If evasion is undetected, the individual also receives a subsidy for the overreported amount g^e. If evasion is detected, the individual has to pay back the evaded amount $s_r g_i^e$ and further, has to pay a fine that is in proportion to the subsidy and the overreported donations $s_r g_i^e \theta$. The differentiable, strictly increasing, and concave function $\beta_i = \beta_i (g_i, G_{-i})$ reflects utility from the charitable good and depends on the individual's donation g_i and the donations of the other individuals G_{-i}. The total amount of the charitable good is given by the sum of the donations of the individual and the other individuals.[7] That is, the utility of the individual increases if somebody else donates to the charity. The individual gets utility E_r if evasion is not detected and utility D_r if evasion is detected:

$$E_{i,r} = \alpha_i (I_i - g_i (1 - s_r) + s_r g_i^e) + a\beta_i (g_i, G_{-i}),$$

$$D_{i,r} = \alpha_i (I_i - g_i (1 - s_r) - s_r g_i^e \theta) + a\beta_i (g_i, G_{-i}),$$

$D_{i,r}$ and $E_{i,r}$ are separable in private consumption and the charitable good. Like in DellaVigna et al. (2012), the utility of donating to the charity β_i permits both pure and impure altruism (warm glow). A purely altruistic individual is concerned about the total amount of the charitable good $g_i + G_{-i}$. The parameter a is non-negative and shows the level of altruism. If the donations of the individual are driven by a warm-glow motive, the function β_i may not depend on the donations of the other individuals G_{-i} and the parameter a reflects the level of the warm glow. Since evasion is detected with probability p and undetected with probability $(1 - p)$, the expected utility of individual i is:

$$\max_{g_i, g_i^e} U_{i,r} = u_i (D_{i,r}) p + u_i (E_{i,r}) (1 - p) \tag{2.1}$$

subject to the reporting and non-negativity constraints:

$$g_i + g_i^e \leq I \text{ and } g_i,\ g_i^e,\ \lambda \geq 0, \tag{2.2}$$

[7] The charity has public good characteristics. Even in the case that the beneficiaries of the charitable good are individuals who receive a *private* good, charitable contributions are contributions to a *public* good if the contributions are motivated by altruism (see references in Breman 2012).

where the function u_i is differentiable, strictly increasing, and concave. The conditions in inequality (2.2) say that the individual cannot report a donation higher than her income, and that the donation cannot be negative. The former constraint is not very restrictive. Total donations, for example, are restricted to be smaller than 50 % of adjusted gross income in the USA (see Feldman and Slemrod 2007).

If the individual faces a match subsidy, the individual reports his or her donation to the charity organization and the charity receives a matched payment from the government or from a company. The function $\beta_i = \beta_i(g_i, g^e, s_m, G_{-i})$ reflects utility from the charitable good, and also depends on the overreported amount g^e and the match subsidy rate s_m. If the charity receives a match subsidy for the donation, the subsidy is equal to the donated amount g_i times the match subsidy rate s_m ($s_m \geq 0$). If the individual is overreporting in favor of the charity, the charity receives the subsidy rate s_m times the overreported donation g^e. If evasion is detected, the individual has to pay back the evaded amount and further, has to pay a fine that is in proportion to the subsidy and the overreported donations $s_m g_i^e \theta$. Under the match subsidy, the individual gets utility E_m if evasion is not detected and utility D_m if evasion is detected:

$$E_m = \alpha_i(I_i - g_i) + a\beta_i(g_i(1 + s_m) + s_m g_i^e, G_{-i}),$$

$$D_m = \alpha_i(I_i - g_i - s_m g_i^e \theta) + a\beta_i(g_i(1 + s_m), G_{-i})$$

Under the match subsidy, the expected utility of individual i becomes the following:

$$\max_{g_i, g_i^e} U_{i,m} = u_i(D_{i,m})\, p + u_i(E_{i,m})(1 - p) \tag{2.3}$$

subject to the reporting and non-negativity constraints:

$$g_i + g_i^e \leq I \text{ and } g_i,\ g_i^e,\ \lambda \geq 0. \tag{2.4}$$

I characterize the optimal levels of giving g^* and overreporting g^{e*} as functions of the parameters a, p, θ, and s_r under the rebate and s_m under the match in Appendix 2.A.1 and 2.A.2, respectively. In the following, I will state five propositions that lead to testable predictions:

Proposition 2.1. *The likelihood of an individual to evade under the match is smaller than under an equivalent rebate.*

Proof. See Appendix 2.A.3. □

The intuition for Proposition 2.1 is as follows. Under the rebate subsidy, individuals who prefer charitable giving over private consumption will donate, while individuals who prefer private consumption over charitable giving will either overreport, donate, or keep their income, depending on the parameters a, p, θ, and s_r. Under the match subsidy, individuals who prefer charitable giving over private consumption will also donate, while individuals who prefer private consumption over charitable giving will either overreport, donate, or keep their income. The marginal benefit of overreporting for individuals is relatively lower under the match than under the rebate, because of the following reason. Those individuals who decide to overreport prefer private consumption over charitable giving. While overreporting under the match does not increase private consumption (but the total amount of the charitable good), it increases private consumption under the rebate. As a consequence, more individuals keep their money under the match than under the rebate. Individuals who prefer charitable giving over private consumption under the match have a higher utility of overreporting than individuals who prefer charitable giving over private consumption under the rebate. However, individuals under the match who prefer charitable giving over private consumption donate rather than take a risk and overreport in favor of the charity, since the individual cannot report a donation higher than the income.

Proposition 2.2. *The likelihood of an individual to evade is weakly decreasing in the probability of detection p under the rebate and match.*

Proof. See Appendix 2.A.4. □

Individuals are less likely to evade if the probability of detection increases under both the rebate and match subsidy, because the marginal utility of evading decreases as the probability of detection increases. As a consequence of the increase in the probability of detection, individuals either substitute to donations or decide to keep their income.[8]

Proposition 2.3. *If there is evasion under the match and rebate, an increase in the probability of detection p leads to a larger reduction of evasion under the match than under the rebate.*

Proof. See Appendix 2.A.5. □

An increase in the probability of detection reduces the marginal utility of overreporting under the match and rebate. Since only individuals who prefer private consumption over charitable giving decide to

[8]If the marginal utility of overreporting is already negative, an increase in the probability does not have an additional effect on evasion, since the individuals either donate or keep their income.

overreport, the marginal utility of overreporting for those individuals who overreport is relatively lower under the match than under the rebate. Thus, it is more likely for an individual to stop overreporting under the match than under the rebate if the probability of detection increases.

Proposition 2.4. *The likelihood of an individual to evade is weakly decreasing in the rebate subsidy rate s_r and in the match subsidy rate s_m.*

Proof. See Appendix 2.A.6. □

An increase in the subsidy rate increases the marginal benefit of donations and the marginal benefit of overreporting. However, the increase in the marginal benefit of overreporting is relatively weaker than the increase in the marginal benefit of donations, since the utility gain of overreporting depends on the probability of detection. In addition, the fine the individual has to pay if overreporting is detected depends on the subsidy rate. As a result, an increase in the subsidy rate makes donations relatively more attractive than overreporting.[9]

Proposition 2.5. *If there is evasion under the match and rebate, an increase in the subsidy rate s_m leads to a larger reduction of evasion under the match than an equivalent increase in the subsidy rate s_r under the rebate.*

Proof. See Appendix 2.A.7. □

An increase in the subsidy rate increases the marginal benefit of donations and the marginal benefit of overreporting. Since only individuals who prefer private consumption over charitable giving decide to overreport, the marginal utility of overreporting for those individuals who overreport is relatively lower under the match than under the rebate. Thus, it is more likely for an individual to stop overreporting under the match than under the rebate if the subsidy rate increases.

The five propositions above lead to the following testable predictions:

Prediction 2.1. *There is less evasion under the match than under the rebate.*

If Prediction 2.1 is true and the differences in evasion under the rebate and match are severe, governments which make use of a rebate subsidy may consider a switch from a rebate to a match subsidy scheme, because a match subsidy may lead to the same amount of donations at a lower cost. Since I am also

[9] If the marginal utility of overreporting is already negative, an increase in the subsidy rate does not have an additional effect on overreporting, since the individuals either donate or keep their income.

interested in whether it makes sense for governments to spend a lot of money on programs to increase the probability of detection under the rebate and match subsidy, respectively, I test:

Prediction 2.2. *An increase in the probability of detection leads to a larger reduction of evasion under the match than under the rebate.*

Finally, I am interested in the implications of an increase in the match and rebate subsidy rate, respectively, with respect to evasion. That is, I would like to know whether it is useful for governments to make use of high rebate and match subsidies, respectively, and thus, I test:

Prediction 2.3. *An increase in the subsidy rate reduces evasion under the match and the rebate, where the increase in the subsidy rate leads to a larger reduction of evasion under the match than under the rebate.*

2.3 Experimental Design

Design Overview Each session of the experiment consisted of four independent parts. In the first two parts of the experiment, the subjects could donate money to a well-known charity organization they chose at the beginning of the experiment from a list of ten charities with a brief description of the services each provides. As the donations were subject to either a match or rebate subsidy, the experiment had two treatments. In the first part of the experiment, called the allocation part, I elicited the subjects' willingness to donate to charities. In the allocation part, the subjects did not have the option to overreport the donation. In the second part, called the reporting part, I elicited the subjects' willingness to overreport donations to charities. In the reporting part, the subjects could first donate money to their previously chosen charity and were then required to self-report their donation. The subjects had an incentive to overreport their donations as this would have increased their subsidy.

Since the donations of the subjects were either subject to a rebate or a match subsidy, I made use of a between-subject design. However, the level of the subsidy and the probability of an audit varied within the subject. In the rebate treatment, the subject received a subsidy for the donation s_r of either 20 %, 50 %, or 75 %. In the match treatment, the charity received a subsidy s_m of either 25 %, 100 %, or 300 %, since the match subsidy and the rebate subsidy imply the same net cost of giving if $s_m = s_r/(1 - s_r)$. For instance, if the rebate subsidy was 50 %, and the subject donated €10 to the charity, the donation effectively only cost €5: the €10 donation minus the €5 rebate. Equivalently, if the match subsidy was 100 %, and the subject donated €5, the charity organization received €10: the donation of €5 plus the

€ 5 match. As the price of giving one euro to charity was either € 0.80, € 0.50, or € 0.25, my experimental design is more salient than Eckel and Grossman (2003) and Blumenthal et al. (2012), where the price was either € 0.80, € 0.75, or € 0.50.

The order of the allocation and the reporting part varied across sessions. Moreover, either the first or the second part of the experiment was paid in order to avoid income effects that may influence the decision to donate in the respective second part of the experiment. Both the variation of the order of allocation and reporting parts and the avoidance of income effects are in opposition to the experiment on tax evasion related to giving by Blumenthal et al. (2012). The allocation and reporting part were completely unrelated otherwise. At the end of the experiment, the subjects drew a chip to determine whether the first or second part of the experiment was relevant for the payoff of the subject and the charity. In general, I did not inform the subjects about their payments in the respective parts of the experiment until the end of the experiment.

I also elicited risk preferences and social preferences in the third and fourth part of the experiment, respectively, where the preference elicitation was incentivized. Risk preferences were elicited by making use of the lottery by Holt and Laury (2002). I elicited social preferences by using the Social Value Orientation Slider by Murphy et al. (2011). At the end of the experiment, the subjects answered a questionnaire, where I asked demographic and motivational questions very similar to Tan and Yim (2014) and Eckel and Grossman (2003) (e.g. age, income, gender). Moreover, the subjects performed the Machiavelli personality test developed by Christie and Geis (1970), which tries to detect cynical and manipulative behavior, and emotional detachment of individuals. The subjects had to show their level of agreement to statements like "One should take action only when sure it is morally right" at the Machiavelli test. The subjects received € 3 for finishing the questionnaire. The responses of the preference elicitation tasks and the questionnaire were used as control variables in the regressions analysis in Section 2.4.[10] The experiment was programmed and conducted in zTree (Fischbacher 2007). Since it was a one-shot experiment, the subjects had to show their clear understanding of the instructions of each part of the experiment. In order to avoid anchoring, the subjects had to answer control questions with randomly generated numbers on the computer.[11] I checked, for example, whether the subjects were able to determine their payments. A brief overview of the experimental design is given in Table 2.1. The instructions of the rebate treatment, questionnaire, and Machiavelli test can be found in Appendix 2.5.

[10] Blumenthal et al. (2012) neither elicit risk nor social preferences and further, do not make use of a Machiavelli test.

[11] The subjects were informed that the numbers were randomly generated.

Table 2.1: Summary of treatments

Task	Rebate treatment	Match treatment
Allocation part		
Price of giving €1	€0.80, €0.50, or €0.25	€0.80, €0.50, or €0.25
Reporting part		
Price of giving €1	€0.80, €0.50, or €0.25	€0.80, €0.50, or €0.25
Probability of detection	4 %, 50 %	4 %, 50 %
Number of subjects	47	42

Notes: In the *allocation part* I test the willingness to donate to charities in the absence of the possibility to overreport the donation. Each subject made three decisions in the *allocation part*, since the price of giving one euro to the charity was either €0.80, €0.50, or €0.25. In the *reporting part* I test the willingness to overreport donations to charities. Each subject made first three decisions to donate and then six decisions to report the donation in the *reporting part*, since the price of giving one euro to the charity was either €0.80, €0.50, or €0.25, and since the probability that the experimenter checked the report was either 4 % or 50 %.

Allocation Part In the allocation part I try to replicate the experiment by Eckel and Grossman (2003) and find out the willingness to donate to charities in the absence of the possibility to overreport the donation. Eckel and Grossman (2003, 2006) and others show that subjects perceive theoretically equivalent match and rebate subsidies differently. In particular, subjects are more likely to increase their donations in response to an increase in the match subsidy than in response to an increase in the rebate subsidy. In the allocation part, the subjects allocate an endowment of €30 between themselves and a self-chosen charity and divide their endowment similar to a dictator game as in Eckel and Grossman (2003).[12] Since each subject faced three subsidies rates in a random order, each subject made three decisions in the allocation part. I framed the subsidy neutrally, because I think that using neutral framing potentially decreases the differences in the rebate and match price elasticities. That is, instead of using the phrases by Eckel and Grossman (2003, 2006) "the experimenter will refund to you" and "the experimenter will match it", I wrote "the experimenter will give to you" and "the experimenter will give to the charity". If this part of the experiment was relevant for the payment, the subjects drew a chip to determine which

[12] I increased the endowment I of the first two parts of the experiment from €20 in the first and second session to €30 in later sessions, since the experiment took a bit longer as initially expected. I control for the level of endowment in all my regressions.

of the three problems of the allocation part was taken to determine the payoff of the subject and the charity.

Reporting Part In this part of the experiment I elicit the subjects' willingness to overreport donations to charities under the match and rebate subsidy, respectively. First, the subjects made three decisions to allocate an endowment of €30 between themselves and a self-chosen charity exactly like in the previously described allocation part. Second, the subjects reported the three allocations made. More precisely, each subject made first three decisions to donate and then six decisions to report the donation in the reporting part as the price of giving one euro to the charity was either €0.80, €0.50, or €0.25, and the probability that the reported donation was audited was either 4 % or 50 % (see Table 2.1).[13] Each subject faced the different prices of giving and the different probabilities in a random order. At the end of the experiment, the subjects drew a chip numbered from 1 to 100 which determined whether their report about the allocation was audited or not. For instance, the report was audited if the drawn chip number was lower than or equal to 4 if the probability of detection was 4 %. If the report was not audited, the subsidy was based on the reported donation. If the report was audited, the subsidy was based on the actual amount the subject decided to donate to the charity.[14] If the report was audited and the subjects overreported the actual donation, the subject had to pay a 30 % penalty of the evaded amount, which is the subsidy rate times the overreported donation.[15] As it is common in the tax evasion literature, the experiment uses neutral wording (compare for example Alm et al. 1992). For example, instead of using the terms 'audit' and 'report', I used the terms 'check' and 'inform'. The subjects are informed that the experiment is funded by the Vienna Center for Experimental Economics (VCEE), which is a public institution of the University of Vienna. If this part of the experiment was relevant for the payment, the subjects drew a chip to determine which of the six problems of the reporting part was taken to determine the payoff of the subject and the charity.

[13] In order to decrease the complexity of the experiment, the probability of an audit is exogenously given. In practice, taxing authorities may make use of both randomized audits (e.g. Taxpayer Compliance Measurement Program of the IRS in the USA) and audits as a result of deviations from the reports of others (see for instance, the discussion in Andreoni et al. 1998).

[14] This means that the subject will get more money if his or her report is audited and the subjects decides to underreport the donation in comparison to the case where the underreported donation is not audited. This is in line with the Austrian tax regulation according to communication with an employee of the Austrian ministry of finance.

[15] The fine rate in the experiment by Blumenthal et al. (2012) was, at 200 %, considerably higher than in this study. Taxpayers in the USA have to pay a penalty that is between 20 % and 40 % if they overreport the value of a property and the evaded amount is more than $ 5,000 (IRS 2013).

Elicitation of Risk and Social Preferences In order to control for different risk-preferences of the subjects, I elicited the risk preferences by following the instructions of Holt and Laury (2002). The subjects saw a table with a list of ten choices between two lotteries. In each of the ten rows, the subjects had the choice between lottery A, where they could earn either €2.00 or €1.60, and lottery B, where they could earn either €3.85 or €0.10. The subjects indicated the option they prefer by either clicking on lottery A or lottery B with the understanding that if they clicked on lottery A or lottery B in any row, all rows above the selected row were automatically selected as lottery A to count as their choice, and all rows below the selected row were automatically selected as lottery B to count as their choice. At the end of the experiment, each subject drew two chips to determine which of the ten choices is chosen for the payment and to determine the probability that decides whether the subject receives the higher or lower payoff.

I measured social preferences by using the Social Value Orientation slider by Murphy et al. (2011).[16] Each subject made six decisions about allocating money between herself and another subject. The subjects were paired in the following way. A subject, say subject SELF, was randomly matched with another subject, say subject A. Subject A was randomly matched with somebody else, namely subject B. At the same time, subject C, who was neither subject A nor subject B, was matched with subject SELF. The choices of the subjects were completely confidential (for more details see the instructions in Appendix 2.C).

Double Anonymity As the subjects should not feel observed by the experimenter, I implemented a double anonymous design, which is in contrast to Blumenthal et al. (2012).[17] This was done as follows. The subjects drew an ID number from a bag when entering the lab. In each session, one subject was chosen to be the monitor. The monitor verified that the instructions of the experiments were followed. An assistant, who was not one of the subjects, helped the monitor and answered the questions of the subjects. Both the monitor and the assistant were located in the room where the experiment was conducted and did not leave this room until the end of the experiment. The experimenter, who was responsible for preparing the payment of the subjects and the charities, was not located in the room where the experiment was conducted. The monitor, the assistant, and the experimenter were not able to relate the decisions and the payoffs to any particular subject for the following reasons. First, the monitor only saw the subjects'

[16] I made partial use of the z-Tree code provided by Crosetto et al. (2012).

[17] Double anonymous procedures are common in the experimental tax evasion literature (see for example, Alm et al. 2010).

IDs and names (and not the payoffs of the subjects).[18] Second, the assistant neither saw the ID numbers and names of the subjects nor the payoffs of the subjects. Third, the experimenter did not face the subjects at all. The subjects were clearly informed about the role of the monitor, the assistant, and the experimenter. The anonymity of the subjects towards all persons in the lab was also insured when the subjects confirmed their payment, because the monitor distributed the earnings in a sealed envelope which was labeled on the front with the ID number. The subjects took the money out of the envelope and received a receipt where they confirmed with their signature on the back of the receipt to have received the amount earned in the experiment indicated on the front side of the receipt. The monitor checked the signature, but the monitor did not see the front side of the receipt. That is, the monitor did not know how much money the subject earned. After the monitor had checked the receipts, the subjects put the signed receipt in new envelopes. Finally, the monitor and the experimenter walked to the nearest mailbox and dropped the envelopes in the mailbox for the receipts to be sent to the accounting department of the University of Vienna in accordance with bookkeeping regulations.[19]

Main Features In contrast to previous studies that have compared donations under the match and rebate subsidy, I used a more salient and neutral framing of the subsidy. Either the first or the second part of the experiment was paid in order to avoid income effects that may influence the decision to donate or overreport in the second part of the experiment. Also, the order of the allocation part and reporting part varied across sessions in order to control for order effects. In order to find out the determinants of evasion, I created a very comprehensive dataset by eliciting the subjects' willingness to donate in the absence of the possibility to overreport, by eliciting risk and social preferences, and by including a comprehensive questionnaire. Since it was a one-shot experiment, and in order to avoid anchoring, the subjects had to show their understanding of the instructions of each part of the experiment by answering control questions with randomly generated numbers. Finally, I implemented a double anonymous design, because I did not want the subjects to feel observed by the experimenter and by the monitor.

[18]The monitor also saw the confirmations of the aggregated online transfers to the charitable organizations, whereas the monitor did not know the donation of the individual subject. Even in the hypothetical case that nobody had donated any money to the charity, the monitor could have not drawn the conclusion that the subjects decided to donate nothing, since only one decision of either the allocation or reporting part determined the payment of the subject and the respective charity.

[19]The details of the double anonymous procedure are explained in the instructions of the experiment (see Appendix 2.C).

2.4 Experimental Results

The experimental results are presented as follows. Section 2.4.1 shows the sample descriptives. I show the levels of donations and estimate price elasticities of donations under the match and rebate subsidy in Section 2.4.2. More importantly, Section 2.4.3 gives an overview of the levels of overreporting under the two treatments and tests the predictions presented in Section 2.2.

2.4.1 Sample Description

In total 100 subjects entered the laboratory, eight out of these were chosen as monitors in the respective sessions, and three subjects left the laboratory before the experiment finished. The average age of a subject was over 26.[20] Roughly 60 % of the subjects were male. The subjects were on average risk-averse according to Holt and Laury (2002) and individualistic according to the Social Value Orientation slider by Murphy et al. (2011). Almost two thirds of the subjects came from the European Economic Area (EEA) and Switzerland. The sample is described in Table 2.2. In general, most subjects found that the instructions of the respective parts were clearly formulated and believed that the donated money was sent to the selected charities (see Table 2.10 in Appendix 2.B).

2.4.2 Donations

In this section, I first compare the levels of donations under the two treatments, and then estimate price elasticities of donations. Figures 2.1 and 2.2 show the distributions of the checkbook donations (i.e. the amount the subjects give out of their endowment) under the rebate and match subsidy, respectively. Roughly 20 % of the subjects do not donate in the rebate treatment, whereas less than 9 % do not donate in the match treatment. Furthermore, only one subject in the rebate treatment and two subjects in the match treatment give their full endowment. Out of these three subjects, a subject in both the rebate and match treatment gives the full amount under the endowment of €20 in the first two sessions of the experiment.

[20] The oldest subject was 57 years as the experiment was not only open to students.

Table 2.2: Description of the sample

Subject characteristics ($n = 89$)	Mean	Std. Dev.	Min	Max
Age	26.51	5.46	18	57
Male	0.61	0.49	0	1
Holt and Laury switch	7.83	2.36	1	11
SVO angle	18.64	13.36	−7.8	61.4
Machiavelli score	79.70	13.69	45	115
Nationality				
Austria	27 %			
Other EEA and Switzerland	38 %			
Third countries	35 %			

Notes: *Holt and Laury switch* reflects risk preferences and indicates the switch to the more risky option in the task of Holt and Laury (2002). *SVO angle* reflects social preferences and indicates the measured angle of the Social Value Orientation slider by Murphy et al. (2011). Murphy et al. classify subjects as altruists if the SVO angle is larger than 57.15°, as prosocial if the angle is between 57.15° and 22.45°, as individualistic if the angle is between 22.45° and −12.04°, and as competitive if the angle is lower than −12.04°. *Machiavelli* indicates the score achieved by the test developed by Christie and Geis (1970). A high score reflects a more cynical and manipulative behavior, and emotional detachment of the subject. *Nationality* indicates the nationality of the subject. *Other EEA* are the countries of the European Economic Area other than Austria. *Third countries* are the countries outside of the EEA and Switzerland.

Figure 2.1: Distribution of checkbook donations in the rebate treatment

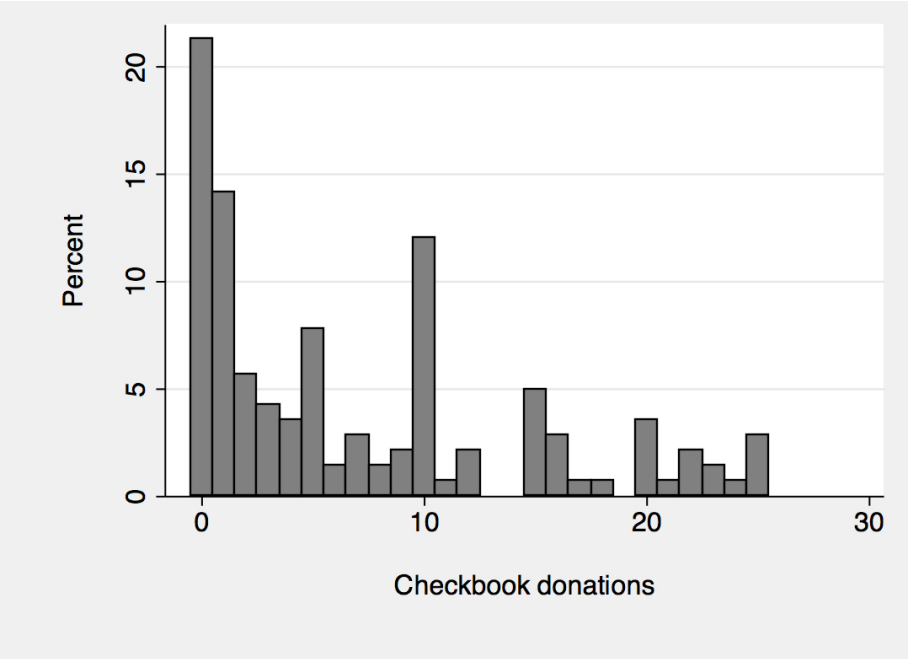
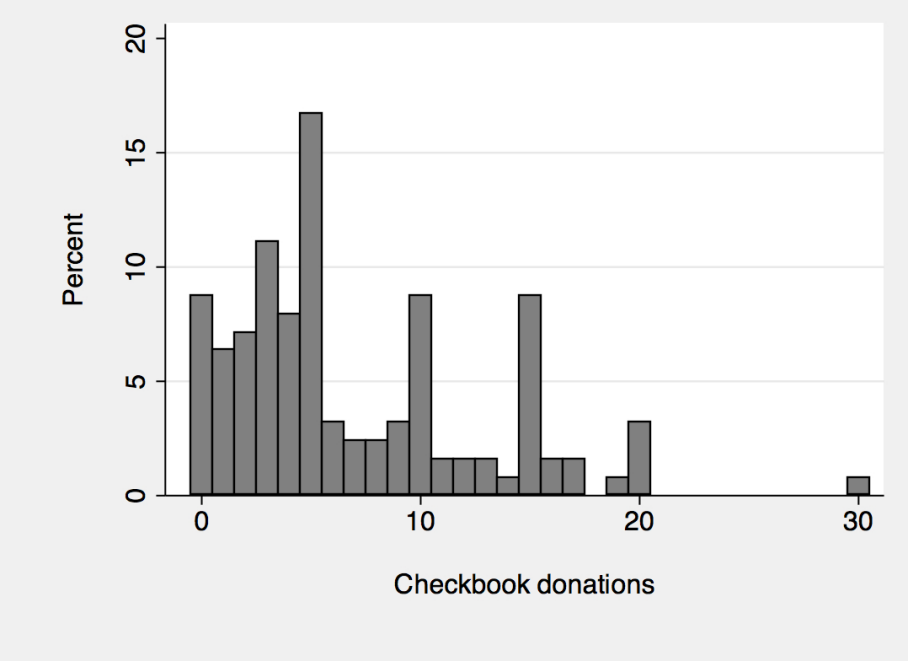


Figure 2.2: Distribution of checkbook donations in the match treatment



In Table 2.3, I compare total charitable contributions under a rebate and match, where the total contribution is the amount the charity receives because of the donation. Under the rebate subsidy, the total contribution is equal to the amount the subject decides to donate. Under the match subsidy, the total contribution is equal to the amount the subject decides to donate times the subsidy rate. Column (1) of Table 2.3 shows the three subsidy levels each subject faced in the allocation part. Columns (2) and (3) show the total contributions of the subjects under the rebate and match, respectively. In column (2) of the first row of Table 2.3 we see that if the price of giving one euro to the charity is €0.80, the total contribution of the subjects in the rebate treatment is on average €5.64, while in column (3) of the first row of Table 2.3 we see that the total contribution of the subjects in the match treatment is on average €7.57. If the price of giving one euro to the charity is €0.25, the charities receive €8.67 under the rebate and €30.87 under the match. In line with Eckel and Grossman (2003), I find that more money is going to the charity organizations under the match than under the rebate subsidy under any price of giving, where the difference between the two subsidies is at least weakly significant (see the p-values of the t test and the Kolmogorov-Smirnov tests in columns (4) and (5) of Table 2.3).[21] The difference between the subsidies is especially high if the price of giving one euro is low. In other words, the higher the level of

[21] When comparing the mean under the rebate and match in column (4), I use a one tailed t test, where I do not assume equal variances under the rebate and match. When comparing the distribution under the rebate and match in column (5) of Table 2.3, I use a Kolmogorov-Smirnov test, since the Mann-Whitney U test has only little power if a lot of observations take the value zero.

the subsidy, the larger the difference under the match and rebate.

Table 2.3: Total contributions to charities

	Observed donations			
(1) Price of giving €1 to charity	(2) Rebate	(3) Match	(4) Equal means p-value	(5) Equal distributions p-value
€0.80	€5.64 (0.93)	€7.57 (1.08)	0.089	0.073
€0.50	€6.71 (1.01)	€14.08 (1.63)	0.000	0.004
€0.25	€8.67 (3.97)	€30.87 (1.23)	0.000	0.000
	$n = 47$	$n = 42$		

Notes: Standard errors in parentheses. n indicates the number of observations under a given price (e.g. €0.80). I compare total contributions under a rebate and match, where the total contribution is the amount the charity receives because of the donation. Under the rebate subsidy, the total contribution is equal to the amount the subject decides to donate. Under the match subsidy, the total contribution is equal to the amount the subject decides to donate times the subsidy rate.

To estimate price elasticities of donations I make use of a tobit model:

$$\ln(donations)_{ij} = \alpha + \beta_1 rebate_i + \beta_2 \ln(price)_j + \beta_3 \left(\ln(price) \times rebate\right)_{ij} + X_i'\gamma + u_{ij}, \tag{2.5}$$

where i is the index of subjects and j is the index of allocation decisions. The variable *rebate* takes the value 1 if the subject faces a rebate subsidy and the value 0 if the subject faces a match subsidy. I control for the price of giving €1 to the charity, which is $1 - s_r$. X is a vector of individual characteristics, including risk preferences, the Machiavelli score, a variable that indicates whether the subjects started with the allocation or the reporting part, age, gender and endowment of the subjects, and dummies for charities. The dependent variable in columns (1) and (2) of Table 2.4 is the total contribution in the allocation part. The dependent variable in column (3) of Table 2.4 is the actual total contribution made in the reporting part. In other words, the dependent variable in column (3) is the true total contribution of the reporting part (i.e. not the reported donation).[22]

[22]Since I would like to estimate price elasticities and the logarithm of zero is not defined, I add 10 cents to the

Table 2.4: Total contributions, marginal effects of a random effects tobit model

Dependent Variable:	(1) Allocation Part ln(Contribution+0.1)	(2) Allocation Part ln(Contribution+0.1)	(3) Reporting Part ln(Contribution+0.1)
Rebate	0.070	0.239	0.461
	(0.648)	(0.634)	(0.705)
ln(Price)	−1.375***	−1.393***	−1.466***
	(0.136)	(0.137)	(0.156)
ln(Price) × Rebate	1.030***	1.046***	0.918***
	(0.190)	(0.192)	(0.217)
Male	−0.694*	−0.454	−0.530
	(0.377)	(0.374)	(0.417)
Machiavelli		−0.047***	−0.033*
		(0.015)	(0.017)
Other controls	Yes	Yes	Yes
Observations	267	267	267
Log Likelihood	−384	−379	−409

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Marginal effects are evaluated at the means. A random effect tobit model is estimated in columns (1) to (3). The dependent variable in columns (1) and (2) is the total contribution of the allocation part, which is the amount the charity receives because of the donation. The dependent variable in column (3) is the total contribution of the reporting part, which is the actual amount the charity receives because of the donation and not the reported amount. Under the rebate subsidy, the total contribution is equal to the amount the subject decides to donate. Under the match subsidy, the total contribution is equal to the amount the subject decides to donate times the subsidy rate. In column (1) I control for age, gender, and the initial endowment. In column (2) and (3) I also control for risk preferences and whether the experiment started with the allocation or reporting part. I include a constant, and dummies for charities and sessions in all regressions.

From the second row of Table 2.4 we see that the match price elasticities of donations range from −1.38 to −1.46, while from adding the second to the third row we get that the rebate price elasticities range from −0.34 to −0.55.[23] The price elasticities that I find are in line with the literature (see Huck and Rasul 2011).[24] For instance, Eckel and Grossman (2003) find match and rebate price elasticities of

dependent variable. I chose 10 cents in order to be comparable to Eckel and Grossman (2003). If I add for instance 50 cents instead of 10 cents to the dependent variable, my results are hardly affected and my main findings are still the same.

[23]If I use a Wilcoxon signed-rank test to compare the total contributions in the allocation part and the (true) total contributions in the reporting part, I cannot reject the null hypothesis that the distributions of total contributions in the allocation part and reporting part are the same (p value is above the 10 % levels under any price of giving).

[24]Many subjects in the experiment do not adjust their donations if the level of the subsidy increases, which was also found by Scharf and Smith (2015), for instance. If the rebate subsidy rate increases, 37 % of the subjects do not adjust their donations. If the match subsidy rate increases, 20 % do not adjust their donations.

-1.07 and -0.34, respectively, while Blumenthal et al. (2012) estimate slightly lower match and rebate elasticities of -0.75 and -0.23, respectively. It is not surprising that the elasticity of donations in my study increases if the subjects also have the possibility to evade (column (3) of Table 2.4). A higher subsidy makes donations relatively more attractive than evasion, and thus there is a substitution from evasion to donations. The neutral wording of the subsidy may not be a very relevant determinant of the rebate and match price elasticity, respectively, because the price elasticities in columns (1) and (2) of Table 2.4 are very similar to the findings of Eckel and Grossman (2003). That is, not framing the match and rebate subsidy does not decrease the difference between the match and rebate price elasticities.

Men donate smaller amounts, which is also in line with previous findings (e.g. Eckel and Grossman 2003). However, the coefficient loses its weak significance if I include additional control variables to the variables from Eckel and Grossman (2003) (see columns (2) and (3) Table 2.4). Whether the experiment started with the allocation or reporting part does not have a significant impact on donations (see full Table 2.11 in Appendix 2.B). Finally, those with low Machiavelli scores donate significantly higher amounts than those with high Machiavelli scores. In other words, subjects who are more cynical and emotionally detached according to the Machiavelli test by Christie and Geis (1970) donate smaller amounts. To summarize, the findings with respect to the true donations are in line with Eckel and Grossman (2003). However, the main focus of this chapter is to determine whether charitable giving is used to evade taxes and if so, what are the differences under the rebate and the match subsidy?

2.4.3 Evasion

In this section, I first compare the levels of overreporting under the two treatments, and then estimate price elasticities of overreported donations. In Table 2.5 I test whether the level of overreporting under the rebate subsidy is higher than under the match subsidy, since the subsidies create different incentives to evade (see Prediction 2.1). *Panel A* of Table 2.5 considers the decisions where the subjects underreport, overreport, and report the donation correctly, while *Panel B* only considers the subset of decisions where the subjects overreport. For instance, in column (3) of the first row of *Panel A* of Table 2.5 we see that if the price of giving one euro to the charity is €0.80 and the probability of detection is 4 %, the subjects in the rebate treatment overreported on average €9.08, while we see in column (4) that the subjects in the match treatment overreported on average €6.84. If the price of giving one euro decreases to €0.25 and the probability of detection increases to 50 %, the level of overreporting under the rebate is still €6.87, while the level of overreporting under the match shrinks to €0.76. A comparison of column (3)

Table 2.5: Levels of overreporting

		Observed overreporting			
(1) Price of giving €1 to charity	(2) Probability of detection	(3) Rebate	(4) Match	(5) Equal means p-value	(6) Equal distributions p-value
Panel A: All decisions					
€0.80	4 %	€9.08	€6.84	0.168	0.696
		(1.74)	(1.54)		
€0.80	50 %	€8.52	€5.10	0.069	0.341
		(1.78)	(1.45)		
€0.50	4 %	€7.67	€2.50	0.002	0.014
		(1.61)	(0.67)		
€0.50	50 %	€7.91	€2.23	0.002	0.046
		(1.74)	(0.77)		
€0.25	4 %	€6.12	€2.49	0.027	0.016
		(1.58)	(0.96)		
€0.25	50 %	€6.87	€0.76	0.000	0.015
		(1.67)	(0.35)		
		$n = 47$	$n = 42$		
Panel B: Conditional on overreporting					
€0.80	4 %	€19.77	€12.84	0.010	0.026
		(1.97)	(2.07)		
		$n = 22$	$n = 23$		
€0.80	50 %	€18.77	€12.39	0.033	0.022
		(2.30)	(2.47)		
		$n = 22$	$n = 18$		
€0.50	4 %	€17.86	€5.73	0.000	0.000
		(1.95)	(1.07)		
		$n = 21$	$n = 19$		
€0.50	50 %	€17.03	€6.11	0.000	0.003
		(2.33)	(1.61)		
		$n = 23$	$n = 16$		
€0.25	4 %	€16.12	€6.22	0.001	0.001
		(1.93)	(2.08)		
		$n = 20$	$n = 17$		
€0.25	50 %	€17.64	€2.98	0.000	0.000
		(2.61)	(1.11)		
		$n = 19$	$n = 11$		

Notes: Standard errors in parentheses. n indicates the number of observations under a given price (e.g. €0.80) or probability (e.g. 4 %). I compare the level of overreporting under a rebate and match, where overreporting is the reported donation minus the actual amount donated. *Panel A* considers the decisions where the subjects underreport, overreport, and report the donation correctly. *Panel B* considers only the subset of decisions where the subjects overreport.

and (4) of Table 2.5 shows that the level of overreporting under the rebate is always higher under the rebate than under the match. Column (5) of *Panel A* of Table 2.5 shows that the null hypothesis that the level of overreporting is higher under the match than under the rebate is rejected under any given price and probability by using one tailed t tests except in the case where the price of giving is €0.80 and the probability of detection is 4 %. If I compare the distribution of overreporting under the match and the rebate by using Kolmogorov-Smirnov tests, I find significant differences between the subsidies unless the price of giving is €0.80 (see column (6) of *Panel A* of Table 2.5).[25] If I only consider the subset of decisions where the subjects overreport in *Panel B* of Table 2.5, I reject the null hypothesis that the level of overreporting is higher under the match than under the rebate under any combination of the price of giving and the probability of detection. We see in column (3) of the first row of *Panel B* of Table 2.5 that if the price of giving is €0.80 and probability of detection is 4 %, the average level of overreporting was €19.77 in the rebate treatment, while we see in column (4) that the average level of overreporting was only €12.84 in the match treatment. Also, the distribution of overreporting under the match and the rebate subsidy differs significantly if I make use of Mann-Whitney U test (see column (6) of *Panel B* of Table 2.5). The finding of higher levels of overreporting under the rebate than under the match is in line with Prediction 2.1.[26]

In order to estimate price elasticities and to find out more about the determinants of evasion, I run several regressions. To estimate whether subjects evade ($evade_{ij} = 1$) or report honestly ($evade_{ij} = 0$) I make use of a probit model:

$$\begin{aligned} evade_{ij} &= \alpha_1 + \beta_1 rebate_i + \beta_2 prob_j + \beta_3 \left(prob \times rebate\right)_{ij} + \\ &\quad \beta_4 \ln(price)_j + \beta_5 \left(\ln(price) \times rebate\right)_{ij} + X'_{ij}\gamma_1 + u_{ij}, \end{aligned} \tag{2.6}$$

where j is the index of reporting decision, X is a vector of other control variables, including risk preferences, social preferences, the Machiavelli score, a variable that indicates the nationality of the subject,

[25] Karlan et al. (2011) argue that optimal match may be at or below a price of giving of €0.50, whereas a lower price of giving than €0.50 may only lead to more donations among certain donors and presentations. In these situations described to be optimal by Karlan et al. (2011), the distributions of overreporting are significantly different under the rebate and match.

[26] If I compare whether the subjects overreported, underreported, or exactly reported the donation by using Fisher's exact test, I only find a significant difference in reporting behavior between the rebate and match subsidy if the probability of detection is 50 % and the price of giving is either €0.50 or €0.25 (see Table 2.12 in Appendix 2.B). This means that the differences between the match and rebate found in Table 2.5 are more likely due to the different *levels* of overreporting (see *Panel B* of Table 2.5) and less likely due to the decision whether to overreport or not.

the donations from the allocation part, and other control variables mentioned before.[27] The two-part hurdle model introduced by Cragg (1971) is useful if the decision whether to evade ($evade_{ij} = 1$) or not ($evade_{ij} = 0$) differs from the decision of how much to overreport (i.e. choice of the level of overreporting given that $evade_{ij} = 1$). For example, if an increase in the price of giving has no effect on the decision whether to overreport or not, but a strong effect on the level of overreporting, I am able to identify these different effects with a hurdle model. The first stage of the hurdle model is given by the probit model shown in equation (2.6). In the second stage of the hurdle model, I condition overreporting on positive amounts of overreporting and I assume that overreporting is log normally distributed (see Wooldridge 2010):

$$\begin{aligned} \ln(overreport)_{ij} &= \alpha_2 + \delta_1 rebate_i + \delta_2 prob_j + \delta_3 \left(prob \times rebate\right)_{ij} + \\ &\quad \delta_4 \ln(price)_j + \delta_5 \left(\ln(price) \times rebate\right)_{ij} + X'_{ij}\gamma_2 + v_{ij} \quad \text{for } evade_{ij} = 1. \quad (2.7) \end{aligned}$$

Since overreporting is limited to €30, I estimate the second stage of the hurdle model shown in equation (2.7) by making use of a tobit model. Finally, I run a tobit model and make use of both decisions where the subjects decided to overreport and the decisions where the subjects decided not to overreport by estimating equation (2.7) with the condition $overreport_{ij} \geq 0$.[28] The results of the tobit estimation in Table 2.6 allow me to estimate price elasticities and the sensitivity to an increase in the probability of detection.[29] First, the likelihood ratio statistics indicate that the random effects models are preferable to ordinary logit and tobit models, respectively, since I reject the null hypothesis that the subject-specific effects are the same across subjects (shown in columns (1) to (3) at the bottom of Table 2.6).[30] Second,

[27] To predict evasion, Blumenthal et al. (2012) are not able to use donations from the part of their experiment where subjects do *not* have the opportunity to overreport as control variable. The reason is that subjects in Blumenthal et al. (2012) did not face the same subsidy rates in the part of the experiment where subjects had to possibility to overreport and the part were subjects did not have the possibility to overreport.

[28] Since the logarithm is only defined for positive values, I do not allow for underreporting and add 10 cents to the level of overreporting in my regressions. That is, the dependent variable takes the value ln(0.1) if a subject is not overreporting.

[29] To shorten the tables, I do not report all controls in Table 2.6. The full estimations of equations (2.6) and (2.7) are shown in Table 2.13 in Appendix 2.B.

[30] I make use of a random effects model, since I want to control for variables that do not vary within the individual (e.g. risk preferences), and since there exists no fixed effects tobit model. My main findings are still the same if I use a fixed effect logit model instead of the random effect probit model of Table 2.6, and if I use linear fixed effects models instead of the random effects tobit models of Table 2.6. I cannot reject the null hypothesis that the coefficients for the price and probability under the match and rebate of the random effects models of Table 2.6 and the fixed effects models are different (p values of two-sided t tests are always larger than 0.48). Similarly, if I perform a Hausman test, I cannot reject the null hypothesis that both the random effect probit estimators of column (1) of Table 2.6 and the fixed effect logit estimators are consistent. In short, the random effects estimators used in Table 2.6 and the fixed effects estimators produce very similar results.

Table 2.6: Overreporting, marginal effects of random effects models

Dependent Variable:	(1) PROBIT Evade	(2) HURDLE ln(Overreport+0.1)	(3) TOBIT ln(Overreport+0.1)
Rebate	22.00***	−6.59	46.81***
	(6.20)	(9.00)	(10.86)
Probability	−0.483***	−0.467*	−0.973***
	(0.185)	(0.272)	(0.347)
Probability × Rebate	0.518**	0.213	1.057**
	(0.249)	(0.383)	(0.470)
ln(Price)	0.258***	0.869***	0.655***
	(0.093)	(0.139)	(0.179)
ln(Price) × Rebate	−0.187	−0.499**	−0.461*
	(0.122)	(0.193)	(0.236)
Male	0.272	0.154	0.776**
	(0.166)	(0.209)	(0.386)
Donation Allocation Part	−0.009	−0.035***	−0.033*
	(0.008)	(0.012)	(0.018)
Rebate versus Match z Test	1.91*	2.44**	2.15**
Other Controls	Yes	Yes	Yes
Observations	534	231	534
Log Likelihood	−216	−948	−677
Likelihood Ratio Test	96.07***	13.91***	167.2***

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Marginal effects are evaluated at the means. A random effect probit model is estimated in column (1), where the dependent variable is equal to one if the subject overreports the donation, and zero otherwise. A random effect tobit model is estimated as the second stage of a lognormal hurdle model in column (2). A random effect tobit model is estimated in column (3). The dependent variable in columns (2) and (3) is the level of overreporting, where overreporting is the reported donation minus the actual amount donated. All analyses include controls for social and risk preferences, the Machiavelli score, initial endowment, whether the experiment started with the allocation or reporting part, the nationality of the subjects. I include a constant, and dummies for charities and sessions in all regressions. The z test statistic tests the null hypothesis that overreporting is the same under the match and the rebate subsidy. The likelihood ratio statistic tests the null hypothesis that each subject has the same individual effect.

in line with Prediction 2.1, the regression analysis confirms the finding of Table 2.5 that the level of overreporting under the rebate is significantly higher than the level under the match (shown at the bottom of Table 2.6):

Result 2.1. *The level of overreporting under the rebate subsidy is higher than under the match subsidy.*

Probability of Detection An increase in the probability of detection leads to significantly less overreporting under the match subsidy. An increase in the probability of detection by ten percentage points under the match subsidy decreases the likelihood of overreporting by 4.83 % (see column (1) of Table 2.6) and the levels of overreporting in the subset of decisions where the subjects overreport by 4.67 % (see column (2) of Table 2.6), and by 9.73 % in the tobit estimation (see column (3) of Table 2.6). The effect of the probability under the rebate is obtained by adding the coefficient of the interaction term of the probability and the rebate dummy to the coefficient of the probability. In my study, the probability has no significant effect on compliance under the rebate subsidy, but the effect of the probability under the match subsidy is significantly negative:

Result 2.2. *A higher probability of an audit under the rebate subsidy has no significant effect on overreporting, whereas a higher probability under the match has a strong negative effect on overreporting.*

Subjects facing the match subsidy are less willing to bear the higher expected costs of evasion if the probability increases than subjects facing the rebate subsidy. The effect of the probability under the match subsidy in my experiment is in line with Prediction 2.2 and findings from the income-tax literature (see Alm 2012). Even though Prediction 2.2 states a negative effect for both the rebate and match subsidy, it also predicts that the increase in the probability leads to a larger reduction of evasion under the match than under the rebate subsidy. As the interaction term of the probability and the rebate dummy is positive and significant in the probit and tobit model in columns (1) and (3) of Table 2.6, I have some evidence for Prediction 2.2. In comparison, Blumenthal et al. (2012) find the probability of detection has a negative impact on overreporting both under the match and rebate subsidy, where the probability in their study was either 0 %, 10 %, or 50 %. In contrast to Blumenthal et al. (2012), my study estimates higher differences in overreporting as the probability increases (in line with Prediction 2.2).

Price Elasticities Column (1) of Table 2.6 shows that the price elasticity of overreported donations under the match is 0.26 for the binary decision to evade or not; column (2) shows that the price elasticity is 0.87 in the second stage of the hurdle model for those decisions where the subjects decide to evade;

and column (3) shows that the price elasticity 0.66 in the tobit model. The rebate price elasticity of overreported donations is obtained by adding the coefficient of the price in row 4 of Table 2.6 to the coefficient of the interaction term of the price and the rebate dummy in row 5. The rebate price elasticity of overreported donations is not significantly different from zero in the probit and tobit model (the elasticities are 0.07, and 0.19, respectively; see columns (1) and (3) of Table 2.6), but the elasticity is 0.37 and highly significant if I consider only those decisions where the subjects decide to evade (see column (2) of Table 2.6). This also shows that the subsidy rate is relatively less important for determining whether to evade or not, but has a relatively high impact on the level of overreporting. As stated in Prediction 2.3, the price elasticity of overreported donations is positive both under the match and rebate (yet not always significant under the rebate). This is in contrast to Fack and Landais (2013) who find a negative price elasticity of overreported donations, but in line with Blumenthal et al. (2012) who also find a positive elasticity of overreported donations. As Fack and Landais (2013) mention, however, the price elasticities may depend strongly on the level of tax enforcement in place and, what is more, on other taxes and policy instruments. In my controlled experiment, I am expecting a positive elasticity of overreported donations, since an increase in the subsidy rate leads to a substitution from evasion to donation if the subsidy rate increases. The reason is that the subjects have a higher incentive to donate and their donation reports are limited by the level of the endowment (see Section 2.2).

The decrease in overreporting as a result of an increase in the subsidy is larger under the match than under the rebate, which is in line with Prediction 2.3. The interaction terms of the price and rebate dummy is significant in the second stage of the hurdle model column (2) and weakly significant in the tobit model column (3) of Table 2.6. Hence, we can state the following result:

Result 2.3. *The increase in the subsidy rate leads to a larger decrease in overreporting under the match subsidy than under the rebate subsidy.*

If subjects who face a rebate evade for selfish reasons to benefit themselves, those subjects may not substitute from evasion to donations if the subsidy rate increases. If subjects who face a match evade for altruistic reasons to benefit the charity, those subjects may substitute from evasion to donations if the subsidy rate increases. The higher price elasticities of *donations* (see column (3) of Table 2.4) and of *overreported donations* (see Table 2.6) under the match than under the rebate show that the subjects are more likely to substitute from evasion to donations under the match than under the rebate if the subsidy rate increases. In comparison, Blumenthal et al. (2012) do not find significant differences in the elasticities of overreported donations under match and rebate. However, their study only compares the

levels of total evasion under the rebate and match, which is the amount the charity or the individual receives because of evasion under the rebate and match, respectively. As total evasion is a function of the subsidy rate, the effect of the subsidy rate on total evasion may not have been properly identified in the regressions by Blumenthal et al. (2012) (compare Section 2.4.4).

2.4.4 Robustness of Results

Instead of comparing the levels of overreporting under the rebate and match in Table 2.6, it is also possible to compare the levels of total evasion, which is the amount the charity or the individual receives because of evasion. This has the drawback that the maximum possible total evasion differs under the match and the rebate because of the budget constraint of the individuals. For instance, if the endowment is €30 and the match is 100 %, the subject can overreport €30 and the charity will end up with the overreported amount times the subsidy rate, which is €30. In contrast, the maximum total evasion under the equivalent rebate of 50 % is the overreported amount times the subsidy rate, which is €15. What is more, in order to estimate the reaction of evasion as a result of an increase in the subsidy rate (i.e. price elasticities), I cannot make use of total evasion as the dependent variable, since total evasion is defined as the overreported amount times the subsidy rate. This is why my preferred specification in Table 2.6 uses the level of overreporting as the dependent variable. The probit model shown in equation (2.6) predicts whether the subject evades or not. Hence, it is not affected by the choice of total evasion instead of overreporting as the dependent variable. Column (1) of Table 2.7 shows the results of the second stage hurdle model, while column (2) of Table 2.7 shows the result of the random effects tobit model. An increase in the probability of detection by ten percentage points under the match subsidy decreases total evasion by 6.3 % conditional on evasion, and decreases total evasion by roughly 10 % in the unconditional tobit model (see columns (1) and (2) of Table 2.7). The increase in the probability of detection is still insignificant under the rebate. The coefficient of the probability under the rebate and match, respectively, of Table 2.7 are not significantly different from the coefficients of Table 2.6 (p values of two-sided t tests are 0.789 and 0.992, respectively). Overall, the coefficients of Table 2.7 are very similar to my preferred specification of Table 2.6.

Table 2.7: Total evasion, marginal effects of random effects models

Dependent Variable:	(1) Hurdle ln(Total evasion+0.1)	(2) TOBIT ln(Total evasion+0.1)
Rebate	−14.86*	37.95***
	(8.16)	(9.02)
Probability	−0.630*	−1.004***
	(0.340)	(0.331)
Probability × Rebate	0.371	0.974**
	(0.465)	(0.440)
Male	0.007	0.697**
	(0.202)	(0.342)
Donation Allocation Part	−0.018	−0.031**
	(0.014)	(0.016)
Other Controls	Yes	Yes
Observations	231	534
Log Likelihood	−861	−689
Likelihood Ratio Test	2.11*	129.39***

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Marginal effects are evaluated at the means. A random effect tobit model is estimated as the second stage of a lognormal hurdle model in column (1). A random effect tobit model is estimated in column (2). The dependent variable in columns (1) and (2) is the level of total evasion, where total evasion is the overreported amount times the subsidy rate (i.e. how much the individual or the charity gets because of overreporting). Other controls include controls for social and risk preferences, the Machiavelli score, initial endowment, gender, whether the experiment started with the allocation or reporting part, the donation of the allocation part, the nationality of the subjects. I include a constant, and dummies for charities and sessions in all regressions. The likelihood ratio statistic tests the null hypothesis that each subject has the same individual effect.

2.5 Conclusion

This study investigates tax evasion through overreporting of donations. It is the first experiment that provides estimates of the elasticity of overreported donations, which is important for determining an effective way of subsidizing giving. Moreover, it is the first study that distinguishes between a match and rebate subsidy in the context of tax evasion. I find higher levels of overreporting under the rebate subsidy than under the match subsidy. In addition, increases of the match subsidy rate lead to larger decreases in overreporting than increases of the rebate subsidy rate. I also confirm the finding of previous studies that

the elasticity of true donations under the rebate is lower than the same elasticity under the match. Since increases of a match subsidy rate lead to larger increases in donations and decreases in overreporting than equivalent increases of a rebate subsidy rate, a match subsidy could lead to the policymaker's desired level of donations at a lower cost. Moreover, an increase in the probability of detection does not have a significant impact on evasion under the rebate, but an increase in the probability leads to a sizeable reduction of overreporting under the match subsidy.

To the extent that my experimental results have implications for policy, the message would be that increases in the subsidy rate and probability rate (e.g. by increasing the frequency of audits) are more likely to lead to increases in welfare under the match than under the rebate subsidy. In other words, my controlled experiment suggests that replacing rebate schemes with match schemes may not only have the potential to increase donations, but also to decrease overreporting of donations. Nevertheless, any implications for policymakers can only be drawn cautiously, since the behavior of individuals is also dependent on other policy instruments and institutions.

Appendix

2.A Proofs

2.A.1 Optimal Levels of Giving and Overreporting under the Rebate

In this section, I characterize the optimal levels of giving g^* and overreporting g^{e*} as functions of the parameters a, p, θ, and s_r under the rebate. The individual maximizes the expected payoff given in equation (2.1) by choosing the level of overreported donations and true charitable donations. I make use of the following notation:

$$D_r \equiv \alpha_i \left(I - g_i \left(1 - s_r\right) - s_r g_i^e \theta\right) + a\beta_i \left(g_i, G_{-i}\right) \equiv \alpha_i \left(d_r\right) + a\beta_i \left(\delta_r, G_{-i}\right)$$

$$E_r \equiv \alpha_i \left(I - g_i \left(1 - s_r\right) + s_r g_i^e\right) + a\beta_i \left(g_i, G_{-i}\right) \equiv \alpha_i \left(e_r\right) + a\beta_i \left(\epsilon_r, g_i\right).$$

The Kuhn-Tucker conditions become:

$$\frac{\partial U_i}{\partial g_i^e} = u_i'(D_r) p \alpha_i' \left(d_r\right) \left(-s_r \theta\right) + u_i'(E_r) \left(1 - p\right) \alpha_i' \left(e_r\right) s_r - \lambda \leq 0 \tag{2.8}$$

$$\frac{\partial U_i}{\partial g_i} = p u_i' \left(D_r\right) \left(\alpha_i' \left(d_r\right) \left(-1 + s_r\right) + a\beta_i' \left(\delta_r, .\right)\right) + \left(1 - p\right) u_i' \left(E_r\right) \left(\alpha_i' \left(e_r\right) \left(-1 + s_r\right) + a\beta_i' \left(\epsilon_r, .\right)\right) - \lambda \leq 0 \tag{2.9}$$

$$\frac{\partial U_i}{\partial \lambda} = I - g_i - g_i^e \geq 0$$

$$g_i,\, g_i^e,\, \lambda \geq 0$$

$$g_i^e = 0 \qquad \vee \qquad u_i'(D_r) p \alpha_i' \left(d_r\right) \left(-s_r \theta\right) + u_i'(E_r) \left(1 - p\right) \alpha_i' \left(e_r\right) s_r - \lambda = 0$$

$$g_i = 0 \;\vee\; p u_i' \left(D_r\right) \left(\alpha_i' \left(d_r\right) \left(s_r - 1\right) + a\beta_i' \left(\delta_r, .\right)\right) + \left(1 - p\right) u_i' \left(E_r\right) \left(\alpha_i' \left(e_r\right) \left(s_r - 1\right) + a\beta_i' \left(\epsilon_r, .\right)\right) - \lambda = 0$$

$$\lambda = 0 \qquad \vee \qquad I - g_i - g_i^e = 0,$$

where λ is the Lagrange multiplier. Equation (2.8) reflects the marginal utility of evading one euro. The marginal cost of evading $\alpha_i'(.)\, s_r p\theta$ depends on the probability of detection times the amount that has to be paid in case of detection. The marginal benefit of evasion depends on the level of the subsidy and is given by $\alpha_i'(.)\, s_r\,(1-p)$. I define the three thresholds from the Kuhn-Tucker conditions:

$$\hat{a}_r\,(p,\theta,s_r) \equiv \frac{pu_i'(D_r)\alpha_i'(d_r)\,(1-s_r-s_r\theta)+(1-p)\,u_i'\,(E_r)\,\alpha_i'\,(e_r)}{\beta_i'\,(\delta_r,.)\,pu_i'\,(D_r)+\beta_i'\,(\epsilon_r,.)\,(1-p)\,u_i'\,(E_r)},$$

$$\bar{a}_r\,(p,s_r) \equiv \frac{(1-s_r)\,(pu_i'\,(D_r)\,\alpha_i'(d)+(1-p)\,u_i'\,(E_r)\,\alpha_i'(e))}{\beta_i'\,(\delta_r,.)\,pu_i'\,(D_r)+\beta_i'\,(\epsilon_r,.)\,(1-p)\,u_i'\,(E_r)},$$

and

$$\phi_r\,(\theta) \equiv \frac{u_i'(E_r)\alpha_i'\,(e_r)}{u_i'(E_r)\alpha_i'\,(e_r)+\theta u_i'(D_r)\alpha_i'\,(d_r)}.$$

For any a, there is a unique optimal level of donation $g^*\,(a,p,\theta,s_r)$ and overreporting $g^{e*}\,(a,p,\theta,s_r)$. The solution of the maximization problem is shown in Table 2.8. For instance, row 1 of Table 2.8 says that at the optimum the individual does not donate any money to the charity ($g^*=0$) but reports a donation of I (i.e. overreport its donation by $g^{e*}=I$) if the probability of detection p is smaller than or equal to the threshold $\phi_r\,(\theta)$ and the altruism parameter a is lower than $\hat{a}_r\,(p,\theta,s_r)$.

Table 2.8: Solution, rebate subsidy

For		Solution
$p \le \phi_r\,(\theta)$	$a < \hat{a}_r\,(p,\theta,s_r)$	$g^*\,(a,\ldots)=0,\ g^{e*}\,(a,\ldots)=I$
$p \le \phi_r\,(\theta)$	$a = \hat{a}_r\,(p,\theta,s_r)$	$g^*\,(a,\ldots)\in[0,I],\ g^{e*}\,(a,\ldots)\in[0,I]$s. t. $g^*\,(a,\ldots)+g^{e*}\,(a,\ldots)=I$
$p \le \phi_r\,(\theta)$	$a > \hat{a}_r\,(p,\theta,s_r)$	$g^*\,(a,\ldots)=I,\ g^{e*}\,(a,\ldots)=0$
$p > \phi_r\,(\theta)$	$a > \bar{a}_r\,(p,s_r)$	$g^*\,(a,\ldots)=I,\ g^{e*}\,(a,\ldots)=0$
$p > \phi_r\,(\theta)$	$a < \bar{a}_r\,(p,s_r)$	$g^*\,(a,\ldots)=0,\ g^{e*}\,(a,\ldots)=0$
$p > \phi_r\,(\theta)$	$a = \bar{a}_r\,(p,s_r)$	$g^*\,(a,\ldots)\in[0,I],\ g^{e*}\,(a,\ldots)=0$
$p = \phi_r\,(\theta)$	$a < \bar{a}_r\,(p,s_r)$	$g^*\,(a,\ldots)=0,\ g^{e*}\,(a,\ldots)\in[0,I]$
$p = \phi_r\,(\theta)$	$a = \bar{a}_r\,(p,s_r)$	$g^*\,(a,\ldots)\in[0,I],\ g^{e*}\,(a,\ldots)\in[0,I]$, s.t. $g^*\,(a,\ldots)+g^{e*}\,(a,\ldots)\le I$

2.A.2 Optimal Levels of Giving and Overreporting under the Match

In this section, I characterize the optimal levels of giving g^* and overreporting g^{e*} as functions of the parameters a, p, θ, and s_m under the match. The individual maximizes the expected payoff given in equation (2.3) by choosing the level of overreported donations and true charitable donations. I make use of the following notation:

$$D_m \equiv \alpha_i \left(I - g_i - s_m g_i^e \theta\right) + a\beta_i \left(g_i \left(1 + s_m\right), G_{-i}\right) \equiv \alpha_i \left(d_m\right) + a\beta_i \left(\delta_m, G_{-i},\right)$$

$$E_m \equiv \alpha_i \left(I - g_i\right) + a\beta_i \left(g_i \left(1 + s_m\right) + s_m g_i^e, G_{-i}\right) \equiv \alpha_i \left(e_m\right) + a\beta_i \left(\epsilon_m, G_{-i}\right)$$

The Kuhn-Tucker conditions become:

$$\frac{\partial U_i}{\partial g_i^e} = u_i' \left(D_m\right) p\alpha_i' \left(d_m\right) \left(-s_m\theta\right) + u_i' \left(E_m\right) \left(1 - p\right) a\beta_i' \left(\epsilon_m, .\right) s_m - \lambda \leq 0 \tag{2.10}$$

$$\frac{\partial U_i}{\partial g_i} = pu_i' \left(D_m\right) \left(a\beta_i' \left(\delta_m, .\right) \left(1 + s_m\right) - \alpha_i' \left(d_m\right)\right) + \left(1 - p\right) u_i' \left(E_m\right) \left(a\beta_i' \left(\epsilon_m, .\right) \left(1 + s_m\right) - \alpha_i' \left(e_m\right)\right) - \lambda \leq 0 \tag{2.11}$$

$$\frac{\partial U_i}{\partial \lambda} = I - g_i - g_i^e \geq 0$$

$$g_i,\, g_i^e,\, \lambda \geq 0$$

$$g_i^e = 0 \;\vee\; u_i' \left(D_m\right) p\alpha_i' \left(d_m\right) \left(-s_m\theta\right) + u_i' \left(E_m\right) \left(1 - p\right) a\beta_i' \left(\epsilon_m, .\right) s_m - \lambda = 0$$

$$g_i = 0 \vee pu_i' \left(D_m\right) \left(a\beta_i' \left(\delta_m, .\right) \left(1 + s_m\right) - \alpha_i' \left(d_m\right)\right) + \left(1 - p\right) u_i' \left(E_m\right) \left(a\beta_i' \left(\epsilon_m, .\right) \left(1 + s_m\right) - \alpha_i' \left(e_m\right)\right) - \lambda = 0$$

$$\lambda = 0 \;\vee\; I - g_i - g_i^e = 0.$$

Equation (2.10) reflects the marginal utility of evading one euro. The marginal cost of evading $\alpha_i s_r p\theta$ depends on the probability of detection times the amount that has to be paid in case of detection. The marginal benefit of evasion depends on the level of the subsidy and is given by $\alpha_i s_m \left(1 - p\right)$. I define the three thresholds from the Kuhn-Tucker conditions:

$$\hat{a}_m \left(p, \theta, s_m\right) \equiv \frac{pu_i'(D_m)\alpha_i' \left(d_r\right) \left(1 - s_m\theta\right) + \left(1 - p\right) u_i'(E_m)\alpha_i' \left(e_m\right)}{pu_i'(D_m)\beta_i' \left(\delta_m, .\right) \left(1 + s_m\right) + \left(1 - p\right) u_i'(E_m)\beta_i' \left(\epsilon_m, .\right)},$$

$$\bar{a}_m \left(p, s_m\right) \equiv \frac{pu_i' \left(D_m\right) \alpha_i' \left(d_m\right) + \left(1 - p\right) u_i' \left(E_m\right) \alpha_i' \left(e\right)}{\left(1 + s_m\right) \left(pu_i' \left(D_m\right) \beta_i' \left(\delta_m, .\right) + \left(1 - p\right) u_i' \left(E_m\right) \beta_i' \left(\epsilon_m, .\right)\right)},$$

and

$$\phi_m(p,\theta) \equiv \frac{pu_i'(D_m)\alpha_i'(d_m)\,\theta}{(1-p)\,u_i'(E_m)\,\beta_i'(\epsilon_m,.)}.$$

For any a, there is a unique optimal level of donation $g^*(a,p,\theta,s_m)$ and overreporting $g^{e*}(a,p,\theta,s_m)$.The solution of the maximization problem is given in Table 2.9. For instance, row 1 of Table 2.9 says that at the optimum the individual does not donate any money to the charity ($g^*=0$) but reports a donation of I (i.e. overreport its donation by $g^{e*}=I$) if the probability of detection p is smaller than or equal to the threshold $\phi_m(\theta)$ and the altruism parameter a is lower than $\hat{a}_m(p,\theta,s_m)$.

Table 2.9: Solution, match subsidy

For		Solution
$a \geq \phi_m(p,\theta)$	$a < \hat{a}_m(p,\theta,s_m)$	$g^*(a,\ldots)=0,\ g^{e*}(a,\ldots)=I$
$a \geq \phi_m(p,\theta)$	$a = \hat{a}_m(p,\theta,s_m)$	$g^*(a,\ldots)\in[0,I],\ g^{e*}(a,\ldots)\in[0,I]$ s. t. $g^*(a,\ldots)+g^{e*}(a,\ldots)=I$
$a \geq \phi_m(p,\theta)$	$a > \hat{a}_m(p,\theta,s_m)$	$g^*(a,\ldots)=I,\ g^{e*}(a,\ldots)=0$
$a < \phi_m(p,\theta)$	$a > \bar{a}_m(p,s_m)$	$g^*(a,\ldots)=I,\ g^{e*}(a,\ldots)=0$
$a < \phi_m(p,\theta)$	$a < \bar{a}_m(p,s_m)$	$g^*(a,\ldots)=0,\ g^{e*}(a,\ldots)=0$
$a < \phi_m(p,\theta)$	$a = \bar{a}_m(p,s_m)$	$g^*(a,\ldots)\in[0,I],\ g^{e*}(a,\ldots)=0$
$a = \phi_m(p,\theta)$	$a < \bar{a}_m(p,s_m)$	$g^*(a,\ldots)=0,\ g^{e*}(a,\ldots)\in[0,I]=0$
$a = \phi_m(p,\theta)$	$a = \bar{a}_m(p,s_m)$	$g^*(a,\ldots)\in[0,I],\ g^{e*}(a,\ldots)\in[0,I]$ s.t. $g^*(a,\ldots)+g^{e*}(a,\ldots)\leq I$

2.A.3 Proof of Proposition 2.1

Proof. First, consider the marginal utility of overreporting and donations under the *rebate*:

$$\frac{\partial U_i}{\partial g_i^e} = u_i'(D_r)p\alpha_i'(d_r)(-s_r\theta) + u_i'(E_r)(1-p)\,\alpha_i'(e_r)\,s_r \tag{2.12}$$

$$\frac{\partial U_i}{\partial g_i} = pu_i'(D_r)\left(\alpha_i'(d_r)(-1+s_r) + a\beta_i'(\delta_r,.)\right) + (1-p)\,u_i'(E_r)\left(\alpha_i'(e_r)(-1+s_r) + a\beta_i'(\epsilon_r,.)\right) \tag{2.13}$$

The marginal utility of donations in equation (2.13) is necessarily higher than the marginal utility of overreporting (2.12) if

$$\alpha_i'(.) < a\beta'(.,.). \tag{2.14}$$

To see this, I plug $\alpha_i'(.) = a\beta'(.,.)$ into equations (2.12) and (2.13):

$$\frac{\partial U_i}{\partial g_i^e} < \frac{\partial U_i}{\partial g_i},$$

which simplifies to:

$$u_i'(D_r)p\alpha_i'(d_r)(-s_r\theta) + u_i'(E_r)(1-p)\left(\alpha_i'(e_r)s_r\right) < pu_i'(D_r)\alpha_i'(d_r)s_r + (1-p)u_i'(E_r)\alpha_i'(e_r)s_r,$$

which is true since θ is non-negative, and α, β, and u are strictly increasing and concave. That is, even in the case where $\alpha_i'(.) = a\beta'(.,.)$, the marginal marginal utility of donations in equation (2.13) is necessarily higher than the marginal utility of overreporting (2.12). This means that there will be evasion under the rebate if and only if $\alpha_i'(.) > a\beta'(.,.)$.

Similarly, there will be never evasion under the *match* if $\alpha_i'(.) < a\beta'(.,.)$. To see this, consider the marginal utility of overreporting and donations under the match:

$$\frac{\partial U_i}{\partial g_i^e} = u_i'(D_m)p\alpha_i'(d_m)(-s_m\theta) + u_i'(E_m)(1-p)a\beta_i'(\epsilon_m,.)s_m \tag{2.15}$$

$$\frac{\partial U_i}{\partial g_i} = pu_i'(D_m)\left(-\alpha_i'(d_m) + a\beta_i'(\delta_m,.)(1+s_m)\right) + (1-p)u_i'(E_m)\left(-\alpha_i'(e_m) + a\beta_i'(\epsilon_m,.)(1+s_m)\right) \tag{2.16}$$

The marginal utility of donations in equation (2.16) is necessarily higher than the marginal utility of overreporting (2.15) if $\alpha_i'(.) < a\beta'(.,.)$. To see this, I plug $\alpha_i'(.) = a\beta'(.,.)$ into equations (2.15) and (2.16):

$$\frac{\partial U_i}{\partial g_i^e} < \frac{\partial U_i}{\partial g_i}$$

which simplifies to:

$$u_i'(D_m)p\alpha_i'(d_m)(-s_m\theta) + u_i'(E_m)(1-p)\alpha_i'(e_m)s_m < pu_i'(D_m)\alpha_i'(d_m)s_m + (1-p)u_i'(E_m)\alpha_i'(e_m)s_m$$

which is true since θ is non-negative, and α, β, and u are strictly increasing and concave. This means that there will be evasion under the match if and only if $\alpha_i'(.) > a\beta'(.,.)$.

Second, in equilibrium, there is evasion if the marginal utility of overreporting is higher than the

marginal utility of donations, and if the marginal utility of donations is positive:

$$\frac{\partial U_i}{\partial g_i^e} \geq \frac{\partial U_i}{\partial g_i} \geq 0.$$

That is, there will be more evasion under the rebate than under the match if the ratio of the marginal utility of overreporting to the marginal utility of donation is higher under the rebate than the match:

$$\left.\frac{\partial U_i/\partial g_i^e}{\partial U_i/\partial g_i}\right|_r > \left.\frac{\partial U_i/\partial g_i^e}{\partial U_i/\partial g_i}\right|_m. \tag{2.17}$$

$$\left.\frac{\partial U_i/\partial g_i^e}{\partial U_i/\partial g_i}\right|_r = \frac{s_r\left(-\alpha_i'\left(d_r\right)p\theta u_i'\left(D_r\right)+\alpha_i'\left(e_r\right)\left(1-p\right)u_i'\left(E_r\right)\right)}{p\left(a\beta_i'\left(\delta_r,.\right)-\alpha_i'\left(d_r\right)\left(1-s_r\right)\right)u_i'\left(D_r\right)+\left(1-p\right)\left(a\beta_i'\left(\epsilon_r,.\right)-\alpha_i'\left(e_r\right)\left(1-s_r\right)\right)u_i'\left(E_r\right)} \tag{2.18}$$

$$\left.\frac{\partial U_i/\partial g_i^e}{\partial U_i/\partial g_i}\right|_m = \frac{s_m\left(-\alpha_i'\left(d_m\right)p\theta u_i'\left(D_m\right)+a\beta_i'\left(\epsilon_m,.\right)\left(1-p\right)u_i'\left(E_m\right)\right)}{pu_i'\left(D_m\right)\left(a\beta_i'\left(\delta_m,.\right)\left(1+s_m\right)-\alpha_i'\left(d_m\right)\right)+\left(1-p\right)u_i'\left(E_m\right)\left(a\beta_i'\left(\epsilon_m,.\right)\left(1+s_m\right)-\alpha_i'\left(e_m\right)\right)}. \tag{2.19}$$

If I plug in the equivalent subsidy $s_m = s_r/(1-s_r)$, equation (2.19) becomes:

$$\left.\frac{\partial U_i/\partial g_i^e}{\partial U_i/\partial g_i}\right|_m = \frac{s_r\left(-\alpha_i'\left(d_m\right)p\theta u_i'\left(D_m\right)+a\beta_i'\left(\epsilon_m,.\right)\left(1-p\right)u_i'\left(E_m\right)\right)}{p\left(a\beta_i'\left(\delta_m,.\right)-\alpha_i'\left(d_m\right)\left(1-s_r\right)\right)u_i'\left(D_m\right)+\left(1-p\right)\left(a\beta_i'\left(\epsilon_m,.\right)-\alpha_i'\left(e_m\right)\left(1-s_r\right)\right)u_i'\left(E_m\right)} \tag{2.20}$$

The marginal utility of donation is the same under the match and rebate (see denominators of equations (2.18) and (2.20)), since α, β, and u are strictly increasing and concave. However, the marginal utility of overeporting is higher under the rebate than under the match, since a necessary condition for overreporting is that $\alpha_i'(.) > a\beta'(.,.)$. Since α and β are strictly increasing and concave, inequality (2.17) must hold whenever there is overreporting and hence, overreporting is more likely under the rebate than under the match. □

2.A.4 Proof of Proposition 2.2

Proof. In equilibrium, there is evasion if the marginal utility of overreporting is higher than the marginal utility of donations, and if the marginal utility of overreporting is positive:

$$\frac{\partial U_i}{\partial g_i^e} \geq \frac{\partial U_i}{\partial g_i} \geq 0.$$

That is, the individual overreports an amount equal to the income if the marginal utility of overreporting is greater than zero and if the ratio of the marginal utility of overreporting to the marginal utility of

donation (i.e. the marginal rate of substitution of overreporting for donations) is greater than one:

$$\left.\frac{\partial U_i/\partial g_i^e}{\partial U_i/\partial g_i}\right|_r > 1, \tag{2.21}$$

$$\left.\frac{\partial U_i/\partial g_i^e}{\partial U_i/\partial g_i}\right|_m > 1. \tag{2.22}$$

The marginal rate of substiution of overreporting for donations under the rebate is given by

$$\left.\frac{\partial U_i/\partial g_i^e}{\partial U_i/\partial g_i}\right|_r = \frac{s_r\left(-\alpha_i'\left(d_r\right)p\theta u_i'\left(D_r\right)+\alpha_i'\left(e_r\right)\left(1-p\right)u_i'\left(E_r\right)\right)}{p\left(a\beta_i'\left(\delta_r,.\right)-\alpha_i'\left(d_r\right)\left(1-s_r\right)\right)u_i'\left(D_r\right)+\left(1-p\right)\left(a\beta_i'\left(\epsilon_r,.\right)-\alpha_i'\left(e_r\right)\left(1-s_r\right)\right)u_i'\left(E_r\right)}. \tag{2.23}$$

If I plug in the equivalent subsidy $s_m = s_r/(1-s_r)$, the marginal rate of substitution of overreporting for donations under the match is given by:

$$\left.\frac{\partial U_i/\partial g_i^e}{\partial U_i/\partial g_i}\right|_m = \frac{s_r\left(-\alpha_i'\left(d_m\right)p\theta u_i'\left(D_m\right)+a\beta_i'\left(\epsilon_m,.\right)\left(1-p\right)u_i'\left(E_m\right)\right)}{p\left(a\beta_i'\left(\delta_m,.\right)-\alpha_i'\left(d_m\right)\left(1-s_r\right)\right)u_i'\left(D_m\right)+\left(1-p\right)\left(a\beta_i'\left(\epsilon_m,.\right)-\alpha_i'\left(e_m\right)\left(1-s_r\right)\right)u_i'\left(E_m\right)} \tag{2.24}$$

We see in equations (2.23) and (2.24) that if there is overreporting, the marginal utility of overreporting and the marginal utility of donations decrease as a result of an increase in the probability, since α, β and u are strictly increasing and concave (Note: the marginal utility of donations stays constanst if there is no overreporting). However, the marginal utility of overreporting decreases relatively stronger than the marginal utility of donations, because of the following reasons. If the probability increases, the marginal utility of donations decreases only due to the concavity of α, β, and u (see denominators of equations (2.23) and (2.24)). In contrast, the marginal utility of overreporting decreases relatively more than the marginal utility of donations. If the probability increases, the marginal cost of overreporting $s_r\alpha_i'\left(d_m\right)\theta u_i'\left(D_m\right)$ increases and the marginal benefits of overreporting $s_r\alpha_i'\left(e_r\right)u_i'\left(E_r\right)$ and $s_r a\beta_i'\left(\epsilon_m,.\right)u_i'\left(E_m\right)$ under the rebate and match, respectively, decrease as α, β, and u are concave and strictly increasing (see numerators of equations (2.23) and (2.24)). As a result, an increase in the probability p reduces overreporting under the rebate and match subsidy. □

2.A.5 Proof of Proposition 2.3

Proof. In equilibrium, there is evasion if the marginal utility of overreporting is higher than the marginal utility of donations, and if the marginal utility of overreporting is positive. I use equations (2.23) and (2.24) to compare an increase in the probability of detection under an equivalent match and rebate

subsidy. If the probability p increases, the marginal utility of donations decreases in the same manner under the match and rebate (see denominators of equations (2.23) and (2.24)) (Note: the marginal utility of donations stays constanst if there is no overreporting). However, we see at the numerators of equations (2.23) and (2.24) that the marginal utility of overreporting is lower under the match than under the rebate, since a necessary condition for overreporting is that $\alpha_i'(.) > a\beta'(.,.)$ and α and β are strictly increasing and concave. Since the marginal utility of overreporting under the match is lower than under the rebate, an increase in the probability under the match is more likely to cause the marginal rate of substitution to become smaller than one than an increase in the probability under the rebate. In other words, an increase in the probability may have no effect on overreporting under the rebate, because inequality (2.21) may be still fulfilled and thus the individual would overreport an amount equal to the income. In contrast, an equivalent increase in the probability under the match may have the consequence that the necessary condition for overreporting shown in inequality (2.22) is no longer fulfilled and thus the individual has no longer an incentive to overreport. □

2.A.6 Proof of Proposition 2.4

Proof. In equilibrium, there is evasion if the marginal utility of overreporting is higher than the marginal utility of donations, and if the marginal utility of overreporting is positive. We see in equations (2.23) and (2.24) that if there is overreporting the marginal utility of overreporting and the marginal utility of donations increase as a result of an increase in the subsidy rate s_r, since α, β and u are strictly increasing and concave. However, the marginal utility of donations increases relatively stronger than the marginal utility of overreporting, because of the following reasons. If the subsidy rate increases, the marginal utility of donations $\alpha_i'(.)\, s_r u_i'(.)$ increases, since α, β and u are strictly increasing and concave (see denominators of equations (2.23) and (2.24)). In contrast, the marginal utility of overreporting increases relatively less than the marginal utility of donations as a result of an increase in the subsidy rate. If the subsidy rate increases, both the marginal cost of overreporting $s_r\alpha_i'(d_m)\,\theta u_i'(D_m)$ and the marginal benefits of overreporting $s_r\alpha_i'(e_r)\,u_i'(E_r)$ and $s_r a\beta_i'(\epsilon_m,.)\,u_i'(E_m)$ under the rebate and match, respectively, increases as α, β, and u are concave and strictly increasing (see numerators of equations (2.23) and (2.24)). As a result, an increase in the subsidy rate s_r reduces overreporting under the rebate and match subsidy. □

2.A.7 Proof of Proposition 2.5

Proof. In equilibrium, there is evasion if the marginal utility of overreporting is higher than the marginal utility of donations, and if the marginal utility of overreporting is positive. I use equations (2.23) and (2.24) to compare an increase of an equivalent match and rebate subsidy rate. If the subsidy rate s_r increases, the marginal utility of donations under the rebate and match increase in the same manner (see denominators of equations (2.23) and (2.24)). However, we see at the numerators of equations (2.23) and (2.24) that the marginal utility of overreporting is lower under the match than under the rebate, since a necessary condition for overreporting is that $\alpha_i'(.) > a\beta'(.,.)$ (see inequality (2.14)), and α and β are strictly increasing and concave. Since the marginal utility of overreporting under the match is lower than under the rebate, an increase in the subsidy rate under the match is more likely to cause the marginal rate of substitution to become smaller than one than an increase in the subsidy rate under the rebate. In other words, an increase in the subsidy rate may have no effect on overreporting under the rebate, because inequality (2.21) may be still fulfilled and thus the individual would overreport an amount equal to the income. In contrast, an equivalent increase in the subsidy rate under the match may have the consequence that the necessary condition for overreporting shown in inequality (2.22) is no longer fulfilled and thus the individual has no longer an incentive to overreport. □

2.B Additional Tables

Table 2.10: Understanding of the instructions

Understanding items ($n = 89$)	Mean	Std. Dev.	Min	Max
The instructions of part 1 were clearly formulated.	6.16	1.30	1	7
The instructions of part 2 were clearly formulated.	5.62	1.56	1	7
The instructions of part 3 were clearly formulated.	6.33	1.31	1	7
The instructions of part 4 were clearly formulated.	6.42	1.23	1	7
The procedures followed in this experiment preserved my anonymity.	6.34	1.25	1	7
The money I passed to my selected charity will be transferred to the charity.	5.97	1.23	1	7

Notes: Responses to the understanding items are from 1 (strongly disagree) to 7 (strongly agree). Part 1 refers to the allocation part. Part 2 refers to the reporting part. Part 3 refers to the risk elicitation task. Part 4 refers to the social preference elicitation task.

Table 2.11: Total contributions, marginal effects of a random effects tobit model (full table)

Dependent Variable:	(1) Allocation Part ln(Contribution+0.1)	(2) Allocation Part ln(Contribution+0.1)	(3) Reporting Part ln(Contribution+0.1)
Rebate	0.0696	0.239	0.461
	(0.648)	(0.634)	(0.705)
ln(Price)	−1.375***	−1.393***	−1.466***
	(0.136)	(0.137)	(0.156)
ln(Price) × Rebate	1.030***	1.046***	0.918***
	(0.190)	(0.192)	(0.217)
Age	0.040	0.010	0.037
	(0.034)	(0.034)	(0.038)
Male	−0.694*	−0.454	−0.530
	(0.377)	(0.374)	(0.417)
ln(Endowment)	−2.409	−2.975	0.063
	(2.111)	(2.191)	(2.475)
Machiavelli		−0.047***	−0.033*
		(0.015)	(0.017)
Holt and Laury switch		−0.069	−0.112
		(0.071)	(0.086)
Allocation Part		−0.113	0.095
		(0.657)	(0.728)
Observations	267	267	267
Log Likelihood	−384	−379	−409

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Marginal effects are evaluated at the means. A random effect tobit model is estimated in columns (1) to (3). The dependent variable in columns (1) and (2) is the total contribution of the allocation part, which is the amount the charity receives because of the donation. The dependent variable in column (3) is the total contribution of the reporting part, which is the actual amount the charity receives because of the donation and not the reported amount. Under the rebate subsidy, the total contribution is equal to the amount the subject decides to donate. Under the match subsidy, the total contribution is equal to the amount the subject decides to donate times the subsidy rate. I include a constant, and dummies for charities and sessions in all regressions.

Table 2.12: Rebate versus match, proportion of misreporting

(1) Price of giving €1 to charity	(2) Probability of detection	(3)	(4) Rebate	(5) Match	(6) Fisher's test p-value
€0.80	4 %	underreporting	5	1	
		exact reporting	20	18	
		overreporting	22	23	
					0.315
€0.80	50 %	underreporting	8	2	
		exact reporting	17	22	
		overreporting	22	18	
					0.122
€0.50	4 %	underreporting	6	1	
		exact reporting	20	22	
		overreporting	21	19	
					0.197
€0.50	50 %	underreporting	9	1	
		exact reporting	15	25	
		overreporting	23	16	
					0.006
€0.25	4 %	underreporting	6	1	
		exact reporting	21	24	
		overreporting	20	17	
					0.182
€0.25	50 %	underreporting	7	1	
		exact reporting	21	30	
		overreporting	19	11	
					0.018

Notes: n indicates the number of observations under a given price or probability. I compare whether the subjects underreport, overreport, or report the donation correctly under the rebate and match subsidy. I compare the proportion under a certain price of giving (e.g. €0.80) and probability (e.g. 4 %).

Table 2.13: Rebate versus match, marginal effects (full table)

	(1) PROBIT	(2) HURDLE	(3) TOBIT
Dependent Variable:	Evade	ln(Overreport+0.1)	ln(Overreport+0.1)
Rebate	22.00***	−6.59	46.81***
	(6.20)	(9.00)	(10.86)
Probability	−0.483***	−0.467*	−0.973***
	(0.185)	(0.272)	(0.347)
Probability × Rebate	0.518**	0.213	1.057**
	(0.249)	(0.383)	(0.470)
ln(Price)	0.258***	0.869***	0.655***
	(0.093)	(0.139)	(0.179)
ln(Price) × Rebate	−0.187	−0.499**	−0.461*
	(0.122)	(0.193)	(0.236)
SVO	0.190***	−0.084	0.430***
	(0.073)	(0.071)	(0.157)
SVO × Rebate	−0.219***	0.019	−0.456***
	(0.084)	(0.071)	(0.173)
SVO^2	−0.00856***	0.00125	−0.0187***
	(0.0031)	(0.0034)	(0.0064)
$(SVO \times Rebate)^2$	0.0087**	0.0039	0.018**
	(0.0037)	(0.0079)	(0.0075)
SVO^3	0.000096***	0.000000082	000020***
	(0.000035)	(0.000033)	(0.000070)
$(SVO \times Rebate)^3$	−0.000085*	−0.000065	−0.00017*
	(0.000046)	(0.000045)	(0.000093)
Machiavelli	0.195**	−0.406*	0.475**
	(0.095)	(0.222)	(0.224)
Machiavelli × Rebate	−0.519***	0.194	−1.082***
	(0.154)	(0.234)	(0.281)

Continued on next page

	(1) PROBIT	(2) HURDLE	(3) TOBIT
Machiavelli^2	−0.0013**	0.0029**	−0.0031**
	(0.00063)	(0.0014)	(0.0015)
(Machiavelli × Rebate)^2	0.00315***	−0.00220	0.00645***
	(0.000968)	(0.00152)	(0.00180)
ln(Endowment)	0.214	2.100	−3.804
	(1.102)	(1.474)	(2.441)
Holt and Laury switch	0.601**	−0.943	1.363**
	(0.253)	(0.585)	(0.593)
(Holt and Laury switch)^2	−0.0379**	0.0649*	−0.0815**
	(0.0165)	(0.0369)	(0.0386)
Male	0.272	0.154	0.776**
	(0.166)	(0.209)	(0.386)
Allocation Part	0.439	−1.452***	0.734
	(0.271)	(0.361)	(0.640)
Donation Allocation Part	−0.00923	−0.0352***	−0.0333*
	(0.00838)	(0.0117)	(0.0181)
Austria	−0.366*	−0.428*	−0.725
	(0.218)	(0.257)	(0.478)
Third Countries	−0.364*	−0.605***	−0.838*
	(0.190)	(0.216)	(0.436)
Observations	534	231	534
Log Likelihood	−216	−948	−677

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Marginal effects are evaluated at the means. A random effect probit model is estimated in column (1), where the dependent variable is equal to one if the subject overreports the donation, and zero otherwise. A random effect tobit model is estimated as the second stage of a lognormal hurdle model in column (2). In column (3) a random effect tobit model is estimated. The dependent variable in columns (2) and (3) is the level of overreporting, where overreporting is the reported donation minus the actual amount donated. I include a constant, and dummies for charities and sessions in all regressions.

2.C Instructions Rebate Treatment

General Instructions

You have been asked to participate in a study of decision making. The study consists of **FOUR INDEPENDENT PARTS**. You will receive compensation for your participation, which will be paid to you in cash at the end of the study. The experiment is **funded by The Vienna Center for Experimental Economics, which is an institution of the University of Vienna.** Please do not talk during the study.

To insure your complete anonymity, you drew an ID number from a bag when entering the lab. One person drew a three-digit ID number. This person will be the monitor in this session. The monitor will receive the average payoff of the participants in this session. The monitor will verify that the instructions of all parts of the experiments will be followed. The monitor is in the room where the experiment is conducted during the experiment. **The monitor cannot associate your decisions and your payoffs with your person.** Also, you will not be informed about the decisions and the payoffs of the other participants.

The person responsible for your payment, called the experimenter, is located in a different room. The experimenter cannot associate your decisions and payoffs with your person, since the experimenter never faces the participants. **Your anonymity towards the experimenter will always be insured, also after the experiment. An assistant guides and assists the monitor, and will answer your questions.** The assistant is located in the room where the experiment is conducted and does not leave this room until the end of the experiment. The assistant will never see your ID numbers. If you have questions during the experiment, hide your ID number and raise your hand. The assistant will come to your seat.

Your earnings will be determined at the end of the experiment, after you have finished all four parts. Your anonymity is also insured when you confirm your payment. The monitor will distribute your earnings in a sealed envelope which will be labeled on the front with your ID number. How the anonymous payment is made, is explained on the next page.

Anonymous Payment

At the end of the experiment, you will receive a receipt where you confirm your payment. This receipt needs to be sent to the accounting department of the University of Vienna because of bookkeeping regulations. Nevertheless, we want to maintain your anonymity towards all persons in the laboratory. For this reason, the payment will be done in the following way.

1. You will receive a receipt that has the following text on the front side:

   "*I confirm with my signature on the back side of this receipt to have received the amount of XX.XX EUR.*

   I participated in Session XX of Experiment 2013_005. The financial summary of this session will arrive separately at DLE Finanzwesen und Controlling."

   The back side of the receipt will state:

   "*Name*_ _ _ _ _ _

   *Place, date*_ _ _ _ _ _ *Signature*_ _ _ _ _ _"

2. The experimenter will put the receipt and your money in an envelope. The experimenter will put a sticker with your ID number on top of the envelope and will seal the envelope.
3. The experimenter will hand over the envelope for the payment, and a new empty, colored envelope to the monitor. (The experimenter will not enter the room where the experiment is conducted.) The colored envelope will have the address of the accounting department of the University of Vienna on top of it.
4. You will receive the envelopes from the monitor.
5. You will be asked to take your money out of the envelope and to sign the back of the receipt. You should also remove the sticker with your ID number from the envelope.
6. The monitor will check the signature. IMPORTANT: The monitor will not see the front side of the receipt. That is, the monitor will not know how much money you earned.
7. You will be asked to put the signed receipt in the new colored envelope and to seal the envelope.
8. The monitor and the experimenter will go to the nearest mailbox and will drop the envelopes in the mailbox for these receipts to be sent to the accounting department.

Selection of Charity

- In part 1 and 2 of the experiment, you are asked to allocate money between yourself and a charity organization.
- Before you start with part 1 of the experiment, you are going to see a list of ten charities with a brief description of the services each provides on the computer screen. **You are asked to select one, and only one, of these ten charities.**
- **You will earn money in either part 1 or part 2 of the experiment.** Otherwise, part 1 and part 2 are completely unrelated! After you have finished all four parts of the experiment, you will draw a chip numbered from 1 to 100 to determine which part is relevant for your payment. If the drawn chip number is between 1 and 50, part 1 is relevant for your payment. If the drawn chip number is between 51 and 100, part 2 is relevant for your payment.
- **In any case, you will earn money for part 3 and part 4 of the experiment.**

Part 1

General Description of Part 1

In part 1 of the experiment, you are asked to allocate money between yourself and the charity organization you selected. For each allocation problem you are given an endowment of **€30** by the experimenter. You are asked to allocate this money between yourself and the charity. For every euro you pass to the charity, the experimenter will give money to you. The amount of money the experimenter gives to you differs in the three allocation problems.

1. In one problem, the experimenter will give to you **€0.20** for every euro you pass to the charity. For instance, if you pass €X to the charity (where X can contain cent amounts), the experimenter will give to you **€0.20** times X.
2. In one problem, the experimenter will give to you **€0.50** for every euro you pass to the charity. For instance, if you pass €X to the charity (where X can contain cent amounts), the experimenter will give to you **€0.50** times X.
3. In one problem, the experimenter will give to you **€0.75** for every euro you pass to the charity. For instance, if you pass €X to the charity (where X can contain cent amounts), the experimenter will give to you **€0.75** times X.

Note that you will see these problems in a random order. For instance, it is possible that in the first problem, the experimenter will give to you €0.75 for every euro you pass to the charity; in the second problem, €0.20 for every euro you pass; and in the third problem, €0.50 for every euro you pass.

Important Note: In all decisions you can choose any amount to keep and any amount to pass, but the amount you keep plus the amount you pass must equal your endowment of €30**.**

Payment of Part 1

Before you start making your three choices, we explain to you exactly how these choices will affect your earnings.

- Remember from the instructions at the beginning that **you will earn money in either part 1 or part 2 of the experiment.** Otherwise, part 1 and part 2 are completely unrelated! After you have finished all four parts of the experiment, you will draw a chip numbered from 1 to 100 to determine which part is relevant for your payment. If the drawn chip number is between 1 and 50, part 1 is relevant for your payment. If the drawn chip number is between 51 and 100, part 2 is relevant for your payment.
- In part 1 of the experiment, you are asked to make three choices and record these in the two final columns of the table with the three allocation problems that you will see on the computer screen. However, only one of the

three choices will be used in the end to determine your earnings if part 1 of the experiment will be paid to you**.** We will determine your earnings in the following way. After you have finished all four parts of the experiment, the monitor and the assistant will come to your desk. Then, you will be asked to **draw a chip numbered from 1 to 3 from a bag held by the monitor to select which of the three problems, i.e. which of the allocation decisions, determines your payment and the payment of the charity.**

  - If the chip number is 1, problem 1 will determine the payment.
  - If the chip number is 2, problem 2 will determine the payment.
  - If the chip number is 3, problem 3 will determine the payment.

  After you have drawn the chip number, the assistant will type in your chip number on the password-protected computer screen. Note that each problem has an equal chance of being selected in the end. Even though you will make three decisions, only one of these will end up affecting your earnings. However, you will only know which problem will be chosen for your payment after you have finished all four parts of the experiment.

- If part 1 is relevant for your payment**, you will be paid in cash** according to the amount you decided to pass to the charity in that problem (i.e. you will get the money you keep, plus the money the experimenter gives additionally to you).
- The experimenter will also calculate the money passed to the charity organization (i.e. the charity will get the money you pass to the charity) after you have finished all four parts of the experiment. If part 1 is relevant for your payment, the **charity organization you selected will receive an online bank transfer** according to the amount you decided to pass to it. The monitor will verify the bank transfer.

Summary of Part 1

- You are asked to make three choices in this part of the experiment.
- For each decision problem you are asked to choose how much money you pass to the charity you selected and how much money you keep for yourself.
- For every euro you pass to the charity, the experimenter will give to you either €0.20, €0.50, or €0.75, depending on the allocation decision as explained above.
- You may choose different allocations in different problems, and you may revise your decisions and make them in any order. When you have made your final decisions, click on "OK" and wait until the experiment continues.

Understanding Part 1

Part 1 of the experiment will start shortly. Before you start with the allocation problems of part 1, you are asked to answer some questions on the computer. With these questions, we just want to make sure that you have complete understanding of how the allocation problem works.

- Your answers will not count towards any payment. You should nevertheless take the questions seriously, since you may gain experience in answering these questions. This experience helps you to make decisions when part 1 starts.
- You are going to see a table with three allocation problems. Note that the numbers that occur in this example on the screen have been randomly generated. They are not meant as examples of "good" or "bad" choices. They only serve to illustrate how part 1 works.
- Do not worry if you have difficulties with finding the answers. The computations you are asked to do here will be done by the computer during the experiment. We will explain the solutions later on.

Are there any questions?

Now you may begin answering the questions on the computer. Remember that you are not allowed do talk with anyone during the entire experiment; raise your hand if you have a question.

Part 2

General Description of Part 2

In part 2 of the experiment, you are asked to make 1. an allocation decision and 2. an information decision.

1. **You are asked to allocate money between yourself and a charity organization**. You are going to see a table with three allocation problems on the *Decision Screen*. You are asked to make an allocation decision for each problem. For each allocation problem you are given an endowment of **€ 30** by the experimenter. You are asked to allocate this money between yourself and the charity you selected.
2. **You are asked to inform the experimenter about your allocation on the *Information Screen*.** For every euro you inform the experimenter to have passed to the charity, the experimenter will give money to you. The amount of money the experimenter gives to you differs in the problems and is either € 0.20, € 0.50, or € 0.75 as explained below.

- On the *Decision Screen*, you are going to see a table with three allocation problems. You are asked to make an allocation decision for each problem and record these decisions in the two final columns of the table.
- On the *Information Screen*, you are going to see a table with six problems. On the *Information Screen*, you will be asked to inform the experimenter about your allocation made on the *Decision Screen*. You will make six decisions and record these in the two final columns, but only one of the six choices will be used in the end to determine your earnings.
- After you finished all four parts of the experiment, you will draw a chip numbered from 1 to 100 to determine whether your information on the *Information Screen* (not on the *Decision Screen*) *will* be checked or not. Your information will be checked if your drawn chip number is lower than or equal to a threshold number. This threshold number differs in the problems and is either 4 or 50, as explained below.
- If your information is checked, the experimenter will give money to you according to the amount you decided to pass to the charity (*Decision Screen*).
- **You have to pay a fee to the experimenter if, and only if, your information is checked AND the amount you inform the experimenter to have passed to the charity (*Information Screen*) is higher** than the amount you decided to pass to the charity (*Decision Screen*). The fee is some amount of money multiplied by the difference between the amount you inform the experimenter to have passed to the charity (on the *Information Screen*) and the amount you decided to pass to the charity (on the *Decision Screen*). The amount of money that is multiplied differs in the problems and is either € 0.06, € 0.15, or € 0.23, as explained below.

Details of Part 2

The amount of money the experimenter gives to you and the possible fee differs in the problems:

1. In one problem, the experimenter will give to you **€0.20** for every euro you inform the experimenter to have passed to the charity. For instance, if you inform the experimenter to have passed €X to the charity (where X can contain cent amounts), the experimenter will give to you **€0.20** times X.

   The possible fee in this case is **€0.06** multiplied by the difference between the amount you inform the experimenter to have passed to the charity (*on the Information Screen*) and the amount you decided to pass to the charity (*on the Decision Screen*).

2. In one problem, the experimenter will give to you **€0.50** for every 100 cents you inform the experimenter to have passed to the charity. For instance, if you inform the experimenter to have passed €X to the charity (where X can contain cent amounts), the experimenter will give to you **€0.50** times X.

   The possible fee in this case is **€0.15** multiplied by the difference between the amount you inform the experimenter to have passed to the charity (on the *Information Screen*) and the amount you decided to pass to the charity (on the *Decision Screen*).

3. In one problem, the experimenter will give to you **€0.75** for every euro you inform the experimenter to have passed to the charity. For instance, if you inform the experimenter to have passed €X to the charity (where X can contain cent amounts), the experimenter will give to you **€0.75** times X.

   The possible fee in this case is **€0.23** multiplied by the difference between the amount you inform the experimenter to have passed to the charity (on the *Information Screen*) and the amount you decided to pass to the charity (on the *Decision Screen*).

   Note that you will see these problems in a random order. For instance, it is possible that in the first problem, the experimenter will give to you €0.75 for every euro you inform the experimenter to have passed to the charity; in the second problem, €0.20 for every euro you inform the experimenter; and in the third problem, €0.50 for every euro you inform the experimenter.

   Important Note: In all decisions you can choose any amount to keep and any amount to pass, but the amount you keep plus the amount you pass must equal your endowment of €30**.**

The threshold that determines whether your information will be checked or not differs in the problems:

1. In three problems, your information will be checked if your drawn chip number is lower than or equal to **4**.
2. In three problems, your information will be checked if your drawn chip number is lower than or equal to **50**.

   You will see these threshold numbers in a random order. For instance, it is possible that the threshold number is 50 in the first three problems, and 4 in the last three problems.

   Important Note: Whether your information will be checked or not is independent of the information you provide on the *Information Screen*.

Payment of Part 2

Before you start making your three choices, we explain to you exactly how these choices will affect your earnings.

- Remember from the instructions at the beginning that **you will earn money in either part 1 or part 2 of the experiment.** Otherwise, part 1 and part 2 are completely unrelated! After you have finished all four parts of the experiment, you will draw a chip numbered from 1 to 100 to determine which part is relevant for your payment. If the drawn chip number is between 1 and 50, part 1 is relevant for your payment. If the drawn chip number is between 51 and 100, part 2 is relevant for your payment.
- In part 2 of the experiment, you are asked to make six choices on the *Information Screen*. However, only one of the six choices will be used in the end to determine your earnings if part 2 of the experiment will be paid to you**.** We will determine your earnings in the following way. After you have finished all four parts of the experiment, the monitor and the assistant will come to your desk. Then, **you are asked to draw a chip numbered from 1 to 6 from a bag held by the monitor to select one of the six problems on the *Information Screen* to determine your payment and the payment of the charity.**
  - If the chip number is 1, problem 1 will determine the payment.
  - If the chip number is 2, problem 2 will determine the payment.

    ...
  - If the chip number is 6, problem 6 will determine the payment.

  After you have drawn the chip number, the assistant will type in your chip number on the password-protected computer screen. Note that each problem on the *Information Screen* has an equal chance of being selected in the end. Even though you will make six decisions on the *Information Screen*, only one of these will end up affecting

your earnings. However, you will only know which problem will be chosen for your payment after you have finished all four parts of the experiment.

- If part 2 is relevant for your payment, **you will be paid in cash** in the selected problem.

- **If your information is not checked, your payment will be the following:**

  You will receive the money you decided to keep (*Decision Screen*) PLUS the money the experimenter gives to you according to the amount you inform the experimenter to have passed to the charity (*Information Screen*).

- **If your information is checked, your payment will be the following:**

  You will receive the money you decided to keep (*Decision Screen*) PLUS the money the experimenter gives to you according to the amount you decided to pass to the charity (*Decision Scree*n). If your information is checked AND the amount you inform the experimenter to have passed to the charity (*Information Screen*) is higher than the amount you decided to pass to the charity (*Decision Screen*), you also have to pay a fee. (Note, this fee will be subtracted from your earnings.)

- The experimenter will also calculate the money passed to the charity organization (i.e. the money you decided to pass to the charity) after you have finished all four parts of the experiment. If part 2 is relevant for your payment, the **charity organization you selected will receive an online bank transfer** according to the amount you decided to pass to it. The monitor will verify the bank transfer. Note, the charity will always receive the money you decided to pass to the charity as you will have indicated on the *Decision Screen*.

Summary of Part 2

1. You are asked to make three choices on the *Decision Screen*. For each decision problem, you are asked to choose how much money you pass to the charity and how much money you keep for yourself.
2. You are asked to make six choices on the *Information Screen*. For each decision problem, you are asked to inform the experimenter about how much money you have passed to the charity and how much money you have decided to keep for yourself.

- For every euro you inform the experimenter to have passed to the charity, the experimenter will give to you either €0.20, €0.50, or €0.75 (depending on the problem as explained above).

- If your drawn chip number is lower than or equal to either 4 or 50 (depending on the problem as explained above), the information you provide on the *Information Screen* will be checked.
- You have to pay a fee to the experimenter if, and only if, there is a check AND the amount you inform the experimenter to have passed to the charity (on the *Information Screen*) is higher than your amount you decided to pass to the charity (on the *Decision Screen*).
- The possible fee is either €0.06, €0.15, or €0.23 (depending on the problem as explained above) multiplied by the difference between the amount you inform the experimenter to have passed to the charity (*Information Screen*) and the amount you decided to pass to the charity (*Decision Screen*).
- You may choose different allocations in different problems, and you may revise your decisions and make them in any order. When you have made your final decisions, click on "OK" and wait until the experiment continues.

Understanding Part 2

Part 2 of the experiment will start shortly. Before you start with part 2, you are asked to answer some questions on the computer. With these questions, we just want to make sure that you have complete understanding of how the allocation and information decisions in part 2 work.

- Your answers will not count towards any payment. You should nevertheless take the questions seriously, since you may gain experience in answering these questions. This experience helps you to make decisions when part 2 starts.
- You are going to see two screens, a *Decision Screen* and an *Information Screen*. First, on the *Decision Screen* you are going to see a table with three problems. Then, on the *Information Screen* you are going to see a table with six problems.
- Note that the numbers that occur in the examples on the screens have been randomly generated. They are not meant as examples of "good" or "bad" choices. They only serve to illustrate how part 2 works.
- Do not worry if you have difficulties with finding the answers. The computations you are asked to do here will be done by the computer during the experiment. We will explain the solutions later on.

Are there any questions?

Now you may begin answering the questions on the computer. Remember that you are not allowed do talk with anyone during the entire experiment; raise your hand if you have a question.

Part 3

General Description of Part 3

- In part 3 of the experiment, you are going to see a table with a list of **ten choices between two options**.
- You have the choice between Option A (left column) and Option B (right column) in each decision row and you are asked to indicate the option you prefer by either clicking on Option A or Option B.
- However, you are just asked to click on one of the decision rows of the table with the understanding that if you click on Option A or Option B in any row, all rows above your selected row are automatically selected as Option A (to count as your choice), and all rows below your selected row are automatically selected as Option B (to count as your choice).
- Your preferred options will have an orange background. You will be able to revise your choice until you click "OK".

Payment of Part 3

Before you start making your ten choices, we explain to you how these choices will affect your earnings.

- After you have finished all four parts of the experiment, the monitor and assistant will come to your desk. Then, you will **draw a chip numbered from 1 to 10 from a bag to select which of the ten rows determines your payment**. If the drawn chip number is 1, the first row will be chosen for your payment.
  - If the chip number is 1, row 1 will determine the payment.
  - If the chip number is 2, row 2 will determine the payment.

    ...
  - If the chip number is 10, row 10 will determine the payment.

  That is, only one of the ten rows will end up affecting your earnings. Note that each of the ten rows has an equal chance of being selected in the end. Even though you will make ten decisions, only one of these will end up affecting your earnings. However, you will only know which decision row will be chosen for your payment after you have finished all four parts of the experiment.
- Then, you **draw a second chip from 1 to 100 to determine your payment for the option you chose in the selected row** (see the description of Option A and Option B in each row on the screen).
- After you have drawn the chip number, the assistant will type in your chip number on the password-protected computer screen.

- That is, your payment from this part is determined by your choice in the selected row and the drawn second chip number.

Summary of Part 3

- You have the choice between Option A and Option B in each of the ten decision rows.
- However, if you click on Option A or Option B in any row, all rows above your selected row are automatically selected as Option A, and all rows below your selected row are automatically selected as Option B.
- Your preferred options will have an orange background.
- You will draw a chip numbered from 1 to 10 to determine which of the ten rows will be selected for your payment. Then, you will draw a second chip from 1 to 100 to determine your payment for the option you chose in the selected row.

Understanding Part 3

Part 3 of the experiment will start shortly. Before you start with part 3, you are asked to answer some questions on the computer. With these questions, we just want to make sure that you have complete understanding of how the problem in part 3 works.

- Your answers will not count towards any payment. You should nevertheless take the questions seriously, since you may gain experience in answering these questions. This experience helps you to make decisions when part 3 starts.
- You are going to see a table with a list of ten choices between two options. Note that the choices of Option A and Option B that occur in this example on the computer screen are randomly generated. The choices are not meant as examples of "good" or "bad" choices. They only serve to illustrate how part 3 works.
- Do not worry if you have difficulties with finding the answers. The computations you are asked to do here will be done by the computer during the experiment. We will explain the solutions later on.

Are there any questions?

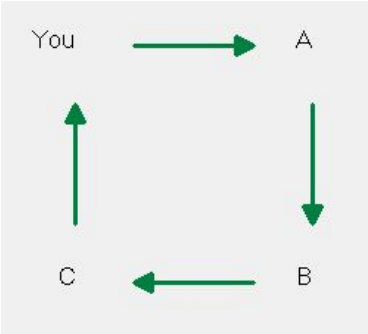
Now you may begin answering the questions on the computer. Remember that you are not allowed do talk with anyone during the entire experiment; raise your hand if you have a question.

Part 4 and Questionnaire

Description of Part 4

- In part 4 of the experiment, you have been randomly matched by the computer with another person in this room. This person will be referred to as *person A* (see Figure 2.3). *Person A* will be randomly matched with somebody else in this room (not you!), namely *person B*. At the same time, *person C*, who is neither *person A* nor *person B*, is matched with you. You will not be informed about who this other persons are, and the other persons will not be informed about you. All of your choices are completely confidential.
- You are asked to make six decisions about distributing money between you and *person A*. For this purpose, you are asked to answer six questions on the computer. In each question, **you are asked to distribute money between yourself and person A**. Please select your preferred distribution by clicking on the respective position on the line for each of these questions. You can select only one distribution for each question. Your decisions will determine amounts of money to be paid to you and *person A*.
- At the same time, *person C* is asked to make six decisions about distributing money between *person C* and you. The decisions of *person C* will determine amounts of money to be paid to you and *person C*.
- In short, you give money to *person* A, *person A* gives to *person B*, *person B* gives to *person C*, and *person C* gives money to you.
- There are no right or wrong answers, this is all about personal preferences. After you have made up your mind, click on your preferred option. As you will see, with your choices you determine both the amount of money you receive as well as the amount of money *person A* receives.

Figure 2.3: Matching



Payment of Part 4

Before you start making your six choices, we explain to you exactly how these choices will affect your earnings for this part of the experiment.

- After you have finished this part of the experiment, the computer will randomly select one of the six decisions you made for your payment and the payment of *person A*. At the same time, the computer will randomly select one of the six decisions person C made for person C's payment and for your payment.
- In short, your payment is the money you keep plus the money *person C* gives to you. Remember that the person that you are giving money *(person A)* differs from the person that is giving money to you (*person C*).

Questionnaire and Payment

- You are asked to fill in a questionnaire. Please note that this questionnaire will be used for research purposes only. If you finish the questionnaire, **you will get € 3 for filling in the questionnaire.**
- While you are completing the questionnaire, the experimenter will determine your compensation. You will receive your compensation in an anonymous way, as explained at the beginning of the experiment. Please, take a look at the *General Instructions* that you received at the beginning of the experiment. Here, we just summarize the most important parts of these instructions.
- Remember, you are asked to sign the back side of the receipt. Then, you are asked to put the signed receipt in the new colored envelope and you are asked to to seal the envelope.
- While you are completing the questionnaire, the experimenter will also calculate the total money passed to each of the charities. The experimenters will make out checks for these amounts, and the monitor will place them in addressed and stamped envelopes.
- Note, the monitor will not see how much each individual passed to the charity. The monitor observes only the aggregated amounts passed to the charity. The monitor and the experimenter will go to the nearest mailbox and drop the envelope in the mailbox. After the monitor has signed a form that verifies that the study was conducted according to instructions, the monitor is free to leave.

Are there any questions?

Please do not talk with anyone while filling out the questionnaire; raise your hand if you have a question.

Questionnaire

Motivation Questionnaire

Please evaluate the following statements:

1=strongly disagree, 2=somewhat disagree, 3=slightly disagree, 4=no opinion, 5=slightly agree, 6=somewhat agree, 7=strongly agree

1. The instructions of part 1 were clearly formulated. (Please take the instructions of part 1 if you do not remember the content of part 1.)
2. The instructions of part 2 were clearly formulated. (Please take the instructions of part 2 if you do not remember the content of part 2.)
3. The instructions of part 3 were clearly formulated. (Please take the instructions of part 3 if you do not remember the content of part 3.)
4. The instructions of part 4 were clearly formulated. (Please take the instructions of part 4 if you do not remember the content of part 4.)
5. The procedures followed in this experiment preserved my anonymity.
6. The money I passed to my selected charity will be transferred to the charity.
7. I received plenty of time to carry out the task.
8. I was motivated to do well on the task.
9. The task was fun to perform, motivating me to achieve a payoff as high as possible.
10. I considered the experiment as fairly complex.
11. My payoff is determined not only by my own decision, but also by the decisions of the other players.
12. When making my decision, I thought about what other players might do.
13. Finally, please describe how you generated your decisions in the experiment.

Demographic Data Questionnaire

1. Birth: In what year were you born?
2. Household Budget: Who in your household would you consider to be primarily in charge of expenses and budget decisions? 1=self, 2=spouse, 3=parent, 4=other(specify), 5=do not know.
3. Gender: What is your gender? 1=male, 2=female
4. Relationship Status: What is your relationship status? 1=married, 2=in a relationship, 3=single, 4=divorced, 5=widowed, 6=other.

5. Employment: How would you best describe your current employment situation? 1=full-time employment outside of university, 2=part-time employment outside of university, 3=student only, 4=work at university as research assistant, 5=other.
6. Household Income: Please indicate the category that best describes your household income from all sources before all taxes in 2012. 1=5,000 and under, 2=5,001-10,000, 3=10,001-20,000, 4=20,001-30,000, 5=30,001-45,000, 6=45,001-60,000, 7=60,001-75,000, 8=75,001-100,000, 9=over 100,001, 10=Don't know.
7. Number in Household: How many people are in your household? (Yourself and those who live with you and share your income and expenses)
8. Own Income: Your own income from all sources before taxes in 2012. Do not include income from other household members. 1=5,000 and under, 2=5,001-10,000, 3=10,001-20,000, 4=20,001-30,000, 5=30,001-45,000, 6=45,001-60,000, 7=60,001-75,000, 8=75,001-100,000, 9=over 100,001, 10=Don't know.
9. Income Source: How do you receive your income? 1=fixed source (salary, pension), 2=hourly rate, 3=hourly rate plus tips, 4=loans/scholarships, 5=parents, 6=other.
10. Student Status: What is your student status? 1=full-time student, 2=part-time student taking less than 10 hours per semester, 3=other, non-student.
11. Study: What is your major? Indicate your field of study.
12. Years of study so far.
13. Which of the following programs are you following? 1=bachelor 2=diploma 3=master 4=doctorate 5=faculty or other non-student.
14. Tuition Fee: Do you pay tuition fee (not ÖH fee)? 1=yes, 0=no
15. Tuition Source: Who is primarily responsible for your living expenses while you are attending your studies? 1=self, 2=parent, 3=shared between self and parent, 4=scholarship/grant, 5=loans, 6=combination/other, 7=not applicable.
16. Vote Participation: Have you ever voted in an election? 1=yes, 2=no.
17. Country background: Please state the country where you were raised. (1=Austria, 2=other EU country or Switzerland, Liechtenstein, Norway, Iceland, 3 other European country 4 other)
18. Have you ever had a course related to game theory or decision theory?

Machiavellian IV personality test

In the following you will find a list of statements. Please read them carefully and answer them to what extent you agree or disagree. Even if in some cases you would like to say that your answers depend on the circumstances, you should

only choose one of the answers. Since all your responses are anonymous, you can answer freely. There is nobody on whom you need to make a good impression. The results can be only used if you answer very honestly.

1=strongly disagree, 2=somewhat disagree, 3=slightly disagree, 4=no opinion, 5=slightly agree, 6=somewhat agree, 7=strongly agree

1. Never tell anyone the real reason you did something unless it is useful to do so.
2. The best way to handle people is to tell them what they want to hear.
3. One should take action only when sure it is morally right.
4. Most people are basically good and kind.
5. It is safest to assume that all people have a vicious streak and it will come out when they are given a chance.
6. Honesty is the best policy in all cases.
7. There is no excuse for lying to someone else.
8. Generally speaking, people will not work hard unless they are forced to do so.
9. All in all, it is better to be humble and honest than to be important and dishonest.
10. When you ask someone to do something for you, it is best to give the real reasons for wanting it rather than giving reasons which carry more weight.
11. Most people who get ahead in the world lead clean, moral lives.
12. Anyone who completely trusts anyone else is asking for trouble.
13. The biggest difference between most criminals and other people is that the criminals are stupid enough to get caught.
14. Most people are brave.
15. It is wise to flatter important people.
16. It is possible to be good in all respects.
17. Barnum was wrong when he said that there's a sucker born every minute.
18. It is hard to get ahead without cutting corners here and there.
19. People suffering from incurable diseases should have the choice of being put painlessly to death.
20. Most people forget more easily the death of their parents than the loss of their property.

Chapter 3

The Impact of Tax Evasion on the Optimal Subsidy on Charitable Giving

3.1 Introduction

This chapter investigates an optimal subsidy for charitable donations considering tax evasion through subsidies for falsely reported donations. Taxpayers in developed countries can frequently deduct donations from their income tax and thus reduce their tax liabilities through charitable giving. If taxpayers overreport cash or gift donations (e.g. used vehicles, domestic appliances), they evade income taxes. This study determines the optimal (i.e. welfare maximizing) subsidy rate for giving under self-reporting and third-party reporting of donations, which are the two reporting schemes for charitable giving in place in developed countries. Under self-reporting of donations, the taxpayer reports the donation and is eligible to a subsidy according to his or her report (e.g. deductions in the USA). Under third-party reporting of donations, the taxpayer reports the donation and the charity is eligible to a subsidy according to the report of the taxpayer.[1] For example in practice, third-party reporting of donations is implemented by the Gift Aid Scheme in the United Kingdom, where the charity organization receives a match subsidy for the donation of the taxpayer. The probability of detecting tax evasion is very high under third-party reporting of tax liabilities as false declarations can easily be detected by matching information reports (e.g. of charities and individuals). In comparison, the detection probability is very low under self-reporting as reports cannot be matched (Dubin et al. 1990, Kleven et al. 2009, 2011, Slemrod 2007, for example). Third-party reporting seems to dominate self-reporting schemes in monetary terms as it

[1] Alternatively, the charity could report and the taxpayer would be eligible to a subsidy.

is relatively cheap to implement, may reduce tax evasion significantly, and can generate relatively high revenues from penalty payments from tax evaders. However, individuals could perceive third-party reporting as an invasion of privacy because of the matching of private reports and thus, it may be difficult for governments to change the reporting scheme (Slemrod 2006, Kleven et al. 2011, Fack and Landais 2012). Consequently, it is important to distinguish between third-party and self-reporting when deriving the optimal subsidy. That is, the focus of this chapter is not to find the best reporting scheme, but to determine an optimal subsidy under a given reporting scheme.

As the volume of charitable donations in many developed countries is sizable, investigations of the optimal subsidy rate on charitable giving are important. The annual report on philanthropy in the USA for the year 2012 shows that the total estimated donations by individual taxpayers accounted for almost $ 230 billion and that about 117 million households donated to charitable organizations (Giving USA 2013). Moreover, 81 % of US taxpayers claimed deductions for charitable giving on their income tax returns in 2012. In the USA gift donations may be used to evade taxes, because taxpayers often self-report the market values of donations without being required to make use of fixed methods for calculating the values (see IRS 2013). A tightening of the rules for vehicle donations in the 2004 US tax reform, for instance, resulted in a 66 % decrease in the number of donated vehicles (Ackerman and Auten 2011). The simplest way to evade taxes through charitable giving might be to falsely declare cash donations at the income tax return. Fack and Landais (2012, 2013) use a tax enforcement reform in France as a natural experiment to provide evidence for tax evasion trough charitable donations and estimate that the share of overreported donations was between 40 % and 60 % before the reform. As a result of the French tax reform 1983, taxpayers must enclose a receipt for each charitable donation when declaring the charitable deductions on their tax returns. The reported donations on tax returns in France decreased by 75 % in the year after the reform. To put it briefly, false declarations of charitable donations may be used in many countries to evade taxes. If taxpayers want to deduct donations from their income in Austria, the taxpayers are only required to provide a receipt of the donation upon request of the tax authority, while taxpayers in the USA have to show an acknowledgment from the charity organization if the donation is larger than $ 250 (IRS 2013).

This chapter offers a model to determine the optimal subsidy rate for charitable donations in the presence of tax evasion, where I distinguish between self-reporting and third-party reporting of donations. First, I show how the optimal subsidy rate depends on the probability of tax evasion being detected. In particular, as the government decides to switch from a self-reporting (low probability of detection)

to a third-party reporting scheme (high probability of detection), the optimal subsidy rate increases under the reasonable assumption that the government does not support tax evasion. Intuitively, under third-party reporting the potential loss of tax revenues as a result of overreporting of donations may be compensated by government revenues from penalties as it is likely that overreporting is detected. Therefore, the government can set a relatively high subsidy rate under third-party reporting. This is in contrast to self reporting, where it is unlikely that overreporting is detected. Second, I show how to adjust the subsidy rate in response to a change in the price elasticity of overreported donations, for example, as a consequence of a tax reform, where the elasticity indicates how overreporting reacts to an increase in the subsidy rate.[2] A marginal decrease in the price elasticity of overreported donations, meaning that an increase in the subsidy results in an increasing level of overreporting, leads to a lower optimal subsidy rate under self-reporting. The reason is that the expected costs of tax evasion for the government under self-reporting are high due to the low detection probability. In contrast, a marginal decrease in the price elasticity of overreported donations can lead to either a lower or higher optimal subsidy rate under third-party reporting. That is, if the probability of detection is high enough that expected government revenues from penalties are higher than expected costs of subsidizing overreported donations, the optimal subsidy rate can rise if an increase in the subsidy results in an increasing level of overreporting. Finally, an increase in the share of true donations in total reported donations (e.g. new tax enforcement technology leading to stricter reporting requirements) leads to a higher optimal subsidy rate under self-reporting, while under third-party reporting a marginal increase in the share of true donations can also lead to a lower optimal subsidy rate if the expected government revenues from penalties are very high.

In simulations, using a range of empirical estimates for the evasion parameters, like the share of true donations in total reported donations or the price elasticity of overreported donations, the optimal subsidy under self-reporting of donation is roughly between 0 % and 38 %. In comparison, the optimal subsidy under third-party reporting is between 20 % and 41 % using the same range of empirical estimates. In the basic calibration, the optimal subsidy is 15 % under self-reporting, while the subsidy under third-party reporting is roughly 35 %. The simulations show that if a one percent increase in the subsidy causes a 1.5 percent increase in evasion, the optimal subsidy is close to zero under self-reporting of donations, while the subsidy under third-party reporting is higher than 40 %. These findings suggest that high subsidy rates under self-reporting of donations, frequently based on marginal income tax rates and found in OECD

[2]In line with the empirical findings of Fack and Landais (2013), I focus on the case where the elasticity of overreported donations is negative.

countries, may constitute deviations from optimality. In the case that the results are confirmed in further research, by knowing the optimal subsidy rates under different probabilities of detection, governments may consider adjusting the level of the subsidy in place.

Related Literature This chapter relates to research on charitable giving and income tax evasion. First, there are numerous empirical and experimental studies that provide estimates for the price elasticity of charitable donations, which reflects the change of donations in response to an increase in the subsidy rate (Taussig 1967, Feldstein and Taylor 1976, Clotfelter 1985, Eckel and Grossman 2003, Karlan and List 2007, Huck and Rasul 2011, for example).[3] In the absence of tax evasion, the literature suggests to increase the subsidy rate if the price elasticity of charitable donations is at least one in absolute terms (*unit elasticity rule*). In other words, a one percent increase in the subsidy should lead to an increase in donations by at least one percent. Karlan et al. (2011) reports that the optimal match subsidy may be at or above 100 percent, while larger match ratios may only lead to more donations among particular donors. Huck and Rasul (2011) find that if charities can make use of lead donors, the charity is better off by merely announcing a substantial lead donor than by additionally trying to match donations (similar results are found by Andreoni 1998 and Rondeau and List 2008). Saez (2004) investigates the size of the optimal subsidy for charitable donations in more detail. There are three goods in his model: private consumption, earnings, and a charitable good to which individuals can voluntarily contribute. Saez finds in his basic specification an optimal subsidy of 40 % and confirms that the optimal subsidy for donations increases with the price elasticity of donations. Diamond (2006) additionally specifies conditions for the optimal subsidy across earnings levels.

Second, there is a rich literature on tax evasion, which can be traced to the theoretical contribution by Allingham and Sandmo (1972).[4] By using data from tax audits Slemrod (1989) and Feldman and Slemrod (2007) show the quantitative importance of overreporting of charitable donations in the USA. Slemrod (1989) and Fack and Landais (2012) argue that the unit elasticity rule is no longer sufficient to infer policy if donations are used to evade taxes, because the *reported* price elasticity of donations overestimates the real social gain of an increase in the subsidy rate. Slemrod (1989) finds that overreported donations are less price responsive than actual donations. Fack and Landais (2013), who make use of the aforementioned tightening in reporting rules in France in 1983, estimate the elasticity of overreported

[3]For a summary of price elasticities of donations found in the literature see Saez (2004) and Huck and Rasul (2011).

[4]For comprehensive summaries of the income tax literature see Andreoni et al. (1998) and Alm (2012).

donations to be large before the tax reform (around -1.5) and small after the reform (around -0.4). Fack and Landais (2012) only provide a formula for the optimal subsidy under tax avoidance (a legal erosion of the tax system) and not under tax evasion (illegal), since they do not model the consequences of tax evasion like penalties.[5] Further, Fack and Landais (2012) do not calibrate the optimal subsidy rate. Finally, Kleven et al. (2011) show in a large-scale field experiment in Denmark that the rate of income tax evasion is almost zero for third-party reported items (see also discussion in Andreoni et al. 1998), while the rate of evasion is nearly 40 % for self-reported items. Moreover, Kleven et al. (2009, 2011) and Slemrod (2007) state that the probability of detection is almost one under third-party reporting of income as false income declaration can be easily detected by matching information reports of employers to tax returns of employees. In contrast, the probability of audits under self-reporting of income was between 1 % and 2.5 % in the USA in the years from 1977 to 1986 (Dubin et al. 1990).

The rest of this chapter is organized as follows. I discuss the model and derive conditions for the optimal subsidy in Section 3.2. Simulations to asses the size of the optimal subsidies under self-reporting and third-party reporting are presented in Section 3.3. Section 3.4 concludes.

3.2 Model

In this section, I present a model to obtain the optimal subsidy on giving considering tax evasion through misreporting of charitable donations. The model is close to standard tax-evasion (e.g. Allingham and Sandmo 1972, Kleven et al. 2011) and optimal-subsidy models (Saez 2004, and Fack and Landais 2012). In this model, the government chooses the income tax rate τ ($0 \leq \tau \leq 1$) and the subsidy rate on donations $-t$ ($0 \leq -t \leq 1$) to maximize social welfare, which is a weighted sum of the utilities of the individuals. In contrast to previous studies, I determine the optimal subsidy under self-reporting and third-party reporting of donations by modeling the probability of detecting false reports and penalties for tax evasion. Moreover, I show how to adapt the optimal subsidy in response to a change in the (observed) share of honest donations and the elasticity of overreported donations. The model is presented as follows. I first discuss the decisions of the individuals (e.g. how much to overreport) and then the problem of the government (i.e. maximizing welfare).

[5] An example of tax avoidance is donations of CEOs to their private foundations, which are often observed directly before sharp declines in their companies' share prices occur. These kind of donations are legal but undesired by the government.

Decisions of the Individuals The optimization problem of individual i is the following. The individual gets utility from private consumption c, earnings z, true donations to the charity g (e.g. warm glow) and overreported donations g^e (e.g. psychological costs of lying), and the total amount of the charitable good G in place.[6] The utility function $u^i = u^i(c, z, g, g^e, G)$ is assumed to be non-decreasing and concave in c, g, and G, because the individual appreciates private consumption and the charitable good. Further, the utility function is decreasing and convex in overreported donations g^e and earnings z, because lying and labor supply are costly. That is, individuals dislike overreporting and working per se but appreciate the increase in consumption as a result of overreporting and working. The arguments g, g^e, and z of the utility function are demand functions, given the policy instruments of the government. Donations and earnings are functions of the price of earnings, which is one minus the marginal tax rate on earnings, τ, and of the price of giving, which is one minus the subsidy rate on donations, $-t$. The price of earnings says how much money remains after taxes from each dollar earned, while the price of giving says how much the individual has to donate such that the charity receives one dollar.[7] In addition, donations and earnings depend on the lump-sum payment that each individual receives from the government, R, and the charitable good, G, so that $g^i = g^i(1-\tau, 1+t, R, G)$, $g^{e^i} = g^{e^i}(1-\tau, 1+t, R, G)$, and $z^i = z^i(1-\tau, 1+t, R, G)$. Since donations enter utility not only as the argument G, but also as individual donations g (similar to consumption), the model is able to capture warm glow of giving (Andreoni 1989, 1990). That is, the individual can get utility from donating, independently of the amount of the charitable good G in place. The number of individuals in the economy is sufficiently large such that each individual takes G as fixed when making her decision to donate.

The consumption of the individual depends on disposable income $(R+(1-\tau)z)$, the income tax and the subsidy rate, the individual's true and overreported donations, and the non-negative penalty rate θ (which is a function of the subsidy rate). The penalty rate $\theta = \theta(t)$ can be in proportion to the subsidy rate (e.g. 30 % of the evaded amount) or can increase with the subsidy rate such that the incentives to evade decrease under a higher subsidy rate: $\theta'(t) \leq 0$ and $\theta''(t) \leq 0$.[8] For example, $R + (1-\tau)z - g$ is

[6] Saez (2004) points out that donations can be seen as a consumption good for individuals that involve external effects.

[7] In practice, the subsidy rate on the charitable good is often linked to the marginal tax rate on earnings (e.g. in the USA). Saez (2004) argues that there is no theoretical justification for linking the subsidy on donations to the tax on earnings, since the elasticity of donations is substantially higher than the elasticity of earnings. Awarding the subsidy rate independently of the marginal tax rate on earnings may lead to large welfare gains if the optimal subsidy rate deviates considerably from the tax rate on earnings. Appendix 3.B.1 also determines the optimal subsidy rate for the case where the subsidy is linked to the marginal income tax rate.

[8] In Appendix 3.B.1, I also consider income-tax evasion and model the penalty rate for income tax evasion in an equivalent way to avoid the puzzling result of Yitzhaki (1974), who finds that a higher marginal income tax rate leads to less income tax evasion under standard assumptions of relative risk aversion.

equal to consumption if donations are not subsidized. If the individual receives a subsidy for the donation, the total subsidy is equal to the donated amount g times the subsidy rate $-t$. An increase in the subsidy rate increases the money available for consumption. If evasion is undetected, the individual also receives a subsidy for the overreported amount g^e. If evasion is detected, the individual has to refund the evaded amount $-tg^e$ and further, has to pay a penalty that is in proportion to the overreported donations θg^e. As at the optimum, the individual consumes all her income after deciding upon earnings, z, true donations, g, and overreported donations, g^e, the individual's consumption is c^E in the case that tax evasion is not detected and c^D if it is detected:

$$c^E = R + (1-\tau)z - g(1+t) - tg^e$$

$$c^D = R + (1-\tau)z - g(1+t) - \theta g^e.$$

The probability of discovering tax evasion p is exogenously given for the following reasons.[9] An exogenous probability simplifies the analysis and is similar to the Taxpayer Compliance Measurement Program of the IRS in the USA, where a random sample of tax returns is subject to in-depth investigations. Furthermore, it might be difficult for governments to implement third-party reporting schemes which have a high probability of detection if individuals think that third-party reporting is an invasion of privacy because of tax authorities accessing private information reports (Slemrod 2006).

Since evasion is detected with probability p and undetected with probability $(1-p)$, the expected utility of individual i is:

$$Max_{z,g,g^e}\, U^i = u^i\left(c^E, z, g, g^e, G\right)(1-p) + u^i\left(c^D, z, g, g^e, G\right)p,$$

where G is the sum of the government's per capita contributions, G^0, and the average donation of the individuals, G^P. The indirect utility function of the individual is given by $\nu^i = \nu^i(1-\tau, 1+t, R, G)$ and depends on the price of giving, $1+t$, and on the price of earnings, $1-\tau$.[10]

[9] In this section, the probability of detection does not depend on the amount of overreported donations. Appendix 3.B.2 shows a model that treats the probability endogenously.

[10] I do not fully specify the utility function u^i and make use of the indirect utility function ν^i as in Saez (2004). I assume that the indirect utility function for each individual is (i) continuous in prices (e.g. tax rate τ) and income (for strictly positive prices and non-negative income). Further, the indirect utility function is (ii) decreasing in prices and non-decreasing in income. Moreover, ν^i is assumed to be (iii) homogeneous of degree zero in prices and income (i.e. no money illusion) and (iv) quasi-convex in prices and income (i.e. if I take two budget lines that result in the same maximum utility, say $\bar{u}$, no budget line in between those two lines results in higher utility than $\bar{u}$). Finally, I assume that the indirect utility function is (v) differentiable (at $t = 0$ and

Decision of the Government The optimization problem of the government is the following. The government aims to maximize welfare, which is a weighted sum of the utilities of the individuals. The indirect utility function, introduced in the previous paragraph, enables the government to maximize the weighted sum of the utilities by choosing the tax and subsidy rate. Since the indirect utility function reflects the maximum utility of the individual given the tax and subsidy rate, changes in utility as a result of changes in the tax and subsidy rates can be derived. That is, as the individuals have already decided upon their optimal level of donations and overreporting, the government takes the demands g and g^e as given and only considers changes in utility in response to changes in the tax and subsidy rate (see discussions of this *sufficient statistics* approach in Saez 2004 and Chetty 2009). I assume that the government takes into account the average true donations $\bar{G} = \bar{G}\left(1-\tau, 1+t, R, G^0\right)$ and overreported donations $\bar{G^e} = \bar{G^e}\left(1-\tau, 1+t, R, G^0\right)$ of the individuals for given levels of tax and subsidy rates, lump-sum transfers, and government contributions.[11] Similarly, average earnings of the individuals are $\bar{Z} = \bar{Z}(1-\tau, 1+t, R, G^0)$. The government maximizes the weighted sum of the indirect utility functions (social welfare) by considering the expected cost of subsidizing the donations:

$$Max_{\tau,t,R,G^0}\, W = \int \mu^i \nu^i (1-\tau, 1+t, R, G) d\nu(i), \tag{3.1}$$

where μ^i denotes the government's weight of individual $i \in I$ (I is the index set). There is a continuum of individuals with unit mass, where $d\nu(i)$ indicates the density of individuals. The government maximizes the welfare function (3.1) subject to its budget constraint and the non-negativity constraint that the government cannot contribute negative amounts to the charitable good:

$$\tau \bar{Z} \geq -tG - t\bar{G^e}\,(1-p) - \theta \bar{G^e} p + R + G^0 + E \tag{3.2}$$

$$G^0 \geq 0, \tag{3.3}$$

where the budget constraint in inequality (3.2) states that the income-tax revenues of the government must be high enough to cover the expected costs of subsidizing donations, the lump-sum transfers to

$\tau = 0$, $\nu^i_R \neq 0$, where subscripts denote derivatives hereafter). Using these standard assumptions about the indirect utility function I can derive the welfare effect of a change in t and τ by making use of Roy's identity, which relates the demand functions (g, g^e, z) to the derivatives of the indirect utility functions (e.g. $\nu^i_{1+t} = -\left[\left(g^i + g^{e^i}\right) u^{i\prime}\left(c^E, \ldots\right)(1-p) + \left(g^i + g^{e^i}\theta_t\right) u^{i\prime}\left(c^D, \ldots\right) p\right] \nu^i_R$, where the prime denotes the outer derivative of $u^i(\ldots)$ hereafter; see Appendix 3.A.1).

[11] For example, the governments could subtract the total revenues by the charities from the total estimated level of individual donations based on statistics by tax authorities like the IRS or reports on charitable giving like Giving USA (2013) to get an estimate of the average level of overreporting, $\bar{G^e}$.

individuals from the government R, the direct contribution to the charitable good by the government G_0, and government consumption E to bear, for instance, the costs of randomized audits.

In line with the related literature, I make use of the following assumptions about government contributions and individual labor supply decisions. First, I assume that the government is able to observe the aggregate level of overreporting such that it can adapt the level of G via direct contributions G^0. An increase in contributions by the government can crowd out private donations to charities ($\bar{G}_{G^0} \leq 0$, where subscripts denote derivatives hereafter). In comparison, an increase in contributions by the government does not crowd out overreported donations ($\bar{G}^e_{G^0} = 0$), which seems a weak assumption. However, $\bar{G}^e_{G^0} = 0$ could be violated if the total level of the charitable good is so low that it encourages individuals to overreport, for example, in order to obtain better living standards. Second, a rise in transfers R does not influence the decisions to work $\left(\partial z^i/\partial R = 0\right)$. Finally, aggregate earnings are not influenced by the subsidy rate $\left(\partial \bar{Z}/\partial(1+t) = 0\right)$ and the level of the charitable good ($\partial \bar{Z}/\partial G^0 = 0$, i.e. government contributions do not influence labor supply) (Saez 2004). If I assume that the indirect utility function ν^i is differentiable and the charitable good is privately underprovided so that the government can contribute to the charitable good (i.e. $G^0 > 0$), the first-order conditions for an interior solution of welfare maximization become:[12]

$$\frac{\partial W}{\partial t} = \int \mu^i \left[\nu^i_{1+t} + \nu^i_G \bar{G}_{1+t}\right] d\nu(i) + \lambda \left[\bar{G} + \bar{G}^e(1 - p + \theta_t p) + t\bar{G}_{1+t} + \bar{G}^e_{1+t}\left(t(1-p) + \theta p\right)\right] = 0 \quad (3.4)$$

$$\frac{\partial W}{\partial \tau} = -\int \mu^i \left[\nu^i_{1-\tau} + \nu^i_G \bar{G}_{1-\tau}\right] d\nu(i) + \lambda \left[\bar{Z} - \tau \bar{Z}_{1-\tau} - t\bar{G}_{1-\tau} - \bar{G}^e_{1-\tau}\left(t(1-p) + \theta p\right)\right] = 0 \quad (3.5)$$

$$\frac{\partial W}{\partial R} = \int \mu^i \left[\nu^i_R + \nu^i_G \bar{G}_R\right] d\nu(i) + \lambda \left[-1 + \tau \bar{Z}_R + t\bar{G}_R + \bar{G}^e_R\left(t(1-p) + \theta p\right)\right] = 0 \quad (3.6)$$

$$\frac{\partial W}{\partial G^0} = \int \mu^i \left[\nu^i_G + \nu^i_G \bar{G}_{G^0}\right] d\nu(i) + \lambda \left[-1 + \tau \bar{Z}_{G^0} + t\bar{G}_{G^0}\right] = 0, \quad (3.7)$$

where λ denotes the multiplier of the budget constraint shown in inequality (3.2).[13] Before I present the condition that determines the optimal subsidy rate I will introduce some concepts that may help to facilitate the implementation of the optimal subsidy in practice, as empirical estimates for the following concepts may be available to policymakers. The elasticity of true donations with respect to one minus the subsidy rate on donations is given by $\varepsilon_g = \frac{1+t}{g}\frac{\partial g}{\partial t}$ and the elasticity of overreported donations by

[12] I can differentiate under the integral sign as the limits of integration are constants (unit mass of individuals) and are not functions of the variable subsidy rate, $-t$, for example.

[13] According to Kuhn-Tucker, the constraint $G^0 \geq 0$ is binding if the left-hand side of equation (3.7) is negative. In this case, private donations are *too* high, because the government cannot contribute negative amounts of the charitable good. As the constraints (3.2) and (3.3) are linear, the solution of the maximization problem is unique if the welfare function shown in equation (3.1) is quasiconcave and twice differentiable (which depends on the specification of the utility functions, compare to footnote 10).

$\varepsilon_{g^e} = \frac{1+t}{g^e}\frac{\partial g^e}{\partial t}$. Further, the ratio of true donations to total reported donations is given by $\alpha = g/g^T$, where total reported donations are $g^T = g + g^e$. It follows that the elasticity of total reported donations is the sum of the elasticity of true donations, ε_g, and the elasticity of overreported donations, ε_{g^e}, weighted by their respective shares in total reported donations: $\varepsilon_{g^T} = \varepsilon_g \alpha + \varepsilon_{g^e}(1-\alpha)$. The elasticities are immutable parameters (i.e. exogenously given), which means that the elasticities should remain roughly constant for small changes in the subsidy rate. The main advantage of the *sufficient statistics* approach used here in comparison to structural approaches is that it reduces the number of parameters that have to be estimated empirically to determine the optimal subsidy rate (e.g. preferences for tax evasion and charitable giving are difficult to measure precisely) (see discussions in Saez 2004, Chetty 2009, Alm et al. 2010, Fack and Landais 2012). Moreover, I define the government's preferences for redistribution similarly to Saez (2004) by

$$\beta\left(G^{T,p}\right) \equiv \int \frac{\mu^i \nu_R^i \left[\left(g^i + g^{e^i}\right) u^{i\prime}\left(c^E, \ldots\right)(1-p) + \left(g^i + g^{e^i}\theta_t\right) u^{i\prime}\left(c^D, \ldots\right) p\right]}{\lambda\left[\bar{G} + \bar{G}^e(1 - p + \theta_t p)\right]} d\nu(i),$$

where $\beta\left(G^{T,p}\right)$ reflects the average government's value $\int \mu^i v_R^i / \lambda d\nu(i)$ of giving one additional dollar to each person weighted by total reported donations (considering the risk due to penalties) $G^{T,p} \equiv \bar{G} + \bar{G}^e\left(1 - p + \theta_t p\right)$.[14] The government's taste for redistribution determines the magnitude of $\beta\left(G^{T,p}\right)$. For example, a high value of $\beta\left(G^{T,p}\right)$ means that the government's weight μ is high for individuals with high reported donations $(g + g^e)$ and the weight is low for individuals with low reported donations. In this case, the government values redistribution from individuals with low donation reports to individuals with high reports, as individuals who report high donations are considered to be more important for the government. If the charitable good is privately underprovided so that $G^0 > 0$, the following condition must be satisfied at the optimum:

$$\varepsilon_{g^T} = \left(1 + \bar{G}_{G^0}\right)\Bigg[- \left[1 - \beta\left(G^{T,p}\right)\right]\left[\alpha + (1-\alpha)\left(1 - p(1-\theta_t)\right)\right] + (1-\alpha)\left(\frac{1}{1 + \bar{G}_{G^0}} + \frac{-t(1-p) - \theta p}{1+t}\right)\varepsilon_{g^e}\Bigg]. \quad (3.8)$$

[14] To see this, note that λ is the multiplier of the budget constraint (3.2). That is, tightening the budget constraint decreases welfare by λ. Further, $\int \mu^i v_R^i / d\nu(i)$ reflects the aggregate welfare gain, measured by the indirect utilities, as a result of an increase in the lump-sum transfer R to all individuals. Lastly, the term $\left[\left(g^i + g^{e^i}\right) u^{i\prime}\left(c^E, \ldots\right)(1-p) + \left(g^i + g^{e^i}\theta_t\right) u^{i\prime}\left(c^D, \ldots\right) p\right]$ measures the change in the utility in response to a change in the subsidy rate (compare Appendix 3.A.1 and Saez 2004).

Proof. See Appendix 3.A.1. □

The interpretation of equation (3.8) follows Saez (2004, p. 2667): "When the elasticity [of total reported donations, ε_{g^T}] is larger than the right-hand side expression [of equation (3.8)], the subsidy rate should be increased up to the point where the elasticity is driven down to the value of the right-hand side." As a result of increasing the subsidy rate so that the elasticity of total reported donations decreases, the optimality of the tax system can be restored. That is, equation (3.8) does not provide an explicit formula, but can evaluate whether the present subsidy is too high or too low (Saez 2004).

Main Findings Inspecting equation (3.8), one makes a number of important observations. First, the only new information in comparison to Fack and Landais (2012) required by the government to determine the optimal subsidy rate are the probability of detection p and the penalty θ.[15] The penalty rate is known by the government, while the probability of detection depends largely on the reporting scheme (self-reporting versus third-party reporting) and the government's resources to audit. The probability of detection has an important influence on the optimal subsidy rate. The following three propositions hold independently of the reporting scheme:

Proposition 3.1. *A marginal increase in the probability of detection p leads to a higher optimal subsidy rate if*

$$\lambda \bar{G}^e (1-\theta_t) \geq \int \mu^i g^{e^i} \left(u^{i\prime} \left(c^E, z, g, g^e, G \right) - u^{i\prime} \left(c^D, z, g, g^e, G \right) \theta_t \right) \nu_R^i d\nu(i). \tag{3.9}$$

Proof. See Appendix 3.A.2. □

The intuition for Proposition 3.1 is as follows. The optimal subsidy rate increases as p marginally increases, for example as a result of improved audit technologies, if the government puts less weight μ (in the welfare function, equation (3.1)) on individuals with high overreported donations g^e than on individuals with low overreported donations.[16] In other words, the optimal subsidy rate increases with

[15] If $p = 0$ and $\theta = 0$, equation (3.8) simplifies to equation (4.4) of Fack and Landais (2012). In other words, Fack and Landais implicitly assume that the government can never detect overreporting.

[16] If $\lambda \bar{G}^e (1-\theta_t) \geq \int \mu^i g^{e^i} \left(u^{i\prime} \left(c^E, \ldots \right) - u^{i\prime} \left(c^D, \ldots \right) \theta_t \right) \nu_R^i d\nu(i)$, the government puts less weight on individuals with high overreported donations than on individuals with low overreported donations for the following reasons. The term $u^{i\prime} \left(c^E, \ldots \right)$ is smaller than $u^{i\prime} \left(c^D, \ldots \right)$ because of concavity, as c^E is larger than c^D because consumption is higher if overreporting is not detected. Further, the average level of overreporting $\bar{G}^e$ is necessarily larger than $\int \mu^i g^{e^i} \nu_R^i d\nu(i)/\lambda$ if the government puts less weight on individuals with low overreported donations g^e. In comparison, $\bar{G}^e$ would be equal to $\int \mu^i g^{e^i} \nu_R^i d\nu(i)/\lambda$ if the government puts equal weight on individuals with low and high overreported donations g^e (compare also footnote 14).

the probability of detection if the government does not support tax evasion. It follows that under the reasonable assumption that the government does not support overreporting, so that condition (3.9) is fulfilled, the optimal subsidy rate increases as the government decides to switch from a self-reporting ($p \to 0$) to a third-party reporting scheme ($p \to 1$) like to a match subsidy.

Proposition 3.2. *A marginal increase in the elasticity of overreported donations ε_{g^e} leads to a higher optimal subsidy if, and only if,*

$$-t(1-p) - \theta p > -(1+t) / \left(1 + \bar{G}_{G^0}\right). \tag{3.10}$$

Proof. See Appendix 3.A.3. □

The intuition for Proposition 3.2 is as follows. If an increase in the subsidy results in a decreasing level of overreporting (e.g. ε_{g^e} becoming less negative as a result of a tax reform), the optimal subsidy rate increases provided that tax evasion is costly for the government. Tax evasion is costly for the government if $-t(1-p) - \theta p > 0$, which is a sufficient condition for a marginal increase in the elasticity of overreported donations to imply a higher optimal subsidy rate as the right-hand side of condition (3.10), $-(1+t) / \left(1 + \bar{G}_{G^0}\right)$, is negative. In other words, if the expected costs of the government from subsidizing overreported donations (loss of tax revenues) are higher than the expected revenues from penalties, a higher elasticity of overreported donations leads to a higher optimal subsidy rate. To put it differently, only if the penalty rate and the probability of detection are very high, such that the government generates a lot of revenues from penalties, could a higher elasticity of overreported donations lead to a lower optimal subsidy rate. As the right-hand side of condition (3.10) is negative, condition (3.10) is always satisfied under self-reporting of donations. In contrast, condition (3.10) might not be satisfied under third-party reporting. As Fack and Landais (2012) do not consider the penalty and the probability of detection, this result is in opposition to their finding that a higher elasticity of overreported donations always leads to a higher subsidy.

Proposition 3.3. *A marginal increase in the share of true donations in total reported donations leads to a higher optimal subsidy if, and only if,*

$$-\left(\frac{1}{1+\bar{G}_{G^0}} + \frac{-t(1-p)-\theta p}{1+t}\right)\varepsilon_{g^e} > p\,(1-\theta_t). \tag{3.11}$$

Proof. See Appendix 3.A.4. □

The intuition for condition (3.11) in Proposition 3.3 is as follows. If the probability of detection, p, and the penalty, θ, are relatively low so that tax evasion is costly for the government as it only generates little revenues from penalties, a marginal increase in the share of true donations (e.g. in response to a new tax enforcement technology) leads to a higher optimal subsidy rate. Proposition 3.3 implies the following. Under self-reporting of donations, when $p \to 0$, condition (3.11) is always fulfilled, as ε_{g^e} and t are negative, and $\bar{G}_{G^0}$ lies between zero and minus one. This means, a marginal increase in the share of true donations in total reported donations leads to a higher optimal subsidy rate under self-reporting of donations. In contrast, a marginal increase in the share of true donations in total reported donations can lead to a higher or lower optimal subsidy rate, depending on the parameters of inequality (3.11). Intuitively, if the probability of detection and the penalty are very high so that the government generates a lot of revenues from penalties, the government could have an incentive to decrease the subsidy rate in response to an increase in the share of true donations. This insight is again in contrast to Fack and Landais (2012) who do not consider the probability of detection and argue that a larger share of true donations necessarily leads to a higher optimal subsidy rate.

The three propositions above lead to the following three corollaries:

Corollary 3.1. *Third-party reporting of donations necessarily leads to a higher optimal subsidy rate than self-reporting if the government puts less or equal weight on tax evaders than on non-evaders and thus, does not support tax evasion.*

Corollary 3.1 is a direct result of Proposition 3.1. If the government decides to switch from a self-reporting to a third-party reporting scheme and does not redistribute from non-evaders to evaders (i.e. the government's weight μ is higher for individuals with low overreported donations than for individuals with high overreported donations), the optimal subsidy rate increases. To put it differently, increasing the subsidy rate may lead to welfare gains if the probability of detection increases as a result of a switch to third-party reporting.

As governments may also be interested in how to adapt the optimal subsidy rate if the observed elasticity of overreported donations changes under self-reporting and third-party reporting, respectively, I will determine the change in the optimal subsidy rate in response to a change in the elasticity of overreported donations in my simulations:

Corollary 3.2. *A marginal decrease in the elasticity of overreported donations ε_{g^e} (i.e. an increase in the subsidy results in an increasing level of overreporting) leads to a lower optimal subsidy rate under*

self-reporting, as overreporting is costly for the government.

In comparison, a marginal decrease in the elasticity of overreported donations can lead to either a lower (if overreporting is costly for the government) or higher (if overreporting generates a lot of government revenues from penalties) optimal subsidy rate under third-party reporting.

Finally, I am interested in the implications of an increase in the share of true donations in total reported donations with respect to the optimal subsidy rate. In other words, I would like to determine whether it is useful for governments to adapt the subsidy rates in the case of decreasing levels of evasion:

Corollary 3.3. *A marginal increase in the share of true donations in total reported donations α leads to a higher optimal subsidy rate under self-reporting, as overreporting is costly for the government.*
In comparison, a marginal increase in the share of true donations can lead to either a higher (if overreporting is costly for the government) or lower (if overreporting generates a lot of government revenues from penalties) optimal subsidy rate under third-party reporting.

Other Observations First, the higher the value of $\beta\left(G^{T,p}\right)$ the more important individuals with high reported donations are relative to individuals with low reported donations for the government. In this case, the government values redistribution from individuals with low reports to individuals with high reports and thus, sets a relatively high subsidy rate in order to support individuals with high reported donations.[17] Second, it is not clear whether a marginal increase in the penalty rate leads to a lower or higher optimal subsidy rate. On the one hand, a higher penalty rate decreases the utility of the individuals, because the penalty that has to be paid in case of detection increases. On the other hand, a higher penalty rate leads to increased government revenues from evaders, which the government can use for redistribution, for example. Finally, the *unit* elasticity rule is in place if the government has Rawlsian redistributive tastes (i.e. preferences for complete redistribution from individuals with high reported donations to individuals with low reported donations: $\beta\left(G^{T,p}\right) = 0$), there is no crowding out ($\bar{G}_{G^0} = 0$) and if there is no tax evasion ($\alpha = 1$). That is, if there are overreported donations, the unit elasticity rule is no longer in place.[18]

[17] As both sides of equation (3.8) are negative, a high value of $\beta\left(G^{T,p}\right)$ means that the absolute value of the left-hand side of equation (3.8) is more likely to be larger than the right-hand side. Thus, the subsidy rate needs to be increased in order to drive down the elasticity of total reported donations so that equation (3.8) holds again (Saez 2004).

[18] In the case of tax evasion, the subsidy rate generally needs to be increased if the elasticity of total reported donations is larger than one in absolute terms. However, if government grants displace a lot of private donations, the elasticity of total reported contributions may be smaller than one in absolute terms and still imply an increase in the subsidy rate. Intuitively, when government grants crowd out a lot of private donations, government grants

3.3 Numerical Application

The simulations based on the model described in Section 3.2 are presented as follows. Section 3.3.1 describes the data and states the assumptions employed in the simulation. Next, by using a range of empirical estimates for the donation and evasion parameters, I determine the optimal subsidy rates under third-party and self-reporting in Section 3.3.2. Moreover, I compute whether an increase in the elasticity of overreported donations and the share of true donations, respectively, leads to a higher or lower optimal subsidy rate under third-party reporting in my simulations (compare Corollaries 3.2 and 3.3).

3.3.1 Calibration Setup

The simulations use individual income microdata from the Survey of Consumer Finances for 2010 of the Federal Reserve Board (2012). The true donations for each income range are based on the charitable deductions reported in the Statistics of Income Bulletin (2012), while for simplicity I assume that the marginal income tax rate of individuals is 30 % (similar to Saez 2004).[19] For example, the mean donation of taxpayers in the income range $ 15,000 to $ 30,000 was $ 180. Consequently, I generate exponentially distributed donations for each income range by making use of the mean donations of each income range (see for example, Carson and Sun 2007). Similarly, I generate exponentially distributed overreported donations, where the mean overreported donation of each income range is calculated considering the share of true donations ($\bar{G}^e = \bar{G}\,(1-\alpha)\,/\alpha$, where the share of true donations varies between 0.25 and 0.75).

Assumptions First, I assume that private contributions to charity are perfect substitutes for government contributions to the charitable good. That is, in line with the model in Section 3.2, the government is as efficient in providing the charitable good as the individual (see Appendix 3.C for the case where the government is more efficient in providing the charitable good as a result of having better knowledge of the needs of charities). Second, in order to simplify the computations, I do not fully specify all individual utility functions (Saez 2004), and assume risk-neutral individuals and a linear penalty function.[20] In particular, the individuals have to pay a 10 %, 30 %, or 50 % penalty of the evaded amount, which is

are inefficient in increasing the level of the charitable good as they decrease private donations considerably. As a result, private donations, instead of inefficient direct government grants, should be encouraged by increasing the subsidy rate on donations.

[19] The numerical results are hardly affected and my findings are still the same if the marginal income tax rates for each income range are chosen according to thresholds for US taxpayers.

[20] The numerical results are hardly affected and my conclusions are still the same if I assume some simple risk-averse utility function for the individuals.

the subsidy rate times the overreported donations.[21] Third, as the estimated donation elasticities of the literature are generally elasticities of total reported donations (and not elasticities of true donations), I assume the elasticity of total reported donations $\varepsilon_{g^T} = -1$. Fourth, the share of true donations in total reported donations varies between 0.25 and 0.75 in my simulations and the elasticity of overreported donations varies between -0.5 and -1.5, which is close to the empirical findings by Fack and Landais (2013). Fifth, I assume that the probability of detection is 5 % under self-reporting, which is in line with the probability of detection under self-reporting, between 1 % and 6 %, used in the experiment by Alm et al. (1992) and the empirical study by Dubin et al. (1990), for example. Lastly, I assume that the probability of detection is 95 % under third-party reporting and thus almost one, as stated in Slemrod (2007), Kleven et al. (2009, 2011), and other studies.

The rest of the simulation is executed using the same assumptions and empirical estimates as the basic specification of Table 1 of Saez (2004). First, the earnings elasticity, which indicates by how much aggregate earnings increase in response to a marginal decrease in income taxes, is 0.25 (required for $\bar{Z}_{1-\tau}$ in condition (3.5)). Second, the disposable income elasticity of donations, which indicates by how much aggregate donations increase in response to a marginal increase in disposable income, is 1 (required for $\bar{G}_{1-\tau}$ in condition (3.5), see technical details in Saez 2004). Third, the positive external effect of donations depends on the total level of donations, which is the sum of donations of the individuals and the government's contribution $\bar{G} + G^0$. The external effect of donations has decreasing returns in the simulations (required for ν_G^i in the first-order conditions, specified as in Saez 2004).[22] Fourth, the marginal welfare weights, required to estimate $\beta\left(G^{T,p}\right)$ in equation (3.8), depend only on the disposable incomes of the individuals: $z(1-\tau)+R$. The marginal weights are specified so that the government values half as much a marginal increase in consumption of an individual with disposable income I relative to an increase in consumption of an individual with disposable income $I/2$. For example, the government values half as much a marginal increase in consumption of an individual with disposable income \$ 100,000 relative to an individual with disposable income \$ 50,000. Finally, the calculations assume that there is no crowding out of private donations by government contributions (i.e. $\bar{G}_{G^0} = 0$), and that government consumption per capita is \$ 6,000.

[21] The penalty rate for US taxpayers is, for example, between 20 % and 40 % if taxpayers overreport the value of a donated property and the evaded amount is higher than \$ 5,000 (IRS 2013).

[22] First, Saez (2004) defines the external effect as $e = \int \nu^i \mu^i \nu_G^i d\nu(\mathrm{i})/\lambda$. For the simulations, he specifies:

$$\frac{\nu_G^i}{\nu_R^i} = B(\bar{G} + G^0)^{-l},$$

where $l = 0.5$ and $B = 60$ in the case of high external effects.

3.3.2 Calibration Results

The results of the simulations under a probability of detection of 5 % (self-reporting) are shown in Table 3.1 and the results under a probability of detection of 95 % (third-party reporting) are shown in Table 3.2. The optimal income tax rate is calibrated in column (1) of each table. The optimal donation subsidy rate is calibrated in column (2) of Table 3.1 under self-reporting and Table 3.2 under third-party reporting. *Panel A* of each table shows the basic specification assuming an elasticity of overreported donations of -1, a 50 % share of true donations, and a 30 % penalty of the evaded amount. *Panels B, C*, and *D* of Tables 3.1 and 3.2 vary the evasion parameters, ε_{g^e}, α, and θ. In column (1) of *Panel A* of Table 3.1 we see that under self-reporting, the optimal tax rate, τ, is 60.9 % and in column (2) we see that the optimal subsidy rate, $-t$, is 15 %.

In column (1) of *Panel A* of Table 3.2 we see that under third-party reporting, the optimal tax rate is also 60.9 %, while in column (2) we see the optimal subsidy rate is 35.4 %. The optimal income tax and subsidy rates under third-party reporting are in line with the result of Saez (2004) who found an optimal tax rate of 60 % and optimal subsidy rate of 40 % under the implicit assumption of no overreporting of donations.[23] In general, the optimal income tax rate is around 61 % and is hardly affected by the choice of the evasion and donation parameters, because donations constitute only a small fraction of income (Saez 2004).[24] Comparing the subsidy rates of Tables 3.1 and 3.2 shows that the optimal subsidy rates under third-party reporting are higher than under self-reporting, everything else equal. This means, the optimal subsidy rate increases as the government decides to switch from a self-reporting to a third-party reporting scheme, which leads to the following result in line with Corollary 3.1:

Result 3.1. *Using the range of empirical estimates for the evasion parameters shown in Tables 3.1 and 3.2, the optimal subsidy rate under self-reporting ranges from 0.2 % to 37.8 % in my simulations, while the optimal subsidy under third-party reporting ranges from 19.7 % and 40.7 %.*

[23] The levels of the optimal subsidy rates shown in Tables 3.1 and 3.2 are affected by the chosen sample of individuals. While Saez (2004) only includes 30 representative individuals whose income range from $ 0–200,000, the simulations of this study are based on more than 30,000 observations and also comprise individuals with higher income. Moreover, the optimal subsidy rates are sensitive to the assumed starting values for the simulations, which for $-t$, τ, G_0 were chosen according to Saez (2004) and for R according to the average income tax payment (i.e. $R = \bar{Z}\tau$). However, in all simulations I executed, the main conclusions were not affected by the choice of the starting values and sample.

[24] Similarly, if the subsidy rate is linked to the marginal income tax rate (deduction) as in Appendix 3.B.1, the optimal subsidy rate is also around 61 %. As the subsidy rate is linked to the marginal tax rate, the choice of the evasion and donation parameters have hardly an impact on the optimal subsidy rate. It follows that linking the subsidy rate to the marginal tax rate can lead to considerable welfare losses (Saez 2004).

Table 3.1: Self-reporting of donations ($p = 0.05$)

	(1) Income tax τ	(2) Donation subsidy $-t$
Panel A: Basic specification		
$\varepsilon_{g^T} = -1$, $\varepsilon_{g^e} = -1$, $\alpha = 0.5$, $\theta = -0.3t$	60.9 %	15.0 %
Panel B: Varying elasticities of overreported donations		
$\varepsilon_{g^T} = -1$, $\varepsilon_{g^e} = -0.5$, $\alpha = 0.5$, $\theta = -0.3t$	61.0 %	29.9 %
$\varepsilon_{g^T} = -1$, $\varepsilon_{g^e} = -1.5$, $\alpha = 0.5$, $\theta = -0.3t$	60.8 %	0.2 %
Panel C: Varying share of true donations		
$\varepsilon_{g^T} = -1$, $\varepsilon_{g^e} = -1$, $\alpha = 0.25$, $\theta = -0.3t$	60.8 %	0.5 %
$\varepsilon_{g^T} = -1$, $\varepsilon_{g^e} = -1$, $\alpha = 0.75$, $\theta = -0.3t$	61.8 %	37.8 %

In column (1) the optimal income tax rate is calibrated. In column (2) the optimal donation subsidy rate is calibrated under self-reporting of donations ($p = 0.05$). *Panel A* shows the basic specification assuming an elasticity of overreported donation of -1, a share of true donations of 50 %, and a 30 % penalty of the evaded amount, which is the subsidy rate times the overreported donations. The elasticity of overreported donations is varied in *Panel B*, the share of true donations is varied in *Panel C*, and the fine rate is varied in *Panel D*. In all calculations, I assume that private contributions to the charitable good are as efficient as government contributions. Otherwise, the calculations are based on the same assumptions and empirical estimates as the basic specification of Table 1 of Saez (2004). That is, the calculations assume that there is no crowding out of private donations by government contributions, the elasticity of total reported donations is -1, the earnings elasticity is 0.25, the disposable income elasticity of donations is 1, and that government consumption per capita is $ 6,000.

Table 3.2: Third-party reporting of donations ($p = 0.95$)

	(1) Income tax τ	(2) Donation subsidy $-t$
Panel A: Basic specification		
$\varepsilon_{g^T} = -1$, $\varepsilon_{g^e} = -1$, $\alpha = 0.5$, $\theta = -0.3t$	60.9 %	35.4 %
Panel B: Varying elasticities of overreported donations		
$\varepsilon_{g^T} = -1$, $\varepsilon_{g^e} = -0.5$, $\alpha = 0.5$, $\theta = -0.3t$	60.9 %	35.3 %
$\varepsilon_{g^T} = -1$, $\varepsilon_{g^e} = -1.5$, $\alpha = 0.5$, $\theta = -0.3t$	60.9 %	40.2 %
Panel C: Varying share of true donations		
$\varepsilon_{g^T} = -1$, $\varepsilon_{g^e} = -1$, $\alpha = 0.25$, $\theta = -0.3t$	61.0 %	19.7 %
$\varepsilon_{g^T} = -1$, $\varepsilon_{g^e} = -1$, $\alpha = 0.75$, $\theta = -0.3t$	61.6 %	40.7 %

In column (1) the optimal income tax rate is calibrated. In column (2) the optimal donation subsidy rate is calibrated under third-party reporting of donations ($p = 0.95$). *Panel A* shows the basic specification assuming an elasticity of overreported donation of -1, a share of true donations of 50 %, and a 30 % penalty of the evaded amount, which is the subsidy rate times the overreported donations. The elasticity of overreported donations is varied in *Panel B*, the share of true donations is varied in *Panel C*, and the fine rate is varied in *Panel D*. In all calculations, I assume that private contributions to the charitable good are as efficient as government contributions. Otherwise, the calculations are based on the same assumptions and empirical estimates as the basic specification of Table 1 of Saez (2004). That is, the calculations assume that there is no crowding out of private donations by government contributions, the elasticity of total reported donations is -1, the earnings elasticity is 0.25, the disposable income elasticity of donations is 1, and that government consumption per capita is $ 6,000.

Elasticity of Overreported Donations In *Panel B* of Table 3.1 we see that the optimal subsidy rate under self-reporting increases from 15 % to 29.9 % if the elasticity of overreported donations changes from $\varepsilon_{g^e} = -1$ to $\varepsilon_{g^e} = -0.5$. Further, the optimal subsidy rate under self-reporting drops to 0.2 % if the elasticity of overreported donations $\varepsilon_{g^e} = -1.5$ (similar to the empirical estimate of the elasticity by Fack and Landais 2013). The intuition for this is as follows. If the elasticity of overreported donations decreases (i.e. becomes more negative), more evasion results from an increase in the subsidy rate. As the probability of detection is low under self-reporting, the expected costs of the government from subsidizing overreported donations (loss of tax revenues) are higher than the expected revenues from penalties from tax evaders. As a result, the government is better off by decreasing the subsidy rate in response to a decrease in the elasticity of overreported donations.

In contrast, in *Panel B* of Table 3.2 we see that the optimal subsidy rate under third-party reporting increases from 35.4 % to 40.2 % if the elasticity of overreported donations decreases from $\varepsilon_{g^e} = -1$ to $\varepsilon_{g^e} = -1.5$. As the probability of detection is high under third-party reporting, the expected government revenues from penalties from tax evaders are higher than the expected costs from subsidizing overreported donations. As a result, the government is better off by increasing the subsidy rate in response to a decrease in the elasticity, which is in line with Corollary 3.2:

Result 3.2. *If an increase in the subsidy results in an increasing level of overreporting, the optimal subsidy rate under self-reporting decreases. In comparison, if an increase in the subsidy results in an increasing level of overreporting under third-party reporting, the optimal subsidy rate increases in my simulations.*

Share of True Donations In *Panels C* of Tables 3.1 and 3.2 we see that if the share of true donations in total reported donations is 25 %, the optimal subsidy rate drops to 0.5 % under self-reporting and to 19.7 % under third-party reporting. We also see that if the share of true donations is 75 %, the optimal subsidy rate increases to 37.8 % under self-reporting and to 40.7 % under third-party reporting (in line with Saez 2004). The optimal subsidy rates under self-reporting and third-party reporting are becoming more similar if there is less overreporting. That is, if there there are more truthful donation reports, the reporting scheme has relatively less impact on the optimal subsidy rate. These results are in line with Corollary 3.3:

Result 3.3. *A decrease in the share of true donations α leads to a lower optimal subsidy rate in my simulations. If the share of true donations is 25 %, the optimal subsidy rate is 19.7 % under third-party*

reporting, while it is only 0.5 % under self-reporting.

3.4 Conclusion

This study determines the optimal subsidy of giving taking into account tax evasion as a result of overreporting of charitable donations. It is the first analysis that provides estimates of the optimal subsidy rate taking into consideration the probability of detecting overreporting and penalties for tax evasion. Furthermore, it is the first analysis of the subsidy rate that distinguishes between subsidies subject to self-reporting of donations (usually in place in OECD countries) and third-party reporting of donations (e.g. match subsidy in the United Kingdom). In my simulations I find that the subsidy ranges from close to 0 % to 38 % under self-reporting and from roughly 20 % to 41 % under third-party reporting. Further, as the government decides to switch from self-reporting to third-party reporting, the optimal subsidy rate increases. Moreover, if an increase in the subsidy results in an increasing level of overreporting, the optimal subsidy rate under self-reporting decreases as government revenues from penalties are lower than losses from overreporting. In comparison, if an increase in the subsidy results in an increasing level of overreporting under third-party reporting, the optimal subsidy rate increases in my simulations as revenues from penalties are higher than losses from overreporting. Finally, the optimal subsidy rate decreases with the share of overreported donations.

To the extent that my simulation results have policy implications, the message would be that high subsidy rates are likely to lead to considerable deviations from optimality under self-reporting of donations, especially if there is a lot of overreporting. Furthermore, subsidies for donations should be rather awarded as tax credits independently of the income tax rate than as deductions linked to the income tax rate, as the optimal subsidy rate often deviates considerably from the tax rate on earnings, especially under self-reporting schemes. However, as the optimal subsidy rates depend on the underlying assumptions of the model and may also depend on other institutions and non-monetary costs, policy recommendations can only be cautiously drawn.

Appendix

3.A Proofs

3.A.1 Proof Derivation of Equation (3.8)

Proof. The optimal subsidy rate can be either obtained by manipulating equations (3.4)–(3.7) or by following the direct proof by Roberts (1987) and Saez (2004). I follow the latter approach. A marginal decrease in the subsidy rate of the charitable good has the following four consequences:

1. The decrease in the subsidy rate increases government revenues in a mechanical way. As a result of the decrease in the subsidy rate, the government needs to subsidize less true and overreported donations. The government's budget improves by:

$$\left(\bar{G} + \bar{G}^e \left(1 - p + \theta_t p\right)\right) dt. \tag{3.12}$$

2. The utility of *each* individual changes, since donations are subsidized less. To see how the welfare of each individual changes, I make use of the indirect utility function. Lowering the subsidy rate can be understood as increasing the price of the donation. This increase in the price decreases the utility of each individual:

$$\begin{aligned} dU^i &= \nu^i_{1+t} dt \\ &= -\left[\left(g^i + g^{e^i}\right) u^{i\prime}\left(c^E, \ldots\right)(1-p) + \left(g^i + g^{e^i}\theta_t\right) u^{i\prime}\left(c^D, \ldots\right) p\right] \nu^i_R dt, \end{aligned}$$

since the expected utility of the individual is $U = u\left(c^E, \ldots\right)(1-p) + u\left(c^D, \ldots\right) p = u(R + (1-\tau)z - g(1+t) - tg^e, \ldots)(1-p) + u(R + (1-\tau)z - g(1+t) - \theta g^e, \ldots)$.[25] Note, the indirect utility

[25] Hereafter, I will omit the superscript i for the utility function u and the demand functions g and g^e of the individual to improve readability.

function is equivalent to the utility function evaluated at the optimal values of the Marshallian demand functions g, g^e and the Lagrange multiplier of the individual Λ: $U\left(g^*, g^{e^*}, \Lambda^*, \ldots\right)$. Thus $\frac{\partial \nu^i(\ldots)}{\partial(1+t)} = \frac{\partial U\left(g^*, g^{e^*}, \Lambda^*, \ldots\right)}{\partial(1+t)} = -\Big[\left(g^* + g^{e^*}\right) u'\left(c^E, \ldots\right)(1-p) + \left(g^* + g^{e^*}\theta_t\right) u'\left(c^D, \ldots\right) p\Big]\Lambda^*$. The Lagrange multiplier Λ^* is equal to ν_R^i, because increasing the lump-sum transfer R by one dollar has the same effect on individual utility as relaxing the budget constraint of the individual by one dollar.[26] Integrating over all individuals leads to the aggregate welfare effect:

$$-\beta\left(G^{T,p}\right)\left(\bar{G} + \bar{G}^e\left(1 - p + \theta_t p\right)\right) dt, \tag{3.13}$$

where $\beta\left(G^{T,p}\right)$ is defined as shown in Section 3.2.

3. Individuals adapt their behavior in response to the lower subsidy rate on donations. That is, individuals donate and overreport less, which increases government revenues by $td\bar{G} + d\bar{G}^e\left(t\left(1-p\right) + \theta p\right)$. The change in private donations consists of a price effect (i.e. change of private donations because of the lower subsidy rate) and crowding-out effect:
   $d\bar{G} = \bar{G}_{1+t} dt + \bar{G}_{G^0} dG^0$
   Since the government adjusts the public contributions to the charitable good, it follows that
   $d\bar{G} = \bar{G}_{1+t} dt - \bar{G}_{G^0} d\bar{G}$
   $d\bar{G} = \frac{\bar{G}_{1+t} dt}{1+\bar{G}_{G^0}}$.
   As there is no crowding out of overreported donations, $d\bar{G}^e = \bar{G}^e_{1+t} dt$. Consequently, the revenue loss of the government due to the adaptation of the individuals is given by:[27]

$$td\bar{G} + d\bar{G}^e\left(t\left(1-p\right) + \theta p\right) = \left[\frac{t\bar{G}_{1+t}}{1+\bar{G}_{G^0}} + \bar{G}^e_{1+t}\left(t\left(1-p\right) + \theta p\right)\right] dt. \tag{3.14}$$

4. Since the decrease in the subsidy rate reduces donations, the government increases the public

[26] The derivative of the indirect utility function with respect to the tax rate ν_{1+t} is similar to Roy's identity, where g and g^e are Marshallian demands.

[27] The effects of 1. and 3. can also be obtained by taking the total differential of the governments revenue $\left(\pi \equiv \tau\bar{Z} + t\bar{G} + t\bar{G}^e\left(1-p\right) + \theta\bar{G}^e p\right)$:

$$d\pi = \bar{G}dt + t\bar{G}_t dt + \bar{G}^e\left(1-p\right)dt + t\bar{G}^e_t(1-p)dt + \theta_t\bar{G}^e p dt + \theta\bar{G}^e_t p dt.$$

Since $d\bar{G} = \bar{G}_t dt$ and $d\bar{G}^e = \bar{G}^e_t dt$, it follows that

$$d\pi = \bar{G}dt + \bar{G}^e\left(1-p\right)dt + \theta_t\bar{G}^e p dt + td\bar{G} + t\left(1-p\right)d\bar{G}^e + \theta p d\bar{G}^e,$$

which is equivalent to the sum of the effects shown in (3.12), the mechanical effect on government revenues, and (3.14), the revenue loss due to the adaptation of the individuals as a result of the decrease in the subsidy rate.

contributions to the charitable good such that $d\bar{G} + dG^0 = 0$. That is, the decrease in the subsidy rate generates costs for the government by:

$$-dG^0 = d\bar{G}. \tag{3.15}$$

At the optimum, these four effects shown in (3.12) to (3.15) must cancel out (i.e. the sum is zero). Making use of my assumptions, the definitions of the share of true donations α, and of the elasticities ε_g and ε_{g^e}, some simple algebraic manipulations of the sum, $(3.12) + (3.13) + (3.14) + (3.15) = 0$, show that the following equation holds at the optimum:

$$\left\{ \frac{-\alpha}{1 + \bar{G}_{G^0}} \varepsilon_g + \frac{1-\alpha}{1+t} \varepsilon_{g^e} \left(-t\,(1-p) - \theta p \right) \right\} \frac{1}{\alpha + (1-\alpha)\,(1 - p\,(1-\theta_t))} = 1 - \beta\left(G^{T,p}\right).$$

Making use of the elasticity of total reported donations $\varepsilon_{g^T} = \varepsilon_g \alpha + \varepsilon_{g^e}(1-\alpha)$ leads to the following condition that has to be satisfied at the optimum:

$$\varepsilon_{g^T} = \left(1 + \bar{G}_{G^0}\right) \Bigg[- \left[1 - \beta\left(G^{T,p}\right)\right] \left[\alpha + (1-\alpha)\,(1 - p(1-\theta_t))\right] + (1-\alpha) \left(\frac{1}{1 + \bar{G}_{G^0}} + \frac{-t(1-p) - \theta p}{1+t} \right) \varepsilon_{g^e} \Bigg].$$

□

3.A.2 Proof of Proposition 3.1

Proof. Recall, even though equation (3.8) does not provide an explicit formula for the optimal subsidy, it can be used to determine whether the current subsidy is too high or too low. In general, if the right-hand side of equation (3.8) increases (i.e. becomes less negative), the subsidy rate needs to be increased in order to drive down the elasticity of total reported donations, ε_{g^T}, so that equation (3.8) holds again (Saez 2004). It follows that if an increase in the probability of detection, p, increases the right-hand side of equation (3.8), the subsidy rate needs to be increased in order to restore the optimality of the tax system by driving down ε_{g^T}. Therefore, I check whether an increase in the probability of detection increases the right-hand side of equation (3.8).

First, I insert $\beta\left(G^{T,p}\right) \equiv \int \frac{\mu^i \nu_R^i \left[(g+g^e)u'\left(c^E,\ldots\right)(1-p) + (g+g^e\theta_t)u'\left(c^D,\ldots\right)p\right]}{\lambda\left[\bar{G} + \bar{G}^e(1-p+\theta_t p)\right]} d\nu(i)$ in the right-hand side of

equation (3.8):

$$\left(1+\bar{G}_{G^0}\right)\Bigg[-\left[\alpha+(1-\alpha)\left(1-p(1-\theta_t)\right)\right]+\int\frac{\mu^i\left[\left(g+g^e\right)u'(c^E,\ldots)\left(1-p\right)+\left(g+g^e\theta_t\right)u'(c^D,\ldots)p\right]\nu_R^i}{\lambda\left[\bar{G}+\bar{G}^e(1-p+\theta_t p)\right]}d\nu(i)+(1-\alpha)\left(\frac{1}{1+\bar{G}_{G^0}}+\frac{-t\left(1-p\right)-\theta p}{1+t}\right)\varepsilon_{g^e}\Bigg]. \quad (3.16)$$

If the first derivative of expression (3.16) with respect to p is positive, the subsidy rate needs to be increased in response to a marginal increase in the probability of detection in order to drive down the elasticity of total reported donations, ε_{g^T}, on the left-hand side of equation (3.8) so that the equality holds again.

The first derivative of expression (3.16) with respect to p is given by:

$$\left(1+\bar{G}_{G^0}\right)\Bigg[(1-\alpha)(1-\theta_t)+\int\frac{\mu^i\left[-\left(g+g^e\right)u'(c^E,\ldots)\left(1-p\right)+\left(g+g^e\theta_t\right)u'(c^D,\ldots)\right]\nu_R^i}{\lambda\bar{G}^T}d\nu(i)+(1-\alpha)\left(\frac{t-\theta}{1+t}\right)\varepsilon_{g^e}\Bigg].$$

Recall that $(1-\alpha)=\bar{G}^e/\bar{G}^T$:

$$\left(1+\bar{G}_{G^0}\right)\Bigg[\frac{\bar{G}^e}{\bar{G}^T}(1-\theta_t)+\int\frac{\mu^i\left[-\left(g+g^e\right)u'(c^E,\ldots)+\left(g+g^e\theta_t\right)u'(c^D,\ldots)\right]\nu_R^i}{\lambda\bar{G}^T}d\nu(i)+(1-\alpha)\left(\frac{t-\theta}{1+t}\right)\varepsilon_{g^e}\Bigg],$$

where the last term in the brackets is always positive, since t and ε_{g^e} are negative and θ and $(1-\alpha)$ are positive. As $\left(1+\bar{G}_{G^0}\right)$ is also positive, a sufficient condition for a positive derivative of expression (3.16) is:

$$\bar{G}^e\left(1-\theta_t\right)\geq\int\frac{\mu^i\left[\left(g+g^e\right)u'\left(c^E,\ldots\right)-\left(g+g^e\theta_t\right)u'\left(c^D,\ldots\right)\right]\nu_R^i}{\lambda}d\nu(i).$$

Since c^E is larger than c^D (i.e. consumption is higher if overreporting is not detected), $u'\left(c^E,\ldots\right)$ is smaller than $u'\left(c^D,\ldots\right)$ because of concavity. It follows that

$$gu'\left(c^E,\ldots\right)<gu'\left(c^D,\ldots\right).$$

Thus, for the derivative of expression (3.16) to be positive, it is sufficient that

$$\lambda \bar{G}^e (1-\theta_t) \geq \int \mu^i \left[g^e \left(u' \left(c^E, \ldots \right) - \theta_t u' \left(c^D, \ldots \right) \right) \right] \nu_R^i d\nu(i). \tag{3.17}$$

If inequality (3.17) holds, the right-hand side of equation (3.8) increases (becomes less negative) as the probability of detection increases. Hence, the subsidy rate needs to be increased as p increases in order to drive down the elasticity of total reported donations so that equation (3.8) holds again and the optimality of the tax system is restored. □

3.A.3 Proof of Proposition 3.2

Proof. Recall, equation (3.8) can be used to determine whether the current subsidy is too high or too low. In general, if the right-hand side of equation (3.8) increases (i.e. becomes less negative), the subsidy rate needs to be increased in order to drive down the elasticity of total reported donations, ε_{g^T}, so that equation (3.8) holds again and the optimality of the tax system is restored (Saez 2004). It follows that if an increase in the elasticity of overreported donations, ε_{g^e}, increases the right-hand side of equation (3.8), the subsidy rate needs to be increased in order to restore the optimality of the tax system by driving down ε_{g^T}. Therefore, I check whether an increase in the elasticity of overreported donations increases the right-hand side of equation (3.8).

If the derivative of expression (3.16), which is equivalent to the right-hand side of equation (3.8), with respect to ε_{g^e} is positive, the subsidy rate needs to be increased in response to a marginal increase in the elasticity of overreported donations in order to drive down the elasticity of total reported donations, ε_{g^T}, on the left-hand side of equation (3.8) so that the equality holds again. The first derivative of expression (3.16) with respect to ε_{g^e} is given by

$$\left(1 + \bar{G}_{G^0}\right)(1-\alpha)\left(\frac{1}{1+\bar{G}_{G^0}} + \frac{-t(1-p)-\theta p}{1+t}\right).$$

Since α and $\left(-\bar{G}_{G^0}\right)$ lie between zero and one, a necessary and sufficient condition for the derivative to be positive is:[28]

$$\frac{1}{1+\bar{G}_{G^0}} + \frac{-t(1-p)-\theta p}{1+t} > 0$$

$$\frac{-t(1-p)-\theta p}{1+t} > -\frac{1}{1+\bar{G}_{G^0}}$$

[28] As $(1+t)$ is positive, another sufficient condition for the derivative to be positive is $-t(1-p)-\theta p > 0$.

$$-t(1-p)-\theta p > -\frac{1+t}{1+\bar{G}_{G^0}}. \tag{3.18}$$

If inequality (3.18) holds, the right-hand side of equation (3.8) increases as the elasticity of overreported donations increases. Hence, the subsidy rate needs to be increased as ε_{g^e} increases in order to drive down the elasticity of total reported donations so that equation (3.8) holds again and the optimality of the tax system is restored. □

3.A.4 Proof of Proposition 3.3

Proof. Recall, equation (3.8) can be used to determine whether the current subsidy is too high or too low. In general, if the right-hand side of equation (3.8) increases, the subsidy rate needs to be increased in order to drive down the elasticity of total reported donations, ε_{g^T}, so that equation (3.8) holds again and the optimality of the tax system is restored (Saez 2004). It follows that if an increase in the share of true donations, α, increases the right-hand side of equation (3.8), the subsidy rate needs to be increased in order to restore the optimality of the tax system by driving down ε_{g^T}. Therefore, I check whether an increase in the share of true donations increases the right-hand side of equation (3.8).

If the derivative of expression (3.16), which is equivalent to the right-hand side of equation (3.8), with respect to α is positive, the subsidy rate needs to be increased in response to a marginal increase in the share of true donations in total reported donations in order to drive down the elasticity of total reported donations, ε_{g^T}, on the left-hand side of equation (3.8) so that the equality holds again. The first derivative of expression (3.16) with respect to α is given by

$$\left(1+\bar{G}_{G^0}\right)\left[-p\left(1-\theta_t\right)-\left(\frac{1}{1+\bar{G}_{G^0}}+\frac{-t(1-p)-\theta p}{1+t}\right)\varepsilon_{g^e}\right].$$

As $\bar{G}_{G^0}$ lies between zero and minus one, a necessary and sufficient condition for the derivative to be positive is:

$$-p\left(1-\theta_t\right)-\left(\frac{1}{1+\bar{G}_{G^0}}+\frac{-t(1-p)-\theta p}{1+t}\right)\varepsilon_{g^e} > 0. \tag{3.19}$$

If inequality (3.19) holds, the right-hand side of equation (3.8) increases as the share of true donations increases. Hence, the subsidy rate needs to be increased as α increases in order to drive down the elasticity of total reported donations so that equation (3.8) holds again and the optimality of the tax system is restored. □

3.B Linking the subsidy rate to the marginal income tax rate

3.B.1 Deduction

In case of the subsidy awarded as a deduction, the optimization problem becomes the following. Since the deduction equals the marginal income tax rate, I allow not only for tax evasion with respect to donations but also for tax evasion with respect to earnings. First, the budget constraint (3.2) is extended by taking into account income tax evasion $\bar{Z}^e$ and the probability of detecting tax evasion with respect to earnings ρ:

$$Max_{\tau,t,R,G^0} W = \int \mu^i \nu^i \left(1-\tau, 1+t, R, \bar{G}+G^0\right) d\nu(i)$$
$$s.t.\ \tau\bar{Z} - \tau\bar{Z}^e(1-\rho) + \varphi\bar{Z}^e\rho + t\bar{G} + t\bar{G}^e(1-p) + \theta\bar{G}^e p \geq a + R + G^0$$
$$G^0 \geq 0,$$

where $\bar{Z}$ stands for average true income and $\bar{Z}^e$ for undeclared income. The probability of detecting a false income report is ρ. In the case of detecting income tax evasion, the taxpayer has to pay back the evaded amount, and further has to pay a fine $\varphi\bar{Z}^e$ that is in proportion to undeclared *earnings* (where $\varphi \geq 0$). That is, the fine rate $\varphi = \varphi(\tau)$ increases if the income tax rate increases: $\varphi'(\tau) > 0$.[29] If the government can contribute to the charitable good, the first-order conditions become:

$$\begin{aligned}\frac{\partial W}{\partial t} = &\int \mu^i \left[\nu^i_{1+t} + \nu^i_{1-t} + \nu^i_G\left(\bar{G}_{1+t} + \bar{G}_{1-t}\right)\right] d\nu(i) \\ &+ \lambda\big[-\bar{Z} + \bar{Z}^e(1-\rho+\varphi_t\rho) - t\left(\bar{Z}_{1+t} + \bar{Z}_{1-t}\right) + \left(\bar{Z}^e_{1+t} + \bar{Z}^e_{1-t}\right)(t(1-\rho)+\varphi\rho) \\ &+ \bar{G} + \bar{G}^e(1-p+\theta_t p) + t\left(\bar{G}_{1+t} + \bar{G}_{1-t}\right) + \left(\bar{G}^e_{1+t} + \bar{G}^e_{1-t}\right)(t(1-p)+\theta p)\big] = 0 \qquad (3.20)\end{aligned}$$

$$\frac{\partial W}{\partial R} = \int \mu^i \left[\nu^i_R + \nu^i_G \bar{G}_R\right] d\nu(i) + \lambda\left[-1 - t\bar{Z}_R + \bar{Z}^e_R\left(t(1-\rho)+\varphi\rho\right) + t\bar{G}_R + \bar{G}^e_R\left(t(1-p)+\theta p\right)\right] = 0 \qquad (3.21)$$

$$\frac{\partial W}{\partial G^0} = \int \mu^i \left[\nu^i_G + \nu^i_G \bar{G}_{G^0}\right] d\nu(i) + \lambda\left[-1 - t\bar{Z}_{G^0} + t\bar{G}_{G^0}\right] = 0. \qquad (3.22)$$

The optimal subsidy rate can either be obtained by manipulating equations (3.20) to (3.22) or by following the proof by Saez (2004) (as in Appendix 3.A.1). A marginal decrease in the subsidy rate ($\tau = -t$) of the charitable good has the following four consequences in the case of the subsidy awarded as a deduction:

[29] The fine is not necessarily in proportion to the evaded amount of income $\tau\bar{Z}^e$ in order to avoid the puzzling result by Yitzhaki (1974) that a higher marginal tax rate leads to less income tax evasion. The reason for the Yitzhaki-puzzle is that a higher tax rate means that the taxpayer has a lower disposable income. If the disposable income decreases, the taxpayer is becoming more risk-averse under decreasing absolute risk-aversion. If the taxpayer is more risk-averse, the taxpayer is less likely to evade.

1. Mechanical effect on government revenues:

$$\left(\bar{G} + \bar{G}^e \left(1 - p + \theta_t p\right) - \bar{Z} + \bar{Z}^e \left(1 - \rho + \varphi_t \rho\right)\right) dt. \tag{3.23}$$

2. The utility of each individual changes, since donations are subsidized less and income is less taxed. Integrating over the individuals leads to the aggregate welfare effect:

$$-\beta \left(G^{T,p}\right) \left(\bar{G} + \bar{G}^e \left(1 - p + \theta_t p\right)\right) + \beta \left(Z^{T,\rho}\right) \left(\bar{Z} - \bar{Z}^e \left(1 - \rho + \varphi_t \rho\right)\right) dt, \tag{3.24}$$

where the average government's value of giving one additional dollar to each individual weighted by total reported earnings (considering the risk due to penalties) $Z^{T,\rho} \equiv \bar{Z} - \bar{Z}^e \left(1 - \rho + \varphi_t \rho\right)$ is given by $\beta \left(Z^{T,\rho}\right) = \int \frac{\mu^i \left[(z - z^e) u'(c^E, ...)(1-\rho) + (z - z^e \varphi_t) u'(c^D, ...) \rho\right] \nu_R^i}{\lambda \left[\bar{Z} - \bar{Z}^e (1 - \rho + \varphi_t \rho)\right]} d\nu(i)$.

3. (a) Individuals adapt their behavior in response to the lower subsidy rate on donations. That is, individuals donate and evade less, which increases government revenues by $t d\bar{G} + d\bar{G}^e \left(t(1-p) + \theta p\right)$. The change in private donations consists of a price effect (i.e. change of private donations because of the lower subsidy and income tax rate): $\left(\bar{G}_{1+t} + \bar{G}_{1-t}\right) dt$, and crowding-out effect: $\bar{G}_{G^0} dG^0$:[30]

$d\bar{G} = \bar{G}_{1+t} dt + \bar{G}_{1-t} dt + \bar{G}_{G^0} dG^0$

$d\bar{G} = \bar{G}_{1+t} dt + \bar{G}_{1-t} dt - \bar{G}_{G^0} d\bar{G}$

$d\bar{G} = \frac{\left(\bar{G}_{1+t} + \bar{G}_{1-t}\right) dt}{1 + \bar{G}_{G^0}}$.

There is no crowding out of overreported donations: $d\bar{G}^e = \left(\bar{G}^e_{1+t} + \bar{G}^e_{1-t}\right) dt$.

(b) Individuals adapt their behavior in response to the lower income tax rate (individuals work more and misreport less), which increases government revenues by $\tau d\bar{Z} - d\bar{Z}^e (\tau \left(1 - \rho\right) + \varphi \rho) = -t d\bar{Z} + d\bar{Z}^e (t \left(1 - \rho\right) + \varphi \rho)$.

I assume aggregate earnings are not affected by the level of the charitable good $\bar{Z}_{G^0} = 0$ and not affected by the subsidy on donations $\bar{Z}_{1+t} = 0$ (Saez 2004). It follows:

$d\bar{Z} = \bar{Z}_{1+t} dt + \bar{Z}_{G^0} dG^0 + \bar{Z}_{1-t} dt = \bar{Z}_{1-t} dt$

$d\bar{Z}^e = \bar{Z}^e_{1+t} dt + \bar{Z}^e_{G^0} dG^0 + \bar{Z}^e_{1-t} dt = \bar{Z}^e_{1-t} dt$

Summing up the effects of (a) and (b) leads to the following change in private contributions and

[30] As $\bar{G}_{1+\tau} < 0$ (a lower marginal tax rate leads to higher earnings and thus higher donations; $\bar{G}_{1-t} dt = \bar{G}_{1+\tau} dt = -\bar{G}_{1+\tau} d\tau$), $\bar{G}_{1-t} dt$ is positive. In contrast, $\bar{G}_{1+t} dt$ is negative, because a lower subsidy rate leads to less donations.

earnings:

$$td\bar{G} + d\bar{G}^e\left(t(1-p)+\theta p\right) - td\bar{Z} + d\bar{Z}^e(t\left(1-\rho\right)+\varphi\rho)$$
$$= \left[\frac{t\left(\bar{G}_{1+t}+\bar{G}_{1-t}\right)}{1+\bar{G}_{G^0}} + (\bar{G}^e_{1+t}+\bar{G}^e_{1-t})\left(t(1-p)+\theta p\right) - t\bar{Z}_{1-t} + \bar{Z}^e_{1-t}\left(t(1-\rho)+\varphi\rho\right)\right]dt. \quad (3.25)$$

4. The government adapts the public contributions to the charitable good, which generates a cost:

$$-dG^0 = d\bar{G}. \quad (3.26)$$

At the optimum, these four effects shown in (3.23) to (3.26) must cancel out (i.e. the sum is zero). Under my assumptions, some algebraic manipulations show that the following equation holds at the optimum:

$$\varepsilon_{g^T} = \left(1+\bar{G}_{G^0}\right)\Bigg[\left[1-\beta\left(Z^{T,\rho}\right)\right]\bar{Z}^{T,\rho} + t\bar{Z}_{1-t} - \bar{Z}^e_{1-t}\left(t(1-\rho)+\varphi\rho\right)\Big]\frac{1}{\bar{G}^T}$$
$$-\left[1-\beta\left(G^{T,p}\right)\right]\left[\alpha+(1-\alpha)\left(1-p(1-\theta_t)\right)\right] + (1-\alpha)\left(\frac{1}{1+\bar{G}_{G^0}} + \frac{-t(1-p)-\theta p}{1+t}\right)\varepsilon_{g^e}\Bigg], \quad (3.27)$$

which is similar to equation (3.8) except that equation (3.27) considers the effects of increasing the tax rate on earnings. The distributional taste of the government reflected by $\beta\left(Z^{T,\rho}\right)$ has a strong impact on the optimal subsidy rate. A high value of $\beta\left(Z^{T,\rho}\right)$ means that the government puts a lot of weight on earnings and little weight on redistribution from rich individuals to poor individuals. As a result, the optimal income tax rate (subsidy rate) decreases if redistribution from rich to poor becomes less important for the government.[31] The second term in the big brackets of equation (3.27) is negative, since t is negative and $\bar{Z}_{1-t}$ is positive.[32] This means that the (absolute value of the) elasticity of total reported donations ε_{g^T} on the left-hand side of equation (3.27) is less likely to be larger than the value of the right-hand side. In other words, the stronger individuals reduce their work effort in response to an increase in the marginal tax rate of earnings, the lower the optimal income tax rate and thus subsidy

[31] As Saez (2004) discusses, the effects of rising the social weights $\beta\left(Z^{T,\rho}\right)$ and $\beta\left(G^{T,p}\right)$ have opposing effects on the optimal subsidy. These effects should not be interpreted separately, because there is usually a considerable correlation between them (a low $\beta\left(Z^{T,\rho}\right)$ usually means a low $\beta\left(G^{T,p}\right)$). On the one hand, a high $\beta\left(Z^{T,\rho}\right)$ leads to a lower subsidy rate, because the government wants to have a low income tax. On the other hand, a high $\beta\left(G^{T,p}\right)$ leads to a higher subsidy rate, because the government values redistribution from individuals with low donation reports to individuals with high reports. In general, the weight $\beta\left(G^{T,p}\right)$ tends to be smaller than $\beta\left(Z^{T,\rho}\right)$, because contributions are less equally distributed than earnings.

[32] As $Z_{1+\tau} < 0$ (higher marginal tax rate reduces earnings; $Z_{1-t}dt = Z_{1+\tau}dt = -Z_{1+\tau}d\tau$), $Z_{1-t}dt$ is positive. As $Z^e_{1+\tau} > 0$ (higher marginal tax rate increases income tax evasion; $Z^e_{1-t}dt = Z^e_{1+\tau}dt = -Z^e_{1+\tau}d\tau$), $Z^e_{1-t}dt$ is negative.

rate.[33]

3.B.2 Deduction, Linear Penalty Rate, and Endogenous Probability

If I assume an endogenous probability of detecting tax evasion and a linear penalty rate $-t\theta$, the optimization problem of the government becomes the following in the case of the subsidy awarded as a deduction:

$$Max_{\tau,t,R,G^0} W = \int \mu^i \nu^i \left(1-\tau, 1+t, R, \bar{G}+G^0\right) d\nu(i)$$
$$s.t.\ \tau\bar{Z} - \tau\bar{Z}^e\left[1-\rho\left(\bar{Z}^e\right)\right] + \tau\bar{Z}^e\varphi\rho\left(\bar{Z}^e\right) + t\bar{G} + t\bar{G}^e\left[1-p\left(\bar{G}^e\right)\right] - t\bar{G}^e\theta p\left(\bar{G}^e\right) \geq R + G^0$$
$$G^0 \geq 0,$$

where the probability of detecting a false income report is $\rho = \rho\left(\bar{Z}^e\right)$ (where $\rho'\left(\bar{Z}^e\right) > 0$) and the probability of detecting an overreported donation is $p = p\left(\bar{G}^e\right)$, for example, as auditors may become more suspicious because of high levels of misreporting. A marginal decrease in the subsidy rate, $\tau = -t$, has the following four effects in the case of the subsidy awarded as a deduction (similar to Appendix 3.B.1):

1. Mechanical effect on government revenues:

$$\left(\bar{G} + \bar{G}^e\left[1-p(1+\theta) - t\frac{\partial p}{\partial \bar{G}^e}\frac{\partial \bar{G}^e}{\partial t}(1+\theta)\right] - \bar{Z} + \bar{Z}^e\left[1-\rho(1+\varphi) - t\frac{\partial \rho}{\partial \bar{Z}^e}\frac{\partial \bar{Z}^e}{\partial t}(1+\varphi)\right]\right)dt. \tag{3.28}$$

2. The utility of each individual changes, since donations are subsidized less and and income is less taxed. Integrating over the individuals leads to the aggregate welfare effect:

$$-\beta\left(G^{T,p}\right)\left(\bar{G} + \bar{G}^e\left[1-p(1+\theta) - t\frac{\partial p}{\partial \bar{G}^e}\frac{\partial \bar{G}^e}{\partial t}(1+\theta)\right]\right)dt + \beta\left(Z^{T,\rho}\right)\left(\bar{Z} - \bar{Z}^e\left[1-\rho(1+\varphi) - t\frac{\partial \rho}{\partial \bar{Z}^e}\frac{\partial \bar{Z}^e}{\partial t}(1+\varphi)\right]\right)dt, \tag{3.29}$$

where $G^{T,p} = \bar{G} + \bar{G}^e\left[1-p(1+\theta) - t\frac{\partial p}{\partial \bar{G}^e}\frac{\partial \bar{G}^e}{\partial t}(1+\theta)\right]$ and
$Z^{T,\rho} \equiv \bar{Z} - \bar{Z}^e\left[1-\rho(1+\varphi) - t\frac{\partial \rho}{\partial \bar{Z}^e}\frac{\partial \bar{Z}^e}{\partial t}(1+\varphi)\right]$.

[33] Similarly to Proof of Proposition 3.1, it can also be shown that a marginal increase in the probability of detection ρ leads to a higher optimal income tax rate if $\lambda\bar{Z}^e(1-\varphi_t) > \int \mu^i z^e\left(u'(c^E,\ldots) - u'(c^D,\ldots)\varphi_t\right)\nu_R^i d\nu(i)$ (sufficient condition). That is, if the government puts less weight on income-tax evaders than on non-evaders, the optimal income tax rate is becoming relatively higher as ρ increases.

3. Individuals adapt their behavior in response to the lower subsidy rate on donations and the lower marginal tax rate of earnings, which increases government revenues:

$$t(d\bar{G} + d\bar{G}^e[1-p(1+\theta)] - d\bar{Z} + d\bar{Z}^e[1-\rho(1+\varphi)])$$
$$= t\left[\left(\frac{\bar{G}_{1+t}+\bar{G}_{1-t}}{1+\bar{G}_{G^0}} + (\bar{G}^e_{1+t}+\bar{G}^e_{1-t})[1-p(1+\theta)] - \bar{Z}_{1-t} + \bar{Z}^e_{1-t}[1-\rho(1+\varphi)]\right)dt\right] \quad (3.30)$$

4. The government adapts the public contributions to the charitable good, which generates a cost:

$$-dG^0 = d\bar{G}. \quad (3.31)$$

At the optimum, these four effects shown in (3.28) to (3.31) must cancel out. Some manipulations show that the following equation holds at the optimum:

$$\varepsilon_{g^T} = (1+\bar{G}_{G^0})\left[\frac{1}{\bar{G}^T}\left([1-\beta\left(Z^{T,\rho}\right)]\bar{Z}^{T,\rho} + t\left[\bar{Z}_{1-t} - \bar{Z}^e_{1-t}(1-\rho[1+\varphi])\right]\right) - [1-\beta\left(G^{T,p}\right)]\right.$$
$$\left.\times\left[\left[\alpha+(1-\alpha)\left(1-p[1+\theta]-t\frac{\partial p}{\partial \bar{G}^e}\frac{\partial \bar{G}^e}{\partial t}(1+\theta)\right)\right] + (1-\alpha)\left(\frac{1}{1+\bar{G}_{G^0}} + \frac{-t[1-p(1+\theta)]}{1+t}\right)\varepsilon_{g^e}\right]\right.$$

If the government puts less weight on tax evaders than on non-evaders, the optimal subsidy considering an endogenous probability is higher in comparison to the case of exogenously given probabilities (as $\frac{\partial \rho}{\partial \bar{Z}^e}\frac{\partial \bar{Z}^e}{\partial t}$ and $\frac{\partial p}{\partial \bar{G}^e}\frac{\partial \bar{G}^e}{\partial t}$ are negative).[34] Intuitively, the government can set a higher subsidy or marginal tax rate without triggering a lot of tax evasion (in comparison to the case of a given probability), since the probability of detection increases with higher levels of misreporting.

3.C Imperfect Substitutability between Private and Government Contributions

Saez (2004) discusses the case of imperfect substitutability between private and public provision of the charitable good (e.g. private railway companies may not run to small towns and thus, the government might have a stronger interest in supporting public railway companies than private ones). The effective total level of the charitable good changes to $G = s\bar{G} + G^0$. The parameter s measures the degree of substitutability and is smaller than one if there is imperfect substitutability. $1/s$ units private contributions

[34] This sufficient condition can be shown in an equivalent way as the Proof of Proposition 3.A.2.

are equivalent to one unit public contributions. The following equation must hold in the optimum:

$$\varepsilon_{g^T} = \frac{(1+t)(1+s\bar{G}_{G^0})}{s+t}\Bigg[- \left[1-\beta\left(G^{T,p}\right)\right]\left[\alpha+(1-\alpha)\left(1-p(1-\theta_t)\right)\right] + (1-\alpha)\left(\frac{s+t}{\left(1+s\bar{G}_{G^0}\right)(1+t)} + \frac{-t(1-p)-\theta p}{1+t}\right)\varepsilon_{g^e}\Bigg], \quad (3.32)$$

which is the same as equation (3.8) if private provision is as efficient as government provision ($s = 1$).[35] As the government is more efficient in contributing to the charitable good directly, the optimal subsidy rate under inefficient private provision is lower than under full efficiency.[36]

[35] If there is no overreporting of donations, α is one (share of true donations is one), and so equation (3.32) simplifies to:

$$\varepsilon_g = \frac{(1+t)\left(1+s\bar{G}_{G^0}\right)}{s+t}\left[-\left(1-\beta(G)\right)\right],$$

which is the same as equation (22) in Saez (2004):

$$t = -s + \frac{1}{\varrho}(1+s\bar{G}_{G^0})[1-\beta(G)].$$

Recall Saez' definition of $\varrho = -\frac{\bar{G}_{1+t}}{\bar{G}}$:

$$t+s = -\frac{\bar{G}}{\bar{G}_{1+t}}(1+s\bar{G}_{G^0})[1-\beta(G)]$$

$$(t+s)\bar{G}_{1+t}\frac{1+t}{\bar{G}}\frac{1}{1+t} = -\left(1+s\bar{G}_{G^0}\right)[1-\beta(G)]$$

$$\varepsilon_g = \frac{(1+t)(1+s\bar{G}_{G^0})}{s+t}\left[-\left(1-\beta(G)\right)\right].$$

If there is no overreporting, α is one. It follows that $\varepsilon_g = \varepsilon_{g^T}$.

[36] It is straightforward to see that the term in front of the big brackets in equation (3.32) is larger than in equation (3.8): $(1+t)\left(1+s\bar{G}_{G^0}\right)/(s+t) > \left(1+\bar{G}_{G^0}\right)$, since $\bar{G}_{G^0}$ is negative and since $(1+t)/(s+t)$ is greater than one. Thus, the (absolute value of the) elasticity of total reported donations ε_{g^T} on the left-hand side of equation (3.32) is less likely to be larger than the value of the right-hand side if $s < 1$.

Chapter 4

Disclosure of Government Grants and Crowding Out

4.1 Introduction

This chapter investigates whether crowding out of donations, which means the displacement of private donations by government grants, depends on the disclosure of the grants. The standard theory of crowding out (e.g. Bergstrom et al. 1986) assumes that the government grants are seen as a substitute for the donations of the individual and that individuals are "aware of the fluctuations in government grants received by the charity and respond accordingly" (p. 334, Andreoni and Payne 2011). That is, if individuals are not aware of the government grants, the grants may no longer crowd out private donations. In the USA, the majority of tax-exempt non-profit organizations are required to file the Internal Revenue Service Form 990.[1] The Form 990 provides financial information about the non-profit organization and depicts administrative and fundraising expenses of the charitable organization, government grants from all government levels (federal, state, and local), and private donations (e.g. from individuals, estates, corporations). Some charities choose to make the Form 990 available to the public online. Charity Navigator, a watchdog that rates charities in the USA, provides information about whether the most recent Form 990 is easily accessible from the charity's website. As individuals can only adjust their private donations in response to government grants if they are privy to them, the disclosure of government grants may have a decisive impact on the crowding out of donations. The focus of this chapter is to determine

[1] Organizations are exempt from filing the tax return Form 990 if they are affiliated with governmental units or with churches.

whether government grants displace private donations and whether individuals reduce donations only in response to a grant if it is disclosed by the charity, where I use the availability of the Form 990 on the charity's website as a proxy for disclosure.

As governments in many developed countries spend substantial portions of their budgets on supporting charitable organizations (e.g. in the form of direct government grants, contracts, subsidies), investigations of crowding out of private donations are important. In 2012, the non-profit sector contributed $ 887.3 billion to the US economy, accounting for 5.4 % of the GDP. Fees for services and goods from *private* sources (e.g. tuition payments, and hospital patient revenues) comprised 50 % of the total revenue of charities. Grants and fees for services and goods from *government* sources (e.g. government contracts, Medicare payments) were responsible for almost a third (32.3 %) of the revenues of the charities, while the rest of the revenues came from other income sources (e.g. investment) and private contributions (McKeever and Pettijohn 2014). A charity may decide to put its Form 990 online in order to make it easier for donors to evaluate the financial performance of the charity. By making the Form 990 available online, the charities also achieve higher ratings from charity watchdogs like Charity Navigator and may generally be perceived as more transparent by donors. On the other hand, if a charity has, for example, low program service but high administrative expenses, the charity may decide not to provide this information by publishing the Form 990 online. Some charities may also make the online provision of the Form 990 dependent on the performance of the respective year. For instance, a charitable organization may publish the Form 990 online in years with high program service revenues, while the organization may decide to take down the Form 990 from its website in other years to hide high expenses for the management. Individuals are entitled access to information regarding the revenue of the charitable organization through the Form 990. However, charities are allowed to ask for a fee for offering copies of their Form 990 to individuals (see IRS 1999). Moreover, if access to the Form 990 must be requested, charities may delay in providing the form (Andreoni and Payne 2011) and individuals could face considerable opportunity costs. In short, individuals may not be aware of governments grants if the Forms 990 are not easily accessible from the websites of the charities. A potential disadvantage of this first attempt to estimate the effect of *disclosure of government grants* to charities on crowding out is that there are no surveys of individuals available that ask whether they actually observed the Forms 990 for the government grants. I will show, however, that the inclusion of additional control variables, reflecting information found on the Form 990 other than government grants, does not lead to significantly different estimates of crowding out than the baseline estimation of this study.

This chapter explores if crowding out is only present if the Form 990 is available on the website of the charity, since individuals can only consciously reduce their donations in response to government grants if they observe the grants. This distinction is important for policymakers as there may be hidden costs not only as a result of the government grants themselves (Andreoni and Payne 2011) but also as a result of the disclosure of the grants through the online availability of the Form 990. These unintended consequences of disclosure may, for example, influence legal disclosure requirements and the welfare-maximizing subsidy on giving as private donations and government grants may be seen as substitutes by the government (Saez 2004). In addition, I examine whether charitable organizations reduce their fundraising expenses if government grants are received. While Andreoni and Payne (2011) argue that crowding out is a direct consequence of the reduction in fundraising efforts, they do not investigate whether individuals are aware of the grants in their analysis. I want to find out if crowding out is due to either reduced fundraising efforts by charities or individuals decreasing their donations after observing government grants for the following reasons. If the government requires an increase in program expenses from the charity to the full amount of the government grant (leading to zero crowding out), this policy can only be sustained if crowding out is a result of reduced fundraising efforts of charities. In other words, a charity may not be able to increase its program expenses to the full amount of the government grant if individuals decrease their donations after observing the grant (Andreoni and Payne 2011). Finally, the investigation of the disclosure of government grants is important for modeling both the individuals' decision to donate (e.g. warm glow of giving, Andreoni 1989, 1990) and the decisions of the charitable organizations (e.g. whether charities maximize net-revenues, Weisbrod 1998, Andreoni and Payne 2011).

In my estimations I find complete crowding out of private donations (i.e. a $ 1,000 government grant reduces private donations by $ 1,149 in a given year) if the Form 990 is accessible from the website of the charity. In comparison, there is no statistically significant crowding out if the Form 990 is not accessible from the website. This indicates considerable costs of disclosure of the government grants through the online availability of the Form 990. Moreover, the regressions show that one additional dollar spent on fundraising increases donations by significantly more than one dollar. This implies that charitable organizations do not maximize net-revenues, because they may target, for example, higher ratings from charity watchdogs. Furthermore, I find that if charitable organizations receive government grants, the charities may decrease fundraising expenses in the year of the government grants. However, the charities increase fundraising in the subsequent year so that the effects cancel out and there is no significant reduction in fundraising expenses in the long run. The charitable organizations might, for instance, aim

for a growth in program expenses as a result of pressure from the government or the supervisory board and thus spend more money on fundraising in the year following the government grants in order to be able to increase their programs. As a consequence, crowding out of private donations cannot be explained by reduced fundraising efforts of charities after receiving government grants in the long run, which contrasts Andreoni and Payne (2011). As crowding out seems to be a result of the behavior of the individuals and not of reduced fundraising efforts by charities, a policy that requires charities to increase their program expenses by the full amount of the government grants may not be feasible.

Related Literature Under the classic theory of crowding out, an increase in government contributions to the charitable good will lead to complete displacement of private contributions (Warr 1982, Roberts 1984, Bergstrom et al. 1986 etc.).[2] The reason being that donors only care about the total amount of the charitable good in place and that the contribution by the government is seen as a substitute for the donor's own contribution. Incomplete crowding out can result if some individuals in the economy do not donate (Bergstrom et al. 1986) or if donors get utility from the act of donating independently of the amount of charitable good in place (impure altruism, Andreoni 1989, 1990). Benabou and Tirole (2006) and Gneezy et al. (2011) mention two psychological channels of how extrinsic incentives may crowd out intrinsic motivations to donate. The first channel is via information. If a donor observes government grants to a charitable organization, the grants may give a signal about the quality of the organization and the donor may start doubting the effectiveness of the charity (e.g. because the grants are smaller than grants that similar charities receive, or the grants are too high such that the donor starts questioning the financial stability of the charity). Payne (1998) states, however, that the quality signal of the charity could also lead to crowding in if the grants serve as a signal of high quality. The second channel is when observing the government grants reduces other motives for donating, like decreasing the altruistic image of the donor. Finally, Andreoni (1998) shows that crowding in can result in situations in which a minimum level of the public good is required before it produces any benefits to individuals (e.g. due to high fixed costs), as a government grant may persuade other individuals to donate.

Empirical studies on crowding out, which make use of organizational, survey, and individual tax return data, have delivered a wide range of results (see Gruber and Hungerman 2007). On the one hand, a considerable number of studies do not find evidence of crowding out (e.g. Yetman and Yetman 2003 for some organization types, Gruber and Hungerman 2007). Some studies even find crowding in, which

[2] A detailed summary of the literature on crowding out of donations in response to government grants can be found in Andreoni and Payne (2011).

means that government grants induce more private donations (e.g. Okten and Weisbrod 2000, Andreoni et al. 2014 for small charities, Heutel 2014). Comparably, Smith et al. (2014) find that donors increase their online donations if they observe higher donations by peers. On the other hand, several studies find that government grants crowd out private donations by more than 50 % (e.g. Payne 1998, Yetman and Yetman 2003, Andreoni and Payne 2011).

Endogeneity between government grants and donations makes it difficult to properly identify crowding out in empirical studies. Payne (1998) tries to overcome this endogeneity by using aggregate government transfers to individuals as instruments for government grants (e.g. a natural disaster may decrease both transfers and grants). Crowding out increases from zero in the OLS analysis to roughly 50 % using two-stage least-squares (2SLS). The 2SLS approach, however, hinges on the assumption that transfers from governments to individuals do not have a partial effect on charitable donations (i.e. transfers do not affect the likelihood of donations). Andreoni and Payne (2011) construct measurements for the seniority and power of the members of the U.S. house of representatives as instruments for grants and find crowding out of 76 % in their basic specification and crowding out of 124 % in a sample resembling the investigated charities of this study. Andreoni and Payne (2003, 2011) argue that crowding out might be explained by reduced fundraising efforts of charitable organizations as a result of receiving grants. They find that charitable organizations reduce their fundraising expenses between 2 % and 27 % (of the value of the grants) after obtaining grants, where the fundraising reduction depends both on the type of organization (arts and social service organizations) and the instrumental variables used (transfers to non-profit organizations, research grants to universities, and seniority and power of congress members). Andreoni and Payne (2011) also find that increasing fundraising expenses by one dollar generates roughly five to six dollars in new private donations. By making use of survey data, Jones (2015) investigates the effect of state lotteries on voluntary contributions to education. State lotteries are often publicized and earmarked for education. Jones (2015) finds that increased *government activity* through the introduction of state lotteries decreases voluntary contributions to education-related organizations by roughly 8 % (without addressing endogeneity that may arise between the lotteries and contributions). In comparison, I test the impact of *government grants* to charitable organizations on private donations. Monti (2010) shows theoretically that crowding out depends on donor awareness of government grants and government spending, respectively. However, the empirical analysis of Monti (2010) only hints at the general differences in crowding out between direct government grants to environmental charities and government spending to improve environmental quality.

The rest of this study is organized as follows. Section 4.2 explains the estimation method of the empirical study. The data sources are described in Section 4.3. Section 4.4 presents the estimation results and Section 4.5 examines the sensitivity of these findings and provides alternative specifications. Finally, Section 4.6 summarizes the most important results and offers suggestions for future research.

4.2 Estimation Strategy

In this section, I present the econometric strategy. I first explain how I estimate the influence of government grants and the availability of the Form 990 on the website of the charities on donations, and further, the effect of fundraising expenses on donations. Next, I describe the estimation strategy for the effect of government grants on fundraising. Lastly, I critically discuss measurement issues of the identification approach.

First, I estimate the response of donations to government grants and quantify how this response depends on the disclosure of the grants. Further, I estimate how donations respond to an increase in fundraising expenses of the charity. As donations to organizations may depend on the previous year's donations, I specify the following dynamic panel data model by including a lagged dependent variable for donations D:

$$D_{ist} = \alpha D_{is,t-1} + G'_{ist}\beta_1 + G'_{is,t-1}\beta_2 + F_{ist}\gamma_1 + \gamma_2 F^2_{ist} + X'_{ist}\omega + \varphi_t + \eta_i + \varepsilon_{ist}, \tag{4.1}$$

where i is the index of charities, s is the index of U.S. states, and t is the index of time. G is a vector of charity level characteristics, including government grants received by the charity, a binary variable that takes the value 1 if the Form 990 is available on the charity's website and the value 0 if the Form 990 is not available online, as well as an interaction effect between the government grants and the online availability. In addition, G contains the ratio of program to total expenses and revenues from federated campaigns as control variables. F is fundraising expenses and X is a vector of state level control measures, including the employment to population ratio, transfers to individuals for income maintenance, and a measure for public corruption (i.e. federal prosecutions of public officials). The charity fixed effect η_i accounts for charity-level time invariant unobserved factors (e.g. location of the charity) and the time-specific effect φ_t reflects trends and events common to all charities (e.g. financial crises or tax reforms). In order to reduce the risks of autocorrelation in the error term ε_{ist}, I control for historical events that have a potential effect on current donations (e.g. how well established is the charity or long term marketing strategies)

by including a lagged dependent variable in equation (4.1). The lagged dependent variable reflects the dependency of the donations of organizations in the current year on donations in the previous year. Furthermore, I include lagged regressors for the government grants, the Form 990, and their interaction for the following reasons. Information about government grants through the Form 990 may not be instantaneously online when the charities receive the government grants (compare measurement issues discussed in Andreoni and Payne 2003, 2011). That is, if a charity receives a grant, there may be a delay before private donations are crowded out (e.g. because of long term direct debits of donors).

Second, I estimate how charitable organizations adapt their fundraising efforts when receiving government grants:

$$F_{ist} = \rho F_{is,t-1} + G'_{ist}\delta_1 + G'_{is,t-1}\delta_2 + X'_{ist}\kappa + \phi_t + \nu_i + \epsilon_{ist}, \tag{4.2}$$

where I use the same control variables as in equation (4.1). The difficulty in estimating equations (4.1) and (4.2) lies in handling the endogeneity between the dependent and independent variables. A bias could result if, for example, low private donations create an incentive for charities to provide financial information of the organization by making the 990s online available, or vice versa. High private donations on the other hand may signal that the charity is of good quality and thus make it more likely for charities to receive grants from government institutions. Moreover, unobserved variables could lead to a rise in the demand for charitable activities (e.g. outbreak of avian flu) and thus simultaneously increase private donations and government grants, which then also influences fundraising efforts (see also discussion in Andreoni and Payne 2003, 2011). In the following, I will present the estimator used to identify equations (4.1) and (4.2).

System GMM Estimation The empirical literature on crowding out usually uses 2SLS estimations to overcome endogeneity concerns of private donations and government grants or fundraising expenses. These studies, however, may suffer from weak instrument bias, since the instrumental variables often explain only small parts of the variation of the endogenous variables (reflected by low values of the first stage F tests). I propose the following estimation strategy that can be employed because of my (almost) balanced micro panel. As the inclusion of a lagged dependent variable produces inconsistent OLS estimates (as the lagged dependent variable is correlated with the charity level effect), Anderson and Hsiao (1981) suggest to transform all regressors by first-differencing the panel data and use twice lagged levels as instruments for the endogenous variables. In order to obtain more efficient results, Arellano and Bond (1991) recognize that additional lags from previous time periods can be exploited

by using General Method of Moments (GMM). Further, if the time dimension of the panel is short and if the dependent variable is very persistent (i.e. strongly dependent on previous events), the efficiency of the estimation can be substantially improved by employing the system GMM by Arellano and Bover (1995) and Blundell and Bond (1998) in comparison to the difference GMM by Arellano and Bond (1991) (Blundell et al. 2000, Bond 2002).[3] The system GMM combines a system of equation in differences and levels, where the estimation uses first-differences as instruments for the equation in levels. The system estimation reduces the finite sample and increases the number of observations if there are some gaps in the data in comparison to Arellano and Bond (1991).[4] Moreover, the system GMM allows the inclusion of charity-level fixed effects and the estimation of time-invariant variables that can be correlated with the charity-level effects. That is, the precision for the coefficients of the regressors in equations (4.1) and (4.2) that vary only little over time (e.g. the within standard deviation is only 0.3 for the Form 990 dummy variable) is improved in comparison to the difference GMM and other estimators. In general, the system GMM can reflect dynamics (e.g. government grants may still effect donations in years subsequent to the grants) and performs best for datasets with only few time periods and many cross-sectional observations (small T and large N panels, like the panel used for this study). Finally, the system GMM estimation can also handle endogenous independent variables by using lagged instruments (Roodman 2009).

Assumptions and Specification Choices The estimations make use of the following assumptions, which can be tested by Difference-in-Hansen tests (Hansen 1982, Arellano and Bond 1991). First, as any panel estimation, the system GMM assumes no autocorrelation in the errors *across* individuals. This means that shocks may lead to serially correlated error terms *within* the charity, but shocks should not affect all organizations equally. Second, the consistency of the estimation depends on constant correlation between the charity-level fixed effects and the endogenous variables (Bun and Sarafidis 2013). That is, even though the estimation allows correlation between the fixed effects and the endogenous variable (e.g. government grants), the relationship should not change over time. In order to mitigate these assumptions, I include time dummies to allow for common trends across charities. Third, all charity-level variables (government grants, fundraising expenses etc.) are treated as *strictly* endogenously determined (e.g. both G'_{ist} and the lags $G'_{is,t-1}$ are taken as endogenous), which leads to less efficient but consistent estimates (Roodman 2009). Finally, I use the two step system GMM estimator and heteroscedasticity-robust

[3]The system GMM estimation is also consistent under unit roots (Blundell et al. 2000).

[4]If observation D_{ist} is missing, then $\triangle D_{ist}$ and $\triangle D_{is,t+1}$ cannot be used under the difference GMM estimation, for example.

standard errors as suggested by Windmeijer (2005) in all my estimations.

4.3 Data

The study makes use of a balanced panel of 1088 charitable organizations observed yearly from 2009 (the earliest year for which information about the online availability of the Form 990 is available) to 2012 by Charity Navigator (2014).[5] Charity Navigator provides information about private donations to the charities, government grants, and fundraising expenses based on the Forms 990. Private donations refer to voluntary contributions from individuals, corporations, trusts, estates, and other entities. Government grants indicate contributions from federal, state, and local governments. Fundraising expenses reflect the expenses for soliciting cash and noncash contributions, gifts, and grants (IRS 2014). The organizations operate in the fields of human services (children, family, food, homeless, social, and youth related), health services (treatment and prevention), and public benefit services (advocacy, civil rights, fundraising, research, public policy, community and housing). I only use data from charitable organizations that are required to file the Form 990 in order to filter out the pure effect of the online disclosure of the government grants. In order to be comparable to the studies of Andreoni and Payne (2003, 2011), I did not obtain data from charities if donations, grants, liabilities, or fundraising expenses were zero over the entire period, and if charities only had one year of positive fundraising expenses (as I used lagged fundraising expenses as instruments).[6] Table 4.1 describes the sample and shows that the average charity received private donations worth about $\$\,11\,\mathrm{m}$ and government grants worth about $\$\,3.3\,\mathrm{m}$, and spent almost $\$\,1.2\,\mathrm{m}$ on fundraising (which is $10.5\,\%$ of private donations).

In addition, the data for the state population, state employment, and the annual state level transfers to individuals and non-profits are drawn from the U.S. Bureau of Economic Analysis (2013) for the years 2009 to 2012. Finally, the figures for the federal public corruption convictions from 2009 to 2012, which reflect federal prosecutions of elected and appointed public officials, are taken from the U.S. Department of Justice (2014).

Table 4.2 compares private donations, fundraising expenses, government grants, and primary revenues

[5] Some charitable organizations do not file the Form 990 at the end of the year. If a charitable organization filed the Form 990 in the first-half of the year, the information from the Form 990 was used for the previous year (compare Andreoni and Payne 2011).

[6] As Andreoni and Payne (2011) mention, including charities without any grants or fundraising expenses over the entire period is not informative for the hypothesis whether grants lead to less donations or fundraising expenses. While the inclusion of all charities leads to inflated standard errors in their study, it does not lead to significantly different results. As I use lagged fundraising expenses as instrumental variables, I also need variation in fundraising expenses within charities.

Table 4.1: Description of the sample

	Mean	Std. Dev.	Min	Max
Charity level measures (in 1,000 $), $n = 4334$				
Private donations	11,032	35,326	0	924,583
Fundraising expenses	1,156	6,251	4	172,406
Government grants	3,288	10,974	−12	220,529
Federated campaigns	467	4,245	0	129,913
Fundraising events	383	1,379	−110	30,732
Related organizations	206	1,777	−46	77,639
Membership dues	43	401	0	7,444
Primary revenue	20,838	106,098	371	3,502,077
Program expense ratio	84 %	9 %	3 %	99 %
State level transfers (in 1,000 $)				
Transfers to individuals	100,982,226	77,130,794	4,107,053	261,781,701
Transfers for income maintenance	12,412,403	10,312,821	445,100	35,346,120
Federal transfers to non-profits	625,032	498,948	21,547	1,826,942
Other state level measures				
Employment	7,832,721	5,975,009	412,903	20,820,306
Population	14,058,984	11,125,670	580,236	38,041,432
Public corruption convictions	39	25	0	112

Notes: *Charity level measures* and *State level transfers* are indicated in thousands of dollars. n indicates the number of observations. *Federated campaigns* reflect contributions due to fundraising efforts with other charitable organizations. *Related organizations* refer to contributions from organizations like parent organizations, subsidiaries, supporting organizations etc. *Primary revenue* is the revenue a charity generates from its work, including contributions and government grants, membership dues, and revenue from programs and services. *Program expense ratio* indicates what percent of its total expenses a charity spends on programs and services. *Transfers to individuals* reflect retirement and disability insurance benefits, medical benefits, unemployment insurance compensation, and other transfer receipts of individuals from governments. *Transfers for income maintenance* consist mainly of supplemental security income payments, family assistance, food stamp payments, and other assistance payments. *Federal transfers to non-profits* refer mainly to the payments to private non-profit hospitals and private educational institutions, and other education and training programs. *Public corruption convictions* reflect federal prosecutions of elected and appointed public officials.

between charities that put their Form 990 online (at least once) in column (2) and charities that never put their form online in column (3). When comparing the means of columns (2) and (3) of Table 4.2, I use a two tailed t test, where I do not assume equal variances. When comparing the distribution of charities that make their Form 990 available and charities that never make their forms available in column (5) of Table 4.2, I use a Mann-Whitney U test.

Table 4.2: Comparison between charities that make and do not make their Forms 990 online available

(1) Charity level measures in 1,000 $	(2) Form 990 at least once online	(3) Form 990 never online	(4) Equal means p-value	(5) Equal distributions p-value
Private donations	12,918 (40,115)	5,712 (13,797)	0.000	0.000
Fundraising expenses	1,351 (7,240)	606 (1,012)	0.000	0.000
Government grants	3,300 (9,620)	3,256 (14,117)	0.923	0.000
Primary revenue	23,428 (122,317)	13,528 (27,104)	0.000	0.000
	$n = 3200$	$n = 1134$		

Notes: *Charity level measures* are indicated in thousands of dollars. Standard errors in parentheses. n indicates the number of observations under a given variable (e.g. private donations). I compare private donations, fundraising expenses, government grants, and primary revenues between charities that put their Forms 990 online and charities that never put their forms online.

Charities that never make their Form 990 available have significantly lower private donations, fundraising expenses, and primary revenues than charities that publish their forms (see p-values in columns (4) of Table 4.2). In other words, larger charitable organizations seem to be more likely to publish the Form 990 than smaller organizations. The distribution of government grants between organizations that publish and do not publish their form online is significantly different (see p-value in column (5) of the third row of Table 4.2). However, the mean government grant of charities that never put their Forms 990 online is *not* significantly different from the mean government grant of charities that make their forms online available (see p-value in column (4) of the third row of Table 4.2). This finding could mean that especially large

organizations may often decide not to publish the Form 990 online after receiving a government grant, as large organizations generally receive higher government grants (not shown here) and are more likely to put their Form 990 online.

4.4 Results

In this section, I present the estimation results as follows. I first show the effects of government grants and fundraising expenses on private donations. Then, I estimate the impact of government grants on fundraising efforts by charities.

The estimated effects of government grants and fundraising expenses on donations are shown in Table 4.3. In column (1) of Table 4.3, I do not control for the online availability of the Form 990 (i.e. ignoring the impact of the online availability of the Form 990 on crowding out as in previous research), while in column (2) I estimate the effect of crowding out as a result of the online availability of the Form 990. First, at the bottom of Table 4.3, we see that the Hansen J and the Difference-in-Hansen tests indicate that the endogeneity assumptions are valid and that the errors are not autocorrelated.[7] In other words, there is no indication that the model is misspecified. Second, we see that more than 40 % of a given year's donations can be explained by donations of the previous year (see coefficients on Lagged Donations in Table 4.3). Third, the impact of publishing the Form 990 online on donations, beyond the effect the Form 990 has on crowding out, is positive but insignificant (see coefficients on Form 990 and Lagged Form 990 in Table 4.3).

Crowding Out of Private Donations In column (1) of Table 4.3 we see that government grants completely crowd out private donations (-1.076) if I do not control for the online availability of the Form 990. In other words, a $\$1{,}000$ government grant for a charity reduces private donations by $\$1{,}076$. This result is in line with Andreoni and Payne (2011), who find for a comparable sample a reduction of private donations by -1.243. In column (2) of Table 4.3 we see that crowding out is statistically not significant if the charities do not put their Forms 990 online. In contrast, crowding out is -1.149

[7] The null hypothesis of the Hansen J statistic and the Difference-in-Hansen test for constant correlation between the charity-level fixed effects and the endogenous variables is that the endogeneity assumptions are valid (Bun and Sarafidis 2013). The Difference-in-Hansen test compares the Hansen statistic that is obtained under the difference GMM with the Hansen statistic that makes use of the additional overidentifying restrictions of the system GMM (combining a system of equation in differences and levels). The difference between the two test statistics has itself an asymptotic χ^2 distribution with degrees of freedom equal to the number of additional instruments. The null hypothesis of the Difference-in-Hansen tests for autocorrelation is that the errors are not serially correlated, where it compares the Hansen J test statistic of equation (4.1) with the Hansen statistic derived under the assumption of a moving average structure of the errors (Arellano and Bond 1991).

if the charities put the Forms 990 online, where this effect is obtained by adding the coefficient on the government grants to the interaction term of the grants and the Form 990.[8] That is, individuals only reduce private donations in response to government grants if the charity discloses the received grants through making the Form 990 available on the charity's website. Policymakers may be interested in these unintended consequences of the disclosure of the government grants through the online availability of the Form 990 when designing legal disclosure requirements. For example, governments may decide to exempt government grants from potential disclosure requirements or charities may choose to blacken government grants on their published Form 990. Finally, the long-run effects of crowding out are obtained by dividing the sum of the coefficients on grants and lagged grants by one minus the coefficient on lagged donations.[9] If I do not consider the effect of the online availability of the Form 990 on donations, crowding out is not significant in the long run (see at the bottom of column (1) of Table 4.3). In contrast, crowding out is equal to -1.60 in the long run if the charities make their Forms 990 online available, while it is insignificant if the charities do not make their Forms 990 available. To summarize, this leads to the following results:

Result 4.1. *There is no significant crowding out if the Form 990 is not available on the website of the charity.*

Result 4.2. *There is complete crowding out if the Form 990 is available on the website of the charity.*

Effect of Fundraising Expenses on Donations In columns (1) and (2) of Table 4.3 we see that one additional dollar spent on fundraising leads to more than $ 13 private donations. In the long run, an extra dollar fundraising increases donations by more than $ 22 (see bottom of Table 4.3).[10] As the charitable organizations raise significantly more than one dollar for an extra dollar spent on fundraising, the organizations are not net-revenue maximizers.[11] Charitable organizations may stop fundraising because,

[8] As I make use of both cross-sectional and time variation (i.e. whether a given charity puts the Form 999 online), I do not run equations (4.1) and (4.2) separately for charities that have their Form 990 online and for charities that do not have their Form 990 online. Besides, this approach would magnify gaps in the data because of differencing the data (e.g. if I do not observe G_{ist}, then $\triangle G_{ist}$ and $\triangle G_{is,t+1}$ is also lost in the difference equation).

[9] The omission of time subscripts and subsequent rearrangement of equation (4.1) yields the long run effect of a given independent variable on donations.

[10] If I include liabilities as an exogenous instrumental variables for fundraising expenses (used by Andreoni and Payne 2011) additional to the lagged instruments used in the system GMM estimation of equation (4.1), the results do not significantly differ from the estimation shown in Table 4.3.

[11] In my sample, the average fundraising efficiency, which are fundraising expenses divided by the charity's total contributions, is $ 10.50 mean ($ 14 median). Andreoni and Payne (2011) estimate that an extra dollar increases donations by $ 5.86. Andreoni and Payne investigate charities for the period 1985 to 2002, where fundraising efficiency of charities could have been considerable lower than in my sample in the period 2009 to 2012 (e.g. plenty

Table 4.3: Effects of government grants and fundraising on private donations

Dependent Variable: Donations	(1) Standard	(2) Control Form 990 Online
Lagged Donations	0.408***	0.428***
	(0.108)	(0.113)
Fundraising Expenses	13.328***	13.450***
	(1.060)	(1.044)
Fundraising Expenses squared	−7.04e-08***	−7.02e-08***
	(3.28e-09)	(3.10e-09)
Government Grants	−1.076***	−0.442
	(0.264)	(0.305)
Lagged Government Grants	0.712***	0.492*
	(0.260)	(0.284)
Form 990 Online		654339
		(2268161)
Lagged Form 990 Online		1695420
		(1673251)
Form 990 Online × Government Grants		−0.707**
		(0.312)
Lagged (Form 990 Online × Government Grants)		−0.257
		(0.187)
Other Controls & Time Dummies	Yes	Yes
# Observations	3244	3244
# Instruments	50	58
Hansen J Statistic	33.32 (p-value 0.64)	35.15 (p-value 0.73)
Difference-in-Hansen Statistic (autocorrelation)	23.52 (p-value 0.43)	29.96 (p-value 0.47)
Difference-in-Hansen Statistic (constant correlation)	13.45 (p-value 0.71)	26.10 (p-value 0.20)
Long Run Fundraising Expenses	22.22***	23.22***
Long Run Crowding Out	−0.62	0.09 (not online)
		−1.60*** (online)

Notes: Windmeijer-corrected robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. A dynamic panel model is estimated by using system GMM estimation, where the dependent variable is the level of private donations. In column (1) I do not control for the online availability of the Form 990, while in column (2) I also estimate crowding out as a result of the online availability of the Form 990. All regressions include control variables, a constant, and time dummies. The charity-level controls are assumed to be strictly endogenous (i.e. instrumented by lags) and include the ratio of program to total expenses and revenues from federated campaigns. The state-level controls are assumed to be exogenous and include the employment to population ratio, transfers to individuals for income maintenance, and federal public corruption convictions. *Hansen* J *statistic* tests the null hypothesis that the endogeneity assumptions are valid and are calculated with Stata's user-written command xtabond2 (Roodman 2009). *Difference-in-Hansen* tests the null hypothesis of no autocorrelation (Arellano and Bond 1991) and the null of constant correlation between the fixed effects and the endogenous variables. Long-run crowding out is obtained by dividing the sum of the coefficients on grants and lagged grants by one minus the coefficient on lagged donations. The long-run effects of fundraising expenses are obtained in a similar way, where fundraising expenses are evaluated at the mean.

for example, charities may feel pressure from donors or the board, the organizations cannot keep the surpluses from fundraising, they may want to meet industry standards by charity experts and fundraising guides, or the charities may target higher ratings from charity watchdogs (e.g. Charity Navigator gives its best rating only to charities that raise more than $ 10 dollars for each dollar spent) (Andreoni and Payne 2011).

Result 4.3. *One additional dollar spent on fundraising increases donations by significantly more than one dollar. It follows that charities do not maximize net-revenues.*

Effect of Grants on Fundraising Efforts I estimate the impact of government grants on fundraising expenses in Table 4.4. First, the Hansen J and Difference-in-Hansen statistics at the bottom of Table 4.4 indicate that the endogeneity and autocorrelation assumptions required to estimate equation (4.2) by the system GMM are valid. Second, the fundraising expenses of the charities grow over time. In particular, a charity's fundraising efforts in a given year is 9.3 % higher than the fundraising efforts of the previous year (see coefficients on Lagged Fundraising Expenses in column (1) of Table 4.4), which may be due to the following reason. Charitable organizations may allocate increasing amounts for fundraising expenses as a result of high fundraising efficiency and as a result of charities not maximizing net revenues (compare Result 4.3 and footnote 11). Third, the fundraising expenses of charities that publish the Form 990 online are not significantly different from the fundraising expenses of charities that do not publish their Forms 990 online (see coefficients of Table 4.4 on the Form 990 and on the interaction effects between the government grants and the Form 990). Finally, a $ 1,000 government grant for a charity leads to a reduction of a given year's fundraising expenses by $ 253 (see column (1) of Table 4.4). However, government grants do not have a significant impact on fundraising efforts in the long run as the charities offset the reductions by increasing the fundraising expenses in the year after receiving the government grants (see insignificant coefficients at bottom of Table 4.4):

Result 4.4. *If charities receive government grants, they do not significantly reduce their fundraising efforts in the long run.*

While Andreoni and Payne (2011) find that charities significantly decrease their fundraising efforts after receiving government grants, the significance in Andreoni and Payne (2003) depends both on the type

of research on how to improve the fundraising efficiency has been available relatively recently). While Andreoni and Payne mention that a positive bias of the coefficient on fundraising expenses as a result of systematic underreporting of expenses is thinkable, the bias should be negligible if underreporting is heterogenous across charities (due to charity-level fixed effects in the regressions).

Table 4.4: Effects of government grants on fundraising

Dependent Variable: Fundraising Expenses	(1) Standard	(2) Control Form 990 Online
Lagged Fundraising Expenses	1.093***	1.081***
	(0.056)	(0.076)
Government Grants	−0.253***	−0.205*
	(0.095)	(0.120)
Lagged Government Grants	0.240***	0.224
	(0.092)	(0.112)
Form 990 Online		218613
		(654144)
Lagged Form 990 Online		106400
		(482226)
Form 990 Online × Government Grants		−0.041
		(0.063)
Lagged (Form 990 Online × Government Grants)		0.021
		(0.073)
Other Controls & Time Dummies	Yes	Yes
# Observations	3244	3244
# Instruments	34	42
Hansen J Statistic	14.28 (p-value 0.92)	15.18 (p-value 0.97)
Difference-in-Hansen Statistic (autocorrelation)	11.01 (p-value 0.75)	13.16 (p-value 0.93)
Difference-in-Hansen Statistic (constant correlation)	3.43 (p-value 0.98)	8.96 (p-value 0.88)
Long Run Government Grants	0.14	−0.23 (not online)
		0.02 (online)

Notes: Windmeijer-corrected robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. A dynamic panel model is estimated by using system GMM estimation, where the dependent variable is the level of private donations. In column (1) I do not control for the online availability of the Form 990, while in column (2) I also estimate the change in fundraising as a result of the online availability of the Form 990. All regressions include control variables, a constant, and time dummies. The charity-level controls are assumed to be strictly endogenous (i.e. instrumented by lags) and include the ratio of program to total expenses and revenues from federated campaigns. The state-level controls are assumed to be exogenous and include the employment to population ratio, transfers to individuals for income maintenance, and federal public corruption convictions. *Hansen* J *Statistic* tests the null hypothesis that the endogeneity assumptions are valid and are calculated with Stata's user-written command xtabond2 (Roodman 2009). *Difference-in-Hansen* tests the null hypothesis of no autocorrelation (Arellano and Bond 1991) and the null of constant correlation between the fixed effects and the endogenous variables. The long-run effects of government grants are obtained by dividing the sum of the coefficients on grants and lagged grants by one minus the coefficient on lagged fundraising expenses.

of organization and instrumental variables used.[12] Charitable organizations might aim for a growth in *program expenses* (e.g. due to demand of supervisory boards) and hence in the year after receiving the grants, the charities may decide to increase the fundraising expenses so that the original levels of fundraising expenses are reestablished.

Indirect Crowding Out Andreoni and Payne (2011) define indirect crowding out as the decrease in donations as a result of reduced fundraising efforts of charities in response to receiving government grants. According to indirect crowding out, the charitable organizations spend less money on fundraising if they receive government grants and thus individuals may donate less. In the short run, crowding out due to reduced fundraising efforts of charities is predicted to be very large in my sample (e.g. for charities that have their Form 990s online: the effect of fundraising expenses on donations 13.29 from equation (4.1) times the effect of government grants on fundraising expenses 0.25 from equation (4.2), which equals 3.27). This means that there would be substantial crowding in if there was no fundraising reduction as a result of government grants (e.g. because the government grants send a quality signal to potential donors, Andreoni and Payne 2011). The finding of substantial crowding in the absence of the fundraising reduction in response to the grants is a result of both the large effect of fundraising on donations (see Table 4.3) and the reduction in fundraising efforts by charities after receiving grants (see Table 4.4). However, this reduction in fundraising efforts by charities after getting grants is not very robust (as will be shown in Section 4.5) and further, the result is not significant in the long run (Result 4.4). This leads to the following result:

Result 4.5. *Crowding out of private donations is not explained by reduced fundraising efforts of charities after receiving government grants.*

Result 4.5 is in line with Jones (2015) who finds that crowding out of voluntary contributions, as a result of higher government activity through the introduction of state lotteries, cannot be explained by a reduction in fundraising of education organizations. As crowding out seems to be a result of the behavior of the individuals and not of reduced fundraising efforts by charity organizations, a policy that requires charities to increase their program expenses by the full amount of the government grants may not be feasible for the charities.

[12] As fundraising expenses are highly persistent, Andreoni and Payne's (2003, 2011) estimations could also be subject to a unit root problem (i.e. spurious regressions). In contrast, my system GMM estimation is consistent under a unit root (Blundell et al. 2000). Moreover, Andreoni and Payne (2003, 2011) only estimate short-run effects (i.e. the impact of government grants on fundraising expenses in the current year).

4.5 Robustness

In this section, the robustness of Results 4.1 to 4.5 is tested. In the following robustness analysis, I omit for parsimony variables indicating the online availability of the Form 990 for estimating equation (4.2), as in column (1) of Table 4.4, since the online availability of the Form 990 does not have a significant impact on fundraising expenses.[13] First, I check if the findings of Section 4.4 differ if a broader definition of private donations is applied when estimating equation (4.1) (i.e. private donations also from fundraising events, related organizations, and membership dues). Next, I test the robustness of the results by adding a measure for the transparency of the charities as a control variable in the regressions. Additionally, I check if information found on the Form 990 other than government grants influences the findings of the previous section. Afterwards, I exclude types of organizations as classified by Charity Navigator (e.g. human service organizations) from my regressions and divide the sample according to the size of the charities. Furthermore, I test different lag structures in my estimations. Finally, I include exogenous instruments for government grants (e.g. seniority of Democratic US Congressional representatives, as in Andreoni and Payne 2011) and for the online availability of the Form 990 additional to the lagged instruments used in system GMM estimation.

Broad Definition of Contributions and Control for Transparency Column (1) of Table 4.5 summarizes the baseline estimation of Section 4.4. For example, column (1) of the first row of Table 4.5 shows that in the short run, crowding out of private donations in response to government grants is not statistically significant if the Form 990 is not available online, while crowding out is -1.15 if the Form 990 is online. In comparison, column (2) of Table 4.5 shows the estimations of equations (4.1) and (4.2) if I make use of a broader definition of private donations which includes donations from fundraising events, related organizations, and membership dues.[14]

As more transparent charities may attract more donations, column (3) includes the "Accountability & Transparency Rating" by Charity Navigator as a measure for the transparency of the charities as an additional control variable for equations (4.1) and (4.2).[15] The Accountability & Transparency Rating

[13]The inclusion of variables indicating the online availability of the Form 990 in this robustness section leads to very similar regression results and the conclusions of this section remain the same. Similarly, the variables related to the online availability of the Form 990 were also insignificant in column (2) of Table 4.4.

[14]More detailed results of the robustness tests summarized in Tables 4.5 to 4.11 are available from the author upon request.

[15]The control variable for transparency is assumed to be endogenous in the regressions. I do not include the control for transparency in my baseline estimations, because the inclusion does not contribute to the explanation of the variation in the dependent variable and increases the number of required instruments (for the problems

Table 4.5: Robustness analysis, broadly defined private donations and transparency

	(1) Base		(2) Broad Definition of Donations		(3) Control for Transparency	
	not online	online	not online	online	not online	online
Panel A: Short-Run Effects						
Grants on Donations	−0.44	**−1.15**	−0.39	**−1.24**	−0.37	**−1.01**
Fundraising on Donations	**13.29**		**13.61**		**13.15**	
Grants on Fundraising	**−0.25**		**−0.25**		**−0.20**	
Panel B: Long-Run Effects						
Grants on Donations	0.09	**−1.60**	0.23	**−1.74**	0.07	**−1.50**
Fundraising on Donations	**23.22**		**22.34**		**23.04**	
Grants on Fundraising	0.14		0.14		0.03	
# Observations	3244		3244		3244	
# Instruments for Equation (4.1)	58		58		66	
# Instruments for Equation (4.2)	34		34		42	

Notes: *Panel A* shows the short-run effects of government grants and fundraising expenses, while *Panel B* depicts the long-run effects. For example, the long-run effects of government grants are obtained by dividing the sum of the coefficients on grants and lagged grants by one minus the coefficient on the lagged dependent variable. Columns (1) to (3) each show the effects of grants on donations for charities that make the Form 990 online available and for charities that do not make the Form 990 available, respectively. Column (1) summarizes the baseline estimation of Section 4.4. Column (2) makes use of a broader definition of donations (i.e. donations also from fundraising events, related organizations, and membership dues). In column (3) a measure for the transparency of the charities is used as an additional control variable. Coefficients in bold are statistically signifcant at $p < 0.05$, where the estimations make use of Windmeijer-corrected robust standard errors. All regressions include control variables, a constant, and time dummies. The charity-level controls are assumed to be strictly endogenous (i.e. instrumented by lags) and include the ratio of program to total expenses and revenues from federated campaigns. The state-level controls are assumed to be exogenous and include the employment to population ratio, transfers to individuals for income maintenance, and federal public corruption convictions.

reflects, for example, whether the charity has a conflict of interest policy, a whistleblower policy, and the CEO's salary listed on the Form 990. The broader definition of private donations as well as the inclusion of this additional control variable for transparency does not lead to significantly different short and long-run effects of government grants and fundraising expenses in comparison to the baseline estimation shown in column (1) of Table 4.5.[16] In short, Results 4.1 to 4.5 are robust and crowding out is only complete if the Form 990 is available on the charity's website.

Other Information on Form 990 As mentioned earlier, a potential drawback of this first attempt to estimate the disclosure of government grants on crowding out is that there are no surveys of individuals available that ask whether they actually observed the government grants on the Form 990. This means it is possible that crowding out is driven by information found on the Form 990 other than grants. In general, the dummy variable for the online availability of the Form 990 used in Table 4.3 should capture the impact of any other information shown on the Form 990 on private donations. Nevertheless, I test if the results of the previous section are robust to the inclusion of control variables reflecting payments to affiliated organizations (e.g. dues paid by a local organization to its affiliated parent organization) and working capital (available net assets minus the charity's total expenses) and their respective interaction effect with the online availability of the Form 990. Table 4.6 depicts the results if the estimation of equation (4.1) includes variables reflecting information found on the Form 990 other than government grants.

Column (1) of the first row of Table 4.6 shows that in the short run one additional dollar in payments to affiliated organizations does not significantly reduce private donations. Column (2) of the first row of Table 4.6 shows that in the short run one additional dollar of working capital does not significantly decrease donations if the charity does not put the Forms 990 online, while it significantly reduces donations by 11 cents if the Form 990 is online. In general, the inclusion of the additional control variables, reflecting information found on the Form 990 other than government grants, does not lead to significantly different short and long-run effects of government grants in comparison to the baseline estimation of Table 4.3. That is, there is no significant crowding out if the Form 990 is not available on the website of the charity, while there is crowding out if the Form 990 is available on the website of the charity. Further, the impact

associated with instrument proliferation see for example, Roodman 2009). Furthermore, more transparent charities may not only attract more donations, but also be more likely to have their 990 Forms online. However, the inclusion of an interaction effect between the online availability of the Form 990 and the transparency measure was not significant and thus omitted from the analysis.

[16]The Accountability & Transparency Rating has positive but insignificant short and long-run effects on private donations ($p = 0.11$ and $p = 0.13$, respectively; not shown in Table 4.5).

Table 4.6: Other Information on Form 990

	(1) Control for Payments to Affiliates on Form 990		(2) Control for Working Capital on Form 990	
	not online	online	not online	online
Panel A: Short-Run Effects				
Additional Control on Donations	−25.93	25.44	0.05	**0.11**
Grants on Donations	−0.04	**−0.96**	−0.07	**−0.75**
Fundraising on Donations	**12.84**		**9.72**	
Grants on Fundraising	**−0.25**		**−0.25**	
Panel B: Long-Run Effects				
Additional Control on Donations	−60.87	39.03	0.03	**0.11**
Grants on Donations	0.22	**−1.95**	0.31	**−1.12**
Fundraising on Donations	**22.38**		**15.16**	
Grants on Fundraising	0.14		0.14	
# Observations	3244		3243	
# Instruments for Equation (4.1)	66		66	
# Instruments for Equation (4.2)	34		34	

Notes: *Panel A* shows the short-run effects of the respective additional control variable (payments to affiliated organizations and working capital), government grants, and fundraising expenses, while *Panel B* depicts the long-run effects. For example, the long-run effects of government grants are obtained by dividing the sum of the coefficients on grants and lagged grants by one minus the coefficient on the lagged dependent variable. Columns (1) to (3) each show the effects of the additional control variable and grants on donations for charities that make the Form 990 online available and for charities that do not make the Form 990 available, respectively. Coefficients in bold are statistically signifcant at $p < 0.05$, where the estimations make use of Windmeijer-corrected robust standard errors. All regressions include control variables, a constant, and time dummies. The charity-level controls are assumed to be strictly endogenous (i.e. instrumented by lags) and include the ratio of program to total expenses and revenues from federated campaigns. The state-level controls are assumed to be exogenous and include the employment to population ratio, transfers to individuals for income maintenance, and federal public corruption convictions.

on private donations from spending an extra dollar on fundraising is lower than in the baseline estimation shown in Table 4.3 if I control for working capital (see column (2) of the third row of Table 4.6). However, Results 4.1 to 4.5 are robust to the inclusion of payments to affiliated organizations and working capital as additional variables depicting information found on the Form 990 other than government grants.

Excluding Types of Organizations Table 4.7 reports the results if certain types of organizations are excluded in the regression analysis.[17] *Panel A* depicts the short-run effects of the estimations of equations (4.1) and (4.2), while *Panel B* shows the corresponding long-run effects. In the first row of columns (1) and (2) of Table 4.7 we see that if I exclude fundraising and multipurpose human service organizations, respectively, there is also significant short-run crowding out of donations if charities do not have their Form 990 online (-0.87 and -1.12 in *Panel A* of columns (1) and (2), respectively). In contrast, in the first row of column (3) of Table 4.7 we see that if the youth development, shelter, and crisis organizations are excluded from the estimations, government grants do not significantly reduce private donations in the short run (i.e. neither for charities that have the Form 990 online nor for charities that do not have the Form 990 online). In columns (1) to (3) of the first row of *Panel B* we see that in the long run, however, crowding out is insignificant for charities that do not have the Form 990 online, while crowding out is significant for charities that have the form online (in line with Results 4.1 and 4.2). Moreover, the impact on private donations from spending an additional dollar on fundraising is considerable lower in comparison to the baseline estimation shown in Table 4.3 if I exclude fundraising organizations and multipurpose human service organizations from my estimations (see the second rows of *Panels A* and *B* of column (1) and (2) of Table 4.7). It seems that the fundraising and multipurpose human service organizations are largely responsible for the high fundraising efficiency found in the baseline estimation. Nevertheless, Result 4.3, which says that one additional dollar spent on fundraising increases donations by significantly more than one dollar and that charities are not net-revenue maximizers, is still valid. Lastly, if human service organizations are excluded from the estimations of equation (4.2), charities do not significantly reduce fundraising efforts as a result of receiving government grants in the short run (see column (2) of third row of Table 4.7 in comparison to the baseline estimation shown in Table 4.3). In general, the effect of government grants on fundraising efforts of charities is never significant in the long

[17] There are no significant differences in the effects of government grants and fundraising expenses in comparison to the baseline estimation shown in Tables 4.3 and 4.4 if I exclude any of the other nine types of charitable organizations in my sample classified by Charity Navigator (i.e. advocacy and civil rights, children's and family services, community foundations, community and housing development, food related services, homeless services, research and public policy institutions, social services, treatment and prevention services).

Table 4.7: Excluding types of organizations

	(1) Excludes Fundraising Organizations		(2) Excludes Multipurpose Human Service		(3) Excludes Youth Development, Shelter, and Crisis	
	not online	online	not online	online	not online	online
Panel A: Short-Run Effects						
Grants on Donations	**−0.87**	**−1.18**	**−1.12**	**−1.28**	0.37	−0.24
Fundraising on Donations	**6.44**		**2.38**		**12.18**	
Grants on Fundraising	**−0.42**		−0.00		**−0.21**	
Panel B: Long-Run Effects						
Grants on Donations	0.06	**−0.66**	−0.23	**−1.03**	0.49	**−1.17**
Fundraising on Donations	**8.59**		**10.33**		**21.65**	
Grants on Fundraising	0.09		0.05		0.13	
# Observations	2818		2999		2788	
# Instruments for Equation (4.1)	58		58		58	
# Instruments for Equation (4.2)	34		34		34	

Notes: *Panel A* shows the short-run effects of government grants and fundraising expenses, while *Panel B* depicts the long-run effects. For example, the long-run effects of government grants are obtained by dividing the sum of the coefficients on grants and lagged grants by one minus the coefficient on the lagged dependent variable. Columns (1) to (3) each show the effects of grants on donations for charities that make the Form 990 online available and for charities that do not make the Form 990 available, respectively. Coefficients in bold are statistically signifcant at $p < 0.05$, where the estimations make use of Windmeijer-corrected robust standard errors. All regressions include control variables, a constant, and time dummies. The charity-level controls are assumed to be strictly endogenous (i.e. instrumented by lags) and include the ratio of program to total expenses and revenues from federated campaigns. The state-level controls are assumed to be exogenous and include the employment to population ratio, transfers to individuals for income maintenance, and federal public corruption convictions.

run (see *Panel B* of Table 4.7, in line with Result 4.4). In other words, crowding out of private donations is unlikely to be explained by reduced fundraising efforts of charities after receiving grants (in line with Result 4.5).

Size of Organizations As an alternative to excluding types of charitable organizations, the sensitivity of the results (e.g. with regard to outliers) is tested by splitting the sample into small and large organizations. Table 4.8 reports the estimations of equations (4.1) and (4.2) if the charitable organizations are divided according to the size of their primary revenue (i.e. revenue a charity generates from its work, including contributions and government grants, membership dues, and revenue from programs and services). The primary revenue of the small organizations in column (1) of Table 4.8 is lower than or equal to the median primary revenue of $ 6,992,639, while the primary revenue of the large organizations is higher than the median. In line with Results 4.1 and 4.2, government grants to both small and large charitable organizations only crowd out private donations if the charities publish the Form 990 online (see first row of Table 4.8). In general, crowding out increases with the size of the charity, which could be a result of well informed large donors. In addition, the difference in crowding out between charities that make the Form 990 online available and charities that do not make the Form 990 available is higher for large organizations (see first rows of *Panels A and B* of Table 4.8, compare also Section 4.3).

Table 4.8 additionally shows that one additional dollar spent on fundraising by charitable organizations leads to an increase in donations to small organizations by more than $ 2 and an increase of donations to large organizations by more than $ 13 (see second row of Table 4.7, in line with Result 4.3). It follows that larger organizations are more efficient in fundraising than smaller organizations, which may be a result of highly professional fundraising and marketing departments among large charities. Finally, the effect of government grants on fundraising efforts of charities is, independently of the size of the organizations, not significant in the long run (see *Panel B* of Table 4.8, in line with with Results 4.4 and 4.5).

Different Lag Structure Table 4.9 reports the estimations if I change the lag structure of equations (4.1) and (4.2).[18] In column (1) of Table 4.9 I use the lag of the ratio of program to total expenses as an additional endogenous control variable in comparison to the baseline estimations shown in Tables 4.3 and 4.4. In column (2) of Table 4.9 I use the lag of revenues from federated campaigns as an

[18] Given the short time dimension of the panel and given GMM estimation using lagged instruments for endogenous variables such as the lagged dependent variable, I do no include further lags of the dependent variable in my estimations.

Table 4.8: Size of organizations

	(1) Small Organizations		(2) Large Organizations	
	not online	online	not online	online
Panel A: Short-Run Effects				
Grants on Donations	0.09	**−0.46**	−0.70	**−1.63**
Fundraising on Donations	**2.17**		**13.50**	
Grants on Fundraising	−0.01		**−0.37**	
Panel B: Long-Run Effects				
Grants on Donations	0.10	**−0.58**	0.26	**−2.15**
Fundraising on Donations	**2.34**		**24.76**	
Grants on Fundraising	−0.02		0.01	
# Observations	1601		1643	
# Instruments for Equation (4.1)	58		58	
# Instruments for Equation (4.2)	34		34	

Notes: *Panel A* shows the short-run effects of government grants and fundraising expenses, while *Panel B* depicts the long-run effects. For example, the long-run effects of government grants are obtained by dividing the sum of the coefficients on grants and lagged grants by one minus the coefficient on the lagged dependent variable. Columns (1) to (3) each show the effects of grants on donations for charities that make the Form 990 online available and for charities that do not make the Form 990 available, respectively. The primary revenue of the small organizations in column (1) is lower than or equal to the median primary revenue, while the primary revenue of the large organizations in column (2) is higher than the median. Coefficients in bold are statistically signifcant at $p < 0.05$, where the estimations make use of Windmeijer-corrected robust standard errors. All regressions include control variables, a constant, and time dummies. The charity-level controls are assumed to be strictly endogenous (i.e. instrumented by lags) and include the ratio of program to total expenses and revenues from federated campaigns. The state-level controls are assumed to be exogenous and include the employment to population ratio, transfers to individuals for income maintenance, and federal public corruption convictions.

Table 4.9: Different lag structure

	(1) Include Lag of Ratio of Program to Total Expenses		(2) Include Lag of Federated Campaigns		(3) Weakly Endogenous Government Grants	
	not online	online	not online	online	not online	online
Panel A: Short-Run Effects						
Grants on Donations	−0.32	**−1.09**	−0.77	**−1.35**	−0.01	−0.11
Fundraising on Donations	**13.54**		**11.55**		**11.96**	
Grants on Fundraising	**−0.31**		**−0.19**		**−0.23**	
Panel B: Long-Run Effects						
Grants on Donations	0.16	**−1.56**	−0.05	**−1.68**	0.11	**−0.70**
Fundraising on Donations	**22.59**		**24.22**		**19.53**	
Grants on Fundraising	0.49		0.02		0.41	
# Observations	3244		3244		3244	
# Instruments for Equation (4.1)	54		54		70	
# Instruments for Equation (4.2)	30		30		38	

Notes: *Panel A* shows the short-run effects of government grants and fundraising expenses, while *Panel B* depicts the long-run effects. For example, the long-run effects of government grants are obtained by dividing the sum of the coefficients on grants and lagged grants by one minus the coefficient on the lagged dependent variable. Columns (1) to (3) each show the effects of grants on donations for charities that make the Form 990 online available and for charities that do not make the Form 990 available, respectively. In column (1) I additionally use the lag of the ratio of program to total expenses, while in column (2) I additionally use the lag of revenues from federated campaigns as an endogenous control variable. Government grants in column (3) are assumed to be weakly endogenous. Coefficients in bold are statistically signifcant at $p < 0.05$, where the estimations make use of Windmeijer-corrected robust standard errors. All regressions include control variables, a constant, and time dummies. The charity-level controls are assumed to be strictly endogenous (i.e. instrumented by lags) and include the ratio of program to total expenses and revenues from federated campaigns. The state-level controls are assumed to be exogenous and include the employment to population ratio, transfers to individuals for income maintenance, and federal public corruption convictions.

additional endogenous control variable in comparison to the baseline estimations. In column (3) of Table 4.9 government grants are assumed to be *weakly* endogenously determined, which means that the lags for government grants $G'_{is,t-1}$ in equations (4.1) and (4.2), are not taken as endogenous (while G'_{ist} is still taken as endogenous). Although assuming weakly endogenously determined government grants leads to more efficient results, the assumption may lead to instrument proliferation and inconsistent estimates (compare Roodman 2009 and instrument count at the bottom of Table 4.9). Therefore I treat government grants as strictly endogenously determined (the lags $G'_{is,t-1}$ are also taken as endogenous) in the baseline estimations shown in Tables 4.3 and 4.4. Nevertheless, I report the estimations of equations (4.1) and (4.2) under the assumption of weakly endogenously determined government grants in column (3) of Table 4.9.

If I include lags for the program expense ratio or federated campaigns as additional control variables in the estimations, government grants only crowd out private donations for charities that have their Form 990 online (see first row of columns (1) and (2) of Table 4.9). In comparison, in the first row of column (3) of Table 4.9 we see that if government grants are treated as weakly endogenously determined, grants do not significantly reduce private donations in the short run (i.e. neither for charities that have their Form 990 online nor for charities that do not have their form online), which may be due to inconsistency of this specification. In columns (1) to (3) of the first row of *Panel B* we see that in the long run, however, crowding out is not significant for charities that do not have their Form 990 online, while crowding out is significant for charities that have their form online (in line with Results 4.1 and 4.2). In all lag specifications shown in Table 4.9, one additional dollar spent on fundraising increases donations by more than one dollar (in line with Result 4.3). Lastly, the effect of government grants on fundraising efforts of charities is not significant in the long run (see third row of *Panel B* of Table 4.8, in line with Results 4.4 and 4.5).

Additional Instruments for Government Grants Table 4.10 reports the results if the regressions include exogenous instrumental variables for government grants that have been used in the literature additional to the lagged instruments used in system GMM estimation of equations (4.1) and (4.2). The additional instruments for government grants included are the seniority of Democratic US Congressional representatives for the state (Andreoni and Payne 2011) in column (1) of Table 4.10, lagged state-level

Table 4.10: Additional instruments for government grants

	(1) Instrument: Seniority		(2) Instrument: Transfers to Non-Profits		(3) Instrument: Transfers to Individuals	
	not online	online	not online	online	not online	online
Panel A: Short-Run Effects						
Grants on Donations	−0.45	**−1.15**	−0.46	**−1.15**	−0.46	**−1.15**
Fundraising on Donations	**13.27**		**13.27**		**13.27**	
Grants on Fundraising	**−0.25**		**−0.25**		**−0.25**	
Panel B: Long-Run Effects						
Grants on Donations	0.08	**−1.59**	0.09	**−1.58**	0.08	**−1.59**
Fundraising on Donations	**23.29**		**23.23**		**23.26**	
Grants on Fundraising	0.07		0.13		0.12	
# Observations	3244		3244		3244	
# Instruments for Equation (4.1)	59		59		59	
# Instruments for Equation (4.2)	35		35		35	

Notes: *Panel A* shows the short-run effects of government grants and fundraising expenses, while *Panel B* depicts the long-run effects. For example, the long-run effects of government grants are obtained by dividing the sum of the coefficients on grants and lagged grants by one minus the coefficient on the lagged dependent variable. Columns (1) to (3) each show the effects of grants on donations for charities that make the Form 990 online available and for charities that do not make the Form 990 available, respectively. In column (1) I use seniority of Democratic Congress members, in column (2) lagged federal transfers to all non-profits, and in column (3) government transfers to individuals as additional exogenous instruments for government grants. Coefficients in bold are statistically signifcant at $p < 0.05$, where the estimations make use of Windmeijer-corrected robust standard errors. All regressions include control variables, a constant, and time dummies. The charity-level controls are assumed to be strictly endogenous (i.e. instrumented by lags) and include the ratio of program to total expenses and revenues from federated campaigns. The state-level controls are assumed to be exogenous and include the employment to population ratio, transfers to individuals for income maintenance, and federal public corruption convictions.

federal transfers to all non-profits in column (2) (Andreoni and Payne 2003), and state-level federal transfers to individuals (Payne 1998) in column (3).[19]

The inclusion of these instruments for government grants does not lead to significantly different effects of government grants and fundraising expenses relative to the baseline estimation shown in Tables 4.3 and 4.4. That is, crowding out is only complete if the Form 990 is available on the website of the charity and Results 4.1 to 4.5 are robust to the inclusion of additional exogenous instruments for government grants.

Additional Instruments for Form 990 Table 4.11 shows the results if the regressions include exogenous instrumental variables for the online availability of the Form 990 additional to the lagged instruments used in system GMM estimation of equations (4.1) and (4.2). The additional instruments for the online availability of the Form 990 included are in column (1) of Table 4.11 a binary variable that takes the value 1 if the charity lists Board members on its website and the value 0 otherwise, and in column (2) a binary variable that takes the value 1 if the charity list their key staff online (i.e. who runs the organization day-to-day). I expect that charities that put their Form 990 online are also more likely to list the Board members and key staff, respectively, on the websites of the charities. To be a valid instrument for the Form 990 I additionally assume that the listing of the Board and key staff does not have an impact on private donations beyond the impact through the provision of the Form 990 on the website. Table 4.11 shows that the inclusion of these additional instruments does not lead to significantly different effects of government grants (depending on the online availability of the Form 990) and fundraising expenses in comparison to the baseline estimation depicted in Tables 4.3 and 4.4. This confirms the robustness of Results 4.1 to 4.5 presented in Section 4.4 and it follows that crowding out is only complete if the Form 990 is available on the charity's website.

[19]The hand-collected data regarding the seniority of Democratic US Congressional representatives for the years 2009 to 2012 is taken from the Office of the Clerk of the U.S. House of Representatives (2014).

Table 4.11: Additional instruments for Form 990

	(1) Instrument: Distributes Form 990 to Board		(2) Instrument: Key Staff Listed	
	not online	online	not online	online
Panel A: Short-Run Effects				
Grants on Donations	−0.34	**−1.08**	−0.36	**−1.10**
Fundraising on Donations	**13.28**		**13.31**	
Grants on Fundraising	**−0.25**		**−0.25**	
Panel B: Long-Run Effects				
Grants on Donations	0.18	**−1.60**	0.13	**−1.62**
Fundraising on Donations	**23.08**		**23.05**	
Grants on Fundraising	0.14		0.14	
# Observations	3244		3244	
# Instruments for Equation (4.1)	59		59	
# Instruments for Equation (4.2)	34		34	

Notes: *Panel A* shows the short-run effects of government grants and fundraising expenses, while *Panel B* depicts the long-run effects. For example, the long-run effects of government grants are obtained by dividing the sum of the coefficients on grants and lagged grants by one minus the coefficient on the lagged dependent variable. Columns (1) to (2) each show the effects of grants on donations for charities that make the Form 990 online available and for charities that do not make the Form 990 available, respectively. In column (1) I use a binary variable that takes the value 1 if the charity lists Board members on its website (and the value 0 otherwise) and in column (2) I use a binary variable that takes the value 1 if the charity list their key staff online as additional exogenous instruments for the online availability of the Form 990. Coefficients in bold are statistically signifcant at $p < 0.05$, where the estimations make use of Windmeijer-corrected robust standard errors. All regressions include control variables, a constant, and time dummies. The charity-level controls are assumed to be strictly endogenous (i.e. instrumented by lags) and include the ratio of program to total expenses and revenues from federated campaigns. The state-level controls are assumed to be exogenous and include the employment to population ratio, transfers to individuals for income maintenance, and federal public corruption convictions.

4.6 Conclusion

This study investigates whether crowding out of private donations depends on the availability of the Form 990 on the website of the charity. It is the first study that explores the consequences of the disclosure of government grants. In the estimations I find complete crowding out of private donations if the Form 990 is available on the website of the charity, while there is no crowding out if the Form 990 is not available on the website. This finding suggests that the disclosure of government grants may lead to unintended expenses. Further, the finding that crowding out depends critically on the disclosure of the government grants may contribute to explain the wide range of estimates for crowding out found in the theoretical and empirical literature on crowding out. In addition, the econometric analysis shows that one additional dollar spent on fundraising raises donations by considerably more than one dollar, which confirms the finding of previous studies that charities do not maximize net-revenues. Finally, I do not find evidence that the explanation for crowding out is due to the reduced fundraising efforts of charities after receiving government grants as charities offset any short-run decrease in fundraising expenses by an increase in fundraising, at the latest, in the year following the grants.

As crowding out seems to be a result of the behavior of individuals rather than of charities (as charities do not reduce fundraising efforts), a policy that requires charities to increase their program expenses by the full amount of the government grants may not be feasible. Moreover, when determining the optimal subsidy of giving and legal disclosure requirements, the study suggests for policymakers to consider the higher levels of crowding out as a result of the disclosure of government grants. As disclosure requirements may lead to hidden costs, future research could aim to reinvestigate disclosure requirements also in other industries. The estimations, however, rely on the validity of the underlying assumptions of the econometric model and the results may depend on institutions and cultural differences as well. Consequently, further studies using other datasets from different countries, additional types of charitable organizations, and other forms of disclosure will be required to confirm the robustness of this attempt to estimate the effect of disclosure on crowding out.

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Abstract

This thesis consists of three articles analyzing government resources devoted to charitable giving. The first article introduces tax evasion through subsidies received for false declarations of charitable donations. This study distinguishes between a rebate and match subsidy in an experimental setting. Under the rebate subsidy the individual receives the subsidy, while under the match subsidy the charity organization receives the subsidy. First, I develop a theoretical model of charitable giving and tax evasion. Second, I test in an experiment whether subjects report higher donations than the actual donations they made, and thus evade taxes. The results show that the level of overreporting is higher under the rebate subsidy than under the match subsidy. A higher probability of an audit under the rebate subsidy has no significant effect on overreporting, whereas a higher probability under the match has a strong negative effect.

The second article analyzes the optimal subsidy rate on charitable giving considering tax evasion through false declarations of charitable donations. The investigation distinguishes between self-reporting and third-party reporting of donations. First, I show that the optimal subsidy depends critically on the probability of tax evasion being detected, which differs under self-reporting and third-party reporting of donations. Second, if an increase in the subsidy results in an increasing level of tax evasion, the optimal subsidy under self-reporting decreases, while the optimal subsidy under third-party reporting either decreases or increases.

The third article tests the crowding out hypothesis, which says that government grants to a private charitable organization will displace private donations, by accessing a large database of US charities. The existing empirical literature on crowding out ignores that private donors are often not aware of government grants to charities. In my estimations I find complete crowding out of private donations if the tax return Form 990 is available on the website of the charity, while there is no crowding out if the Form 990 is not available on the website. I do not find evidence that reduced fundraising efforts of charities after receiving government grants explain crowding out.

Zusammenfassung

Diese Dissertation umfasst drei Artikel, die staatliche Zuschüsse und Spenden an wohltätige Organisationen untersuchen. Der erste Artikel beschäftigt sich mit Steuerhinterziehung durch den Bezug von Subventionen aufgrund falsch deklarierter Spenden. Diese Studie unterscheidet zwischen einer "Rebate"- und "Match"-Subvention. Die Rebate-Subvention wird von den Spendern und die Match-Subvention von den wohltätigen Organisationen bezogen. In einem theoretischen Modell wird zunächst Steuerhinterziehung in Zusammenhang mit Spenden gebracht. Anschließend wird in einem Experiment getestet, ob die Spendenangaben der Probanden die tatsächlichen Spenden überschreiten. Die Ergebnisse zeigen, dass unter der Rebate-Subvention ein höherer Anteil hinterzogen wird als unter der Match-Subvention. Eine höhere Wahrscheinlichkeit einer Überprüfung der Spendenangaben hat keinen Einfluss auf die Spendenangaben unter der Rebate-Subvention, verringert die Falschangaben jedoch unter der Match-Subvention.

Der zweite Artikel untersucht die optimale Subventionsrate von Spenden an wohltätige Organisationen unter Berücksichtigung von Steuerhinterziehung durch falsch deklarierte Spenden. Die Untersuchung unterscheidet zwischen Selbstdeklarierung der Spenden von den Subventionsbeziehern und Angaben von Dritten. Die Analyse zeigt, dass die optimal gewählte Subvention entscheidend von der Wahrscheinlichkeit Steuerhinterziehung zu entdecken abhängt. Falls eine Erhöhung der Subvention zu einem stärkeren Anstieg an Steuerhinterziehung führt, verringert sich die optimale Subventionsrate bei Selbstdeklarierung von Spenden, während sich die optimale Subventionsrate bei Angaben von Dritten erhöhen *kann*.

Der dritte Artikel schätzt ob direkte Staatszuschüsse an Wohltätigkeitsorganisationen eine Verringerung der Spendeneinnahmen zur Folge hat ("Crowding Out"). Bisherige empirische Arbeiten zu diesem Thema basieren auf der Annahme, dass die privaten Spender über Staatszuschüsse an die Organisationen Bescheid wissen. Meine Schätzungen zeigen, dass es nur dann zu einer Reduktion von Spendeneinnahmen aufgrund eines Staatszuschusses kommt, wenn die Jahresberichte der Wohltätigkeitsorganisationen online leicht verfügbar sind. Crowding Out wird nicht durch eine Verringerung der Fundraisingaufwendungen der Wohltätigkeitsorganisationen in Folge eines Staatszuschusses begründet.

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Education and Training

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08/2011	Course in Experimental Economics, University of Amsterdam, Netherlands
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09/2009–11/2010	*MSc in Economics (with distinction), University of Warwick, United Kingdom* Thesis: 'The Impact of Environmental Tax Reforms – A Dynamic Panel Approach'
10/2006–06/2009	*BA in Economics (with distinction), University of Graz, Austria* Thesis: 'What Influences the Outcome of an Environmental Kuznets Curve?'
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Research Interests

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Research Papers

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2014	'Mobility of Ringlet Butterflies in High-elevation Alpine Grassland: Effects of Habitat Barriers, Resources and Age' (*joint with D. Polic, K. Fiedler, A. Grill*), *Journal of Insect Conservation 18*: 1153–1161
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Seminars, Workshops, and Conferences

05/2014	BET Seminar at Monash University (*presented*), Melbourne, Australia
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06/2013	French Experimental Economics Association (*presented*), Lyon, France
04/2013	VCEE Away Workshop (*presented*), Payerbach-Reichenau, Austria
09/2012	ESA European Conference (*attended*), Cologne, Germany
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Scholarships and Awards

01/2012–12/2012	Research Fellowship (*12,000 EUR*), University of Vienna
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