UNIVERSIDADE CATÓLICA PORTUGUESA

Competition Among Non-Profit Organizations for Private Donations

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by

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Abstract

This Master thesis aims firstly, to evaluate the influence that fundraising expenditures made by a non-profit organization has on its own private donations and on the private donations received by all the other non-profit organizations, in the non-profit market. The relationship between own-fundraising expenditures and own-private donations will be useful in answering a second research question, which aims to discover the objective function of a non-profit organization, which can be a net revenue maximizer or a budget maximizer. The latter attribution is related on the fundraising behaviour of the considered non-profit. Thirdly, this thesis purposes to evaluate the effect government grants have on private donations received by a given non-profit organization and on private donations received by all the other non-profits.

Using U.S. non-profit organizations' yearly tax return data from 2005 to 2010, the answers to the three research issues will be given by the estimation of a demand model, more precisely, by the estimation of a discrete choice demand model, which is the Multinomial Logit (MNL) developed by McFadden (1978, 1981).

The empirical findings suggest that fundraising expenditures made by a given non-profit organization affect positively its own private donations and affect the private donations of some other non-profits, not of all of them. Besides, at the aggregate level by grouping non-profits into sectors, the effect of own-fundraising expenditures on own-private donations is positive, however when considering the cross-effect of fundraising expenditures made by one sector on private donations received by other sectors, the effect is zero, thus there is no cross-effect when considering non-profits at the aggregate level. Grounded on the fundraising effect results, this master thesis finds out that that the non-profits considered are neither net revenue maximizer nor budget maximizer organizations.

Subsequently, the empirical results indicate that government grants have no effect on private donations, because the parameter that captures the effect is statistically not significant.

Keywords: Non-Profit Organization(s), Fundraising Expenditures, Private Donations, Government Grants.

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Introduction

Over the last decade, a significant and rapid growth of the non-profit sector has been observed in the United States. Bose (2015) goes further and specifies that the number of non-profit organizations has increased by 24 percent between 2000 and 2010. More precisely, in 2005, slightly over 1,4 million tax-exempt organizations were registered with the U.S. Internal Revenue Service (IRS).[1] According to Bose (2015), in 2010, there were almost 1,6 million non-profit organizations registered.[2]

Thornton (2006) as Bose (2015) also underlines, on the one side, the fast increase of the non-profit sector by indicating a 128% increase in charities between 1982 and 1997, which Bose (2015) considers as "beneficial", because this translates into a greater offer of goods and services by the non-profit sector. Nonetheless, Thornton (2006) alerts on the other side, for the increase of contributions, which has only increased by 72% in real terms. Thus, between 1982 and 1997, charities compared to contributions increased by nearly the double. Bose (2015) believes that the greater number of non-profits can lead to a higher competition among non-profits organizations for contributions, a "limited resource".

Khanna *et al.* (1995) consider that many non-profits provide only a public good rather than a private good. Those non-profits that provide a public good are perceived as a private provider of a public good. There are two important characteristics that define pure public goods or simply public goods, which are the following (Kotchen,

[1] The registered number of non-profits in the U.S. in 2005 has been taken from https://www.statista.com/statistics/189245/number-of-non-profit-organizations-in-the-united-states-since-1998/ , it excludes religious congregations and non-profits with an annual revenue lower than $5,000.

[2] Again, without including religion congregations and smaller organizations.

2012): “non-rivalry” and “non-excludability”. By “non-rivalry” is meant that, the consumption of a public good by one person does not reduce the availability of the same good to be consumed by other persons. The second characteristic, “non-excludability”, means that everyone can use the public good, thus no one can be restricted from consuming the good. Kingma (1989) illustrates public radio or public television as an example of a pure public good provided by non-profit organizations. A private good, in contrast to a public good, is “rival and excludable” Kotchen (2012).

Andreoni and Payne (2003) argues that it is fundamentally via the donations that individuals made that they demonstrate their demand for those public goods. Much charities are dependent on private donations from the general public “as a major source of revenue” (Bose, 2015). These results demonstrate a persistent incentive for non-profits to compete for their major source of revenue.

Consequently, for Bose (2015), non-profit organizations compete for donations by adjusting their fundraising expenses, since these expenses “in turn impact the donors”. Fundraising expenditures comprises the costs in attracting contributions from the public (Bose, 2015). Thornton (2006) referred to them as an “important strategic decision in the face of scarce donor resources”.

Private donations constitute a major source of a non-profit organization’s revenues, but they not constitute their only source of revenue. Non-profit organizations, in addition to private donations, can receive government grants and other independent revenues (Khanna & Sandler, 2000). Payne (1998) clarifies that an important part of a non-profit organization’s revenues comes from private donations and government grants.

The above raises three important research questions. First, how do fundraising expenditures from a given non-profit organization affect the private donations it receives received from the general public and affect the private donations received by competing non-profit organizations? Second, how do non-profit organizations decide the amount of fundraising expenditures? In order words, what is the objective function of a non-profit organization? Is the observed fundraising behaviour of non-profits consistent with a net revenue maximizing objective or with a budget maximizing objective? Finally, do government grants, in their turn, influence the private donations received by a specific non-profit organization and the private donations received by competing non-profit organizations? The latter is known in the literature as a "crowding out" research question, which Andreoni and Payne (2011) described as "one of the oldest and most important questions in public economics". Thus, we can reformulate our third research question as following: do government grants crowd-out private donations received by non-profit organizations? The importance of this last research question can be reinforced when we recognise that individual donors are also tax payers and that individual donors can eventually consider their involuntary payment through taxation and their voluntary charitable contributions as substitutes. In such a case, when government grants are transferred to charities, it may yield a decrease in the amount of private donations.

We will explore the three research questions both theoretical and empirical perspectives. We will do so by focusing as Bose (2015), Andreoni and Payne (2003), Bilodeau and Slivinski (1997) on charitable organizations that rely on government grants and private donations, that report expenditures on fundraising activities and lastly, that use their private donations to produce public goods or private goods "with some external benefits" (Bose, 2015). In particular, we will estimate a discrete choice demand model for private donations – and, more precisely, a Multinomial Logit (MNL) demand model for private donations – using a sample of 10,261 U.S. non-profit organizations in the period between 2005 and 2010. We first examine the impact that fundraising expenses and government grants have, respectively, on private donations and, finally based on the fundraising results infer the objective function of the different non-profit organizations. The details of the procedure are as follows. First, we will collect data from the annual tax returns of U.S. public charities, known as the non-profits IRS Form 990 and in which the amount of private donations, government grants and fundraising expenses of each non-profit organization are separately categorized for the year in which the form was filled. Second, we will use the MNL estimates to compute the own- and cross-elasticities of private donations with respect to fundraising expenses and government grants. Those elasticities are the key of our study because they will allow us, in the end, to evaluate (i) the own- and cross-effect that fundraising expenses have on private donations and, in turn, also the related objective function of the non-profit in question, and (ii) the own- and cross-influence that government grants have on private donations. We will compute these own- and cross-elasticities at two levels: at the non-profit level and at the aggregate level, by aggregating non-profits into sectors.

The results suggest that own fundraising expenses affecting positively own private donations, at both the aggregate level and at the individual level (for all non-profits considered). Further, the results for this own-fundraising elasticity suggest that all our non-profit organizations are neither net revenue maximizing nor budget maximizing.

The results also suggest that there is no evidence of any cross-effect of fundraising expenses on private donations at the aggregate level. In contrast, at the individual non-profit level, the results suggest that, for a subset of non-profits, there is evidence of a cross-effect, in which own fundraising expenses affecting negatively other charities' private donations, while, for another subset of non-profits, the cross-effect is almost null.

Finally, regarding the impact government grants have on private donations, the results suggest that there is no evidence for the crowding out hypothesis of government grants on private donations.

The structure of this Master thesis is organized as follows: Chapter 1 reviews the literature (i) on non-profit organizations, on the relationship between fundraising expenditures and private donations, on the objective functions attributed to non-profits, and on the crowding out hypothesis; (ii) on the discrete-choice demand models we will use in the empirical application. Chapter 2 describes the theoretical framework and the estimation methodology used as well as the way we will use it to answer our research questions. Chapter 3 presents (i) the data used in the estimation (including the instruments), (ii) a preliminary analysis of the data, and (iii) the empirical findings. Finally, we conclude.

CHAPTER 1

1. THE LITERATURE REVIEW

This first chapter encompasses the literature review used in this Master thesis to examine the research questions. The literature review is itself divided in two parts. First, we review the most dominant literature concerning non-profit organizations. Second, we review the literature review concerning demand models in order to base our choice of empirical methodology.

1.1. Non-Profit Organizations

We begin by defining what is a non-profit organization. Then, we will address the non-profit organization's revenue sources followed by the determinants of the private donations received by a non-profit organization. Finally, we address the objective functions of non-profit organizations depending on their behavior.

1.1.1. Definition of a Charity

A non-profit organization, or in other words, a charity, provides public and private goods that are appreciated by the general public. However, we will focus as Bose (2015), Okten and Weisbrod (2000), Weisbrod and Dominguez (1986) on non-profit organizations providing public goods. Many authors define the role of a non-profit as "a substitute for government provision" (Weisbrod and Dominguez, 1986; Kotchen, 2012; Heutel, 2014). Donors have their preference for a public good, which can be satisfied by either private provision or public provision, where private provision concerns the non-profit organizations and, where public provision concerns the government. For Thornton (2006), non-profit organizations are "a merely passive mechanism", by which the donors' preferences for public goods are satisfied.

Non-profit organizations are, similarly to for-profit firms, allowed by law to "accrue profits". However, managers of non-profits are completely forbidden to take the surplus or any part of the surplus for themselves (Steinberg, 1986).

1.1.2. Revenue Sources

As we just mentioned in the previous *subsection 1.1.1. Definition of a Charity*, a charity furnishes goods and services that are publicly valued, but to be able to supply the publicly appreciated goods and services, a charity requires revenues. Non-profit organizations can obtain revenues from two different sources: private source and public source. However, we should be aware that a non-profit organization's revenue is not just composed by private sources and public sources but also by program service revenues, investment incomes and other revenues, which all three will be explained in detail below, in the next subsection of this thesis (Heutel, 2014).

The charities' private source comprises the private donations non-profit organizations receive from voluntary donors. Weisbrod and Dominguez (1986) emphasize that private donations are important for non-profits, since the "nature" of the non-profit's "output", which is a public good "limits direct sales as the principal source of revenue". So, donors contribute voluntarily with their money to a non-profit organization of their choice, in return for "an implicitly agreed-upon level of provision and quality of output" (Okten and Weisbrod, 2000). The total amount of charitable donations includes direct and indirect public support (Heutel, 2014; Bose, 2015). The direct public support corresponds to the amount of contributions a charitable organization "directly" receives from "individuals, foundations, estates, corporations, public charities or raised by an outside professional fundraiser" (Bose, 2015). Thenceforth, as Bose (2015) and Heutel (2014), we also include as private donations, the indirect public support, which corresponds to contributions received "indirectly through solicitation from a parents or subordinate organization or from campaigns conducted by federated fundraising agencies". Both authors justify the inclusion of indirect public support, by the fact that "such charitable giving is typically motivated by the same reasons as individual donors" (Bose, 2015). Charitable donations are measured for each non-profit, individually, by summing the total amount of direct and indirect public support received by a charitable organization in a year (Bose, 2015). The amount of private donations received is different for each non-profit organization and varies across periods (Steinberg ,1986).

Besides, the public source includes the grants charities receive from a governmental unit, which is also known as public funding. Government grants comprises grants received from "all levels of government, excluding reimbursements for services provided by the non-profit under a government contract" (Andreoni and Payne, 2011). Those government grants are transferred to charities to request the "private sector to expand the government's activities in areas, where the government involvement is reduced" (Weisbrod and Dominguez, 1986). Heutel (2009) explains that the government transfers charitable grants to non-profits to "overcome the market's failure". The problem is according to Kotchen (2012) the "free-riding" problem. "Individuals have little incentive to voluntarily provide public goods when they can simply enjoy the benefits non-rival and non-excludable public goods provided by others", emphasize Kotchen (2012). This author illustrates an example of reflecting the necessity of constructing a bridge, which would benefit the entire population. The problem of "free-riding" is that individuals would never donate for the construction of the bridge, hoping that other individuals contribute. The market failure in this case would be that the bridge would not be constructed. Consequently, the intervention of the government is necessary for "the efficient or even reasonable allocation of public goods" (Kotchen, 2012). Governments must "serve as a coordinating mechanism that provides public goods for the benefit of society". Heutel (2009) emphasizes further that a government has on mind "an optimal level of provision of a charity or public good" and the government will adjust its grants transferred to non-profits to achieve that "optimal" level.

1.1.3. Determinants of Donations

The most important determinants of a charity's private donations are (i) the charity's fundraising expenditure and (ii) due to the crowding-out problem discussed above, the government grants received. We will discuss both in turn below. However, they do not constitute its sole determinants. As such, we will also discuss a series of additional determinants, which we will group in a category denoted "others".

1.1.3.1. Fundraising Expenditures

Fundraising expenditures are the expenditures made by a non-profit in soliciting contributions, gifts and grants, which influence the amount of charitable donations received by them.[3] As Bose (2015) describes, those fundraising expenses can also include "campaign printing, publicity, mailing, staffing and other costs". Charities incur in fundraising activities with the ambition of increasing their amount of private contributions (Bose, 2015). The author insists that fundraising expenses are responsible for more than a half of the change in charitable donations, which indicates the importance of fundraising expenses in bringing charitable donations into a non-profit organization.

Khanna and Sandler (2000), Weisbrod and Dominguez (1986), Okten and Weisbrod (2000), Thornton (2006), Rose-Ackerman (1982) and, lastly, Bose (2015) argue that fundraising expenditures influence the amount of private donations in two opposite ways. On the one hand, fundraising expenses encourage individuals to donate, because fundraising activities inform the public about the non-profit and its important characteristics and values and, thus, reduces or even eliminates the cost for donors of

[3] Definition of fundraising expenditures consulted on the official website of the Instruction for Form 990 Return of Organization Exempt from Income Tax: https://www.irs.gov/pub/irs-prior/i990--2008.pdf

searching their favourite charity. So, “fundraising acts like advertising” and, therefore increases charitable contributions (Khanna and Sandler, 2000). On the other hand, fundraising expenses can also have a negative effect on private donations, since they represent a cost for charitable organizations and donors perceive these costs as deviating the non-profit’s income “away from” the non-profit’s “final output” (Weisbrod and Dominguez, 1986). In other words, an increase in fundraising expenses reduces the amount spent on the non-profit’s charitable output, which will in turn decrease private donations (Weisbrod and Dominguez, 1986; Khanna and Sandler, 2000). What is important to donors is that their donations contribute to the production of public goods (Weisbrod and Dominguez, 1986). The literature captures this idea in the concept of “price of giving”, which demotes the after-tax cost for donors, in dollars, of increasing (by contributing) the output of the non-profit by $1. “Increased fundraising increases the price of giving, which is anticipated to reduce contributions”, because donors perceive the expenditures dedicated to fundraising activities as a cost not as creating charitable output (Khanna & Sandler, 2000; Rose-Ackerman, 1982; Thornton, 2006; Weisbrod and Dominguez, 1986; Okten and Weisbrod, 2000; Bose, 2015). Consequently, the price of giving “reflects expenditures that are not directly output-creating such as fundraising expenditures” (Weisbrod and Dominguez, 1986). Okten and Weisbrod (2000) emphasize that “donors perceive their marginal contribution to output to be proportional to the amount of money given, net of fundraising expenses, and that donors perceive the marginal fundraising expense associated with their particular donations as equal to the non-profit’s average overall ratio of fundraising expenditures to donations”.

In summary, Khanna and Sandler (2000), Weisbrod and Dominguez (1986), and Okten and Weisbrod (2000) consider that, in theory, fundraising expenses have, on the one hand, a positive advertising effect on private donations, but, on the other hand, a negative price effect on private donations. The direct or partial fundraising effect on charitable donations comprises the positive effect through advertising (Okten & Weisbrod, 2000). The indirect effect of fundraising on private donations covers the negative price of giving effect. Finally, the total effect of fundraising expenses on private donations includes the negative indirect effect and the positive direct (or partial effect), where the total effect is according to Weisbrod and Dominguez (1986) measured by the marginal donative product of fundraising, which informs about the non-profit organization's objective. This distinction is important, because the empirical literature typically separates the direct, the indirect and the total fundraising effect on private donations.

Bose (2015) shares the same theoretically point of view of Khanna and Sandler (2000) and Weisbrod and Dominguez (1986), but instead of fundraising expenses, she studies the effect competition among non-profits has on private donations. Similarly, Bose (2015) considers that there is a positive advertising and a negative price effect of competition on private donations.

According to Thornton (2006), the negative effect of fundraising on private donations arises because donors have the possibility to observe the price of giving or equivalently the "average overall ratio of fundraising expenditures to donations" as denoted by Okten and Weisbrod (2000), or the "fundraising-expense ratio", as denoted by Thornton (2006). All these concepts measure the non-profits efficiency, which is made public by the non-profits themselves or by the so-called "watchdog websites". Thornton (2006) as Andreoni and Payne (2003) add a new issue for non-profits, by alerting that "watchdog" websites become increasingly important for donors. Donors are sensitive to high non-profit "expense ratios" and a charity with a high fundraising-expense ratio is perceived as inefficient by the public, which would lead to a decline of its general donor's demand for this non-profit's goods and services (Thornton, 2006; Andreoni and Payne, 2003). Consequently, non-profit organizations face a "dilemma", emphasizes Thornton (2006): charities can achieve an increase in private donations by having higher efficiency ratings on watchdog websites or by rising their fundraising expenses, which can cause them to be viewed as "less efficient". Bose (2015) argues that donors trust and make increasingly use of public financial information. The argument is made by Lammers (2003), who explains that the latest research demonstrates that donors make more and more use of publicly available information on the non-profits financial situation, which helps them identify those charities that are efficient providers of public goods. Donors surely prefer to donate to those non-profit organizations with higher ratings (Okten and Weisbrod, 2000). Regarding the publicly available ratings, it is important to note that each website has its own rating criteria to measure the non-profits degree of efficiency. Andreoni and Payne (2011) and Thornton (2006) cite websites like the American Institute of Philanthropy, Give.org or Charity Navigator, described as being "industry experts and non-profits watchdogs" that inform the public with "independent quality ratings of non-profits". In order to have a better notion of how those websites evaluate non-profits, we will analyse deeper the website *Charity Watch* and take it as an example**.** This website considers, for instance, that in terms of fundraising efficiency, a non-profit organization is considered as "excellent" if the charity's cost to raise $100 stands between $0 and $15. The cost to raise $100 corresponds to the amount the organization spends to bring $100 of donations from the public in a given year. A non-profit organization is considered as being qualitative "good" if the charity's cost to raise $100 stands between $16 and $30. The non-profit is assessed with the efficiency rating "satisfactory/average" if its cost to raise $100 is between $31 and$40. The qualitative rating "unsatisfactory" is for those charitable organizations with a cost between $41 and $59 to raise $100. Lastly, those non-profits expressed as "failing" support an expenditure between $60 and $ 100 to raise $100.[4] All the watchdog websites have one thing in common: a charity is only considered as efficient if the amount it spends to raise their funds is less than the amount it finally raises. For instance, in the case of *Charity Watch*, a non-profit who presents a cost of $65 to raise $100 belongs to the last efficiency scale, and is therefore, according to our interpretation of the rating criteria,

[4] All the information regarding the rating criteria of Charity Watch was obtained on its official website under "Criteria and Methodology": https://www.charitywatch.org/charitywatch-criteria-methodology

less efficient than the non-profits stated at the top scale, but it remains efficient even at the last efficiency scale.

Andreoni and Payne (2003) examines, from a theoretical perspective, the disutility that arises from fundraising. They argue that those non-profit managers that care about the provision of charitable services and engage in fundraising dislike spending money on fundraising activities and would prefer to spend that money on "their charitable activities". For Andreoni and Payne (2003), managers of non-profits, as donors, often share the idea that a high amount of fundraising expenditures, "rightly or wrongly", is an indicator of "a low-quality charity" and specify that non-profits with "low quality ratings may seem their donations suffer as a result". Nevertheless, managers know that increasing their fundraising expenditures will encourage new donations and that non-profits must support the expenditure "to provide services they value" (Andreoni and Payne, 2003).

The first author to analyse the problem of excessive fundraising expenses was Rose-Ackerman (1982). In her models, fundraising expenditures are "purely informative". For Rose-Ackerman (1982), donors gain through charities' fundraising expenses in two ways. First, donors obtain information about the charity, what eliminates or at least reduces completely their searching costs. The second way that benefits donors, is that fundraising campaigns can lead individuals "to substitute gifts for private consumption" or to substitute donations from one charity the donor likes to another charity the donor likes even more (Rose-Ackerman, 1982). This substitution effect is according to this author a waste of funds, because it does not enlarge the size of donor market, donors simply switch from one non-profit organization to another non-profit organization. The author shows, from a theoretical perspective, that the competition for charitable donations make charitable organizations practice fundraising expenditures at a level that reduces the aggregate service provision by following their private incentives. In the presence of increased competition, the competition for donations increases, which causes non-profits to practice too high fundraising expenditures, i.e. at an inefficient level, even knowing that donors strongly dislike high fundraising expenditures, because resources are diverted from the charitable output. The theoretical model used by Rose-Ackerman (1982) assumes that non-profit organizations choose the amount of their fundraising expenses that maximizes their contributions, which is a theory also shared by Thornton (2006), who suggests that ideally non-profits “should keep fundraising until the last dollar spent returns only one dollar in new donations”.

Thornton (2006) follows the steps of Rose-Ackerman (1982), Khanna and Sandler (2000), Weisbrod and Dominguez (1986), Okten and Weisbrod (2000) and Bose (2015) regarding the positive effects fundraising expenses have for donors but further adds the positive effects fundraising expenses have for charities. For Thornton (2006), the positive consequences fundraising has for non-profits is that it attracts new donations and stimulates the attentiveness and curiosity of individuals regarding the charity. The author continues by specifying that “fundraisers” attempt to maximize revenues from donations at the lowest cost, emphasizing that it is not evident for non-profit managers to define the part of their own funds to devote to fundraising activities (Thornton, 2006).

Moreover, Bose (2015) highlights that often it is believed in community that fundraising expenditures is the unique way through which information is circulated from non-profits to donors, which is an error. There are other sources that enables donors to obtain information about non-profits in order to decide to which non-profit to donate and how much to donate. As examples of such sources, the author indicates the independent websites that publish charity ratings, websites that are also known as charity watchdog sites, which importance is shared by Andreoni and Payne (2003) as discussed above in this same *subsection 1.1.1. Fundraising Expenditures*. Bose (2015) continues by mentioning, as other sources that inform the public about non-profits, the obligatory public revelation of non-profits annual returns, like the organization’s IRS Form 990 and, finally, the access to information about non-profits on internet, more exactly, on social networks where information on non-profits circulates speedily. Bose (2015) emphasizes that donors no longer depend on fundraising expenditures to be awaken into giving. She continues underlying that the existence of "external sources of information" gives donors the possibility to observe all non-profit organization types and their relative efficiency. This allows donors to adjust their private donations on non-profits behaviour even without fundraising.

Having discussed the theoretical literature on the impact of fundraising expenditures on private donations, We now address the empirical evidence. Khanna and Sandler (2000) examined the determinants of charitable giving of 159 UK most successful and largest non-profit organizations between the years 1983 and 1990. To do so, they regress voluntary contributions on the price of giving, fundraising expenditures, government grants, legacies, autonomous income and, finally, the natural log of non-profit's age.[5] Khanna and Sandler (2000) estimate their equation using the generalized least-squares (GLS) and random-effects methods, but after identifying the possible endogeneity of government grants, they estimate it using instrumental variables jointly with fixed-effects. The instruments used for government grants are legacies and autonomous income and so, when accounting for endogeineity, the equation is run without those two variables.

Weisbrod and Dominguez (1986) used pooled data on around 300,000 U.S. non-profit organizations required to file IRS Form 990 between the years 1973 and 1976. The authors group the non-profits into the seven following industries: library, art, poor and aged, hospital, aid to the handicapped, scientific research and school. Weisbrod and Dominguez (1986) select in their empirical equation as dependent variable the logarithm of total charitable contributions, which comprise private donations, gifts and grants, expressed in dollars, regressed on various dependent variables, all expressed in logarithm with the exception of the age, including fundraising expenditures, price of giving, the age of the non-profit and, finally, the product between age and fundraising expenses. The latter independent variable denotes "the

[5] Legacies corresponds to the amount of "earnings derived from estates" and autonomous income refers to the amount of "fees, investment earnings, rental income and other activities" received by the non-profit (Khanna and Sandler, 2000).

marginal productivity of additional fundraising given the" non-profit's "stock of goodwill". In other terms, the coefficient of this independent variable will tell us how the effectiveness of additional fundraising varies with the age of the non-profit. Weisbrod and Dominguez (1986) estimate their empirical equation by OLS.

In a follow-up paper to Weisbrod and Dominguez (1986), Okten and Weisbrod (2000) improve previous work by analysing data from IRS Form 990 of U.S. charities between the years 1982 and 1994 (except 1984). Okten and Weisbrod (2000) use panel data and consider the same seven industries studied previously by Weisbrod and Dominguez (1986). The empirical model used by Okten and Weisbrod (2000) contains the natural logarithm of private donations, expressed in dollars, as dependent variable and fundraising expenditures, government grants, program service revenues, price of giving and finally, the organization's age as independent variables. All the independent variables are expressed in logarithm except for age. Okten and Weisbrod (2000) also include in their estimation equation dummy variables "to control for the effects on private donations of changes in income tax laws in 1984 and 1986. Okten and Weisbrod (2000) estimate their model, firstly, by OLS and, then, so to overcome the bias, by two-stage least-squares, to accounting for the endogeneity of fundraising expenditures and price of giving. To instrument fundraising expenditures, they uses the fundraising expenses of the previous year, the government grants of the year and the program revenue service of the year. To instrument the price of giving, they use the government grants and the price of giving of the previous year.

More recently, Bose (2015) used data from the IRS Form 990 of U.S. charitable organizations between the years 1998 and 2003. The empirical equation used by Bose (2015) includes private donations as the explained variable and as explanatory variables, the index of market competition, which is "measured by the Herfindahl-Hirschman index" (HHI), fundraising expenses, price of giving and government grants. Bose (2015) adds as explanatory variables in her estimation equation, "vectors of exogenous non-profit and geographic level controls" that affect private donations, and further adds year and sector fixed-effects. The variables used by Bose (2015) as controls for the non-profit specification are "all sources of non-profit income, value of assets and the age of the nonprofits". The geographic control variables selected by Bose (2015) are the following: Metropolitan Statistical Area (MSA) "level per capita income, population and unemployment rate, the share of the population over the age of 65 in the state, a dummy variable equal to one if the governor is affiliated with the Democratic party and the share of US Congressional and Senate representatives for the state affiliated with the Democratic party". Bose (2015) estimates its empirical equation, firstly, by OLS at the non-profit and at the market levels. She then estimates its equation by two-stage least squares (2SLS) only at the non-profit level regression, to account for the endogeneity of fundraising expenses and government grants. Bose (2015) uses "total non-profit liabilities" as instrument for fundraising expenses and "government transfers at the market level" as instrument for government grants.

Thornton (2006) uses data on the U.S. non-profits annual tax returns for the period between 1990 and 2000. This author regresses fundraising expenditures on total contributions, the age of a non-profit, total assets and finally, on Herfindahl-Hirschman index (HHI). Thornton (2006) adds sector, year and MSA fixed-effects.[6] Thornton (2006) estimates his model at the non-profit level and at the market level using OLS and Tobit techniques.

Having described the methodology of the different empirical applications, we now address their empirical results. Weisbrod and Dominguez (1986) and Okten and Weisbrod (2000); Khanna and Sandler (2000) and Bose (2015) confirm that fundraising expenses have two opposite effects on private donations. All the mentioned authors confirm their theory by demonstrating that the direct fundraising impact is in general positive and, consequently, there is an influence of fundraising expenses through advertising on charitable contributions. Weisbrod and Dominguez (1986) find, as a secondary influence, that donors have a "distaste" for expenses in fundraising and

[6] The Herfindahl-Hirschman index (HHI) used by Thornton (2006) is the same than previously mentioned by Bose (2015). The HHI index measures the market competitiveness and is calculated by "summing the squared market shares" of each charity in a market (Bose, 2015).

decrease their donations when non-profits are "less efficient" by spending too much in fundraising activities.

Regarding the indirect fundraising effect, Okten and Weisbrod (2000), Weisbrod and Dominguez (1986), Khanna and Sandler (2000) and Bose (2015) findings confirm that the indirect fundraising effect, which is the price effect, has a significantly negative impact on private donations, consequently higher fundraising expenses leads to a decrease in private donations. Okten and Weisbrod (2000) additionally find that non-profit organizations often do not spend on fundraising activities at an efficient level, "given the absence in non-profit organizations, of owners having residual property rights".

The estimates found by Okten and Weisbrod (2000) and Weisbrod and Dominguez (1986) using OLS estimation are similar and indicate that, when measuring the **total fundraising** influence on private contributions, in general higher fundraising expenses do not lead to any rise in charitable donations. These empirical estimates suggest that non-profit are total revenue maximizers (Weisbrod and Dominguez, 1986).

On the contrary, Okten and Weisbrod (2000) discover based on their 2SLS estimation results that these results differ with those obtained by OLS. The 2SLS estimation is made on three out of seven industries, because the other industries lose their significance due to their smaller sample size (Okten and Weisbrod, 2000). The authors find that for two of the three industries studied, the effect of total fundraising expenses on private donations is significantly positive. The industries in question are libraries and hospitals. Consequently, an increase in fundraising expenses made by libraries or hospitals leads to an increase in the private donations received. Okten and Weisbrod (2000) additionally mention that "hospitals and libraries fall short of fundraising" that maximize net revenue.

Khanna and Sandler (2000) is in line with Okten and Weisbrod (2000) and likewise underline that the total fundraising effect on private donations is positive and end up concluding that UK religion charities are net revenue maximizers, because UK religion charities elasticity is lower than one, while all the other UK charities analysed "fundraise short of net revenue maximization", because their elasticities of voluntary contributions on fundraising expenditures exceed one.

Bose (2015) clarifies that an increase in the number of non-profits causes, on the one hand, an increase in the aggregate donations provided by all the donors in the sector but, on the other hand, causes a decrease in charitable contributions received on average by a charity. This author indicates based on her findings that the relationship between non-profit organization competition and fundraising expenses is positive. Competition causes an increase in aggregate donations "but not by very large amounts" clarifies Bose (2015) and insists that what is damaging is the "excessive fundraising" spent by non-profit to deal with the competition, which is disliked by donors.

Thornton (2006) empirical work results are conflicting with Bose (2015) empirical findings. Thornton (2006) results confirm his expectation that with increased competition, non-profits reduce their fundraising expenses, so "per-firm fundraising declines". Thornton (2006) justifies this result by explaining that non-profits recognise that donors are able to constantly observe expense ratios of non-profits on fundraising activities. "As better information is made available to a wider number of donors, price competition among non-profits firms will likely become even more effective", argues Thornton (2006). The author explains its view further by underlining that as non-profit's "private benefit" derived from fundraising expenses decreases "in a saturated market", consequently non-profit organizations "will voluntary reduce their fund-raising outlays" (Thornton, 2006). Further, Thornton (2006) finds that the "per-firm fundraising" decreases, but the aggregate fundraising increases with increased competition, even if the number of donors who donate is held constant. And although non-profit's managers are preoccupied with the high aggregate amount of fundraising, Thornton (2006) believes that the real problem concerns the number of non-profits in the market and not the non-profit's amount of fundraising expenses. For the author, the simplest way to reduce the excessive aggregate fundraising is through imposing a higher cost for entering the non-profit market and thus reduce the number of firms in the market. However, on the other hand, this would push non-profits to individually increase their fundraising expenses. Thornton (2006) is conclusively not in line with Bose (2015), who considers that charities, when confronted to increased competition spent more on fundraising activities, supporting the idea that greater competition leads to excessive fundraising.

Finally, from the literature regarding the effect of fundraising expenditures on private donations, we can retain that a large set of theoretical and empirical research has been dedicated to study the relationship between charitable donations and fundraising expenditures. At the theoretical level, the literature, in general, agrees that fundraising expenditures have two opposite effects on private donations. Nevertheless, the empirical findings are mixed.

1.1.3.2. Government Grants

According to the literature, the level of private donations also depends on other sources of income as the level of government grants. Thus, in this thesis, the other main determinant of private donations, jointly with fundraising expenditures, is government grants, also known as public funding or public grant, which is a transfer that can be perceived as a gift to non-profit organizations made by "local, state or federal government sources" or even "foreign governments".[7] Government grants represent an expenditure for the governmental unit. The principal objective of the transfer is to allow the charitable organization to provide a service. In other words, the primary objective of the grant must be "the direct benefit of the public" and not "to assist the direct needs of the government".[8] Hence, the grant can serve the needs of the government, but this must be indirect and weak compared to the public benefit. Non-profit organizations are viewed by the government as private suppliers of public goods and according to Khanna and Sandler (2000) non-profit organizations "perform a crucial allocative role in the provision of charitable collective goods in modern

[7] Information found on the official United States IRS website: https://www.irs.gov/pub/irs-prior/i990--2008.pdf

[8] All the details that define government grants are picked from page 30, 1st column, on the following link (Instructions for Form 990 website): https://www.irs.gov/pub/irs-prior/i990--2008.pdf

economies". The intervention of the government is necessary to assure the "efficient allocation of public goods" states Kotchen (2012). Furthermore, the government may choose the "optimal level of provision of a charity or a public good and adjust its funding to reach that level" clarifies Heutel (2014). Thus, in other words, governments transfer grants to non-profit organizations to assure social welfare at a maximum level and to provide by the intermediation of non-profits, public goods, which the government by itself is unable to provide.

The official website of *Instructions for Form 990 Return of Organization Exempt from Income Tax* illustrates some examples of government grants: Payments for the construction or maintenance of libraries or museums, payments to nursing homes to offer health care to the citizens and payments to better help children in the community by furnishing "child placement" or "child guidance organizations".[9]

A significant theoretical and empirical literature seeks to examine the impact that government grants have on charitable donations, focusing primarily on evaluating the crowding-out hypothesis. The crowding-out occurs whenever a decrease in government grants pushes donors to increase their voluntary contributions, hence substituting private for public funding (Khanna & Sandler, 2000). However, the opposite, an increase in government grants causing a decrease in private contributions, thereby substituting public for private support is also recognized as the "crowding-out" hypothesis, when government grants crowd-out private donations (Khanna & Sandler, 2000).

Rose-Ackerman (1987) highlights that government grants are "exogenous resources", whose value is not affected by donors or managers of non-profits, so its value is "independently of any actions taken by managers or donors". The author alerts, however, for the fact that government grants affect donors and the non-profit managers' behaviour, and a non-profit manager must be mindful that its own behaviour impact the choice of donors. Rose-Ackerman (1987), who only analyses the

[9] https://www.irs.gov/pub/irs-prior/i990--2008.pdf

issue theoretically, believes that from the donors point of view, government grants are perceived as ameliorating the image and reputation of a non-profit and, consequently, government grants would crowd-in private donations.

Khanna & Sandler (2000) consider that "government grants are usually accompanied by monitoring of the clients by governmental officials, which can limit informational asymmetries". Consequently, the transfer of government grants to a non-profit by limiting the lack of information leads to an increase of the willingness of donors to donate to non-profits that receive grants from the government.

In line with Khanna and Sandler (2000) and Rose-Ackerman (1987), who consider that government grants push private donations upwards by signalling the non-profit's quality, are Okten and Weisbrod (2000), who support the same idea: government grants crowd-in private donations, but by signalling "government approval and social need". However, Okten and Weisbrod (2000) believe that, on the other hand, there are also motives that could sustain crowding-out. For instance, any "exogenous change" in the non-profits revenue like government grants could affect the individual's willingness to donate and, consequently, Okten and Weisbrod (2000) consider that an increase in government grants could, on the other hand, probably decrease the donor's "marginal valuation of output".

In contrast, Payne (1998) contradicts Rose-Ackerman (1987), arguying that government grants are affected by individuals, because individuals are voters and, consequently, they affect government policies. Payne (1998) points out that the government's choice about the transfer of grants to non-profits reveals "political and economic conditions of its constituents and the heterogeneity of the non-profit firms". Individuals behaviour on how much and if to donate is "based on the government's choice, the political and economic conditions, and the heterogeneity in the firms' production of the charitable good". The author considers that individuals have altruistic and egoistic characteristics and so investigates the relationship between government grants and private donations with the objective to determine if government grants effectively crowd-out private donations. Payne (1998) considers that non-profits produce the charitable good and individuals are donors and voters.

In line with Payne (1998) are Andreoni and Payne (2011), who theoretically consider that, firstly, government grants can decrease charitable donations for two reasons. First, donors are also taxpayers and could consider their "involuntary contributions through taxation" and their charitable donations as substitutes.[10] The latter would lead to a decrease in private donations by the total amount of government grant to a non-profit. Second, the authors find that there is strong evidence for the fact that government grants to charitable organizations make non-profits reduce their fundraising expenses. This result is important because this means that the behaviour of non-profit organizations "is consistent with the predictions of an economic model within a strategic environment", where charities are "active players in the market for donations". Andreoni and Payne (2011) point out that when a government attributes a grant, the government should take into account the behavioural reaction of non-profits and the behavioural response of voluntary donors.

Roberts (1984) and Warr (1982) analysis the crowding-out hypothesis merely theoretically and consider that donors have a completely altruistic behaviour, caring only about the charitable good. Both authors indicate that an increase in governments grants decrease private donations in a "one-for-one basis", which means that the crowding-out happens dollar for dollar. Roberts (1984) clarifies its findings by explaining that the enormous increase in government transfers in the 1930s (so during the Great Depression which occurred from 1929-1941) crowded out private "antipoverty efforts" and "fundamentally changed the nature of private charity". Altruistic donors considered that governments "overprovide" public grants "in the sense that more resources are transferred to the poor than altruistic desire". The author supports this conclusion even after the great depression. Additionally, the author advises that government grants should be eliminated when the crowding out is

[10] Government grants are financed by the government through the citizen's taxes, where some of them (citizen) are also donors.

complete[11], except if the amount of government grants is optimal and higher than the level of the existing donations. The complete crowding-out is because the increase in public funding is financed by taxing the donors.

In line with Andreoni and Payne (2011), Roberts (1987) and Warr (1987) state that donors are taxed and that donors consider their amount paid in terms of taxes as substituting private donations. According to Roberts (1987) individuals consider that the government "overprovides" transfers of grants to non-profits, by transferring an amount higher than "altruistic desire", yielding null private donations. Warr (1982) goes further and specifies that when donors are purely altruistic, caring only about the charitable output, the crowding out should be "one-for-one", which means that when government grants increase by one dollar, private donations should decrease by one dollar. The one-for-one is explained by the fact that private donations and government grants are considered as substitutes. When the crowding-out is negative, government grants are productive conclude Roberts (1984) and Warr (1982). Roberts (1984) end up recommending that when crowd-out exists and is complete, so dollar for dollar, government grants should be removed, because in this case a subsidy to private donations is always more effective than direct taxation. Government grants should be eliminated unless the optimal level of government grants is significantly higher than the current level of private donations.

Kingma (1989) and Reece (1979) consider that the "correct" model of charitable contribution is the model in which "agents act as if they receive utility from their contribution and the overall level of charity", therefore both authors study an "impure altruist model" and aim to evaluate if the crowd-out effect exists. Reece (1979) and Kingma (1989) consider that there is no crowding-out effect of government grants on private donations, because, according to these authors, government grants are not substitute of a donor's contribution.

[11] By complete is meant that the crowding out happens in a one for one basis, for instance, an increase of government grants by one dollar will decrease or crowd-out private donations by exactly one dollar.

Having described the theoretical implications of government grants on private donation, we now address the empirical literature. The differences between all the empirical results identified by the different authors lies, considered Kingma (1989), on the broad definition of non-profit organizations and government grants that each of the authors mentioned. The correct evaluation of the crowding-out hypothesis should, according to Kingma (1989) and Payne (1998), focus on how private donations are affected by government grants for a given type of charitable good, i.e, if government grants for a particular public good crowd out private donations for that good.

We begin by detailing the empirical data, estimation equation and estimation method used by Andreoni and Payne (2011). They used data on annual tax returns of over 8000 non-profit organizations between the years 1985 and 2002. The authors' empirical equation comprises private donations as the explained variable and involves as explanatory variables the government grants, fundraising expenses, non-profit organization, year fixed-effects, and a vector of non-profit organization and state level controls. The control variables used by the Andreoni and Payne (2011) are the following: "program dues revenues collected by the charity, state level individual per capita income, state population, state population squared, the share of the population under the age of 18, the share of the population over the age of 65, annual state level expenditures for Medicare, Medicaid, and income assistance, a dummy variable equal to one if the governor is affiliated with the Democratic party, the share of US Congressional representatives for the state affiliated with the Democratic party, a year trend interacted with the NTEE1 code, and a set of year dummies". The empirical equation is estimated using instrumental variables techniques. Andreoni and Payne (2011) consider that either fundraising expenditures and government grants are endogenous variables, since there exist "unmeasured influences" that are captured by the error term and that may affect both variables. The authors illustrate examples of those "unmeasured influences" as, for instance, shocks or natural disasters as a hurricane. The instruments used for government grants are the "total years of experience of congressional Representatives affiliated with Democratic party", the “total years of experience of congressional Representatives affiliated with Republican Party” and thirdly, the difference between the “experience of Representatives affiliated with political party with most representatives” and “the experience of other representatives”. Fundraising expenditures are instrumented by the liabilities and by the occupancy expenditures, also known as management expenditures or administrative expenditures.

Payne (1998) used a panel data set of 430 non-profit organizations for the period between 1982 and 1992. The estimation equation involves a dependent variable, private donations, regressed on government grants, on a “vector of political and/or economic measures for the state in which the non-profit is located” and on non-profit organization and year fixed-effects. The economic measures selected are the following: “per capita income” by state (in which the non-profit is situated), unemployment rate by state, the percentage of population with more than 65 years by state, the percentage of population with an age between 5 and 17 again by state and, finally, the population by state. The political measures used are the following: “a dummy variable indicating if the governor is affiliated with the Democratic Party, the number of Democratic US Senators, the ratio of Democratic to total US Representatives, the ratio of Democratic to total members in the state’s upper legislature and the ratio of Democratic members in the state’s lower legislature”. The method used by Payne (1998) to estimate her empirical model was OLS and 2SLS. When estimating the above equation by 2SLS, Payne (1998) account for endogeneity by using instrumental variables for government grants. Government grants are instrumented by transfers made by the government to individuals and transfers made by the government to non-profit organizations situated in the same state.

Reece (1979) analysed data for the years 1972-1973 on income, expenses and personal characteristics of households, relying on the Bureau of Labour Statistics consumer expenditure surveys (CEX) and on the location of the households, which is given by the state and the Standard Metropolitan Statistical Area (SMSA). The estimation equation involves as a dependent variable, total contributions, which is regressed on the price of contributions, on the family income, on the age of the "household head", on the "average public assistance", "on the lower quintile family income for the Standard Metropolitan Statistical Area, within which the household resides", on "the intermediate family budget index for the Standard Metropolitan Statistical Area in which the household resides", and finally on a dummy variable that takes "unity for those observations from the 1973 sample and zero for those observations from the 1972 sample" (Reece, 1979). The equation is estimated using maximum likelihood Tobit techniques.

Kingma (1989) used data on "3,541 individual observations across" 66 U.S. public radio stations (non-profit organizations) for the year 1986. Kingma (1989) formed an equation, where private contributions are regressed on the before-tax income of donors, on the total level of membership support, on the government grants, on the price of contribution, on the education level of donors and on the age of donors. The parameters of Kingma (1989) selected equations are estimated using a "Tobit model".

Having described the data and methodologies of the different authors, we now address the corresponding empirical results.

Khanna and Sandler (2000) find that there is a greater evidence of government grants crowding-in significantly charitable donations as it was expected by Rose-Ackerman (1987) and by themselves. Additionally, Khanna and Sandler (2000) believe that if crowding-in is related to government grants and governments limit their public support to non-profits, the latter can lead "to devastating effects by losing public and private support".

In line with Khanna and Sandler (2000) and Rose-Ackerman (1987) are Okten and Weisbrod (2000), who find, as Khanna and Sandler (2000), that there is evidence of government grants crowding-in private donations. The authors found evidence of significant positive effects in most industries and justify it with the positive message that government grants transmit to potential voluntary givers regarding the "reputation" or the "trustworthiness" of a charity. Okten and Weisbrod (2000) also refer to the tax law changes in 1984 and in 1986, which for them seem to have caused a negative influence on donations for some industries.

In contrast, Payne (1998) finds that after accounting for endogeneity, a crowding-out effect exists, but is partial, being "significantly different from zero and one dollar". On average, the crowd-out is, according to Payne (1998), approximately 50 cents. In other words, this would imply that an increase in government grants by one dollar will decrease private donations by 50 cents.

Andreoni (1990) is in line with Payne (1998) by finding a partial crowd-out effect, between zero and one. Andreoni (1990) also emphasizes that "redistributions to more altruistic people from less altruistic people will increase total provision and that crowding out will be incomplete". Thus, according to Andreoni (1990), the crowding-out depends on if individuals are more or less altruistic.

Kingma (1989) also finds evidence for the crowding-out hypothesis. For this author, a change in government contributions to a non-profit can negatively affect private contributions.

Andreoni and Payne (2011) find that an increase in government grants generates a decrease in the non-profit organization's fundraising expenses and that the latter is what causes the crowding-out and that the crowding-out is around 75%. For instance, an increase in government grants by $10,000 would reduce private donations by $7,570. We have to note that Andreoni and Payne (2011) assume that there is no "warm-glow from giving" but the results are generalized to impure altruism, where "people give partly for the private pleasure of giving".

In contrast, Reece (1979) finds that there is no evidence of government grants "crowding-out" private contributions.

To sum up, in general, the empirical results suggest mixed findings. The results have shown, in general, either a small level of crowding-out or a small level of crowding-in, but there are also results that indicate a crowding-out at 50% and 75%, which must be taken into account. Besides, the findings of the different authors cannot be compared directly because they used different panel data for different years, and the way the different authors constructed their empirical model also plays an important role.

1.1.3.3. Other Determinants

As the review in subsection *1.1.3. Fundraising Expenses* and subsection *1.3.2 Government Grants* suggest, private donations do not uniquely depend on fundraising expenses and on government grants. They do also depend on observed characteristics of non-profit organizations.

One of the most used characteristic of a non-profit organization by the literature is the age of a non-profit organization (Okten and Weisbrod, 2000; Khanna and Sandler, 2000; Bose, 2015; Heutel, 2014). The age of a non-profit organization is computed by the date the IRS attributed the tax-exempt non-profit status to the charity (Heutel, 2014; Bose, 2015). According to Khanna and Sandler (2000) and Heutel (2014), the inclusion of the age as a determinant of private donations is important because a charity's age represents its "reputation" and, therefore, signals about its quality and about the quality of its output, which could have an impact on private donations. Okten and Weisbrod (2000) believe that the age of a non-profit affects private donations in two different ways, "directly" and "indirectly". On the one hand, the age informs about the non-profit reputation and, therefore, could affect directly private donations. On the other hand, the age influences the productivity of fundraising, which could affect indirectly private donations. Okten and Weisbrod (2000) expect that older non-profit organizations directly "benefit from a reputational effect" and that, indirectly, the "effectiveness of fundraising depends on the stock of reputational goodwill".

Another determinant of private donations is program service revenue and all other revenues, as "investment income" and "other revenue" of a non-profit organization or even the value of its total assets. In the literature, some authors refer to the program service revenue, others state the "autonomous income". The autonomous income comprises income from rent and fees and the latter are components of program service revenue, consequently we will focus on the program service revenue. Program service revenue includes “the fees and other monies received by an organization for services rendered”: the revenue from the non-profit’s program services, for instance, from “sales activities” (Okten and Weisbrod, 2000). These services must obligatory be “directly” associated with the commitment for which the non-profit organization obtained “its tax-exempt status”. According to Okten and Weisbrod (2000), program service revenues are similar to government grants, which can have positive and negative influences on private donations. On the one hand, an increase in program service revenues could decrease private donations, “as the marginal utility of output decreases”. However, on the other hand, an increase in program service revenue could encourage donors to donate more to recompense the non-profit for its “self-help”, because program service revenue could be perceived as informing “about management’s motivation to pursue its social mission” (Okten and Weisbrod, 2000). Heutel (2015) examines the impact of program service revenue on private donations.

The amount of private donations also depends on “legacies” (Khanna and Sandler, 2000). Legacies are incomes to non-profits resultant from “estates bequeath” and are “contributions of deceased individuals”, which are determined in advance and do neither depend on fundraising expenses nor on the price of giving, nor on private donations (Khanna and Sandler, 2000). Those legacies could affect private donations in two ways according to Khanna and Sandler (2000). Donors may decrease their private donations as the non-profit’s revenue increases. This if they consider alternative incomes as substitutes for their private donations. However, if donors consider other incomes as a complement support, then higher legacies would increase private donations.

Some authors as Bose (2015) and Heutel (2014) consider also state geographical characteristics as influencing private donations. Both authors include as geographical characteristics the unemployment rate, the per capita income, the total population and the share of the population with more than 65 years in the region where the non-profit is located. Within the geographical characteristics are also included political variables, which have important influence on the private donations received by non-profit organizations (Heutel, 2014). The political variables used by Bose (2015) and Heutel (2015) are the following: the share of democrats in a state's Senate, the share of Democrats in a state's Congress and the share of states with a Democrat governor. The introduction of those political variables can be supported by the fact that regions or states with a Democrat governor or with a higher percentage of Democrats in power are more willing to transfer higher grants to non-profits and those states are more probable "to be composed of more liberal citizens", willing to furnish monetary grants and support to non-profit organizations (Heutel, 2015).

Heutel (2014) uses data on non-profit organizations Forms 990 for the period between 1998 and 2003. The estimation equation explains private donations using the following explanatory variables: government grants, fundraising expenses, non-profit age, other revenues, program service revenue, a vector of non-profit and geographic control variables, organization- and year- fixed effects. Heutel (2014) estimates his equation empirically using fixed-effects regression and accounting for endogeneity of fundraising expenses and government grants. The author uses two instruments for fundraising expenses, administrative expenses and total liabilities. Government grants are instrumented by the total amount of transfers made by the government in a region and in a certain year.

Okten and Weisbrod (2000) find that there are important differences among industries concerning the effect the age of a non-profit has on private donations. The authors' OLS estimates show that for six industries out of seven, there is "no statistically significant direct effect" of the non-profit's age on private donations. For the seventh industry, which is the scientific research industry, the direct effect is negative, more precisely, "a loss of 1% of donations per year of organization age". The indirect effect of an organization's age on private donations is statistically significant but small for three industries. For instance, for libraries, it is positive but small, indicating that "an additional 10 years of organization age, other variables constant, is associated with a 3% increase in the productivity of fundraising". However, for higher education industry, for instance, it is negative and small, indicating that "an additional

10 years of organization age is associated with a decrease of one-tenth of 1% in the productivity of fundraising”. Concerning the effect of total age on private donations, when estimating the equation by 2SLS, the effect is significant in only “two out of three industries”. To sum up, the effect of a non-profit’s age on private donations is positive in certain industries and negative in the others (Okten and Weisbrod, 2000). The authors add further that the organizational age is an indicator of reputation but possibly also an indicator of the non-profit wealth, indicating that donors seem to prefer younger non-profits with less wealth, which are a sign of non-profits that are less traditional but more up-to-date fighting for present concerns. For Heutel (2014), the marginal effect of age on private donations is positive but not significant in most cases. In contrast, Khanna and Sandler (2000) find an insignificant coefficient capturing the effect age has on private donations. The latter leads Khanna and Sandler (2000) to the conclusion that donors rely more on government grants than on the age of the organization “to circumvent the asymmetric information problem” and to represent the reputation of the non-profit. This limits the necessity of the variable age.

Regarding the empirical findings on the effect of program service revenue on private donations, Okten and Weisbrod (2000) find that there is no evidence for program service revenue crowding-out private donations. In contrast, Okten and Weisbrod (2000) find evidence, based on their empirical OLS and 2SLS results, for program service revenue “crowding-in” private donations.

Khanna and Sandler (2000) find that there is evidence of legacies “crowding-in” private donations for some industries as health and religion industries. However, there is also evidence for legacies “crowding-out” private donations as, for instance, for social welfare industry. Consequently, Khanna and Sandler (2000) conclude that the study of the relationship between legacies and private donations must be made on the “type of charity”. Heutel (2014) argues, based on his empirical results, that program service revenue as other revenue have significantly no impact on private donations.

Unfortunately, there is no empirical evidence that examines the influence that geographical characteristics could have on private donations. Bose (2015) as Heutel

(2015) use the geographical characteristics as control variables in their empirical approach. However, only Heutel (2014) presents the results and concludes that the geographical characteristics, which serve as control variables are generally insignificant.

1.1.4. Non-Profit Objective Function

Khanna et al. (1995) claimed that when fundraising expenditures were examined by previous authors (Steinberg, 1986; Weisbrod & Dominguez, 1986), those authors made initially an important distinction between two different objective functions for non-profit organizations. Charities are either a "total revenue maximizing" charity, also called "budget maximizing" charity, or a "net revenue maximizing" charity, also designated by Steinberg (1986) as a "service maximizing" charity. A net revenue maximizing charity attempts to increase its fundraising expenses until an extra unit of money spend on fundraising brings in an extra unit of money of donations. In other terms, such a charity will spent money on fundraising only as long as "the marginal returns are at least as great as the marginal expenditures" (Steinberg, 1986). In contrast, a budget maximizing charity pushes "the beneficial effect of fundraising to zero" (Khanna et al., 1995). In other terms, a budget maximizing organization increases its fundraising expenses as long as its marginal donative product is non-negative (Steinberg, 1986).

According to Steinberg (1986), the marginal donative product of fundraising ($\partial don/\partial fe$), or in other terms, the elasticity of private donations with respect to total fundraising expenses reveals the non-profit organization's objective. More precisely, if the estimated total fundraising elasticity is equal to one or not significantly different from one, the non-profit in question is a service maximizing non-profit organization. This non-profit organization aims to maximize net revenue and will fundraise until $\partial don/\partial fe = 1$. However, when the estimated total fundraising elasticity equals zero or is not significantly different from zero, then the non-profit in question has a budget maximizing objective and will push the beneficial influence of fundraising until

$\partial don/\partial fe$ = 0. In order to calculate the elasticity, we must use the total effect of fundraising on private donations, the direct and the indirect influences of fundraising expenditures.

Consequently, the measure of total effect of fundraising on private donations is important because it reveals the objective function of a charity. There are non-profit organization, who can have mixed objectives and include both budget and service maximizing objective. This can be recognised by intermediate estimate values of the total fundraising elasticity, which would represent mixed objectives (Steinberg, 1986).

Finally, if the estimated fundraising elasticity exceeds significantly one, this would indicate that the non-profit organization in question is neither a net revenue maximizing organizations nor a budget maximizing organization. However, because the estimated elasticity is higher than one, this suggests that non-profit organization "fall short of net revenue maximization", which implies that there is no evidence of excessive fundraising expenses related with the non-profit organization in question (Khanna *et al.*, 1995).

1.2. Demand Modelling

This subsection aims to present a brief literature review regarding demand models, in particular the Multinomial Logit (MNL) discrete choice demand model, which will be used in our empirical application.

1.2.1. Demand Models

According to Ackerberg *et al.* (2007), demand models are the greatest instrument used for "comparative static analysis" or, in other words, for analysing the impact of any change in a market that has not a direct effect on costs. Ackerberg *et al.* (2007) describes demand models from the perspective of for-profit products and firms. However, we could adapt the models described in Ackerberg *et al.* (2007) to our case. First, demand models would be useful in analysing the probable impact of changes in fundraising expenditures or government grants on private donations. Second, demand models could also be useful to analyse the impact of introducing new non-profits in the non-profit sector and the impact of the latter on private donations. Third, demand models could also be useful to study welfare changes. Consequently, we could use the demand models described by Ackerberg *et al.* (2007), adapted for our case with the objective to estimate the impact of fundraising expenditures on donor demand for non-profits and to estimate the impact of government grants on donor demand for non-profits.

We realize from the literature that an important part of a non-profits revenues derives from private donations, and many non-profit's survival even depends strongly on charitable giving (Bose, 2015). Since private donations depend on the donor's preferences, the donor's demand is clearly considered as crucial in determining the results of the non-profit market. Consequently, we must necessary estimate the donors demand for each non-profit to be able to answer our research questions.

Whenever we assume that in a market there are only homogenous non-profit organizations, we are, in this case, facing a convenient hypothesis, because in such a case we would just need to estimate one demand equation for the entire market (Davis and Garcés, 2010). Nevertheless, in practice almost all non-profits are differentiated, which violates the above homogenous hypothesis. Consequently, we will focus on modelling and estimating donor's demand in a market with many differentiated non-profit organizations.

We could use as the most direct way to estimate demand for a set of "closely related" but not identical non-profits, inspired in Nevo (2000), a system with various demand equations, where one equation stands for a non-profit organization. Every equation would identify the demand for a non-profit, which is a function of the non-profit's fundraising expenditures, the fundraising expenditures of all the other non-profits and other variable. An example of such a method is *The Linear Expenditure model* (Stone, 1954), in which private donations would be linear functions of fundraising expenditures, government grants and other variables. Examples of other demand model systems that could be used to identify the relation between private donations and fundraising expenditures, in a custom that is flexible and consistent with economic theory are the following: *The Rotterdam model* (Theil, 1965; Barten, 1966), *The Translog model* (Christensen, Jorgenson, and Lau, 1975) and finally, the *Almost Ideal Demand System (AIDS)* (Deaton and Muellbauer, 1980).[12]

However, there are preoccupations regarding the estimation demand for differentiated products. An important preoccupation concerns the dimensionality problem which appears, due to the large number of non-profit organizations we observe and consequently the required large number of parameters necessary to be estimated. Just to have an idea, if we study, for instance, 200 non-profit organizations, without additional restrictions, we need to estimate at least 40,000 parameters.[13] However, the dimensionality problem is not the only concern. Estimating those demand systems leads to empirical problems because fundraising expenditures and government grants are correlated with the error term, which would require the use of instrumental variables for each endogenous variable to solve the endogeneity problem. The difficult is that it is not simple to find a unique instrumental variable or even to find enough instrumental variables that must be correlated with the potentially endogenous variables and uncorrelated with the unobserved component, thus with the error term.

As a solution, to try to solve the dimensionality problem, we can aggregate the individual differentiated non-profits into more large aggregates. For instance, if we are analysing museums, we could aggregate for instance all types of museums like the aviation museums, fashion museums, science museums, transport museums, technology museums and so on. If we are analysing a large aggregate, then this solution of aggregating individual differentiated non-profits is perfect, but if we

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[12] By flexible is meant flexible in terms of substitution patterns: For instance, when the fundraising expenses of one non-profit increases it must impact the private donations of another non-profit in order to be flexible.
An estimation equation is not consistent with economic theory when, for instance, the average income is used rather than the income of all the donors, in a world where donors do not have the same income.

[13] 200 private donation equations: one for each non-profit, with 200 fundraising expenditures in each: 200*200 = 40,000 parameters.

analyse specific non-profit organizations than aggregation makes no sense.

Another solution that tries to solve the dimensionality problem in a way that allows the study to focus on specific non-profit organizations consists of the discrete choice models, which we now describe.

1.2.2. Discrete Models

Following the discrete choice literature (see Davis and Garcés, 2010), we specify that non-profit organizations would be defined in the characteristic space. According to Davis and Garcés (2010), defining non-profits in a characteristic space solves the dimensionality problem since it is the number of characteristics that matters and not the number of non-profit organizations in a non-profit market.

Discrete choice demand models remain grounded on the traditional utility maximization framework, with donors not being able to donate infinite amounts because of their budget constraint. The donations made by an individual to a specific non-profit organization reflects its preferences. However, we must be conscious that different donors can donate the same, but have different utilities. In the traditional demand model, each donor is normally assumed to choose the amount of donations that maximize his or her utility. However, in discrete choice demand models, the great difference is that there are restrictions on the consumer's choice set, where each donor can only choose at most one non-profit organization to which donate, from all the non-profit organizations available (inside option). However, the donor can also decide not to donate at all and allocate all its resources to an external alternative (outside option). Further, if he or she donates, then it will only donate to one non-profit organization. We can reformulate this in the following way: each donor i must choose to donate each $1 of each budget to at most one non-profit j within the inside options available in year t (don_{i1t}, …, don_{iJt}) or to apply it on some alternative "outside" option don_{i0t} in year t.

The most popular discrete choice model used by econometric researchers is the Multinomial Logit (MNL) demand model developed by McFadden (1978, 1981). The

Multinomial Logit demand model will involve the estimation of a single equation that regresses the mean utility associated to each non-profit in each year (δ_{jt}) on its fundraising expenditures, government grants and other non-profit characteristics. The mean utility δ_{jt} denotes the mean utility associated to donating \$1 to non-profit *j* in year *t* across donors, which is assumed to be a linear function of the non-profit's fundraising expenditures, government grants and other characteristics. Some donors like non-profit *j* more than the average while others like the non-profit *j* less than the average. This difference towards the mean defines a donor type or preference and is characterized by *J+1* dimensions, capturing the difference towards the mean for each option, as expressed in the vector of error terms below:

$\varepsilon_{it} \equiv (\varepsilon_{i0t}, \varepsilon_{i1t}, \dots, \varepsilon_{iJt})$.

In the Multinomial Logit demand model, this error term captures all the preferences of the donors and is assumed to be independent and identically distributed across non-profits (*j*), donors (*i*) and year (*t*). Further, each ε_{ijt} is assumed to follow a standard type I extreme value density function:

$f(\varepsilon_{ijt}) = e^{-\varepsilon_{ijt}} e^{-e^{-\varepsilon_{ijt}}}$.

This assumption allows the donations of each non-profit in a given year to be a function of the mean-utilities of the competing non-profits.

The estimation of this function is problematic for two reasons. First, the function is highly non-linear. Second, as discussed above, the mean utility is assumed to be a linear function of the non-profit's characteristics. But not all the non-profit's characteristics are observed (Berry, 1994). The set of non-profit characteristics must therefore be split between those that are observed and those that are not observed. We can interpret those non-observed characteristics as the error term. But the fact that the donations of each non-profit in a given year is a function of the mean-utilities of the competing non-profits implies a multitude of error terms in each (non-linear) equation.

Berry (1994) demonstrates we can transform the donations equation into a linear equation that can be estimated by instrumental variables (IV) techniques. The endogeneity problem will be explained in more detail further below in this thesis. This yields that the estimation of the Multinomial Logit demand model becomes relatively straightforward. However, where are strengths are always a weakness. The weakness of the MNL model is that it assumes that donors' preferences are independent to charities. The problem of this "independency" is that a donor can have a big preference for a non-profit *j* and a large bad preference for a **similar** non-profit *g*, which will not make sense when non-profit *j* and non-profit *g* are closer substitutes. In order to illustrate this problem, consider the following example: if we consider a new non-profit organization in the market with completely identical non-profit characteristics to an already existing non-profit, the new non-profit can be considered as an "irrelevant alternative". This is justified by the following: we expect that this new non-profit will impact significantly the market share of the already existing and similar non-profit with similar characteristics, because the demand would be split between them. Besides, we expect that the new non-profit will have little impact, if any impact, on those existing non-profits that have completely different characteristics, since we assume that donors already had choose the option of donating to the already existing and similar non-profit. The problem with the MNL demand model is that it implies results that differ from this intuition: the "irrelevant alternative" charity does not just impact the market shares of the similar non-profits, considered closer substitutes, which seems to intuitive, but also impacts the market shares of all the other non-profits, even of those that have completely different characteristics, which seems to be less intuitive.

In order to answer our research questions, we estimate a Multinomial Logit demand model, taking advantage of the benefits of using it. This option for the MNL model is mostly due to its simplicity that derives from the type I extreme value assumption. Naturally, we do so considering the inherent problems of the Multinomial Logit (MNL) demand model and, therefore, examining the results with caution.

CHAPTER 2

2. THE EMPIRICAL FRAMEWORK

In the present chapter, we describe the Multinomial Logit (MNL) demand model developed by McFadden (1978, 1981). The motivation for the latter demand model is supported on the arguments detailed on the previous chapter, *Chapter 2, subsection 1.2.2. Discrete Models*.

2.1. Demand Model for Donations

Following the literature, we consider the following variables as key characteristics of donations: fundraising expenditures (fe_{jmt}) of non-profit *j* in market m and year t, the amount of government grants (gg_{jmt}) received by non-profit *j* in market m and year t and a vector of other observed non-profit characteristics ($x1_{jmt}$) of non-profit *j* in market m and year t. Further, following Bose (2015) and Heutel (2014), we consider also a vector of geographical observed characteristics ($x2_{mt}$) that vary only by market m and year t. The geographical observed characteristics comprise details about the geographical area, for instance, regarding the total population by market, the per-capita income by market, the unemployment rate by market, among others. We integrate them in our set of key variables since they are considered to influence the donor's demand for non-profits.

Following the Multinomial Logit demand model, we define the utility of donor *i* by choosing to donate to non-profit *j* in market m in year t or its choice for the outside option, is expressed as follows:

$$u_{ijmt} = \delta_{jmt} + \varepsilon_{ijmt} \qquad \text{if } j > 0 \qquad (1)$$

$$= \beta_0 + \beta_1 fe_{jmt} + \beta_2\, gg_{jmt} + \boldsymbol{\beta_3 x1}_{jmt} + \boldsymbol{\beta_4 x2}_{mt} + \xi_{jmt} + \varepsilon_{ijmt}$$

$$u_{i0mt} = \delta_{0mt} + \varepsilon_{i0mt} \qquad \text{if } j = 0, \qquad (2)$$

where δ_{jmt} represents the mean utility (across donors) of choosing the non-profit *j* in market *m* and year *t* and ε_{ijmt} denotes the error term, which captures the donor *i*'s preferences (donor type) specifically regarding the non-profit *j* in market *m* and year *t*. Different donor "types" have different preferences and thus will take different choices regarding the non-profit *j* to which donate.

The non-profit *j*'s specific common mean utility across donors in market *m* and year *t*, δ_{jmt}, is assumed to depend on the fundraising expenditures of non-profit organization *j* in market *m* and year *t* (fe_{jmt}), on the government grants obtained by non-profit organization *j* in market *m* and year *t* (gg_{jmt}), on the vector $\boldsymbol{x1}_{jmt}$, which denotes the observable characteristics of non-profit *j* in market *m* and year *t* (such as the age of the non-profit, all the sources of non-profit income, the value of all assets, among others), on the vector $\boldsymbol{x2}_{mt}$, which represents the observable geographic characteristics in market *m* and year *t* and, lastly, on the mean valuation for the unobserved characteristics of non-profit *j* and year *t*, ξ_{jmt}.

β_1, β_2, $\boldsymbol{\beta_3}$ and $\boldsymbol{\beta_4}$ are the parameters that need to be estimated. β_1 represents the change in the mean utility (across donors) of non-profit *j* in market *m* and year *t* (δ_{jmt}) when fundraising expenditures made by non-profit *j* in market *m* and year *t* (fe_{jmt}) increase by one million dollars, while all other regressors and the error term are held constant. $\boldsymbol{\beta_2}$ denotes the change in the mean utility (across donors) of non-profit *j* in market *m* and year *t* (δ_{jmt}) when government grants obtained by non-profit *j* in market *m* and year *t* (gg_{jmt}) increase by one million dollars, while all other regressors and the error term are held constant. $\boldsymbol{\beta_3}$ measures the effect the observed non-profit *j*'s characteristics in market *m* and year *t* ($x1_{jmt}$) have on the mean utility (across donors) of non-profit *j* in market *m* and year *t*. Lastly, $\boldsymbol{\beta_4}$ measures the effect the observed geographical characteristics in market m and year t ($x2_{mt}$) have on the mean utility (across donors) of non-profit *j* in market *m* and year *t.*

The terms ξ_{jmt} and ε_{ijmt} are both random variables. The term ξ_{jmt} captures the mean valuation for the non-observed characteristics of non-profit organization *j* in market *m* and year *t*. The term ε_{ijt} represents the unobserved type of donor *i* associated to choosing non-profit *j* in market *m* and year *t*. As discussed in *Chapter 1, subsection 1.2.2. Discrete Models*, one of the Multinomial Logit (MNL) demand model assumptions impose that the error term ε_{ijmt}, which captures the type of donor *I*, is assumed to be independent and identically distributed according to type I extreme value density function, which allows us the aggregate donations received by non-profit *j* in market *m* in year *t* to be written the following way:[14]

$$\begin{aligned} don_{jmt}(fe_{jmt}, gg_{jmt}, \boldsymbol{x1}_{jmt}, \boldsymbol{x2}_{mt}) &= M_{mt} \frac{e^{\delta_{jmt}}}{\sum_{k=0}^{J} e^{\delta_{kmt}}} \\ &= M_{mt} s_{jmt} \\ &= don_{jmt}(\boldsymbol{\delta}_{mt}), \end{aligned} \tag{3}$$

where M_{mt} denotes the total size of the donor market in market *m* and year *t* expressed in a monetary value, captured in our study by the total household income in market *m* and year *t*. s_{jmt} denotes the proportion of individuals that choose the particular non-profit organization *j* in market *m* and year *t*. The vector $\boldsymbol{\delta}_{mt}$ corresponds to $\boldsymbol{\delta}_{mt}$= (δ_{0mt}, δ_{1mt}, …,δ_{Jmt}), which denotes the vector of common mean utilities in market *m* and year *t*, where δ_{0mt} denotes the mean utility across donors of choosing the outside option in market *m* in year *t*, normalized to zero, δ_{1t} denotes the mean utility across donors of choosing non-profit *j* in market *m* and year *t* and δ_{Jt} denotes the mean utility across donors of choosing non-profit *J* in market *m* and year *t*.

[14] An error term of extreme density value type I, is assumed to have a logistic distribution very similar to a normal distribution. The advantage of this is that it allows us to express analytically all the aggregate donation functions.

2.2. Estimation Procedure

We now address the estimation procedure. We will use the transformation proposed by Berry (1994), which shows that even though the model is non-linear, it can be transformed into a linear model. In particular, Berry (1994) shows that, in the MNL model, it is possible to recuperate the unobserved non-profit specific common mean utility for all non-profits. We describe his derivation in what follows.

Let s_{jmt}^{*} denote the observed (or actual) market share of non-profit *j* in market *m* and year *t* and choose $\boldsymbol{\delta}_{mt}$ so that the MNL model's predicted market share in market *m* and year *t* exactly equals the observed market share in market *m* and year *t*:

$don_{jmt}(\boldsymbol{\delta_t}) = don_{jmt}{}^{*}$ for j= 1, …, J. (5)

$M_{mt}\ s_{jmt}(\delta_t) = M_{mt}\ s_{jmt}^{*}$

$s_{jmt}(\delta_t) = \ s_{jmt}^{*}$

Since the mean utility of the outside option is normalized to zero, $\delta_{0mt} = 0$, the vector of the common utilities across donors can be presented by: $\boldsymbol{\delta}_{mt}$ = (0, δ_{1mt}, …, δ_{Jmt}). Equation (5), consequently involves a system of *J* equations with *J* unknowns. And if the *J* equations equal predicted and actual market shares for all inside non-profit organizations, the predicted and actual market share of the outside option will also be equal since the sum of the inside market share when $j > 0$ with the outside market share when $j = 0$ must add to one.

$s_{0mt}(\delta_t) = s_{0mt}{}^{*}$. (6)

Then, dividing the market share of non-profit *j* in market *m* and year *t* from (5) by the market share of the outside option in market *m* and year *t* from (6) yields the following:

$\frac{s_{jmt}\,(\delta_t)}{s_{0mt}(\delta_t)} = e^{\delta_{jmt}} = \frac{s_{jmt}*}{s_{0mt}*}$ for $j = 1, \dots,$ J (7)

Applying logarithms to both sides leads to the following simple analytical expression:

$\ln s_{jmt}(\delta_t) - \ln s_{0mt}(\delta_t) = \delta_{jt} = \ln s_{jmt}^{*} - \ln s_{0mt}^{*}$ for $j = 1, \dots,$ J (8)

According to the equation (8), for the MNL model, we only need data on market shares to calculate the unobserved non-profit specific common mean utility of each inside non-profit organization. Thus, "the mean utility vector $\boldsymbol{\delta_{mt}}$ is uniquely determined by the observed market shares".

The result of equation (8) allows us to write and estimate a linear MNL equation with a now observed dependent variable:

$$\ln s_{jmt}^{*} - \ln s_{0mt}^{*} = \delta_{jmt} = \beta_0 + \beta_1{}^{*}\, fe_{jmt} + \beta_2{}^{*} gg_{jmt} + \beta_3{}^{*} x1_{jmt} + \beta_4{}^{*} x2_{mt} + \xi_{jmt} \qquad (9)$$

Equation (9) shows that we can obtain a simple linear-in-the-parameters regression model that we are able to estimate, since the mean level of utility, which is the dependent variable of our estimation equation is now observed. All the independent variables, fe_{jmt}, gg_{jmt}, $\boldsymbol{x1}_{jmt}$ and $\boldsymbol{x2}_{mt}$ are observed, where $\boldsymbol{x1}_{jmt}$ denotes the following vector of exogenous non-profit organizations level controls that influence the charitable donations: all sources of charity j's income in market m and year t (including the level of program service revenues, the level of other revenues, the level of the investment income, the total amount of total contributions, gifts and grants), the value of the total assets of charity j in market m and year t and the age of the non-profit j in market m and year t. $\boldsymbol{x2}_{mt}$ denotes the vector of exogenous geographic level controls that influence private donations and, which vary only by market and year. The variables used as controls at the geographic level to "control for economic, demographic and political conditions" are the following (Heutel, 2014): unemployment rate in market m and year t, per capita income in market m and year t, total population in market m and year t, the share of population aged sixty-five or older in market m and year t, the share of Democrats in a State's Senate in market m and year t, and the share of Democrats in a State's Congress in market m and year t. All the control variables at the non-profit level and at the geographical level follow Bose (2015) and Heutel (2014). Additionally, we created a dummy variable, which is equal to one if the governor is from the democratic party in market m and year t. The control variables on political or economic information are important, because it influences the private donations transferred to non-profit organizations by donors but they also influence the grants or any public contribution made to non-profit organizations (Heutel, 2014; Bose, 2015).

The parameters that we are interested in estimating are β_1, β_2, $\boldsymbol{\beta_3}$, $\boldsymbol{\beta_4}$. The error term of the estimation equation is ξ_{jmt}, which represents the mean valuation for all the unobserved non-profit characteristics of non-profit j in market m and year t. Thus, expression (9) gives an explicit interpretation of the error term (ξ_{jmt}), incorporating it entirely into the donor's behavioural model.

2.3. Endogeneity

Whenever the non-profit organization's managers know about unobserved characteristics (ξ_{jmt}), while analysts do not, independent variables like fundraising expenditures and government grants are likely to be correlated with the unobserved characteristics, the error term. This implies that those variables are considered endogenous variables and, as a consequence, the OLS estimates of our parameters would be biased. The OLS estimator assumes that explanatory variables cannot be correlated with the error term, which captures the unobserved non-profit characteristics. In order to deal with this endogeneity problem, we need to use instrumental variables (IV) techniques. The instruments must satisfy two basic requirements according to Davis and Garcés (2010):

1) The instrumental variables must be correlated with the potential endogenous variable.
2) The instrumental variables must be uncorrelated with the unobserved component of demand, the error term.

Bose (2015) underlines that to assure reliable estimates from the estimation equation, we must account for the possibility of some of our dependent variables being endogenous variables, which bias the independent variables' coefficient estimates. For Bose (2015) and Heutel (2014), whenever an "exogenous event", for instance, a hurricane or a common shock, which is captured by the error term causes the dependent variable to be correlated with the error term, then we are facing an endogeneity problem biasing the parameter upward, but other situations can bias the estimate downward. The problem is that those "exogenous events" are unobserved and captured by the error term, which by causing variations in the independent variables are correlated with them.

In our case, we are facing an endogeneity problem due to the presence of endogenous independent variables, when the unobserved characteristics of a non-profit are correlated with our independent variables. An unobserved characteristic is, for instance, correlated to fundraising expenditures, if the particular unobserved characteristic causes an increase in the willingness of donors to donate. Further, government grants are also considered an endogenous variable if an unobserved non-profit characteristic increases the willingness of governments to provide grants to the non-profit with the concerned non-profit characteristic. Another illustration of this problem can be the following. Consider, for instance, the personality or the gender of the director, who leads the non-profit. Donors, who know a non-profit and their executives by participating in the non-profits fundraising campaigns and events, may appreciate the character of the director, which increases private donations. But this characteristic is unknown and unobserved in the data for us researchers. Moreover, in the same line another unobserved non-profit characteristic as, for instance, the reputation or engagement in contemporary social troubles probably leads to an increase of grants transferred by the government. Thus, if the error term will cause variation in the independent variables, then the error term and independent variables will be correlated. In this case, the introduction of instrumental variables (IV) would be required.

The estimation of a Multinomial Logit (MNL) equation with instrumental variables favours strong instruments, because otherwise the results are not really "conclusive", but merely "indicative" (Andreoni and Payne, 2011). Bose (2015), Andreoni and Payne (2011) clarify that our chosen instruments are weak instruments when the correlation between the instrument and the endogenous variable (which is stated above as the first condition necessary to be satisfied) is weak.

2.3.1. Instruments for Fundraising Expenditures

Regarding the instrument for the fundraising expenditures, Bose (2015), as Andreoni and Payne (2011), argues for the use of the aggregate amount of total liabilities as instrument for fundraising expenditures.

Both authors argue that a change in total liabilities leads to an adjustment in fundraising expenditures made by non-profit organizations. Consequently, the first condition for a valid instrument is satisfied, since there is correlation between the instrument and the endogenous variable, fundraising expenditures. The second condition regarding the instrumental variables is likewise satisfied. Bose (2015) argues that the amount of total liabilities does not affect the amount of private donations and, consequently, the error term. The reason for the latter is that, according to Bose (2015), donors have no access to the current "financial conditions" of a non-profit organization.

2.3.2. Instruments for Government Grants

The sole instrument used for government grants by Bose (2015) and Heutel (2014) is the aggregate amount of "government transfers at the market level". By government transfers at the market level is meant the total amount of transfers made by the government to non-profit organizations by region area "for which no current services are performed". The latter instrument satisfies the first condition for a valid instrument since Heutel (2014) argues that the instrument "captures something about the government itself" being correlated with the government grants. The second requirement regarding the instrument used is also satisfied because it is not correlated with private donations and consequently not correlated with the error term, since the total government transfers at the market level do not "reflect the actions of the donors" (Bose, 2015).

2.4. Research Questions

This subsection aims to clarify how we will use the demand model described above to answer our three research questions: (i) examine if there is an own- and cross-effect of fundraising expenditures on private donations, (ii) examine the objective function of the non-profit organizations, and (iii) examine if there is an own- or cross-effect of government grants on private donations.

In order answer these questions, we will use the demand model to compute (i) own and cross-fundraising expenditure elasticities and (ii) own- and cross- government grant elasticities. Specifically, we will compute the mean own- and cross-fundraising expenditure elasticities and the mean own- and cross-government grant elasticities across markets and years.

The mean own-fundraising expenditure elasticity will evaluate, if the mean amount of fundraising expenditures of non-profit *j* affects the non-profit *j*'s mean own amount of private donations received. The cross-fundraising expenditure elasticity will capture, if the mean fundraising expenditures made, for instance, by non-profit *j* affects the mean amount of private donations received by non-profit *k.*

The results of the own- and cross-elasticities will enable us to conclude if the competition among non-profit organizations is real, because if fundraising expenditures made by one non-profit affects largely its own amount of donations received but also affects largely the amount of donations received by other non-profits, we can conclude that non-profit organizations truly compete for private donations. If the cross-elasticity is small, then we can conclude that there is no competition among non-profit organizations. If the cross-elasticity is negative, then we can conclude that there is competition and the greater the elasticity, the greater the competition for private donations among non-profit organizations in the non-profit market. The analysis is similar for government grants.

We now address the procedure to compute the mean own- and cross-fundraising expenditure elasticities. To do so, recall the non-profit *j*'s market share in market *m* and year *t*:

$$s_{jmt}(\boldsymbol{\delta_{mt}}) = \frac{e^{\delta_{jmt}}}{\sum_{k=0}^{J} e^{\delta_{kmt}}} = \frac{e^{\beta_0 + \beta_1 fe_{jmt} + \beta_2 gg_{jmt} + \boldsymbol{\beta_3 x1}_{jmt} + \boldsymbol{\beta_4 x2}_{mt} + \xi_{jmt}}}{1+ \sum_{k=1}^{J} e^{\beta_0 + \beta_1 fe_{kmt} + \beta_2 gg_{kmt} + \boldsymbol{\beta_3 x1}_{kmt} + \boldsymbol{\beta_4 x2}_{mt} + \xi_{kmt}}} \quad (4)$$

If we differentiate equation (4) with respect to the fundraising expenditures, we obtain the own- ($\varepsilon_{jj,t}$) and cross-fundraising expenditure ($\varepsilon_{jk,t}$) elasticities in market *m* and year *t*:

$$\varepsilon_{jj,mt} = \frac{\partial don_{jmt(\delta_{mt})}}{\partial fe_{jmt}} \frac{fe_{jmt}}{don_{jmt(\delta_{mt})}} = \beta_1 fe_{jmt}\,(1 - s^*_{jmt}) \quad (10)$$

$$\varepsilon_{jk,mt} = \frac{\partial don_{jmt(\delta_{mt})}}{\partial fe_{kmt}} * \frac{fe_{kmt}}{don_{jmt(\delta_{mt})}} = -\, \beta_1 fe_{kmt}\, s^*_{kmt} \quad (11)$$

Own- and cross-fundraising expenditure elasticities are uniquely determined by one parameter, β_1, the market share of donations associated to the non-profit in question and the fundraising expenditures incurred by the non-profit in question. As discussed above, we will compute the averages of those elasticities across markets and years. From the own-fundraising expenditure elasticity of non-profit *j*, we can estimate the percentage change in the mean donations of non-profit *j* as a response to a one percent change in its own mean amount of fundraising expenditures, holding all the other determinants of demand constant. From the cross-fundraising expenditure elasticity of non-profit *j* with non-profit *k,* we can estimate the percentage change in the mean donations of non-profit *j* as a response to a one percent change in non-profit *k*'s mean fundraising expenditures, holding constant all the other determinants of demand.

The mean own- and cross-fundraising expenditure are not just crucial in answering our first research question, but they are also useful in answering our second research question, which seeks to infer the objective function of a non-profit organization. Steinberg (1986) underlines that the fundraising expenditure elasticity expresses the non-profit organizations objective. The non-profit organization is a "net revenue maximizer" when the estimated fundraising elasticity is equal to one while the non-profit organization is a "budget maximizer" when the estimated fundraising elasticity is null. As we already referred in *subsection 1.4. Objective Function* if the elasticity presents middle values between zero and one, in this case, we can conclude that the concerned non-profit organization has mixed objectives, including both budget maximizing objectives and net revenue maximizing objectives.

The mean own and cross-government grants elasticities will be also crucial in answering our third research question. The mean own-government grant elasticity will examine if the mean amount of government grants received by a non-profit affects the non-profit's own mean amount of private donations. The cross-government grant elasticity will examine if the mean government grants received by a non-profit affects the mean amount of private donations received by competing non-profits.

The mean own- and cross- government grant elasticities are obtained by the following formulas:

$$\varepsilon_{jj,mt} = \frac{\partial don_{jmt}(\delta_{mt})}{\partial gg_{jmt}} \frac{gg_{jmt}}{don_{jmt}(\delta_{mt})} = \beta_2 gg_{jmt}\,(1 - s^*_{jmt}) \tag{12}$$

$$\varepsilon_{jk,mt} = \frac{\partial don_{jmt}(\delta_{mt})}{\partial gg_{kmt}} * \frac{gg_{kmt}}{don_{jmt}(\delta_{mt})} = -\,\beta_2 gg_{kmt}\, s^*_{kmt} \tag{13}$$

Similarly to above, own- and cross-government grants elasticities are uniquely determined by one parameter, β_2, the market share of donations associated to the non-profit in question and the government grants received by the non-profit in question. As discussed above, we will compute the averages of those elasticities across markets and years. From the own-government grant elasticity of non-profit *j*, we can estimate the percentage change in the mean donations of non-profit *j* as a response to a one percent change in the received mean amount of government grants, holding all the other determinants of demand constant. From the cross-government grant elasticity of non-profit *j* with non-profit *k*, we can estimate the percentage change in the mean donations of non-profit *j* as a response to a one percent change in mean amount of government grants received by non-profit *k*.

CHAPTER 3

3. THE EMPIRICAL APPLICATION

The aim of this third chapter is to empirically apply the framework described in the previous chapter. We begin by describing how we obtained the data about the charities and how this data was cleaned. We, then, describe the data used for the estimation procedure. Finally, we perform some preliminary analysis on the data present the estimation results.

3.1. Charity Data Collection

The data on non-profit organizations comes from the federal tax returns, which are annually filed by IRS Section 501(c)(3) U.S. charities for the period 2005 to 2010. All 501(c)(3) non-profit organizations, except religious organizations, with an annual gross receipt higher than $25.000,00 must file Form 990.[15] The form is a United States Internal Revenue Service information form, which provides the public with information on non-profit organizations' mission, plans and mainly on their finances (Bose, 2015). Non-profit organizations are exempt from paying taxes under Section 501(c)(3), but they are, in return, forced to file the information form with the IRS. If an organization does not file its required annual tax return until the by law predicted due

[15] Consulted on the official website of the United States Internal Revenue Service: https://www.irs.gov/charities-non-profits/churches-religious-organizations/filing-requirements

dates, then there will be penalties applied to the organization in question.[16] However, if an organization does not file the required annual tax return during "three consecutive tax years" until the required filing limit date of the third year, in this case, the non-profit in question will "automatically lose its tax-exempt status".[17]

In this thesis, we focus on non-profit organizations, which are required to file Form 990 or Form 990-EZ and we do not include data on 501(c)(3) private foundations, which have annually to file IRS Form 990-PF. The reason for the exclusion of 501(c)(3) private foundations is the fact that the major part of their revenues comes from investments and "endowments" and is mainly used to award grants to other non-profits rather than to produce "charitable actions" (Heutel, 2014; Harrison and Laincz, 2008).

The National Center for Charitable Statistics (NCCS) at the Urban Institute collects the principal information from the forms and makes them online available in form of useful databases for eventual "researchers and policy-makers", as specified in their official website.[18] The data used in this thesis for the years 2005 to 2010 comes from the NCCS Data Archive, more precisely, from the NCCS Core Files, which contains 2 081 478 observations referent to 410 231 charities required to file Form 990 and Form 990-EZ within our considered years. The sizeable database is helpful for analysis at the organization level and for the comparison between organizations, but there are also disadvantages related with a large database.[19]

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16 Information consulted on the official website of the United States Internal Revenue Service: https://www.irs.gov/charities-non-profits/annual-exempt-organization-return-consequences-of-not-filing

17 Regulation consulted on the official website of the United States Internal Revenue Service: https://www.irs.gov/charities-non-profits/automatic-revocation-of-exemption

18 The link for the NCCS's official website is the following: http://nccs-data.urban.org/index.php

19 The large database contains erroneous and disordered data, which constitutes a problem. This problem became even more relevant and problematic for us during the decision of the years. By years is meant the years for which we study the non-profit data with the objective to answer our empirical questions. Initially, our idea was to analyse data for the most recent years for which there is obviously data available. The problem of the recent years' available data like 2013, 2012 or even 2011 was the following: The most important key variables as indirect public support and direct public support, which the sum of them represents the private donations obtained by a non-profit, such a variable did not appear in the dataset of each recent year. For instance, these key variables like indirect public support and direct public support appeared in the dataset of 2013 and 2011 but not in the dataset of 2012. The same happened with other important key variable as fundraising expenses. A dataset in which key variables are missing is worthless. Consequently, I felt the obligation to took less recent and more anterior datasets, where the key variables are presented the same way in all the years and the value of those key variables corresponds to the value reported by the non-profit organizations in their corresponding Form. This was possible for datasets prior to 2010.

Each year is recorded by the NCCS in a different dataset. The data contained in the six datasets (one for each year) must then be appended, yielding one unique dataset. This resulting database must be – prior to any empirical analysis – cleaned. The cleaning method follows the steps described by Heutel (2014) and Bose (2015).

First, all non-profit organizations with a clear evidence of reporting error are eliminated from the dataset: This first method includes organizations reporting a missing value or a negative value for private donations (direct public support and indirect public support), government grants, fundraising expenditures or program service revenue. Charitable contributions from either public or private sources are reported jointly under "Contributions and grants" on the non-profits IRS Form 990 that charities are required to file each year. This first method leads to a dataset with 1 518 696 observations referent to 405 551 charities (in other words, 4 680 charities and 562 782 observations were eliminated). Organizations, which report their revenues by category (for instance, private donations, government grants, other revenues, investment income or program service revenue) that do not add up correctly to the reported amount of total revenues, as well as organizations that report an amount of fundraising expenditures or other expenditures exceeding the total amount of expenditures are dropped from the dataset. This eliminates 94 081 observations and 10 037 charities yielding 1 424 615 observations on 395 514 charities.

Second, in the case of incapability to calculate the age of a non-profit organization, because of an incorrect or missing ruling year, which is the year "the organization received recognition of its tax-exempt status", causes the concerned non-profit being eliminated from the sample.[20] This yields a dataset comprising 1 411 313 observations referent to 390,682 charities, so 13 302 observations have been eliminated as also 4 832

For this reason, I decide to work with more former years, more precisely, to work with data from the year 2005 to 2010.

[20] The ruling years must be distinguished from the year on which the organization was created, because both dates do not "necessarily coincide", consulted on the National Center of Charitable Statistics website: http://nccs-data.urban.org/index.php. The age of a non-profit is obtained with the variable *rule date* available in the collected database. Subtracting the actual year from the rule year allows us to obtain the non-profit's age for the actual year. For instance, we are in present of the 2008 annual tax return, the non-profit corresponding rule year is 1993, subtracting 1993 from 2008 gives 15. Thus, the concerned non-profit is aged 15 years in the 2008 annual tax return.

charities. Similarly to the variable age of a non-profit, which needs to be created by using the ruling year, the variables revenues and investment income likewise need to be calculated with the help of the available data furnished by the NCCS Core files databases.[21]

Third, the database is restricted to those organizations with an identifiable county, ending up with 1 219 490 observations referent to 389 778 charities. The geographical location of a non-profit organization is considered by county rather than by Metropolitan Statistical Area (MSA), which is used by previous authors.[22] We do not consider the geographical location of our non-profits by MSAs, because the definition of MSA changes with the time and when the definition changes, up to this moment the new statistics will begin to be collected for the new definition of the MSA. The change of the definition turns our data files incomparable along the years, because there were revisions of the definition of the Metropolitan Statistical Area in quasi all the years we analyze, except for the year of 2010.[23] For this reason, we began collecting data by county, because the definition of county is much more stable over time. A county is "the largest political and administrative division of a state in the United States".[24] The United States counts in total 50 States, from which 48 are divided into 3 007 counties. For instance, the state of New York counts 62 counties, Texas is the state with the highest number of counties, it counts 254 counties.[25]

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[21] The value of *Other Revenues* is obtained by the following calculation*: Other Revenues = Other Income + Special Events Net Income + Net Rental Income + Inventory Gross Profit*. The amount of *Investment Income* is obtained by the following calculation: *Investment Income = Total Investment Income + Net Gain or Loss derived from the Sales of Securities + Total Net Gain or Loss derived from the Sales of Other Assets*

[22] By previous authors, we mean Bose (2015), Thornton (2006).

[23] There were revisions in December 2005 (OMB Bulletin No. 06-01), December 2006 (OMB Bulletin No. 07-01), November 2007 (OMB Bulletin No. 08-01), November 2008 (OMB Bulletin No. 08-01) and finally, also in December 2009 (OMB Bulletin No. 10-02). The Office of Management and Budget (OMB) is responsible for the reviews of the United States' MSA's definitions and the respective revised dates are found on the official website of the United States Census Bureau: https://www.census.gov/programs-surveys/metro-micro/about/omb-bulletins/historical.html

[24] Definition retrieved from the online Cambridge Dictionary: https://dictionary.cambridge.org/dictionary/english/county

[25] Information about counties consulted on: http://enacademic.com/dic.nsf/enwiki/236364

Fourth, duplicate organizations or organizations with missing data are likewise eliminated from the sample, leaving so, 1 108 927 observations on 389 778 charities.

Fifth, only organizations that appear in at least 2 years of the 6 years we are analyzing are retained in the dataset, eliminating 164 972 observations and 164 972 charities.

Sixth, we guarantee that merely organizations reporting positive private donations, positive fundraising expenditures and positive government grants are retained in our data set. This is particularly important, because some charities rely completely on grants from individuals or from the government and therefore do not need to compete for private donations (Bose, 2015). As confirmed by Bose (2015), such organizations with no private donations and no fundraising expenditures "over the entire panel will not inform the hypothesis and can lead to biased conclusions".

Seventh, I merged the database with geographic level variables from the United States Census Bureau (American Factfinder) and from the United States House of Representatives (where I found election statistics from 1920 to the present). The added geographical level variables are the following: population by county and year, per-capita income by county and year, total income by county and year, unemployment rate by county and year, the share of population over 65 years by county and year, the share of Democrats in a state's Senate, share of Democrats in a state's Congress and finally, the share of States with a Democrat governor. These variables will serve as control variables for demographic, economic and political conditions. Heutel (2014) clarifies that "these variables are matched to the charity by the state or county where the charity is located". All the observations containing missing values for each control variable added were eliminated, removing this way 122 780 observations and 25 807 charities from our unique data set.

Eighth, using the National Taxonomy of Exempt Entities (NTEE) established by the NCCS, I will proceed to the creation of sectors, where each charity will be allocated to its corresponding sector depending on the good or service it supplies. The NTEE is an organization classification system that classifies non-profits into 26 "major groups under 10 broad categories based on the type, the mission and the activities provided" (Thornton, 2006; Bose, 2015). The National Taxonomy of Exempt Entities – Core Codes (NTEE-CC) is a code, which contains as a first digit an alphabetic and as a second digit a decile number. The alphabetic gives us information about the major group or, in other terms, the broad subsector of the charitable organization, for instance, health, education, religion related, environment and animals are examples of major groups in which non-profits are placed. The decile number subdivide the respective organization, which already belongs to a major group, in specific activity areas, such as higher education within the education major group or such as recycling within the environment major group. Based on the NTEE-CC, I follow the method used by Thornton (2006) and Bose (2015), who put together those charities that are considered substitutes by the services and goods they supply. For instance, non-profits working to support and to provide hot lines and crisis intervention for people that are going through dark times of depression (F40) or to provide sexual assault services for people who have been sexually attacked (F42) are grouped under one unique sector: Hotlines and Crisis Prevention, Sector 8 on the above presented Table 1.

We removed in total 792 439 observations and 188 738 charities from the data set by establishing the sectors and by eliminating all the observations containing missing values for the variable sector. We end up with a final sample, counting 10 261 charities and 28 736 observations, after the cleaning processes around the introduction of the geographical level variables and the sectors. Regressions are made on this final sample. All non-profit organizations are classed into 16 different Sectors. The 16 Sectors by Thornton (2006) and Bose (2015) designated are listed below in Table 1, with their corresponding NTEE-CC and description:

Table 1. Selected Sectors for Years 2005-2010

Sector	Description	NTEE Code	Number of Non-profits
1	Museums	A50-A57	871
2	Performing arts	A62-A6C	2855
3	Community health treatment	E30-E42	760
4	Abuse prevention	I70-I73	253
5	Employment and vocational training	J20-J33	721
6	Nursing, home health care	E90-E92	643
7	Substance abuse prevention and treatment	F20-F22	711
8	Hotlines and crisis prevention	F40-F42	94
9	Crime prevention and rehabilitation	I20-I44	387
10	Food pantries and programs	K30-K36	399
11	Public housing and rehabilitation	L21-L25	718
12	Homeless shelters	L40-L41 & P85	497
13	Community centers	P28	442
14	Family counselling	P46	175
15	Senior centers	P81	498
16	Residential care and group homes	P73	237
Total			10261

Source: Sector selections, sector descriptions and the NTEE codes are established on Thornton (2006) and on Bose (2015). The calculation of the average number of non-profits by sector are based on a sample from the NCCS Core Files for the period, 2005-2010.

Note: NTEE stands for National Taxonomy of Exempt Entities and NCCS stands for the National Center for Charitable Statistics

3.2. Market Definition

We will create and define a market as a geographical market, which is an approach used and mentioned by previous authors[26]. Our market will comprise all the charities that supply goods and services within a "well-defined area", a county.

3.3. Data Description

The data required to estimate the MNL model previously described in *Chapter 2.* involves the following main variables: Private donations (or market shares of donations) received by a non-profit organization *j* in market *m* and year *t,* fundraising

[26] Harrison Laincz (2008); Nunnenkamp Ohler (2012); Bose (2015)

expenditures made by a non-profit organization *j* in market *m* and year *t*, and government grants received by a non-profit organization *j* in market *m* and year *t*. It involves also a set of observed non-profit organization *j*'s characteristics in market *m* and year *t* and a set of observed geographical characteristics, which vary only by market *m* and year *t.*

The definition of all the variables evoked and necessary for the estimation of the MNL equation and eventual details about their construction was already given in *Chapter 1, subsection 1.1.3. Determinants of Donations.* How all those variables were obtained was already mentioned in this current *Chapter 3, in the subsection 3.1. Charity Data Collection*.

Table 2, accessible in the next page, provides summary statistics for all the variables used and necessary for the estimation of the MNL equation.

Table 2. Summary Statistics of Key Variables for the Period: 2005-2010

Variable	Mean	Median	Std	Min	Max
Private Donations*: don_{jmt}	1.092	0.133	8.698	0.001^{k}	663.603
Fundraising Expenditures*: fe_{jmt}	0.074	0.000	0.422	0.000	22.394
Government Grants*: gg_{jmt}	0.789	0.000	4.236	0.000	160.928
Market share (inside) %: s_{jmt}	0.003	0.001^{k}	0.000	0.001^{k}	0.7
Market share (outside) %: s_{0mt}	99.60	99.70	0.004	97.90	99.90
Mean utility: y_{jmt}	- 12.639	- 12.548	2.258	- 24.632	- 4.969
Non-Profit Level Variables					
Program Service Revenue*	3.916	0.112	38.395	0.000	2431.120
Other Revenue*	0.128	0.004	1.002	-7.026	49.367
Assets*	8.170	0.589	50.698	-78.360	2972.734
Liabilities*	3.386	0.086	25.218	-78.896	1388.891
Age	24.786	22	16.582	0	108
Investment Income*	0.162	0.002	1.718	-7.788	115.265
Total Contributions*	1.884	0.235	9.945	0.000	663.603
Geographic Level Control Variables					
County Total Population§	1.538	1.215	1.166	0.494	5.295
County Per-Capita Income*	0.032	0.029	0.011	0.013	0.063
County Unemployment Rate %	7.942	7.200	2.775	3.000	21.500
County Share of Population >= 65 %	12.264	12.141	0.026	5.549	23.558
Share of Democrats in a State's Senate %	56.263	59.00	0.139	0.000	97.000
Share of Democrats in a State's Congress %	52.651	52.553	0.102	30.558	97.341
Share of States with a Democrat Governor%	51.718	52.000	0.115	20.000	90.000
Dummy Variable for Democrat Governor	0.653	1	0.476	0	1

Note 1: The Summary Statistics are based on our sample from the NCCS Core Files for the years 2005-2010. The Geographical Area Level Variables are from the American Factfinder and from the United States House of Representatives.

Note 2: All the variables containing the star symbol (*) are expressed in millions of US dollars. The variable "County Total Population" is expressed in millions of citizens and contains therefore the symbol (§). All the variables containing a (%) symbol are expressed in percentage. All the values in the table are rounded up to the 3th decimal place and are grounded on 28736 observations referred to 10261 charities.

Note 3: Std = Standard deviation; Min = Minimum; Max = Maximum.

Note 4: 0.001^{k} denotes values smaller than 0.001.

The summary statistics of our key variables reported on Table 2, indicate that private contributions are the greatest source of revenue for the charitable organizations considered in our model. The median non-profit organization obtains 133,000.00 US dollars in private donations, does not incur in fundraising expenditures and receives no government grants. The market share of donations hold by the median non-profit is lower than 0.001% and 99.58% of the total household income by county is not allocated in private donations. The median non-profit organization receives 112,000.00 US dollars in program service revenue and 4,000.00 US dollars in other revenues. Moreover, the median non-profit organization has 589,000.00 US dollars in assets and 3,386,000.00 US dollars in liabilities and received the tax-exempt status 22 years ago.

The remaining summary statistics also indicate that the county where the median non-profit organization is located has a population of 1,215,000 citizens, a per-capita income equal to 29,000.00 US dollars, an unemployment rate equal to 7.2% and a share of population with an age equal or higher than 65 of 12.1 %. Further, the share of Democrats in the State's Senate where the median non-profit is located is 59%, the share of Democrats in the State's Congress where the median non-profit organization is located is 53% and the State, where the median non-profit is working contains a Democrat Governor with 52% of the votes.

Table 3 provides summary statistics of the instruments to be used in the estimation.

Table 3. Instrumental Variables (IV)

Variable	Mean	Median	Std	Min	Max
z1 = Total Liabilities	3,386	0,086	25,218	-78,896	1388,891
z2 = County GG	143,000	64,600	175,000	0,000	662,000

The median non-profit organization has 86,000.00 US dollars in total liabilities and is located in a county, where aggregate transfers made in form of grants by the government reach an amount equal to 64,600,000.00 US dollars.

3.3.1. Estimation at the Non-Profit Level

In order to be able to answer our research questions, we will use the mean own- and cross-fundraising expenditure elasticities and the mean own- and cross-government grant elasticities to evaluate, on the one hand, the effect of own- mean fundraising on own-mean private donations and the effect of own- mean government grant on own-mean private donations. Additionally, we will use the fundraising and government grant elasticities mean own and cross- elasticities to evaluate, on the other hand, the effect of own-mean fundraising on rivals'-mean private donations and the effect of own-mean government grant on rivals'- mean private donations.

In total, our data set contains 10.261 charities and for the calculation of the own- and cross- mean fundraising expenditure elasticities we need the estimation result of parameter β_1 detailed in equation (9), the amount of total mean fundraising expenditures made by each of the 10 261 non-profit organizations and the mean market share of donations hold by each out of 10 261 non-profit organizations. Equally for the calculation of the own- and cross-mean government grant elasticities. The challenge here is the high number of charities investigated, because this implies the unreasonable calculation of 20 522 own- and cross mean fundraising expenditure elasticities plus 20 255 own- and cross mean government grant elasticities. Due to the impossibility to calculate all the mean own-and cross-elasticities, we decide to select from the 10 261 studied non-profits in our data set, 16 non-profits, which would have the mission to furnish results representing all the other non-profits considered. The 16 charities are not randomly chosen. We select 6 non-profits reporting the lowest amount of fundraising expenditures, 6 other non-profits reporting the highest amount of fundraising expenditures and, lastly 5 non-profits reporting a fundraising expenditures amount, which is approximately around the mean value of total fundraising expenditures made by all the non-profits in the non-profit sector. Consequently, we end up with a sample of 16 non-profit organizations and the estimation of the own- and cross- fundraising expenditures and government grant elasticities will be made considering those 16 charities out of the 10 261 charities stated in our data set. The latter is what we designate as estimating "at the non-profit level", which simply means considering the effect charities have on each other.

3.3.2. Estimation at the Non-profit Sector Level

Additionally, we intend to evaluate our research questions at the sector level, considering 16 Sectors. By "at the sector level", we mean measuring the effect sectors have on each other. The considered 16 Sectors are described, in detail, further ahead in this Master thesis. A sector comprises a given number of non-profit organizations, which differs from one sector to the other. All the non-profit organizations comprised within the same sector are similar in terms of their provided charitable output and are therefore considered as close substitutes.

Basically, we aim, nearby the elasticity calculations at the non-profit level, calculate the own- and cross-fundraising elasticity by revealing if the fundraising expenditures made by a sector s in year t influence its own private donations received and by discovering if the fundraising expenditures spent by a sector s in year t affect the private donations obtained by a different sector z in year t. Moreover, we intend to calculate the own- and cross- government grant elasticities to evaluate the effect government grants have on the private donations received by a particular sector s in year t and on the private donations received by other sectors z in year t.

3.4. Preliminary Analysis

We now perform a preliminary analysis of the relationship between the total amount of private donations vis-à-vis to the total fundraising expenses and to the total amount of government grants. The relationship can be positive or negative. If it is positive then the two variables move in the same direction. For instance, an increase in one variable would imply an increase in the other variable. If, however, the relationship is negative, then both variables would move in opposite directions. A decrease in one variable would imply an increase in the other variable.

The cleaned data from the NCCS Core Files for the years 2005 to 2010 suggests the following concerning the relationship between private donations and fundraising expenditures.

Figure 1.: Fundraising Expenditures and Private Donations

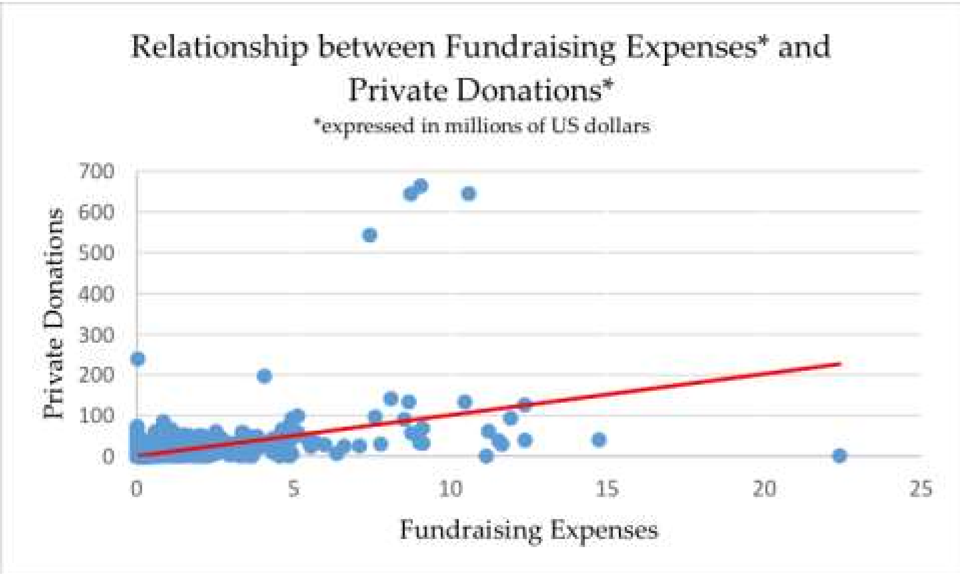

Figure 1 demonstrates a positive relationship between private donations and fundraising expenditures: An increase in fundraising expenditures causes an increase in private donations, both key variables move in the same direction. By the slope and the direction of the red tendency line draw on the figure, we can conclude that the relationship between private donations and fundraising expenditures is significantly positive. Consequently, we could theoretically imagine, based on the Figure 1, that the results of the estimation equation in the next section demonstrate a positive relationship between private donations and fundraising expenditures, in other terms, that parameter β_1 is positive. The latter parameter, as already described in *Chapter 2*, *subsection 2.2. Estimation Procedure*, measures the effect fundraising expenditures have on private donations.

Figure 2 displays the relationship between private donations and government grants.

Figure 2.: Government Grants and Private Donations

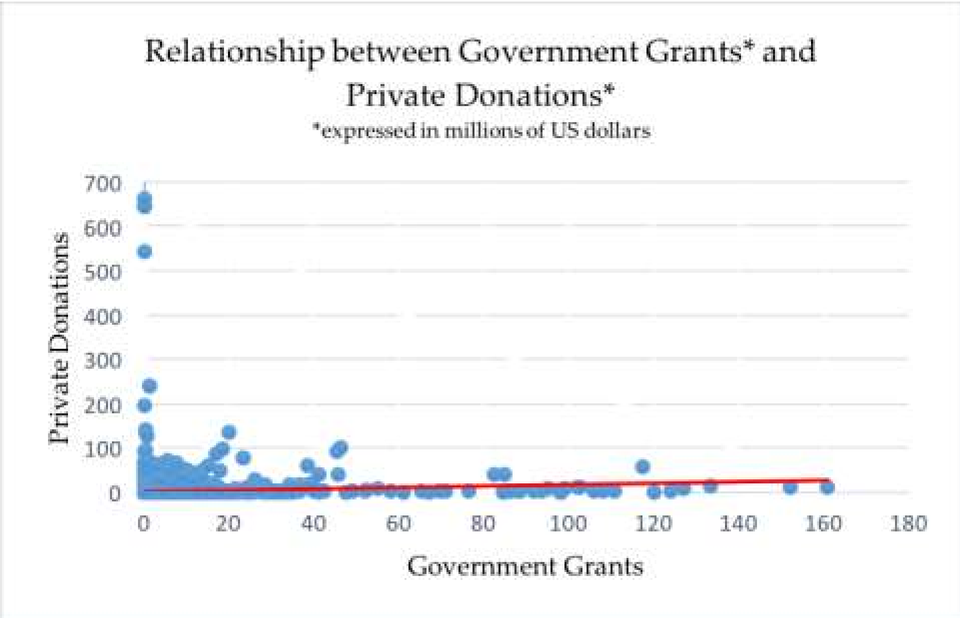

Figure 2 demonstrates a positive relationship between government grants and private donations, which suggests that an increase in government grants leads to an increase in private donations, consequently suggests that there is a crowding-in. The increase is a slight increase. Thus, we could theoretically imagine that parameter β_2 is positive, demonstrating that government grants effectively have a positive effect on private donations.

We must emphasize that this preliminary analysis is definitely not enough to conclude the effects the key variables have on each other and, therefore must be interpreted with caution. We can expect that the relationship demonstrated on either Figure 1 and Figure 2 is biased. Nevertheless, this preliminary analysis is useful in the sense that it helps us to construct an idea regarding the influence they have on each other. In order to obtain deeper detail and consistent detail on the parameters, we must estimate the model.

3.5. Estimation Results

The Multinomial Logit demand model will involve the estimation of a single equation. Given the panel data collected and described above on several non-profit organizations, markets and years, this equation takes the following form:

$$\delta_{\text{jmt}} = \beta_0 + \beta_1 * fe_{jmt} + \beta_2 * gg_{jmt} + \beta_3 * \boldsymbol{X_{1jmt}} + \beta_4 * \boldsymbol{X_{2mt}} + \beta_5 * Y_t + \beta_6 * Sector_t + \beta_7 * County_t + \xi_{jmt}. \quad (14)$$

Where, as discussed above, δ_{jmt} denotes the mean utility (across donors) of non-profit organization j in market m and year t, fe_{jmt}denotes the fundraising expenditures of non-profit organization j in market m and year t, gg_{jmt} denotes the government grants obtained by non-profit organization j in market m and year t, $\boldsymbol{x1}_{jmt}$ denotes the vector of exogenous non-profit level controls that influence the amount of private donations received by charity j in market m and year t. $x2_{mt}$ denotes the vector of exogenous geographic level controls that influence the private donations, which vary only by market and year.

Further, the estimation equation also includes year fixed effects (Y_t) to consider temporary differences across years, sector fixed effects ($Sector_{jm}$) to account for time invariant differences across sectors, and county fixed effects ($County_{jm}$), to account for time invariant differences across counties. Lastly, as discussed above, ξ_{jmt} denotes the mean utility valuation for the unobserved characteristics of non-profit organization j in market m and year t, which constitutes the error term of the estimation equation.

The dependent variable of the estimation equation is δ_{jmt} and it is unobserved by the us and by the researchers in general, since the utility is not included in our data collected and, so is not observed. Nevertheless, according to the multinomial logit model, we can compute the mean utility using a simple mathematical formula that depends only on the observed market shares of donations of each non-profit organization and on the outside option: δ_{jmt} = ln s_{jmt}– ln s_{0mt}, which can be computed from the data collected. The market share of non-profit organization j in year t can be computed as: $s_{jmt} = \frac{TotalPublicSupport_{jt}}{M_{mt}}$, while the market share of the outside option in year t can be computed as: $s_{Omt} = 1 - (s_{1mt} + s_{2mt} + s_{3mt} + \ldots + s_{Jmt})$. The denominator M_{mt} denotes the size of the donor market, captured by total household income in market m and year t. The independent variables of the estimation equation are fe_{jmt}, gg_{jmt}, $\boldsymbol{x1}_{jmt}$, $\boldsymbol{x2}_{mt}$, Y_t, $Sector_{jm}$ and$County_{jm}$. The main parameters are β_1 and β_2. β_1 represents the change in the amount of private donations with respect to one unit change in the fundraising expenditures (fe_{jt}). β_2 gives us the change in the amount of private donations with respect to one unit change on government grants (gg_{jt}).

Finally, the MNL estimation equation (9) is estimated using instrumental variables techniques by generalized method of moments (GMM).

The estimation results obtained from the Multinomial Logit (MNL) demand model are displayed in Table 5, which comprises three specifications. For all three specifications, the dependent variable considered is the same and the independent variables considered are likewise the same except for the indicator variables used.

The dependent variable considered in all three columns is the following: s_{jt} = lns_{jt} - ln s_{0t} . In all the specifications, the independent variables considered includes fundraising expenditures, government grants, a vector of observed non-profit characteristics and a vector of geographical characteristics.

Regarding the indicator variables, specification (1) includes county fixed-effects, but neither year and sector fixed-effects. Specification (2) includes county and year fixed-effects but not sector fixed-effects. Finally, specification (3) includes county, year and sector fixed-effects. The fixed effect of a specific group (as in our case, county, year and sector) is an indicator variable that controls the effect of omitted variables that are considered constant between members of the same group, but that may vary among groups. The introduction of fixed-effects is important, not just because it permits us to identify the preferences of the donors for a specific sector, county and year but also, because they reduce the requirements for the instruments. For instance, specification (1) includes county-fixed effects, which will control for the specific unobserved effects of each county. The county-fixed effects are captured via a set of indicator variables for the different counties (1, 2, ..., 102), where each county-fixed effect control for those omitted variables that are assumed constant for each county but may vary across counties, consequently it takes the value 1 when a given observation refers to a given county and 0, otherwise. Based on the coefficient obtained for the county-fixed effects, we can determine the preferences of the donors for each county. The county with the highest coefficient is the preferred county by the donors for contributing with their donations. The same is valid for the sector and year-fixed effects, where sector-fixed effects will control for the specific unobserved effects of each sector and year-fixed effects will control for the specific unobserved effects of each year.

The three specifications are estimated using instrumental variables techniques. The endogenous independent variable fundraising expenditures is instrumented by total liabilities (Z1). The other independent endogenous variable, government grants, is instrumented by the total amount of transfers from the government by county (Z2).

Table 4. Multinomial Logit Estimation Results[A]

Estimation Equation	(1)	(2)	(3)
Variables	Coefficients	Coefficients	Coefficients
Fundraising Expenditures	9,038**	6,091***	4,961**
	(4,098)	(2,217)	(2,220)
Government Grants	0,849**	0,130	0,139
	(0,3620)	(0,226)	(0,213)
Fixed Effects[B]:	County	County	County
		Year	Year
			Sector
Instruments[C]	Z1; Z2	Z1; Z2	Z1; Z2
Observations	28736	28736	28736
Number of Organizations	10261	10261	10261

Note A: The dependent variable of the regression of each column is y_{jt} ($lns_{jt} - lns_{0t}$), based on 28736 observations and 10261 charities. Robust standard-errors are presented in parenthesis. All the values reported in the table are rounded up to the 3th decimal place. All regressions include the introduction of two instruments: Z1 and Z2. The regression in column (1) include county-fixed effects. The regression in column (2) include county- and year-fixed effects. The regression in column (3) include county-, year- and sector-fixed effects.

Note B: The omitted fixed-effects variables are: County 102, Year 2010 and Sector Residential care and group homes.

Note C: Z1 corresponds to the total amount of total liabilities; Z2 corresponds to the total amount of total transfers made by the government by county.

General Note: *** denote p-values < 0.01, ** denote p-values <0.05, and * denote p-values <0.10

We verify, based on the coefficient of fundraising expenditures on Table 4, specification (1), where just year-fixed effects are considered, that the coefficient is effectively positive (9.038). The sign of the coefficient implies that the relationship between fundraising expenditures and the mean utility (across donors) is positive, meaning that fundraising expenditures positively influence private donations. The sign corresponds to our expectations, grounded on the literature review and on our preliminary analysis, and this is probably due to the use of instrumental variables, which permit us to deal with the endogeneity problem, counteracting biased results. Besides, the coefficient of government grants indicates a positive impact of government grants on the mean utility (among donors), but is near zero (0.849).

Fundamentally, we can perceive based on the first specification results using merely count-fixed effects that the use of the latter approach reduces the correlation problem between the error term and any independent variable, because it contributes for an error term, which is now much smaller, in the sense that part of the unobserved characteristics is captured by the series of county- fixed effects.

Furthermore, considering the results obtained from the second specification regression, we notice that the coefficient representing the impact of fundraising expenditures on mean utility (across donors) remains positive (6.091), but compared to the fundraising expenditures coefficient obtained in the first specification, the impact of fundraising expenses on mean utility (across donors) is somewhat lower in the second specification. The latter can be explained by the introduction of year-fixed effects nearby the already introduced county-fixed effects, which causes a decrease in the influence that fundraising expenditures have on private donations, thus reduces the biases. The error term is now even smaller with the introduction of year-fixed effects, because we are reducing the correlation between the error term and any independent variable. The indicator variable year is a set of indicator variables that captures the effect of each year (2005, 2006, 2007, 2008, 2009, 2010) and takes the value 1, when a given observation refers to a given year *t* and 0, otherwise. Quite surprising is the coefficient measuring the impact of government grants on the mean utility (across donors), where we realize the impact is now smaller compared to the first specification results, but most importantly remains zero and is statistically not significant.

Finally, considering the third specification presented on column (3), where we introduce sector fixed-effects nearby county- and year- fixed effects, we diagnose that the coefficients are even slightly smaller now compared to specification (1) and (2). The variable sector fixed-effects is a set of indicator variables for the different sectors stated in our data set (1, 2, 3, …, 16), which takes the value 1 when a given observation refers to a given sector *s*. Each sector fixed-effect control for those omitted variables that are assumed constant for each sector but may vary across sectors. Looking back to the previous conclusions take on the results, we are conscious that by the introduction of the sector-fixed effects, the error is even small now and the coefficients are less biased, which caused them to change compared to the last specification. We conclude, grounded on the last specification, that the impact of fundraising expenditures on the mean utility (across donors) remains positive (4.961), implying that an increase in fundraising expenditures by one million US dollars leads to an increase in the mean utility (across donors) of choosing non-profit *j* in market *m* in year *t* by 4.961. However, concerning the government grants impact on the mean utility (across donors) of choosing non-profit *j* in market *m* in year *t,* we highlight that the government grant coefficient is statistically not significant, meaning that government grants have no impact on donors and consequently have no impact on private donations transferred by donors and on the market share of donations hold by donors.

Irreversibly, we emphasize based on the conclusions draw and detailed above regarding each specification (1), (2) and (3), that specification (3) presents the most reliable results due to the introduction of year-, county- and sector-fixed effects and, therefore is our preferred regression and all our posterior analyses will be based on this specification. The omitted fixed effects are Milwaukee County in Wisconsin, the year of 2010 and the sector "Residential care and group homes".

The complete table, discriminating all the variables and their respective estimated coefficients and standard errors, obtained from the estimation of our MNL demand model is presented in the Appendix.

In summary, we can retain the following principal conclusions: Firstly, donors react positively to fundraising expenditures, given the positive coefficient of fundraising expenditures (4.9611), which confirms that an increase in fundraising expenditures causes an increase in private donations, more specifically, an increase in fundraising expenditures by one million US dollars spent by non-profit j in market m in year t, causes the mean utility (across donors) for choosing non-profit j in market m in year t to increase by approximately 5 units. Secondly, our results demonstrate that government grants have no impact on donors, because the coefficient that captures this effect is statistically not significant in specification (2) and (3). Consequently, we can immediately answer our third research question concerning the effect of government grants on private donations by highlighting that there is no significant effect according to our estimation results, thus according to our results the crowding-out does not exist.

Afterwards, regarding our first research question, which studies the influence fundraising expenditures have on private donations, we can highlight that the MNL estimation results brought us a step forward. We discover based on the results, that fundraising expenditures affect positively the mean utility (across donors) of donations, which is an effect captured by β_1 and, which equals 4.961. However, to discover the exact effect fundraising expenditures have on private donations, we need to calculate the elasticities previously described in *Chapter 2, subsection 2.4. Answering* *the Research Questions*, which will be done in the next section. Unfortunately, we will use the elasticity to enquire only the effect fundraising expenditures have on private donations, because the MNL estimation results reveal that there is no evidence for an effect of government grants on private donations and, therefore, it is useless to calculate the elasticities to get further detail on the own- and cross- government grants effect when the effect is statistically not significant.

Finally, it is important to address the quality of the instruments. Table 5 reveals the correlation between the instruments chosen and the endogenous variables. Thus, the table above discloses if the first condition of using IV techniques is satisfied, this with the objective to demonstrate the strength of our instruments used. The results suggest that first condition of a valid instrument is satisfied, indicating the strength of our instruments used.

Table 5. First-stage Regression Coefficients

	(1)	(2)
Instruments	Fundraising Expenditures	Government Grants
R-squared	0.318	0.245
F-statistic	42.228***	4.895**

Note 1: *** denote p-values <0.01, ** denote p-values <0.05, and * denote p-values <0.10

Note 2: R-squared represents the part of variance in the dependent variable that can be explained by the independent variables and it can take a value between 0 and 1. In other words, it is an indicator that tells us the degree on which the independent variables are able to explain the variation on the dependent variable.

Grounded on Table 5, we emphasize that looking at the results of the F-statistic obtained in column (1), we reject the null hypothesis at 1% that the coefficient of both instruments, total liabilities (Z1) and total government transfers (Z2) is zero, meaning that both instruments explain the variable fundraising expenditures. In other words, this means that fundraising expenditures and its instrument total liabilities are correlated and, thus the first condition of applying instrument Z1 is satisfied. Then, perceiving column (2), we underline that we reject the null hypothesis at 5% that the coefficients of both instruments, Z1 and Z2 are zero implying that both instruments explain government grants. Consequently, the instrument Z2, total government transfers, is correlated with government grants, so the first condition is likewise satisfied for instrument Z2.

However, to be able to definitely conclude that both instruments are strong by satisfying both conditions of using IV techniques, we must confirm the satisfaction of the second condition, which requires that the instruments cannot be correlated with the error term. Unfortunately, we are not able to prove the second condition, because the statistical program STATA allows us to evaluate it, but only when presenting at least two instruments for each endogenous variable. Many authors mentioned only one instrument for each endogenous variable, however Heutel (2014) mentioned a second instrument for the endogenous variable fundraising expenditures, which were the administrative expenditures, also named management expenditures. Disappointingly, those expenditures were not included in our data set from the NCCS Core Files and leave it impossible for us to evaluate the strengthens of our instruments by demonstrating the satisfaction of the second condition regarding the use of IV techniques.

3.6. Elasticities

The elasticities, as described above, will allow us to answer our first research question concerning the own- and cross-impact of fundraising on private donations and, in turn, answer our second research question concerning the objective function of the non-profit organizations considered.

The fundraising elasticities give us the percentage change in the private donations of a non-profit in response to a one percent change in the fundraising expenditures of the same or of a competing non-profit, *ceteris paribus*. The own-elasticity captures the responsiveness of the private donations of a non-profit to a change in its own fundraising expenses. The cross-elasticity captures the responsiveness of the private donations of a non-profit to a change in the fundraising expenditures of some competing non-profit organization.

Thus, the own- and the cross-fundraising elasticities will be useful in drawing the final conclusions to our first research question. These elasticities will also allow us to determine if the competition among charities for private donations is real and to infer is the objective function of the corresponding non-profit organizations.

3.6.1. Elasticity Results at the Sector Level

Given the 16 Sectors described in *Chapter 3, subsection 3.1. Charity Data Collection,* Table 6 (*see below*) reports the 256 own- and cross-fundraising expenditure elasticities corresponding to each Sector:

Table 6. Mean Own- and Cross-Price Elasticities by Sector

Sector	1	2	3	4	5	6	7	8
1. Museums	**1.1403702**	-0.0000065	-0.0000152	-0.0000032	-0.0000067	-0.0000020	-0.0000031	-0.0000019
2. Performing arts	-0.0000798	**0.3698877**	-0.0000145	-0.0000030	-0.0000064	-0.0000019	-0.0000030	-0.0000018
3. Community health treatment	-0.0000798	-0.0000065	**0.3683886**	-0.0000030	-0.0000064	-0.0000019	-0.0000030	-0.0000018
4. Abuse prevention	-0.0000798	-0.0000065	-0.0000145	**0.2282023**	-0.0000064	-0.0000019	-0.0000030	-0.0000018
5. Employment and vocational training	-0.0000798	-0.0000065	-0.0000145	-0.0000030	**0.2154517**	-0.0000019	-0.0000030	-0.0000018
6. Nursing, home health care	-0.0000798	-0.0000065	-0.0000145	-0.0000030	-0.0000064	**0.1159097**	-0.0000030	-0.0000018
7. Substance abuse prevention and treatment	-0.0000798	-0.0000065	-0.0000145	-0.0000030	-0.0000064	-0.0000019	**0.2738124**	-0.0000018
8. Hotlines and crisis prevention	-0.0000798	-0.0000065	-0.0000145	-0.0000030	-0.0000064	-0.0000019	-0.0000030	**0.1673098**
9. Crime prevention and rehabilitation	-0.0000798	-0.0000065	-0.0000145	-0.0000030	-0.0000064	-0.0000019	-0.0000030	-0.0000018
10. Food pantries and programs	-0.0000798	-0.0000065	-0.0000145	-0.0000030	-0.0000064	-0.0000019	-0.0000030	-0.0000018
11. Public housing and rehabilitation	-0.0000798	-0.0000065	-0.0000145	-0.0000030	-0.0000064	-0.0000019	-0.0000030	-0.0000018
12. Homeless shelters	-0.0000798	-0.0000065	-0.0000145	-0.0000030	-0.0000064	-0.0000019	-0.0000030	-0.0000018
13. Community centers	-0.0000798	-0.0000065	-0.0000145	-0.0000030	-0.0000064	-0.0000019	-0.0000030	-0.0000018
14. Family counselling	-0.0000798	-0.0000065	-0.0000145	-0.0000030	-0.0000064	-0.0000019	-0.0000030	-0.0000018
15. Senior centers	-0.0000798	-0.0000065	-0.0000145	-0.0000030	-0.0000064	-0.0000019	-0.0000030	-0.0000018
16. Residential care and group homes	-0.0000798	-0.0000065	-0.0000145	-0.0000030	-0.0000064	-0.0000019	-0.0000030	-0.0000018

Note: The mean elasticity in row s and column j represents the percentage change in the mean market share of sector s with a 1% change in the mean fundraising expenditures of sector j.

Table 6. (continued)

Sector	9	10	11	12	13	14	15	16
1. Museums	-0.0000038	-0.0001636	-0.0000008	-0.0000113	-0.0000087	-0.0000016	-0.0000013	-0.0000015
2. Performing arts	-0.0000038	-0.0001636	-0.0000008	-0.0000113	-0.0000087	-0.0000016	-0.0000013	-0.0000015
3. Community health treatment	-0.0000038	-0.0001636	-0.0000008	-0.0000113	-0.0000087	-0.0000016	-0.0000013	-0.0000015
4. Abuse prevention	-0.0000038	-0.0001636	-0.0000008	-0.0000113	-0.0000087	-0.0000016	-0.0000013	-0.0000015
5. Employment and vocational training	-0.0000038	-0.0001636	-0.0000008	-0.0000113	-0.0000087	-0.0000016	-0.0000013	-0.0000015
6. Nursing, home health care	-0.0000038	-0.0001636	-0.0000008	-0.0000113	-0.0000087	-0.0000016	-0.0000013	-0.0000015
7. Substance abuse prevention and treatment	-0.0000038	-0.0001636	-0.0000008	-0.0000113	-0.0000087	-0.0000016	-0.0000013	-0.0000015
8. Hotlines and crisis prevention	-0.0000038	-0.0001636	-0.0000008	-0.0000113	-0.0000087	-0.0000016	-0.0000013	-0.0000015
9. Crime prevention and rehabilitation	**0,2879059**	-0.0001636	-0.0000008	-0.0000113	-0.0000087	-0.0000016	-0.0000013	-0.0000015
10. Food pantries and programs	-0.0000038	**0,7818961**	-0.0000008	-0.0000113	-0.0000087	-0.0000016	-0.0000013	-0.0000015
11. Public housing and rehabilitation	-0.0000038	-0.0001636	**0,0646492**	-0.0000113	-0.0000087	-0.0000016	-0.0000013	-0.0000015
12. Homeless shelters	-0.0000038	-0.0001636	-0.0000008	**0,4020235**	-0.0000087	-0.0000016	-0.0000013	-0.0000015
13. Community centers	-0.0000038	-0.0001636	-0.0000008	-0.0000113	**0,3094784**	-0.0000016	-0.0000013	-0.0000015
14. Family counselling	-0.0000038	-0.0001636	-0.0000008	-0.0000113	-0.0000087	**0,1458331**	-0.0000013	-0.0000015
15. Senior centers	-0.0000038	-0.0001636	-0.0000008	-0.0000113	-0.0000087	-0.0000016	**0,1301766**	-0.0000015
16. Residential care and group homes	-0.0000038	-0.0001636	-0.0000008	-0.0000113	-0.0000087	-0.0000016	-0.0000013	**0,139382**

Note: The mean elasticity in row *s* and column *j* represents the percentage change in the mean market share of sector *s* with a 1% change in the mean fundraising expenditures of sector *j*.

The mean own-fundraising expenditure elasticities are estimated to be positive for each of the selected 16 sectors. This implies that increasing the fundraising expenditures is estimated to lead to an increase in the private donations obtained by the non-profits of the same sector. As an example, we can illustrate, Senior centers (sector 15). By increasing their total amount of fundraising by 1%, they cause an increase in their own market share of donations by 13%. Notably, Museums is the sector where fundraising expenditures have the highest effect on own market share of donations, increasing the latter by 114%, when fundraising expenditures increase by 1%. Thus, according to our results, Museum is the sector with the most successful effect of own-fundraising expenditures on own-private donations. The fact that museums are a sector different from other sectors is not new for previous authors as Thornton (2006), Andreoni and Payne (2003). Andreoni and Payne (2003) express that museums rely mostly on private donations. According to Smithsonian Institution (2001), which focused on the existing literature and interviewed various art museums, justify the successful effect museums' fundraising have on their own private donations by referring to the way how museums fundraise, which as we could see based on our estimation results makes the difference. The most important for museums when asking for funds is "developing personal relationships" Smithsonian Institution (2001). Museums guarantee that donors are invited to all of their events, they are caring about their donors and treat them like "family". Moreover, museums differ from other sectors, because they "spend money more efficiently", by spending money to ask for money. According to Smithsonian Institution (2001), museums also bet a lot on campaigns, through which they can present their needs and future objectives. Thus, according to Smithsonian Institution (2001), museums' successful effect of fundraising on their own private donations is possibly due to the particularly way how they fundraise. Remarkably is also the sector, where own fundraising expenditures have the lowest impact on own market share of donations, which is attributed to "Public housing and rehabilitation". As Andreoni and Payne (2003) mention, non-profit organizations with "human services" and "housing related services" rely significantly more on government grants. This may be an explanation, why their effect of fundraising expenditures on private donations is not as efficient as for other sectors. Perhaps, in our point of view, because they rely importantly more on government grants, their fundraising efforts would be less of effort. Coincidence or not, the fact is that Andreoni and Payne (2003) analyze only data on two types of organizations, the arts non-profit organizations and the social service non-profit organizations, which are the sectors that in our estimation results capture the most our attention, arts organizations, because their fundraising expenditures' impact on market share of donations is the greatest. The social service organizations, because their impact of fundraising expenditures on market share of donations is the lowest. Regarding the objective function of the sectors considered, grounded on the own-fundraising elasticity results at the sector level, we can indicate that the non-profits of the sectors considered seem neither to have a net revenue maximizer objective nor a budget maximizer objective, since each sector obtains an own-fundraising elasticity result, which is significantly higher than one.

In contrast, the mean cross-fundraising expenditure elasticities are estimated to be closed to zero for sectors. This implies that the fundraising expenditures made by non-profits of a sector is estimated to have almost no impact on the donations obtained by non-profits from competing sectors.

The mean own- and cross-elasticity results reported are crucial in answering our first research question regarding the effect of fundraising expenditures on market share of donations, at the sector level. We can conclude and thereby answer that effectively fundraising expenditures made by a particular non-profit sector affect its own market share of donations, by increasing its private donations and, nearby highlight that museums are the sector with the highest effect. However, we can also conclude that fundraising expenditures made by non-profits of a sector seem not to impact private donations in rival sectors.

3.6.2. Elasticity Results at the Non-Profit Level

The 16 non-profit organizations chosen regarding the selection method described in *Chapter 3, subsection 3.3.1. Estimation at the Non-Profit Level,* are presented on Table 7 (*see below*) with their corresponding own- and cross- fundraising expenditure elasticities:

Table 7. Mean Own- and Cross-Price Elasticities by Charity

Charity	1	2	3	4	5	6	7	8
1. Metropolitan Opera Association Inc.	**60.092202**	-0.1010483	-0.0372831	-0.1961807	-0.0563353	-0.0220315	-0.0007867	-0.0077944
2. United States Holocaust Memorial Council	-0.0804731	**59.166921**	-0.0372831	-0.1961807	-0.0563353	-0.0220315	-0.0007867	-0.0077944
3. Planned Parenthood Federation of America	-0.0804731	-0.1010483	**46.542175**	-0.1961807	-0.0563353	-0.0220315	-0.0007867	-0.0077944
4. Feeding America	-0.0804731	-0.1010483	-0.0372831	**44.114312**	-0.0563353	-0.0220315	-0.0007867	-0.0077944
5. The Metropolitan Museum of Art	-0.0804731	-0.1010483	-0.0372831	-0.1961807	**40.229463**	-0.0220315	-0.0007867	-0.0077944
6. Mothers Against Drunk Driving	-0.0804731	-0.1010483	-0.0372831	-0.1961807	-0.0563353	**40.238033**	-0.0007867	-0.0077944
7. Childrens Theater Company and School	-0.0804731	-0.1010483	-0.0372831	-0.1961807	-0.0563353	-0.0220315	**5.0521034**	-0.0077944
8. The Greater Boston Food Bank Inc.	-0.0804731	-0.1010483	-0.0372831	-0.1961807	-0.0563353	-0.0220315	-0.0007867	**5.0385670**
9. Steppenwolf Theater Co	-0.0804731	-0.1010483	-0.0372831	-0.1961807	-0.0563353	-0.0220315	-0.0007867	-0.0077944
10. Isabella Stewart Gardner Museum Inc.	-0.0804731	-0.1010483	-0.0372831	-0.1961807	-0.0563353	-0.0220315	-0.0007867	-0.0077944
11. Indiana State Symphony Society Inc.	-0.0804731	-0.1010483	-0.0372831	-0.1961807	-0.0563353	-0.0220315	-0.0007867	-0.0077944
12. Philabundance	-0.0804731	-0.1010483	-0.0372831	-0.1961807	-0.0563353	-0.0220315	-0.0007867	-0.0077944
13. Second Harvest Food Bank of Middle Tennessee Inc.	-0.0804731	-0.1010483	-0.0372831	-0.1961807	-0.0563353	-0.0220315	-0.0007867	-0.0077944
14. Harvesters-The Community Food Network	-0.0804731	-0.1010483	-0.0372831	-0.1961807	-0.0563353	-0.0220315	-0.0007867	-0.0077944
15. Childrens Museum Inc.	-0.0804731	-0.1010483	-0.0372831	-0.1961807	-0.0563353	-0.0220315	-0.0007867	-0.0077944
16. Memphis Symphony Orchestra Inc.	-0.0804731	-0.1010483	-0.0372831	-0.1961807	-0.0563353	-0.0220315	-0.0007867	-0.0077944

Note 1: The name of the different charities is obtained with the help of their identification number (EIN) on the IRS Official Website[27]. *Note 2:* The mean elasticity in row *i* and column *j* represents the percentage change in the mean market share of charity *i* with a 1% change in the mean fundraising expenditures of charity *j*.

[27] See https://apps.irs.gov/app/eos/mainSearch.do?mainSearchChoice=pub78&dispatchMethod=selectSearch

Table 7. (continued)

Charity	9	10	11	12	13	14	15	16
1. Metropolitan Opera Association Inc.	-0.0001754	-0.0055071	-0.0042328	-0.0052994	-0.0024608	-0.0075078	-0.0002419	-0.0001384
2. United States Holocaust Memorial Council	-0.0001754	0.0055071	-0.0042328	-0.0052994	-0.0024608	-0.0075078	-0.0002419	-0.0001384
3. Planned Parenthood Federation of America	-0.0001754	0.0055071	-0.0042328	-0.0052994	-0.0024608	-0.0075078	-0.0002419	-0.0001384
4. Feeding America	-0.0001754	0.0055071	-0.0042328	-0.0052994	-0.0024608	-0.0075078	-0.0002419	-0.0001384
5. The Metropolitan Museum of Art	-0.0001754	0.0055071	-0.0042328	-0.0052994	-0.0024608	-0.0075078	-0.0002419	-0.0001384
6. Mothers Against Drunk Driving	-0.0001754	0.0055071	-0.0042328	-0.0052994	-0.0024608	-0.0075078	-0.0002419	-0.0001384
7. Childrens Theater Company and School	-0.0001754	0.0055071	-0.0042328	-0.0052994	-0.0024608	-0.0075078	-0.0002419	-0.0001384
8. The Greater Boston Food Bank Inc.	-0.0001754	0.0055071	-0.0042328	-0.0052994	-0.0024608	-0.0075078	-0.0002419	-0.0001384
9. Steppenwolf Theater Co	**5.0162656**	0.0055071	-0.0042328	-0.0052994	-0.0024608	-0.0075078	-0.0002419	-0.0001384
10. Isabella Stewart Gardner Museum Inc.	-0.0001754	**5.0069750**	-0.0042328	-0.0052994	-0.0024608	-0.0075078	-0.0002419	-0.0001384
11. Indiana State Symphony Society Inc.	-0.0001754	0.0055071	**4.9661841**	-0.0052994	-0.0024608	-0.0075078	-0.0002419	-0.0001384
12. Philabundance	-0.0001754	0.0055071	-0.0042328	**4.9563116**	-0.0024608	-0.0075078	-0.0002419	-0.0001384
13. Second Harvest Food Bank of Middle Tennessee Inc.	-0.0001754	0.0055071	-0.0042328	-0.0052994	**2.4875411**	-0.0075078	-0.0002419	-0.0001384
14. Harvesters-The Community Food Network	-0.0001754	0.0055071	-0.0042328	-0.0052994	-0.0024608	**2.4822356**	-0.0002419	-0.0001384
15. Childrens Museum Inc.	-0.0001754	0.0055071	-0.0042328	-0.0052994	-0.0024608	-0.0075078	**2.4874447**	-0.0001384
16. Memphis Symphony Orchestra Inc.	-0.0001754	0.0055071	-0.0042328	-0.0052994	-0.0024608	-0.0075078	-0.0002419	**2.486567**

Note 1: The name of the different charities is obtained with the help of their identification number (EIN) on the IRS Official Website[28]. *Note 2:* The mean elasticity in row *i* and column *j* represents the percentage change in the mean market share of charity *i* with a 1% change in the mean fundraising expenditures of charity *j*.

[28] See https://apps.irs.gov/app/eos/mainSearch.do?mainSearchChoice=pub78&dispatchMethod=selectSearch

The detailed non-profits mean elasticities results suggest, as the sector level analysis, that all the own-elasticities are estimated to be positive. This implies that the influence that fundraising expenditures of one non-profit has on its own private donations is positive. The non-profit with the highest influence is Metropolitan Opera Association Inc.: increasing fundraising expenditures by 1% is estimated to impact own private donations by 60.09%. The United States Holocaust Memorial Council is the non-profit which exhibits the second highest effect: increasing fundraising expenditures by 1% is estimated to impact own private donations by 59.17%, which is not distant from the impact of the Metropolitan Opera Association Inc.

We can use the elasticities above to address the objective function of the different non-profit organizations. As discussed above, when a charity's own-fundraising expenditure elasticity presents a value equal or near one, the charity is a net revenue maximizer while when a charity's own-fundraising expenditure elasticity presents a value equal or close to zero, the charity is a budget maximizer. The results in Table 7 suggest that none of the 16 charities under analysis can be inferred to have a budget maximizing objective function, since all the 16 charities are estimated to have a positive "marginal donative product of fundraising". The results also suggest that none of the charities can be inferred to be net revenue maximizers, since all charities are estimated to have fundraising expenditure elasticities greater than one. Therefore, we can conclude, as Khanna *et al.* (1995), Khanna and Sandler (2000), Andreoni (2006) and Okten and Weisbrod (2000) that non-profits "fundraise short of net revenue maximization", which means that there is no evidence of excessive fundraising related to these non-profit organizations.

The cross-elasticities, in turn, are estimated to be close to zero for some non-profit organizations (for instance, the impact of fundraising expenditures from all the non-profit organizations has practically no impact on the private donations of The Greater Boston Food Bank Inc.) and estimated to be positive (although negative) for other non-profit organizations (for instance, increasing fundraising expenditures by United States Holocaust Memorial Council is estimated to decrease private donations of all non-profit organizations by 0.10%). The weakness of the Multinomial Logit demand model becomes clear when observing our cross-elasticities results. We would expect that non-profit organizations which are very close substitutes, due to similar characteristics, should induce a higher impact on each other. In other words, fundraising expenditures by a non-profit must, in theory, have a greater impact on the private donations obtained by a non-profit providing a similar output than one that provides something completely different. For instance, looking at our 16 non-profit organizations, we would expect that The Metropolitan Museum of Art, Childrens Theater Company and School, Isabella Stewart Gardner Musuem Inc. and Childrens Musuem Inc., all art non-profit organizations, to be close substitutes. Therefore, we would expect that the fundraising expenditures made, for instance, by The Metropolitan Musuem of Art would have a higher impact on the private donations of the Childrens Theater Company and School, Isabella Stewart Gardner Musuem Inc. and the Childrens Musuem Inc. than in non-profit organizations like Feeding America or Indianca State Symphony Society Inc. Unfortunately, this is a pattern that the MNL demand model cannot capture. The impact that the fundraising expenditures of a non-profit organization has on the private donation of other non-profit organizations is the same for every single non-profit organization. This is the price we have to pay for a simple model.

CONCLUSION

In this Master thesis, we seek to answer three research questions. To do so, I estimate a Multinomial Logit demand model, where different independent variables (which are all determinants of private donations) were regressed on a dependent variable, which is uniquely determined by the observed market shares of donations. The MNL estimation results were crucial in answering our three research questions.

The conclusions are as follows. First, at the sector level, fundraising expenditures made by non-profits of a sector positively affects their own private donations (the sector with the greatest impact was the museum sector), but do not affect at all the private donations obtained by non-profits comprised of other sectors. At the non-profit level the results were slightly different. Fundraising expenditures made by a non-profit organization positively affects its own private donations and affects negatively the private donations obtained by some non-profit organizations, but not by all of them. Consequently, the results imply that, at the sector level, non-profit organizations do not compete for private donations while, at the non-profit level, there is competition among some non-profit organizations for private donations.

Second, regarding the objective function of the different non-profit organizations, the results suggest that all the 16 non-profit organizations considered in our analysis, are neither net revenue maximizers nor budget maximizers, but that all the non-profit organizations spent in fundraising activities short of the objective of net revenue maximization, because they all present a mean-own fundraising elasticity higher than one.

Finally, the results also suggest that the effect of government grants on private donations is null, since the government grants coefficient is statistically not significant. Therefore, the results indicate no crowding-out of government grants on private donations, in contrast to some of the previous literature.

These conclusions are, however, limited by the data. The quality of the data was sometimes questionable. This is particularly clear when we analysed the data and when we compared it to the respective Form 990 of various non-profits. Some data on the files were incorrect, other were missing. This is comprehensible because the data was manually inserted into the files. Therefore, a potential suggestion for the future is to find a solution to improve those datasets in order to allow researchers to have access to a more trustworthy data set, which would be enormous beneficial.

As a final note, since our results demonstrate that for some non-profits, there is a cross-impact of fundraising expenditures on private donations and, since the latter effect implies that the competition among some non-profits for private donations exists, we would incentive researchers to investigate further at the non-profit level.

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Appendix: Multinomial Logit Estimation Results

Table 9. Multinomial Logit Estimation Results [A]

	(1)	(2)	(3)
Variables	Coefficients (Standard Errors)	Coefficients (Standard Errors)	Coefficients (Standard Errors)
Fundraising Expense	9.037**	6.091***	4.961**
	(4.10)	(2.22)	(2.22)
Government Grants	0.849**	0.130	0.139
	(0.362)	(0.226)	(0.213)
Program Service Revenue	0.006*	0.005***	0.004*
	(0.003)	(0.002)	(0.002)
Other Revenue	- 0.055	- 0.011	- 0.012
	(0.104)	(0.063)	(0.052)
Investment Income	- 0.380	- 0.335*	- 0.278*
	(0.258)	(0.184)	(0.164)
Total Contributions	-0.279*	-0.080	-0.069
	(0.166)	(0.071)	(0.069)
Assets	0.003	- 0.000	0.001
	(0.003)	(0.002)	(0.002)
Age	- 0.000	0.012**	0.014***
	(0.009)	(0.005)	(0.005)
Share of Democrats in a State's Senate	-0.117	0.106	0.132
	(0.321)	(0.240)	(0.218)

Share of Democrats in a State's Congress	-0.991	-0.027	0.057
	(-0.778)	(0.529)	(0.480)
Dummy variable for Democratic Governor	0.028	0.003	- 0.011
	(0.111)	(0.065)	(0.060)
Constant	- 13.424***	- 8.900***	- 10.616***
	(1.731)	(1.823)	(1.756)
Fixed Effects – Year: [C]			
2005		- 0.597*	- 0.429
		(0.313)	(0.306)
2006		- 0.438*	- 0.298
		(0.259)	(0.255)
2007		- 0.420*	- 0.298
		(0.264)	(0.258)
2008		-0.306	- 0.198
		(0.252)	(0.243)
2009		-0.502***	- 0.467***
		(0.090)	(0.087)
Fixed Effects – Sector: [C]			
Museums			1.096***
			(0.225)
Performing Arts			0.568***
			(0.177)
Community health treatment			1.342***
			(0.132)
Abuse prevention			1.385***
			(0.122)
Employment and vocational training			0.865***

			(0.146)
Nursing, home health care			0.734***
			(0.227)
Substance abuse prevention and treatment			0.182
			(0.140)
Hotlines and crisis prevention			1.186***
			(0.112)
Crime prevention and rehabilitation			0.489***
			(0.125)
Food pantries and programs			2.122***
			(0.348)
Public housing and rehabilitation			- 0.020
			(0.158)
Homeless shelters			1.445***
			(0.131)
Community centers			1.435***
			(0.100)
Family counselling			0.624***
			(0.162)
Senior centers			0.532
			(0.225)
Fixed Effects – County: [D]	County	County	County
Observations	28736	28736	28736
Number of Organizations	10261	10261	10261
Instruments[B]		Z1; Z2	

Note A: The dependent variable is: y_{jt} $(lns_{jt} - lns_{0t})$. Data is from the years: 2005 to 2010. The estimation equation includes a constant term and is based on 28,736 observations. Robust Standard-errors associated with the coefficients are in parenthesis, presented in column (2). All the values in the table are rounded up to the 4^{th} decimal place. Charity-fixed effects, County-fixed effects and Year-fixed effects are included in the regression.

Note B: We use instruments for our two endogenous variables: Fundraising Expenses and Government Grants. Z1 denotes total liabilities, which is the instrument used for Fundraising Expenses. Z2 is the instrument used for Government grants, which corresponds to the total transfers made from a governmental unit, by county.

Note C: Omitted variables are: The year 2010; Sector 16 and County 102, which is Milwaukee County, Wisconsin. Due to the high number of County fixed-effects, we just list four county indicator variables, those with the highest coefficient.

Note D: County-Fixed Effects Coefficients are not presented in Table 9 for specification (1), (2) and (3) due to the high number of county-fixed effects. In total, we count 101 county fixed-effects.

General Note: *** denote p-values < 0.01, ** denote p-values <0.05, and * denote p-values <0.10, where * and ** means statistically significant at their respective level and *** means statistically highly significant.