The Economics of Charitable Activities in Canada

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Abstract

This thesis explores how macroeconomic conditions and local community characteristics shape charitable behaviour and the dynamics of charities in Canada. It comprises three chapters that analyse private giving, government funding, and the location decisions of charities. Using the Canada Revenue Agency's Registered Charity Information Returns (Form T3010), macroeconomic indicators, and census data from 1990 to 2021, it combines time-series, panel, and spatial analyses to examine funding flows and organisational behaviour in response to both national economic fluctuations and neighbourhood-level socio-economic variation.

The first two chapters focus on the relationship between macroeconomic conditions and charitable giving and funding. Chapter One analyses the relationship between business cycles and private donations across charitable fields, building on and extending the approach of List and Peysakhovich (2011). Using autoregressive distributed lag (ARDL) and nonlinear ARDL (NARDL) models, the chapter finds that total donations and giving to Foundations increase with GDP growth, while donations to Relief of Poverty respond countercyclically. Panel analysis across ten provinces confirms the procyclicality of total donations and giving to Religion, and the countercyclicality of giving to Relief of Poverty during downturns. Asymmetric patterns are evident in Education at the national level and in Relief of Poverty at the provincial level.

Chapter Two examines how government funding to charities responds to macroeconomic conditions, using ARDL, NARDL, and panel models across federal, provincial, and municipal levels. The findings show that funding patterns vary by government tier, charity field, and business cycle phase. Federal funding is generally countercyclical, stabilising key sectors such as Relief of Poverty and Religion. In contrast, provincial and municipal funding is largely procyclical, targeting local priorities like Community and Health. Religion funding increases during downturns and remains stable during upturns, reflecting its role in supporting social cohesion. Education and Community funding rise with economic expansions, while Arts funding increases during contractions. In the Education sector, public funding closely follows GDP growth, with no clear evidence of crowding-in or crowding-out by private donations. In contrast, the Arts sector shows signs of crowding out, where increased government support appears to substitute for private giving. Overall, the chapter highlights the complex and field-specific ways in which public funding strategies interact with macroeconomic conditions.

Chapter Three shifts the focus to the spatial and temporal dynamics of charity entry and exit across Census Subdivisions. It examines how neighbourhood-level socio-economic conditions – such as poverty rates, expectations of government support, and the existing charity landscape – influence where and when charities form or close. Using a Poisson Pseudo Maximum Likelihood model with high-dimensional fixed effects, the analysis finds that charity entry is positively associated with local poverty and anticipated funding, particularly in need-responsive sectors like Relief of Poverty and Education. Exit, by contrast, is more closely tied to prior funding shortfalls. The chapter also identifies patterns of complementarity and substitution across charity types and shows that charities serving remote or underserved areas are more likely to enter in response to local needs. More broadly, the analysis reveals a mix of coordination and competition in both entry and exit dynamics. Extending the analysis to include a macroeconomic focus to tie into the earlier chapters, the chapter shows that charity entry and exit decisions respond to broader economic conditions, offering a macro-geographic perspective on the charitable sector.

Keywords: charitable giving by fields, Business cycles, macroeconomic conditions, giving amounts, government funding to charities by fields, funding to charities from governments at different levels, charity entry and exit, poverty, inter-organisational competition and substitution, spatial analysis

Dedication

To:

my beloved mother, Xingjun Li (李兴俊）— the source of my strength and courage.

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This thesis does not mark the end of my exploration of study and ideas, but rather the beginning of a new journey.

Statement on the Use of Artificial Intelligence

In preparing this dissertation, I used artificial intelligence tools for language polishing, such as grammar, style, and clarity. All research ideas, data analysis, interpretation of results, and conclusions are entirely my own.

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General Introduction

This thesis contributes to the economics of philanthropy and public finance by investigating how macroeconomic fluctuations and local socioeconomic conditions shape charitable giving, government funding, and the geographic dynamics of the nonprofit sector in Canada. It studies how charitable activity moves over the business cycle and responds over time to aggregate macroeconomic shocks. The goal is not to identify causal treatment effects, but to characterise dynamic and possibly asymmetric responses. These dynamics provide forward looking information about future charitable activity.

As providers of public goods, charities rely on both private and public resources to deliver essential services in education, health, poverty relief, community development, and the arts. Understanding how these funding streams and the behaviour of charities respond to economic cycles and local needs is critical, especially during downturns when demand for charitable services rises and revenues become increasingly uncertain.

In Canada, the charitable sector constitutes a notable part of the broader landscape of social service delivery. According to the Canada Revenue Agency (CRA), 84,267 registered charities were active in 2021. That year, real individual donations to charities totaled over 9 billion CAD (CRA T3010, line 4500), and roughly one-third of charities reported receiving non-zero government funding. On average, government funding accounted for 22.4% of total revenue between 1990 and 2021 (author's calculations). Yet despite the sector's economic and social significance, there remains limited empirical work – especially in the Canadian context – on how macroeconomic and community-level conditions influence charitable activity across funding sources, regions, and time.

This thesis is comprised of three chapters designed to address these gaps. Each chapter draws on a unique combination of administrative charity records (CRA Form T3010), national census data, and macroeconomic indicators between 1990 and 2021. The analysis uses a range of empirical tools – ARDL and NARDL models, panel ARDL and NARDL models, and Poisson pseudo-maximum likelihood estimators with high-dimensional fixed effects (PPMLHDFE) – to uncover national and provincial patterns as well as community-level dynamics. Together, the chapters offer a multidimensional view of how charities respond to economic cycles and neighbourhood conditions, with implications for public finance and nonprofit strategies.

The first chapter focuses on the relationship between macroeconomic conditions and private charitable giving. While much of the literature emphasises the role of individual income in shaping donation behaviour (e.g., Bakija & Heim, 2011; Meer et al., 2017), relatively few studies examine how giving varies over the business cycle. Building on List and Peysakhovich (2011), the chapter uses Canadian data to examine whether donations to eight broad charitable fields – Relief of Poverty, Education, Religion, Health, Community, Arts, Foundations, and "Other" – respond to economic expansions and contractions. Applying ARDL and NARDL models, the analysis shows that total donations and giving to Foundations and Religion rise with GDP growth. In contrast, donations to Relief of Poverty are countercyclical, rising during downturns, particularly at the provincial level. Giving to Education shows asymmetric responsiveness: donations fall sharply during recessions but rise more slowly during expansions. These findings underscore the heterogeneity of philanthropic responses across sectors and business cycle phases, with implications for charity planning and fundraising strategy.

The second chapter turns to public funding and how transfers from federal, provincial, and municipal governments to charities respond to macroeconomic fluctuations. While prior studies suggest that nonprofits face increased demand during recessions alongside reductions in government support (Smith & Lipsky, 1993; Hastings et al., 2015), empirical evidence on how public funding to charities responds to economic cycles remains limited (Clifford, 2017; Exley et al., 2023). This chapter fills that gap by using ARDL, NARDL, and panel models to evaluate the responsiveness of government funding by sector and level of government. The findings show that federal funding tends to be countercyclical – stabilising critical sectors like Religion and Relief of Poverty – while provincial and municipal funding is more procyclical, responding to local economic pressures. Arts funding tends to increase during downturns but also shows evidence of crowding-out private donations, suggesting a substitution effect. In Education and Community sectors, funding increases during expansions but stabilises in contractions, aligning with a procyclical pattern. The chapter also identifies asymmetric responses: for instance, Health and Arts funding are more sensitive to negative shocks, while Education funding responds more strongly to positive ones. These patterns reveal the complex ways in which governments manage nonprofit funding across economic conditions, with implications for policy coordination and sectoral resilience.

The third chapter examines the spatial and temporal dynamics of charity formation and closure across Canadian Census Subdivisions (CSDs) from 1991 to 2021. Little is known about where charities choose to locate and what drives their persistence or exit, particularly in the Canadian context (Twombly, 2003; Clément, 2019; Devlin & Planatscher, 2023). Using a PPML estimator with high-dimensional fixed effects, the chapter analyses how charity entry and exit decisions respond to local socioeconomic factors – such as poverty rates, rent burdens, and demographic composition – as well as government funding exposure. The results show that charity formation is positively associated with local poverty and expected funding, particularly in Relief of Poverty and Education. In contrast, exits are driven by lagged funding shortfalls, especially in Community and Relief of Poverty sectors. The chapter also reveals patterns of complementarity and substitution across charity types and finds that organisations are more likely to enter underserved or remote regions when needs are high, and funding is anticipated. Extending the macroeconomic focus of the previous chapters, the analysis shows that entry and exit patterns are also influenced by national business cycles, offering a spatial lens on charitable sector resilience.

Together, these chapters provide new evidence on how economic conditions – both national and neighbourhood-level – shape giving, public funding, and organisational behaviour in the charitable sector. By linking macroeconomic indicators with administrative data on donations, government transfers, and organisational location, the thesis contributes to a richer understanding of the cyclical and geographic drivers of charitable activity. The findings offer insights for policymakers and charity leaders seeking to improve funding systems, especially during periods of economic stress.

Chapter One: Do Macroeconomic Conditions affect Private Donations? Evidence from Canada

1.1 Introduction

Researchers have studied charitable donations for decades, with much attention being paid to the impact of personal income on giving decisions (e.g., Steinberg, 1990; Bakija & Heim 2011; Meer et al., 2017; Drouvelis et al., 2019; Ring & Thoresen, 2021). Much less attention has been paid to the impact of macroeconomic conditions and business cycles (defined below) on giving even though it is of interest to policy makers and charities themselves to know the extent to which donations vary with the business cycle. According to tax filing data from the Canada Revenue Agency (CRA) (T3010 line 4500) in 2021 real individual donations to charities in Canada totaled 9 billion CAD.[1] Meanwhile, the proportion of real individual giving to real GDP hovered in the 0.38% to 0.44% range (author's calculation). The data indicate that individual giving constitutes a stable component of public service provision in Canada. This paper investigates how changes in macroeconomic indicators – GDP per capita, the output gap, and unemployment – affect aggregate charitable giving at the national and provincial levels, with particular attention to whether donations to specific fields of activity respond differently to these economic fluctuations. I refer to changes in these macroeconomic variables as generally reflecting business cycles, which I discuss later in the paper.

In periods of high unemployment and economic uncertainty, one would expect the need for donations to charities to be greater than during periods of growth. Natural questions to ask are whether people donate less or more in bad times; and how giving to different fields of charitable services react during economic fluctuations? People may donate less as the growth in income shrinks or donate more when they feel their donations mean a lot more to a cause during recessions. Unfortunately, current studies do not reach unanimous agreement on this issue. Only a few studies examine giving by charitable fields and include information on business cycles: most focus on the Great Recession of 2008.

Only one paper has examined individual giving by fields over time which captures several business cycles, and that paper used data from the United States. List and Peysakhovich (2011) classify charities into seven types based on the services provided and examine four types of macroeconomic indicators: GDP, the S&P 500 index, unemployment rate, and consumption expenditures. They highlight the importance of the S&P 500 index and

[1] The T3010 Registered Charity Information Return data are available upon request from the CRA; see: https://www.canada.ca/en/revenue-agency/services/charities-giving/charities/guidance-videos-forms/request-charities-listings.html.

its lagged term. One interesting finding from this paper is that it highlights the stickiness of total giving in bad times versus good times.

My paper distinguishes itself from List and Peysakhovich (2011) (L&P) in at least three ways: Firstly, they use US data while I use Canadian data.[2] Secondly, I examine the link between donations to charities that provide services locally and/or nationally and the business cycle, ignoring charities that provide services internationally at the aggregate level.[3] Donations to services at the provincial/local area may respond to local macroeconomic conditions differently than would donations to international causes, that may be influenced by conditions overseas. Thirdly, a more up-to-date data set that spans to 2021, rather than ending in 2008, means that I can capture the 'Great Recession' of 2008/09. In addition to conducting an analysis that is inspired by L&P, I also contribute to the literature on business cycles and giving by extending the analysis to include a time series autoregressive distributed lag (ARDL) model and nonlinear autoregressive distributed lag (NARDL) model for aggregate donations. The ARDL model is commonly used in the time series data in the field of social sciences (Jordan & Philips, 2018). The NARDL model is analogous to the ARDL model but allows us to test if asymmetric effects on charitable giving arise from contractions and expansions. I also apply a panel ARDL and panel NARDL model to try to detect how provincial donations respond to macroeconomic fluctuations.

The T3010 data set used in this paper classifies the activities of registered charities into eight broad categories: Relief of Poverty, Education, Religion, Health, Community, Arts, Foundations, and "Other". I examine the associations between giving to these categories and business cycles for Canada as a whole and for the ten provinces.

Some of my results are consistent with the correlations highlighted by L&P. For example, the percentage change of real GDP (unemployment rate) is positively (negatively) correlated with percentage changes in total giving and giving by fields (except for Health). However, there are differences: for instance, L&P find that the percentage change of total giving in the United States is sticky (less responsive) in bad times relative to good times while my paper finds that the magnitude of the change in total giving, giving to Relief of Poverty, Education, as well as Health in bad times is larger (more responsive) than in good times. I do find stickiness in donations to religious charities, Community, and Foundations during economic downturns. L&P also find stickiness when looking at the reaction of the growth in aggregate donations relative to the growth in the lagged S&P 500 (t-1) index:

[2] Andreoni and Payne (2011) discuss the benefits of the T3010 data set over the US counterpart. In section 1.4, I discuss the data in detail.
[3] A charity is defined as international if the proportion of total expenditures on activities/programs/projects carried on outside Canada during the fiscal period is more than 50%.

donations grow more in ‘good’ times relative to the contraction in the growth of donations in ‘bad’ times. I also find the contrary – the growth of donations in ‘good’ times (reflected in the lagged percentage change in the S&P/TSX Composite Index price) is not as large as the percentage fall in donations in ‘bad’ times.

Exploiting the fact that the T3010 annual report requires charities to indicate whether they are providing services that are mainly international in scope, I show that after excluding internationally operated charities, correlation coefficients of total giving and giving to religious organisations with the percentage changes in real GDP become larger than the coefficients including international charities, indicating that domestically operated charities in total and by the field of religion are responsive to the change in GDP. When further excluding charities whose primary funding source is government, such as universities and hospitals, the correlation coefficient of percentage changes in giving to Education and Health with percentage changes in lagged GDP is apparently larger, suggesting that private donations to organisations in Education and Health are positively correlated with macroeconomic conditions.

In the bootstrapped ARDL model, estimates of the response of aggregate donations during fluctuating macroeconomic periods show that the growth in real GDP per capita has a significantly positive association with the growth in total giving per capita, giving to Religion and to Foundations. In the NARDL model, total giving and giving to Foundations also respond to expansions and contractions significantly. Giving to Relief of Poverty shows countercyclicality in bad times. Significant asymmetries of donations over economic fluctuations are found in giving to Education, implying that people cut more of their charitable giving during economic downturn than increase their donations during economic prosperity. My results provide some insights into the relationships between donations and macroeconomic conditions at the aggregate level.

In the panel ARDL model, the growth rate of private giving per capita in total, and for Religion, and Arts is significantly associated with the growth rate of GDP per capita. While total giving and donations to Religion are procyclical, giving to Arts exhibits a countercyclical pattern. Donations to Relief of Poverty also display a negative association with GDP growth, although this relationship is not statistically significant. The panel NARDL model yields broadly consistent results, while uncovering important asymmetries. As in the panel ARDL specification, total giving and donations to Religion remain significantly linked to economic growth. In addition, giving to Relief of Poverty shows a significant relationship with periods of negative GDP growth. Specifically, giving to Relief of

Poverty is countercyclical at the provincial level. The results from the panel NARDL model suggest asymmetric effects of economic fluctuations to the growth in giving to Relief of Poverty, indicating that donations to this field of charitable services is more responsive to contractions than expansions.

This investigation offers a comprehensive examination of the interplay between charitable giving and macroeconomic fluctuations across various sectors in Canada, including how these dynamics correlate with provincial economic indicators. This innovative approach not only highlights the distinct reactions of charitable donations to economic cycles within different provincial contexts but also introduces the application of ARDL and NARDL models to assess both the symmetric and asymmetric impacts of economic variations on philanthropic activities.

This chapter is organised as follows: Section 1.2 presents a short literature review on charitable contributions with a focus on the few papers that look at recessions and business cycles, section 1.3 clarifies what is meant by a recession, discussing the various approaches to defining and operationalising this concept, section 1.4 discusses my data set (a long data appendix provides details as to how I rendered the data set research ready), section 1.5 provides the empirical strategy and results, section 1.6 discusses robustness, and section 1.7 concludes.

1.2 Charitable Giving and Macroeconomic Conditions: Literature Review

The early work on charitable giving focused on the role played by income and tax-price on individual giving (e.g., Feldstein, 1975; Clotfelter & Steuerle, 1981), and has been reviewed by many papers (e.g., Brooks, 2007; Meer & Priday, 2021). Overall, it shows that individuals respond to the fact that charitable donations are tax deductible (resulting in a 'tax-price' of giving), by giving more to charity; this price elasticity has been the subject of a large body of work (e.g., Randolph, 1995; Almunia et al., 2020; Hickey et al., 2023). The role played by income in charitable giving and whether donations are normal goods, is another focus of the earlier work in this area (e.g., Clotfelter & Steuerle, 1981; Brooks, 2007; Meer & Priday, 2021).

Researchers also study other aspects of tax-price and income effects. Randolph (1995) points out the importance of distinguishing between permanent and transitory fluctuations in tax-price and income and concludes that when there is an unusually high transitory tax rate, individuals are inclined to increase their gifts. Auten et al. (2002) find that permanent price and income changes have much larger impacts on charitable donations than transitory fluctuations. A more recent study by Hickey et al. (2023) estimates the tax price elasticity of charitable giving across the income distribution in Canada and documents a non-monotonic pattern. In the lowest income quintile, the tax price elasticity is relatively high, falls toward zero in the middle of the income distribution, and then rises again among top-income donors. Almunia et al. (2020) find that when estimating the price and income elasticity of giving by income level, people should focus on both intensive and extensive margin elasticity. They find that when incomes rise, the intensive margin price elasticity increases while extensive margin price and income elasticities decrease. Overall, the decreasing extensive margin elasticity price response dominates the rising intensive margin one.

Income and price considerations are not the only incentives affecting individual donations. Bekkers and Wiepking (2011) present an overview of more than 500 articles on the determinants of charitable giving and they identify eight key mechanisms that drive donations: Awareness of the needy to support; Solicitation for a contribution; Material costs and benefits; Altruism; Reputation; Psychological benefits; Attitudes and values; and Efficacy. Among these motives, several of them are likely to work simultaneously. Although they attempt to present a comprehensive picture about determinants to giving, their paper lacks up-to-date information on donations. In addition, donors inevitably face economic fluctuations in practice, how economic conditions affect the donation behaviour remains underexplored.

Much less work has focussed on giving by fields of charitable services. Most of this group of papers distinguish between giving to religious and secular charities. For example, Lunn et al. (2001) investigate how theological beliefs affect religious giving and they find that conservative Presbyterians tend to donate more to religious organisations than liberals who donate more to non-religious institutions. Forbes and Zampelli (2013) also show that people with strong religious beliefs are inclined to increase their religious donations. Concerning tax incentives for donations, Helms and Thornton (2012) categorise donors into religious and nonreligious types. Their results show that among religious groups, religious giving is less responsive to price changes than secular giving, in comparison, within nonreligious groups, secular giving has higher responsiveness to price changes than religious giving.

Rather than focusing on religious and non-religious charitable services, a few researchers extend their studies into more diverse donation fields. They tend to study the price and income elasticities of donations to particular charitable organisations, beginning as early as in the 1970s. Feldstein (1975) appears to be the first one to use donation by fields such as religion, education, hospital, health and social welfare as a dependent variable. Evidence shows that tax-price elasticity of giving differs substantially across various types of charities. Besides that, giving to education and hospital charities has a larger absolute value of price and income elasticities than giving to religious charities. Reece's (1979) finding conflict with Feldstein's (1975). Specifically, the absolute values of price elasticity for donations to religious organisations and educational institutions are 1.6 and 0.08, compared with 0.49 and 2.23 respectively in Feldstein's (1975) paper.

Of more interest to my paper, is the work that looks at the link between giving and macroeconomic conditions. To this end, the impact of the Great Recession of 2008/9 on general charitable giving has been the focus of most papers that deal with macroeconomic conditions. Marx and Carter (2014) examine factors influencing US charitable giving in 2008 and focus on donations to four types of vulnerable organisations: the needy, youth, international organisation, combined purpose organisations. Their findings show that total household wealth and computer ownership are significant factors in giving to these organisations during the recession. Meer et al. (2017) study the impacts of the Great Recession on the decision to give and the amount given. They claim that the fall in the likelihood of giving and giving amount during the Great Recession did not result from changes in income, wealth or tastes for altruism, but rather from factors like uncertainties. Brooks (2018) appears to be the first to estimate price and income giving elasticities during the Great Recession, and reports that, in general, donations are less responsive to income and more responsive to price.

Osili et al. (2019b) explore how pre- and post-recession charitable giving changes between 2000 and 2014. They attempt to control for heterogeneity by classifying givers into four demographic groups: young versus old; gender and marital status; race; education. Their results suggest that the overall giving rate and average overall giving amount differ among demographic groups.

While the Great Recession seems to have had a profound impact on giving, it is of interest to see if aggregate giving typically responds to economic cycles and whether people donate relatively less in economic hard times than in prosperous ones. Looking at the existing research, Drezner (2006) emphasises the impacts of recessions on giving to higher education from 1954 to 2005, finding that such giving declines in recessions. Osili et al. (2019a) distinguish themselves from prior papers by focusing on million-dollar plus donors at a quarterly aggregate level. They find that foundation giving increases significantly to both human services organisations, and arts and culture organisations in recessions, whereas individual giving to both areas tends to decline with the rise of the quarterly unemployment rate. Exley et al. (2023) examine whether nonprofit organisations in the United States (1990-2013) that are expected to be countercyclical in downturns are indeed countercyclical. They investigate how nationwide and regional economic fluctuations affect the financial conditions of nonprofits in terms of their expenditures, revenues, assets and liabilities. They uncover procyclicality in the financial outcomes of US nonprofits and the procyclicality persists in nonprofits with higher desired countercyclicality rating (DCR), such as food banks and housing assistance organisations. A few studies have looked at corporate giving and how it reacts to economic cycles (Amato & Amato, 2012; Peterson & Su, 2017; Heist & Vance-McMullen, 2019).

Several mechanisms may explain why individuals' donations respond to macroeconomic fluctuations. They may respond, for instance, if a discrepancy is perceived between the provision of public services by nonprofits or charities and the demand for these services from individuals and families during economic downturns (Salamon, 1987; Smith & Grønbjerg, 2006; Morreale, 2011). On the one hand, economic downturns may increase the demand from those in need of fundamental necessities like food and housing (Sard, 2009; Lombe et al., 2018). On the other hand, the ability of voluntary organisations to meet these needs may decline during economic downturns due to diminished funding from governmental sources (Hastings et al., 2015; Lupton et al., 2015). Duncan (2004) suggests that individual donors may be motivated to increase their contributions in response to the growing needs during economic downturns. Additionally, household donations may reallocate among different organisational types and subsectors if donors believe their contributions yield greater value to particular causes or organisations (Osili et al., 2019a).

List and Peysakhovich (2011) explain that while donations increase during economic expansions, they do not decrease comparably during contractions, citing reasons such as a shift toward charitable giving when it is perceived as more valuable, societal pressures to uphold previous donation levels, and influences of mental accounting. Specifically, during economic downturns, if charitable giving is deemed more valuable to the recipients (where each dollar contributes significantly more to a cause), a reduction in overall donations due to diminished disposable income may be offset by a substitution effect favoring charitable contributions. Moreover, charitable donations tend to be resistant to decreases in income because of social pressures and a general desire to maintain previous giving levels. This societal expectation to maintain or increase donation levels can pressure donors into contributing more than they might otherwise choose during financial hardships. Lastly, donors tend to allocate windfall gains to charity, particularly when the stock market is flourishing, though such generosity might not occur if the financial upturn had been anticipated. This behaviour aligns with Richard Thaler's mental accounting theory (1985), which posits that individuals categorise and evaluate economic outcomes differently based on subjective criteria.

The relationship between macroeconomic conditions and charitable donations is influenced by specific contextual factors. In the United States, List and Peysakhovich (2011) demonstrate that charitable contributions are more responsive to stock market increases than to declines. Clifford (2017) reports that in the United Kingdom, the recession of 2008 had a substantial negative impact on the revenues of charities, with small to medium-sized organisations, particularly those earning between £10k and £1m annually, experiencing the most significant downturns. The extent of the impact on charities also varies by sector, depending on the nature of their activities and their dependence on government funding. For instance, infrastructure and social service organisations saw notable decreases, primarily due to cuts in government and local support. Charities located in economically disadvantaged areas faced more severe financial challenges than those in more affluent regions. Additionally, health and social services sectors encountered considerable difficulties because of reduced funding and an increase in demand for services.

There is some evidence suggesting that higher education may have also suffered during the Global Financial Crisis, although this is primarily supported by a single press report (European University Association, 2011). Breeze (2011) confirms a significant reduction in million-pound donations to UK universities, which had been a favored category among donors, alongside arts and culture. During the recession, there was also a shift with more large donations directed towards international aid and public welfare than before.

According to Pape et al. (2016), in the European Union, economic recessions have variably affected donations and the development of third sector organisations (TSOs). In countries like Spain and France, TSOs faced considerable challenges due to prolonged economic downturns. Conversely, in Germany and Poland, the impact was less pronounced, allowing TSOs to maintain a relatively stable development despite the recession. The ability of sectors to withstand economic stress appears to be correlated with their reliance on government funding; those less dependent on such funding were more capable of adapting and sustaining their operations during financial adversities.

As far as I can see, only one study looks at aggregate individual giving and how total giving and giving by fields of activity fluctuate with macroeconomic conditions. List and

Peysakhovich (2011)'s study is most related to my analysis. It uses US data on aggregate giving and looks at how total giving and giving by fields of activity are correlated with several macroeconomic variables. I therefore start my empirical analysis by re-doing L&P's paper using Canadian data to explore the differences and similarities in giving behaviours at the aggregate level between the US donors and Canadian donors. Before discussing my data and empirical approach, it is useful to look at what is meant by business cycles and the definition of recessions.

1.3 Definitions: Business Cycles, Recessions, and Macroeconomic Conditions

Business cycles reflect alternate periods of expansion and contraction in key macroeconomic indicators. Normally, these indicators are in terms of growth in GDP, per capita GDP, unemployment and/or employment. According to Cross and Bergevin (2012), one full business cycle contains a peak, a trough, a boom, and a recession.

There is some variation in how a recession is defined, including whether all contractions are recessions. The basic definition of a recession is a decline in the seasonally and calendar adjusted real gross domestic product (GDP) for at least two successive quarters (e.g., Shiskin, 1974; Abberger & Nierhaus, 2008). This definition in its application has been nuanced and has changed over time. For example, Cross and Bergevin (2012) in a C.D. Howe Institute commentary identify a recession based on three dimensions: duration, amplitude, and scope, and not consecutive quarterly declines in GDP. Duration means with at least one quarter of declining economic activity, amplitude means a 0.1 percent drop in economic activity as a necessary but not sufficient condition, and scope is measured by diffusion indices. A diffusion index was developed by the National Bureau of Economic Research (NBER) and it measures the share of industries that experience increasing output, employment, prices, profits and other relevant variables over a given period of time (Moore, 1961; Cross, 2004). In Canada, Cross's (2004) seminal work calculates a comprehensive diffusion index using 83 industries. He built the diffusion index as follows: expanding industries over a given period (monthly data) received a score of 100, those falling received a score of zero, and those with unchanged output received a score of 50. An average was then calculated using the scores for each industry. No weights were attached to sectoral changes. This approach was improved by Kronick (2016), a paper written for the C.D. Howe Institute's Business Cycle Council. In his paper, he uses the Principal Components Analysis Methodology to construct a vector of weights to apply to the diffusion index. Kronick (2016) also developed a "Median Cut-Off Diffusion Index" where he first estimates the percent share of GDP for each sub-industry, then calculates the median of these shares, and finally, calculates the final diffusion index using Cross' (2004) methodology but only including the 51 industries that sit above that median.

The NBER describes the concept of recession as "a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales" (from Business Cycle Dating Committee Announcement October 21, 2003).[4]

To motivate and clarify the business cycle concepts used in the analysis, I draw on Cross and Bergevin (2012), who provide a historical chronology of Canadian recessions since 1926 and document how these episodes are defined. The recessions in 1947/49 and 1951 were defined based on real average GDP growth and real average GDP per capita growth. These recessions were defined based on at least three out of four of the following indicators being negative: quarterly real average GDP growth, two-quarter real average GDP growth, quarterly real average GDP per capita growth, two-quarter real average GDP per capita growth. The recessions in 1953/54, 1957/58 and 1960/61 were defined based on real average GDP growth, real average GDP per capita growth and employment rate growth – with at least three out of now five indicators (rather than the previous four) being negative: quarterly real average GDP growth, two-quarter real average GDP growth, quarterly real average GDP per capita growth, two-quarter real average GDP per capita growth, and employment rate growth. The recessions after 1974 were defined based on diffusion indices and quarterly economic activities. To qualify as a recession in Canada, the diffusion index had to be below 50 and at least two out of five indicators be negative (i.e., indicators are quarterly real average GDP growth, two-quarter real average GDP growth, quarterly real average GDP per capita growth, two-quarter real average GDP per capita growth, employment rate growth).

According to Cross and Bergevin (2012) and C.D. Howe Business Cycle Council (2021), there have been three economic recessions since 1990. These recessions are 1990 Q1 to 1992 Q2, 2008 Q3 to 2009 Q2, and 2020 March to 2020 April. This means that my data set spans three recessions (but more periods with declining macroeconomic activity that are not necessarily reflecting a formal 'recession'.)

To sum up, recessions are defined based on economic activities (i.e., employment growth rate, quarterly average real GDP growth, the two-quarter average real GDP growth, as well as average per capita GDP growth), and diffusion indices. The United States and Canada

[4] https://www.nber.org/news/business-cycle-dating-committee-announcement-october-21-2003

have differences in their definitions. In this chapter, I focus on how private donations react to changes in two key macroeconomic variables: annual real GDP per capita growth and unemployment rate. I therefore am looking at how donations react to economic cycles or fluctuations which may or may not entail a formal 'recession'.

Since this paper examines how expansions and contractions are associated with private donations, it is important to define these concepts within the broader context of economic cycles. I define these phases using thresholds based on positive and negative GDP growth or changes in the unemployment rate. Section 1.5 provides the details.

1.4 Data Discussion

This chapter uses administrative data from the CRA's Registered Charity Information Return (T3010), covering the years 1990 to 2021. This dataset provides annual fiscal information and service fields of registered charities in Canada. The analysis focuses on aggregate giving at the national and provincial levels, across charitable fields, and links these patterns to macroeconomic conditions

1.4.1 CRA Data: T3010 - Registered Charity Information Return

The analysis relies primarily on annual T3010 filings submitted by registered charities to the CRA. These returns provide detailed information on financial activities, program areas, and operations from 1990 to 2021. All registered charities in Canada are required to file a T3010 annual return with the CRA within six months of the end of their fiscal periods in order to receive an income tax exemption and to be able to issue tax receipts for donations. The T3010 records all tax-receipted donations from both individuals and corporations. However, corporations often favour sponsorship arrangements over tax-receipted gifts, since issuing a tax receipt restricts public recognition of corporate donations (Khovrenkov, 2019). As a result, donations reported in the T3010 largely reflect individual giving. In the information return, charities report their national and international activities, revenues and expenditures, liabilities and assets, and area of activities. Failure to submit the information return means that the charity may have its charitable status revoked. T3010 is the main tool used by the Charities Directorate of the CRA to verify if a registered charity meets its tax requirements.[5]

[5] See reports on the charities program from 2015-2021. Available at https://www.canada.ca/en/revenue-agency/services/charities-giving/charities/about-charities-directorate/report-on-charities-program.html.

The T3010 data set has been increasingly used by researchers to address a variety of questions. Since 2011, a group has centred on the use of this data set for research purposes. I quote from its web site:

> The T3010 DATA USERS RESEARCH GROUP is a group of interested individuals who want to share information about the T3010 data.… It is operated on a voluntary basis. Since 2011, members of the T3010 Data Users Research Group have regular discussion by teleconference on different challenges associated with the use of T3010 data. The interests of the members of the T3010 data users group are wide ranging in terms of applicability, but are also focused on a) having access to a common data set that would provide a basis for comparative research; b) identifying the incidence of errors and oversights which could be addressed, either by CRA or researchers; c) identifying gaps in T3010 data which prevents research from taking place; and d) engaging in collaborative research. (T3010 Research Group – Professor François Brouard (carleton.ca))

The CRA regularly participates in these discussions with the view to ensuring that the T3010 data are useful for researchers and as a means of improving the data quality over time. A review of the research undertaken by members of this group is provided by Brouard et al. (2021). In addition to the papers cited therein, other researchers interested in philanthropy have used the T3010 data set. Andreoni and Payne (2011) discuss the benefits of the T3010 data set over the US counterpart. Devlin (2017) uses the data set to discuss political contributions to registered charities. Devlin and Planatscher (2023) focus on the funding decision of governments to charities serving Indigenous individuals. Armstrong et al. (2023) use information on the location of charities from the T3010 to demonstrate how location affects individual volunteering decisions.

The T3010 dataset provides detailed information at the organisational level, including donations, government grants, expenditures, and areas of activity. It does not, however, contain information from the perspective of individual donors. This is a potential limitation of the data. I encountered several data issues when attempting to create a consistent data set over time. I discuss in detail these issues in the data appendix to this paper.

Care has been taken over time to ensure that the T3010 data set provides accurate information. For instance, charities must file this information directly online which reduces the likelihood of transcribing errors. However, the main purpose of the data set is not research, it is an administrative data set, and hence it required work to render it suitable for my research projects. For instance, the T3010 form changed over time necessitating a careful matching up of information necessary for this project: sometimes, the line number for a particular piece of information changed and other times, the definition of the variable changed. One big change occurred in the number and type of areas of activities which required me to match up old and new definitions. I was also missing information on receipted gifts for about 15.8% of the sample. I was able to recover most of this by carefully backing out this information from other lines in the data set. The data appendix 1.A explains the problems and solutions. Overall, this paper focuses on aggregate donations to the charities across the board, by province, and by field of service. Therefore, although I have a very large data set on charitable organisations, I am only using aggregate data over 32 years for much of this analysis.

1.4.2 Macroeconomic Data

In addition to the T3010 data, this study incorporates macroeconomic data, including the output gap (to reflect cyclical economic slack), real GDP (to measure overall economic performance), the unemployment rate (to capture labour market conditions), household final consumption expenditure (as a proxy for domestic demand), and the S&P/TSX Composite Index. The TSX Index is included as a proxy for financial market performance and investor sentiment. It reflects changes in wealth, expectations about future growth, and economic uncertainty – all of which can influence government fiscal capacity and policy priorities. Stronger equity markets may signal higher tax revenues (e.g. via capital gains) and greater fiscal space, potentially supporting higher discretionary transfers, including funding to charities. Conversely, downturns in financial markets may prompt funding cuts or reprioritisation. Together, these indicators allow for a broad assessment of how macroeconomic fluctuations shape government funding decisions.

Real GDP and consumption data are sourced from Statistics Canada. To express funding amounts and the S&P/TSX Index in real terms, I adjust for inflation using the Consumer Price Index (CPI), rebased from its original 2002 base to 2017 to align with the GDP series. The equation to rebase CPI is: $CPI_{new} = CPI_t / CPI_{2017} * 100$, where CPI_{new} denotes the new CPI with base year 2017, CPI_t means the CPI in year t and CPI_{2017} represents the CPI in year 2017 using data with initial base year 2017 from Statistics Canada (see table 1.1 with data sources). After that I calculate the real value of donations and donations by charitable areas by dividing the value with CPI_{new} of base year 2017 times 100. For provincial analyses, I also include real GDP per capita and unemployment rates. All data sources are documented in table 1.1.

Table 1.2 defines the variables used in the empirical analysis. Table 1.3 reports the percentage changes of four macro indicators and aggregate total giving as well as giving by fields. To compare with L&P's results, I include all the variables they did except for the S&P

500, since the analysis should be how volatilities of stock market in Canada rather than in the United States affect donations: GDP, the S&P/TSX Composite Index, unemployment, and consumer expenditure. In table 1.3, on average, the percentage change of real GDP is 2.20% and the change of unemployment rate is 0.82% over the sample period. S&P/TSX has the largest change among four macro indicators. For the components of charitable giving, the mean value of percentage change of donation to "Other" is the largest among the other three areas, followed by giving to Foundations and Relief of Poverty.

Table 1.4 presents averages by province for the panel of 32 years. Although they are averaged over 32 years, we can see clearly that there are differences across provinces for most of the variables. Ontario has the highest real GDP with 660 billion dollars followed by Quebec with 340 billion dollars. Prince Edward Island has the lowest real GDP at around 5 billion dollars. Looking at the average value of real GDP per capita, Alberta ranks the highest with 70 thousand dollars. In terms of real donations per capita, Ontario is by far the most generous province, and thus has the highest level of total donations, followed by Alberta and Manitoba. Giving to Religion per capita accounts for the highest proportion in each province. In contrast, giving to Arts has the smallest share relative to other fields in most of provinces. In terms of organisational counts, Ontario hosts the largest number of charities, with an average of 25,093, followed by Quebec with 13,063. At the other end of the distribution, Prince Edward Island has the fewest, averaging 496 charities.

1.5 Empirical Strategy

I use three different approaches to address the question as to how aggregate charitable donations respond to fluctuations in macroeconomic variables. The first approach follows that of List and Peysakhovich (2011) which examines correlations using aggregate data on giving in total and by field of activity, and several macroeconomic variables. Their study is the only field-based analysis of how charitable giving responds to economic fluctuations, making it a natural reference point. I also extend L&P's analysis by excluding charities that are conducting their activities internationally on the grounds that domestic macro conditions may play a smaller role in, say, humanitarian responses. I exclude hospitals and universities because, in Canada, they are largely publicly provided and government funded. Their funding structures differ from those of other charities, and, as a consequence, their donation flows may be less sensitive to short-run economic fluctuations. I also analyse aggregate giving and macroeconomic conditions by examining aggregate giving by province. Two other empirical approaches are taken: the ARDL and NARDL models for the annual time-series data; panel

ARDL and NARDL models for the provincial data. The two models are designed to investigate the linear and non-linear links between macroeconomic variables and charitable donations.

1.5.1 Comparison with L&P

Like L&P's paper, I calculate the real values of private giving and giving by charitable areas. Real GDP, real household final consumption expenditures are available in Statistics Canada from 1990 to 2021. I use the consumer price index (CPI, 1990-2021) to adjust for inflation in donations and S&P/TSX Composite Index.[6]

Figure 1.1 corresponds to Fig. 1 in L&P. It shows a substantial increase in real charitable giving over the sample period, reaching around $9 billion from less than 6 billion in 1990s. L&P also find a dramatic increase in real charitable giving over time in the United States. Within this trend, we see that giving to Foundations has increased dramatically, nearly three times larger than what they received in 1990s. While giving to religious organisations has been stable. Giving to Education has increased as well though not as substantially as giving to Foundations. Giving to Arts accounts for the smallest share of total giving. In the United States, the trend of giving to charitable sectors differs from Canada. For example, L&P show that giving to religious organisations and giving to education are doubled and tripled respectively since 1970s.

Table 1.5 provides the correlations between changes in giving in total and by fields and changes in several macroeconomic indicators. I find similar signs to that reported by L&P on several fronts: the sign of the correlation coefficients of the percentage changes of total giving and giving by fields (except for giving to Health) against the percentage changes of real GDP (positive), unemployment rate (negative) and real consumption expenditures (positive). However, I also find some notable differences between my work using Canadian data and L&P's US analysis. Differences include that L&P find that the percentage change in lagged GDP and S&P 500 are negatively correlated with Religion with absolute value less than 0.1, but in mine, the correlation coefficients are positive with absolute value around 0.3. Additionally, L&P suggest that lagged S&P 500 has the highest correlation with changes in Education (0.71), While I find that the change in lagged S&P/TSX has the largest correlation with the percentage change in Religion (0.32) and the smallest correlation with the percentage change in Health (0.06). As the health care systems are highly publicly funded in Canada, it is not surprising that giving to Health is not responsive to stock market volatility.

[6] The links of the variable sources are available in table 1.1.

Finally, among all macroeconomic indicators, the change in S&P/TSX has the largest correlation coefficient with changes in total giving and giving to Foundations (around 0.57-0.70).

Figure 1.2 plots the levels of charitable giving and the S&P/TSX Composite Index, and we see that they follow a similar trend over the years. What is different from L&P's paper is that they find that charitable giving in the United States increased significantly more in percentage changes than the S&P 500, while in Canada, the percentage change in total giving and S&P/TSX Composite Index has no substantial difference.

L&P suggest that changes in total charitable giving are more responsive to changes in the S&P 500 at time *t-1* in the positive domain than in the negative domain. Their findings imply that asymmetric effects of macroeconomic conditions on donations might exist in terms of a non-linear relationship in the percentage changes between the S&P 500 and total giving. Figure 1.3 shows that changes in charitable giving move in the same direction as lagged changes in the S&P/TSX index: when the index declines (rises), total giving also tends to decline (rise). The response, however, is asymmetric. In the negative domain, the slope is 0.21, compared with 0.09 in the positive domain. Unlike the relative stickiness of giving documented in the United States, the Canadian evidence indicates greater sensitivity to downturns than to upturns. In particular, in the negative GDP domain the confidence interval lies entirely above zero, implying a statistically significant pro-cyclical response of giving to economic contractions.

Then I graphically present if the non-linear relationship exists in giving by fields (see figures 1.4-1.11). Given the limited number of time-series observations, these figures are intended to illustrate patterns and sign stability rather than to provide precise estimates. To assess whether the estimated coefficients differ from zero despite the small sample, I use bootstrapping, which evaluates the sensitivity of the estimates to resampling from a limited dataset. Figure 1.4 shows that donations to Relief of Poverty are more responsive in downturns. The slope in bad times is 0.29, with a 95% confidence interval entirely above zero, compared with 0.03 in good times. This asymmetry suggests that donations to poverty relief decline more sharply during recessions, likely reflecting income effects. By contrast, figures 1.5-1.11 indicate that giving to other fields also moves pro-cyclically but with weaker effects that are not statistically significant. The plots invite a further investigation of the asymmetric relationships between macroeconomic indicators and giving in total and by fields.

In addition to replicating L&P's approach, I was also able to separate the charities into those providing international and non-international activities (as detailed in the data appendix

1.2A). A charity is defined as international if the proportion of total expenditures on activities/programs/projects carried out outside Canada during the fiscal period is more than 50%. Only 4.91% of charities are operating internationally, with corresponding donations accounting for 6.29%. I can use this classification to extend L&P's analysis to see if the geographic scope of the charity affects how donations are correlated with macroeconomic activity. Because universities and hospitals are primarily government funded, they differ from other charities and are therefore excluded from the analysis (1.7% charities are universities and hospitals and the corresponding donations on average account for 5.81%). Table 1.6 provides correlations using non-international charities. Table 1.7 reports correlations by restricting charities that are not highly dependent on government funding.

Tables 1.6 and 1.7 show some similarities to L&P's study. Firstly, the percentage changes in GDP, as well as in consumption expenditures have positive correlations with the percentage change in giving in total and by fields (except for Health), while changes in the unemployment rate have a negative correlation with the percentage change in donations. However, there are some differences in terms of the reaction of giving to changes in macroeconomic variables associated with the location of the services of charities. Table 1.6 reveals that it is the change in current stock market index that has the largest correlation with total giving not the percentage change in lagged stock market index as found by L&P. Moreover, the change in current stock market index has the strongest correlation with giving to Foundations while L&P find that the percentage change in lagged S&P 500 has the highest correlation with the percentage change in giving to Education. Table 1.7 suggests that after excluding universities and hospitals, the correlation coefficients of giving to Education in response to changes in lagged GDP become the largest among changes in other components of donations.

Canada is a large, diverse country with major regional differences when it comes to economic activities. Looking at data at the national level is likely to mask differences across provinces. For instance, during times of increasing oil prices, the oil producing province of Alberta tends to do much better than, say, the province of Ontario which uses energy for much of its manufacturing base. To allow for the difference of giving and business cycles in different provinces, I present the percentage changes in total giving per capita and real GDP per capita (since the change of real GDP is highly correlated with the change of total giving in table 1.5) for the provinces of Alberta and Ontario. As shown in figure 1.12, the change in the real GDP in Alberta fluctuates more than in Ontario. Specifically, there are five periods of economic contractions in Alberta (i.e., 1991, 1999, 2007-2009, 2015-2016, and 2019-2020) and five in Ontario (i.e., 1991-1992, 2001, 2003, 2008-2009, and 2020).

In figures 1.13 and 1.14, we see that the change in total giving per capita appears to be positively linked to the change in real GDP per capita for both provinces. The fitted slope in Alberta is steeper than in Ontario, particularly during economic contractions, indicating stronger within-province sensitivity of charitable giving to local macroeconomic fluctuations in Alberta than in Ontario. The figures help to visualise differences that require further examinations in donations by province during economic expansions and contractions.

The variance in donation patterns across different provinces, with a specific focus on organ and blood donations, has been analysed in various studies. Gill et al. (2008) point to differences in provincial legislation, the allocation of resources, and the operational capabilities of Organ Procurement Organisations as key factors contributing to these geographic discrepancies. Grubesic (2000) also identifies multiple causes for variations in organ donations, such as divergent provincial laws, inconsistent dedication of resources, and the absence of standardised practices and transparent performance metrics across provinces. Bekkers and Veldhuizen (2008) explores the spatial differences in blood donation and philanthropy within the Netherlands, examining whether these discrepancies might be linked to varying levels of social capital among municipalities. The research identifies considerable spatial differences in blood donation and philanthropy across municipalities but ultimately concludes that these variations do not strongly correlate with social capital indicators, such as prosocial norms or participation in voluntary associations. Wei and Marinova (2016) discuss the reasons behind geographical variations in disaster donation decisions on a global scale. The study highlights that donations are influenced by factors such as the magnitude of the disaster, the political and economic characteristics of the affected countries, and the geographical proximity of the donor to the disaster area. Extending this framework to provincial differences, donation behaviours during economic downturns might similarly be affected by the scale of macroeconomic shocks, the specific political and economic conditions of the province, and the geographical closeness of the donor to charities.

Using L&P's approach to analyse donations in Canada, I find similarities to the US giving in the sign of the correlation coefficients of the percentage changes of total giving and giving by fields against the percentage changes of macroeconomic indicators, such as GDP, unemployment rate and consumption expenditures. I also find the change of magnitude in the percentage change in total giving varies in good times and bad times. However, differences include that L&P highlight the important role of the S&P 500 index at time *t-1* in giving in total and by fields, with the largest correlation with giving to Education, while in my study, the change of lagged S&P/TSX index seems less important than GDP and has the lowest correlation with giving to Health. The different response of giving to Health to the stock market indicator in Canada might be because the health care institutions in Canada are highly publicly funded compared with privately funded counterparts in the United States. Besides that, L&P point out that changes in total charitable giving are more responsive to changes in the lagged S&P 500 in the positive domain than in the negative domain, whereas the situation in Canada is to the opposite. This finding suggests that it is worthy of exploring empirically if Canadian people tend to cut more of their donations in economic contractions than increasing their giving in economic expansions. Moreover, I distinguish my study from L&P's by differentiating between charitable services provided domestically and internationally, as well as by examining provincial differences of giving. Like L&P, I find an asymmetry in the response of donations to 'good' and 'bad' times, which I now examine in more detail.

While L&P provide the conceptual motivation for studying asymmetries over the economic cycle, the empirical strategy in this chapter is driven by the structure of the Canadian data and the dynamic nature of the research question. Charitable giving and macroeconomic indicators change gradually over time and often respond with delays. They may also react differently in economic expansions and contractions. These features call for a framework that models lagged and asymmetric responses directly, rather than relying only on contemporaneous or lagged correlations.

1.5.2 Time Series ARDL and NARDL Models

I apply time series models (ARDL and NARDL) to provide additional evidence as to the links between macroeconomic indicators and charitable giving (in total and by field of charitable activities) across the country. Because 32 years of annual data represents a relatively short time series, my results will provide suggestive insights into the relationships between macroeconomic conditions and aggregate donations (excluding international charities, 4.91% out of total charities with corresponding donations accounting for 6.29%) and will help to support the results obtained from my earlier graphical/correlation analyses. In the aggregate data and provincial data, I choose GDP per capita as the key variable of interests from other macroeconomic indicators, which adjusts for population size and allows comparisons across provinces. Although the S&P/TSX index is strongly correlated with total and Foundation giving in the aggregate data, it has no provincial counterpart and cannot be used consistently in the regional analysis. GDP therefore serves as the main indicator of economic conditions, while the S&P/TSX index is included as a complementary national level measure of financial market conditions.

The study is not designed to estimate causal effects, but to describe how aggregate private donations adjust over time to macroeconomic conditions. The use of ARDL and NARDL models reflects this objective. These models trace short run dynamics and allow for asymmetric responses to expansions and contractions.

One might ask whether moving to charity level data would enable causal identification. In this setting, however, macroeconomic shocks are economy wide and affect all charities at the same time. This leaves little scope for constructing credible counterfactuals, so disaggregation alone does not solve the identification problem. Given this constraint, the contribution of the paper is best framed as providing a dynamic and forward looking interpretation of the link between the growth of charitable contributions and economic fluctuations, rather than as providing causal inference or formal forecasting. While ARDL and NARDL are not forecasting models in the technical sense, the estimated adjustment paths provide information about how future charitable activity is likely to evolve following macroeconomic fluctuations.

The Autoregressive Distributed Lag (ARDL) model developed by Pesaran et al. (2001) is commonly used with time-series data, analysing issues such as how income inequality affects welfare policy (Kelly & Enns, 2010), the determinants of the super-rich in the United States (Volscho & Kelly, 2012), as well as how external debts are linked to GDP growth (Kharusi & Ada, 2018). To test a level relationship between an explained variable and a set of explanatory variables, regressors should not be of a higher order of integration than one *I(1)* (Pesaran et al., 2001). That is, all regressors should be purely stationary *I(0),* purely *I(1),* or a mix of *I(0) and I(1).* The ARDL model in the error correction form is capable of estimating both the long run (cointegration) and short run relationships between the independent and dependent variables (detailed derivations of the ARDL model in error correction form is available in the appendix 1.1B).[7] The literature can be quite vague when it comes to the definition of long run in the ARDL model (Pesaran et al., 2001; Kelly & Enns, 2010; Volscho & Kelly, 2012; Kharusi & Ada, 2018; Philips, 2018). Exceptionally, de Boef and Keele (2008) explain that the error correction model estimates the rate at which the dependent

[7] According to Pesaran et al. (2001) and Philips (2018), the error correction form of the ARDL model is equivalent to the general form of the ARDL model. Taking ARDL(1,1) as an example, the general form should be $Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 X_t + \alpha_3 X_{t-1} + \varepsilon_t$, and the short-run effect of X_t on Y_t is described by α_2. The long-run effect is captured by $(\alpha_2 + \alpha_3)/(1 - \alpha_1)$. Let $Y^* = E(Y_t)$, $X^* = E(X_t)$ for all t, then we can solve Y^* in terms of X^* in the equation of $Y^* = \alpha_0 + \alpha_1 Y^* + \alpha_2 X^* + \alpha_3 X^*$. If the error correction model is applied, $\Delta Y_t = \alpha_0 + \alpha_1^* Y_{t-1} + \alpha_2 \Delta X_t + \alpha_3^* X_{t-1} + \varepsilon_t$, the short-run effect of X_t on Y_t at time *t* is still explained by α_2. The long-run effect of X_t on Y_t of all *t* is captured by $\alpha_3^*/(-\alpha_1^*)$, thinking about $\Delta Y_t = \alpha_0 + \alpha_1^*(Y_{t-1} - \alpha_3^*/(-\alpha_1^*)X_{t-1}) + \alpha_2 \Delta X_t + \varepsilon_t$, where $\alpha_1^* = (\alpha_1 - 1)$, $\alpha_3^* = (\alpha_2 + \alpha_3)$. Long-run relationship exists when the residual of regressing Y_{t-1} on X_{t-1} is stationary and both dependent and independent variables are integrated of order one *I(1).*

variable changes to return to equilibrium, after a change in explanatory variables. They interpret the estimated long-run coefficient as the total effect of a change in independent variables on the change in dependent variable, distributed over future periods.[8] Exploring how donations converge to equilibrium is not the interest of this paper, thus I focus on the short-run relationships between economic conditions and donations, which is captured by the first-difference of (lagged) variables.

It is indicated that the growth in real GDP has a higher correlation with the growth in private donations, than the lagged S&P/TSX index does in tables 1.5 and 1.6. I therefore apply the Nonlinear Autoregressive Distributed Lag (NARDL) model to assess asymmetric responsiveness between GDP and giving in total and by fields. The NARDL model extends the ARDL framework by allowing for nonlinear relationships between the dependent and independent variables. Although asymmetry can also be modeled using alternative specifications such as a quadratic term in GDP, NARDL preserves the underlying ARDL structure. This choice ensures consistency across specifications and allows for the analysis of asymmetry without altering the modeling framework. As a result, the NARDL estimates are directly comparable to those from the linear ARDL model, rather than relying on a different functional form. The NARDL model was first proposed by Shin and Yu (2004), and then developed by Shin, Yu and Greenwood-Nimmo (2014). There is a growing literature that has adopted this technique to analyse issues such as asymmetric wealth effects on US consumption (van Treeck, 2008), and alcohol consumptions during business cycles (Sadik-Zada & Niklas, 2021).

The ARDL model can shed light on the potential role played by lagged dependent and independent variables, thus helping to assess the short run stickiness of donations, as well as responsiveness of private donations to GDP. The NARDL model is designed to answer whether there is an asymmetric response of donations to expansions and contractions. Of the small group of studies addressing this issue, a majority examine only the symmetric influence of economic fluctuations to donations, assuming that the impact of a unit increase and a unit decrease in macroeconomic indicators are equal in magnitude but opposite in direction (Meer et al., 2017; Osili et al., 2019a; Osili et al., 2019b). However, macro economists studying issues such as the fiscal multiplier during business cycles (for example, Auerbach &

[8] In terms of how to interpret the estimated coefficient in the error correction term, based on footnote 6, let $\alpha_3^*/(-\alpha_1^*)= \beta_1 = 2, \alpha_1^*= \gamma_1 =-0.5$. The parameter γ_1 denotes the adjustment rate to equilibrium in the long-term dynamics. Only when γ_1 is negative and significant, donations converge to stabilization. β_1 indicates the long-run relationship between the changes in X_t and Y_t, which it should be interpreted as the total effect of a change in X_t on the change in Y_t, distributed over future periods. For example, when X increases by 1%, Y increases by 2% over the time periods, that is to say, at time t, X changes by 2%*0.5=1%, at time $t+1$, changes by 1%*0.5=0.5%, at time $t+2$, changes by 0.5%*0.5=0.25%, and so on until the total effect of X_t on Y_t, the sum of the changes equal to 2%.

Gorodnichenko, 2012) suggest that fiscal policy is considerably more effective in recessions than in expansions, through using a nonlinear state-dependent method.[9] Ramey and Zubairy (2018), however, find no evidence of large government spending multipliers in the US economy during economic slacks, with the unemployment rate being used to distinguish weak from strong economic conditions.

Different perceptions of the effect of government spending on charities may motivate people to donate. When people believe that the ability of voluntary organisations to meet fundamental needs like food and housing declines during economic downturns due to diminished funding from governmental sources, they may increase their donations (Hastings et al., 2015; Lupton et al., 2015). Similarly, when individuals witness an increase in these needs during economic downturns, that too may encourage more giving. In L&P (2011)'s study, Fig.6 suggests a potential asymmetric relationship between lagged S&P 500 and total giving, calling for a further investigation of the asymmetric effects of macroeconomic conditions to donations. The NARDL model provides a flexible and transparent framework for testing this hypothesis and is therefore the preferred specification in this study.

The ARDL and NARDL models used in this thesis rely on three core assumptions. First, the variables must be either stationary or integrated of order one, but not of higher order. This condition ensures that the dynamic specification is well defined and that the estimated marginal effects are not driven by shared trends or persistence in the data. Second, the estimated coefficients are interpreted as short run dynamic responses rather than long run equilibrium effects. The models trace how donations adjust following macroeconomic movements, not how they converge to a stable steady state. Third, the macroeconomic variables are treated as weakly exogenous with respect to donation dynamics. This assumption is standard in ARDL and NARDL models (Pesaran et al., 2001) and allows consistent estimation of short-run responses without imposing a strict causal or structural interpretation.

According to Pesaran et al. (2001) and Philips (2018), the general time-series short run ARDL(*J, K*) model is specified as follows:

$$\Delta D_t = \alpha_0 + Trend + \sum_{j=1}^{J} \theta_j \, \Delta D_{t-j} + \sum_{k=0}^{K} \delta_k \, \Delta GDPC_{t-k} + \mu_t \qquad (1.1)$$

[9] Auerbach and Gorodnichenko (2012) apply a regime-switch SVAR model to measure the effect of business cycle to fiscal multiplier. I do not follow this method since SVAR assumes that independent and dependent variables are mutually explained. For example, when the dependent variable is a three-dimensional vector of government purchase, tax and GDP, it is assumed that current GDP is a function of lagged GDP, lagged government purchase and lagged tax. If using SVAR, when my dependent variables is a vector of donations and GDP, it is assumed that current GDP is a function of lagged GDP and lagged donations. Therefore, I do not think this method fits my research question.

where t = 1, 2, ..., T is the time; j is the number of lags; ΔD_t represents the first difference of natural logarithm of donations in total and by fields at time t; $\Delta GDPC_t$ is the first difference of natural logarithm of GDP per capita at time t; μ_t is the identically distributed error term; p and q are the optimal lag length for ΔD_t and $\Delta GDPC_t$. All variables are in real values with the base year of 2017. It is possible that the trend term is non-linear, i.e., in the quadratic form. If time trend is non-linear in donations, this term will not be cancelled out through first differences. I include a constant term, since the average growth of donation may not be zero, holding other variables fixed. In the analysis, I also include a trend variable in the regressions.

Following Shin, Yu and Greenwood-Nimmo (2014), I construct my NARDL model:

$$\Delta D_t = \alpha_0 + Trend + \sum_{j=1}^{J} \theta_j \Delta D_{t-j} + \sum_{k=0}^{K} (\delta_k^+ \Delta GDPC_{t-k}^+ + \delta_k^- \Delta GDPC_{t-k}^-) + \mu_t \qquad (1.2)$$

Borenstein and Shepard (1996), Borenstein et al. (1997), Hansen (2000), Lee (2000), and Virén (2001) reach an agreement on the construction of asymmetric first difference variables. I thus define the asymmetric first difference variables based on their studies as follows:

$$\Delta GDPC_t^+ = \Delta GDPC_t I_t^+, \text{ where } I_t^+ = \begin{cases} 1, if\ \Delta GDPC_t \geq 0 \\ 0, if\ \Delta GDPC_t < 0 \end{cases} \qquad (1.3)$$

$$\Delta GDPC_t^- = \Delta GDPC_t I_t^-, \text{ where } I_t^- = \begin{cases} 1, if\ \Delta GDPC_t \leq 0 \\ 0, if\ \Delta GDPC_t > 0 \end{cases} \qquad (1.4)$$

The basic idea of equation (1.3) and (1.4) is piecewise linearization through the introduction of an indicator function. The indicator function acts as a switching mechanism (Hansen 2000; Tong 2011). The intuition behind this approach (terminology: threshold approach) is straightforward: a first difference variable $\Delta GDPC_t^+$ is categorised as "positive" based on a positive change in GDP per capita at time t, otherwise it is zero. In other words, when a negative shock occurs, $\Delta GDPC_t^+$ switches from $\Delta GDPC_{t-1}$ to zero.

Several points should be considered about how lags perform in small sample scenarios. First, with fewer observations there are fewer degrees of freedom, thus the estimated coefficients associated with the lags can be less accurate and reliable. Second, the standard errors of estimated coefficients typically increase when lagged variables are added in a small sample. Larger standard errors imply less statistical confidence in the estimates. Third, when multiple lagged variables are included, they can be highly correlated with each other, especially in small samples. This multicollinearity can exacerbate the problems of high standard errors and biased estimates, making it difficult to discern the individual effects of each lagged variable.

Choosing the right number of lags in small samples is very important. Traditional criteria for lag selection, like Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQIC) and Schwarz Bayesian Information Criterion (SBIC), also known simply as the Bayesian Information Criterion (BIC) have been used in table 1.1C to decide the optimal lags (up to four lags). The smaller of the value, the better of fitness. Table 1.1C shows that in most of cases, the optimal lags of each variable based on the three criteria are the same.

Before estimating the ARDL and NARDL models, I conduct a unit root test to ensure that no dependent and independent variables are integrated higher than order one *I(1)*. Results from four unit-root tests are shown in table 1.8, where I report the tests for dependent and independent variables in both models. The tests conducted are Phillips-Perron (PP) (Phillips and Perron, 1988), the augmented Dicky-Fuller (ADF),[10] Dicky-Fuller Generalised Least Squares (DF-GLS), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski et al., 1992). I separately test the variables with and without a trend. It can be seen that after including a trend in the test, all variables are *I(1)* in the PP test, DF-GLS test, ADF test and KPSS test, except for *ln(Other)* which is *I(0)*, which satisfy the requirement that no variables are integrated higher than order *I(1)*. Small sample adjusted critical values in the above mentioned unit-root tests are not available, in this case, I rely on four tests to show that variables in small sample are indeed not higher than order *I(1)*.[11] The unit root results are used only to establish the integration order needed for the modeling framework, rather than to make strong claims about exact stochastic properties.

I conduct diagnostic tests regarding normality, heteroscedasticity, autocorrelation and misspecification. Strictly speaking, if one of first three assumptions is violated, *t*-tests and *F*-tests are invalid. The last one tests if there are any omitted variables in the regression, if so, the estimation is biased and inconsistent. The Shapiro-Francia normality test can be used with sample sizes ranging from 5 to 5,000 observations (Shapiro & Francia, 1972). According to the test results reported in the appendix 1.C tables 1.2C and 1.3C, there are no autocorrelation and misspecification problems. However, giving to Health and Arts are not normally distributed. Giving to Health has heteroskedasticity. In this case, I use wild cluster bootstrap (see details in appendix 1.6B) to address heteroskedasticity and autocorrelation in a

[10] Consider an autoregressive AR(1) model in the case of ADF test, $X_t = \mu X_{t-1} + \varepsilon_t$, the null hypothesis H_0 is: $|\mu| = 1$; H_1 is: $|\mu| < 1$.
[11] Unit root tests based on the ADF procedure indicate that none of the variables is integrated of order two or higher.

small-sample setting. The procedure is based on 10,000 repetitions with a resample size of 32.[12]

Table 1.9 presents the symmetric effects of how the growth in donations per capita react to the changes in GDP per capita, using the wild cluster bootstrap. The estimated effect is characterised by Δ*ln(RGDPC)*, showing how the growth in D_t reacts to the change in real GDP per capita at lag orders *k*=0, ..., *K* (the selection of the optimal lag is based on Akaike Information Criterion (AIC), see Pesaran et al. (2001)). It is indicated that a one percentage point increase in the real GDP at time *t* is significantly associated with 0.730 percentage points increase in the growth of total giving per capita, 0.416 percentage points of giving to Religion per capita, and 2.562 percentage points of giving to Foundations per capita at time *t*. Due to the small sample size of annual data, the results serve as suggestive evidence but not conclusive.

Table 1.10 presents the asymmetric effects of real GDP per capita on donations across the country, using the NARDL model with wild cluster bootstrap. I add Wald tests for asymmetry in the variables Δ *ln(RGDPC_pos)* (Δ *ln(RGDPC_neg)*) . As with the ARDL model, the growth in total giving and giving to Foundations respond significantly to the growth in GDP in good times and bad times. Specifically, during economic expansions (contractions), one percentage point increase (decrease) in GDP at time *t* is significantly and positively related to 0.715 (0.747) percentage points increase (decrease) in total giving and 2.658 (2.455) percentage points increase (decrease) in giving to Foundations at time *t,* respectively. The significance of giving to Religion in response to expansions and contractions disappears after allowing for positive and negative growth in GDP separately, suggesting that charitable giving to Religion is not sensitive to economic fluctuations. In addition, giving to Relief of Poverty shows countercyclicality in downturns, which increases by 0.763 percentage points with one percentage point decrease in GDP. Giving to Education, however, decreases by 1.105 percentage points associated with one percentage point decrease in GDP and the asymmetry of giving is significant, indicating people cut more of their donations to Education in bad times than they increase their donations in good times. The results indicate that at the aggregate level, some fields of charitable donations, such as Relief of Poverty and Education are sensitive to economic contractions while insensitive to economic expansions. Total giving and giving to Foundations are sensitive to both expansions and contractions. To further test the sensitivity of results to lags, in table 1.4C, I

[12] Comparing normal-based and bootstrapped inference shows that point estimates are nearly unchanged, while standard errors are generally larger under the bootstrap. As a result, statistical significance is often weaker, not stronger. This indicates that the bootstrap does not inflate precision.

set lag equal to one in real GDP per capita in both the ARDL and NARDL models. Findings are that the growth of giving in total and by fields are not sensitive to lags, and only the growth of giving to Arts and Foundations respond to lagged growth of real GDP per capita in the ARDL. In the NARDL, the growth of giving to Community and Foundations is positively associated with economic expansions at time *t-1*.

The ARDL and NARDL models using aggregate data cannot capture provincial differences, since provincial dummy variables are not applicable in the time series data. To compare across provinces, I therefore apply ARDL (1,0) and NARDL(1,0,0) models to data in each of the ten provinces (see tables 1.5C and 1.6C in appendix 1.C). The lag of choice for the independent variable of each province is based on the optimal lag in the ARDL and NARDL model at the aggregate level, which is zero. In terms of the lag of the dependent variable, it is selected by the common lag in each province based on AIC, and that turns out to be one. In the ARDL(1,0) model, the key independent variable is real GDP per capita in each province. It is revealed that the growth in real GDP per capita in British Columbia and Ontario at time *t* is positively associated with growth in total giving per capita, and giving to Religion and Foundations per capita. Besides that, the growth in real GDP per capita in Alberta, Prince Edward Island and Saskatchewan at time *t* is positively associated with giving to Foundations per capita. In addition, the growth in real GDP per capita in Manitoba at time *t* is also positively related to giving to Religion per capita. The cross-sectional data show that the responsiveness of donations to Religion (Foundations) to macroeconomic fluctuations at time *t* in the national aggregate data in ARDL model is mainly from provinces British Columbia, Manitoba, and Ontario (British Columbia, Ontario, Prince Edward Island, and Saskatchewan). In terms of the NARDL(1,0,0) estimation results, asymmetries of donation in periods of economic contractions at time *t* are significant in total giving per capita in Alberta, Ontario, Prince Edward Island, and Quebec, in Relief of Poverty per capita in British Columbia, Nova Scotia, Ontario, Quebec, and Saskatchewan, in Education per capita in Manitoba, in Foundations per capita in Alberta, Ontario, Prince Edward Island, Quebec,, and Saskatchewan. The asymmetry of giving to Education in the NARDL model at aggregate level appears to be driven by the province Manitoba.

This subsection examines the symmetric and asymmetric effects of GDP on national aggregate donations in total and by fields of activities. The ARDL model shows that the growth in total giving, and giving to Religion and Foundations, respond to changes in real GDP per capita significantly in the short run. The NARDL model suggests that in addition to the significant response of total giving and giving to Foundations to the growth of GDP, the growth of giving to Relief of Poverty and Education also respond to contractions in GDP significantly. Specifically giving to Relief of Poverty is countercyclical in downturns and the change of magnitude in giving to Education is larger in bad times than the corresponding estimate in good times. Donations to Religion becomes non-significant when decomposing growth of GDP into positive and negative growth. When applying the ARDL and NARDL models to each province, significant symmetric and asymmetric relationships between private donations per capita and provincial GDP per capita are found. These results suggest that it is worthwhile to estimate panel ARDL and NARDL models.

1.5.3 Panel ARDL and NARDL Models

I use provincial panel data to explore the symmetric and asymmetric relationships of growth in real GDP per capita and growth in private donations per capita. Applying the panel ARDL and NARDL models, I can investigate how economic fluctuations affect donations by province and ease the concern that national giving might mask regional differences. In addition, the concept of the two models is like the ARDL and NARDL models for time-series data, which makes them ideal tools to ensure consistency and the robustness of my analysis.

While both panel models build on the logic of their time-series counterparts, the panel approach offers two key advantages: (1) it increases statistical power by leveraging variation across provinces and over time, and (2) it allows for the inclusion of fixed effects to account for unobserved provincial characteristics. The panel NARDL model extends this further by allowing the effects of positive and negative GDP shocks to differ, making it well suited to test whether funding responses are asymmetric over the business cycle.

Given the fluidity of money donations, it is possible that charities located in one province receive donations from residents of another province, which could weaken the link between provincial economic conditions and provincial donations. I therefore restrict the sample to charities which provide services within national boarders in this subsection on the assumption that charities that specialise in international causes, like the International Red Cross, are more likely to garner donations from across Canada, as opposed to charities that provide local or national services.[13] In the robustness check, I further base my sample on

[13] A charity is defined as local if its program was carried on in a single rural, city, or metropolitan area or a single provincial or territory. A charity is defined as national when its program was carried on in more than one province or territory. Finally, a charity is international if the proportion of total expenditures on activities/programs/projects carried on outside Canada during the fiscal period is more than 50%.

charities providing only local services to see whether this causes my main results to change.[14] The following analysis is based on data excluding international charities.

Following Pesaran et al. (1999), I specify my panel ARDL(*J, K*) model as:

$$\Delta D_{pt} = \alpha_0 + \sum_{j=1}^{J} \theta_{pj}\, \Delta D_{p,\, t-j} + \sum_{k=0}^{K} \delta_{pk}\, \Delta GDPC_{p,\, t-k} + u_t + \omega_{pt} \tag{1.5}$$

where all variables are in the form of natural logarithm of real values, ΔD_{pt} denotes the growth of donation per capita in total and by fields in province p at time *t;* $\Delta GDPC_{pt}$ is the growth of GDP in province p at time *t*; θ_{pk} *and* δ_{pk} are scalars; p = 1, 2, ..., P; t = 1, 2, ..., T; J and K are time lags; u_t denotes year fixed effects, absorbing common shocks or nonlinear trends across all provinces in a given year; $\omega_{pt} = e_{p,t} - e_{p,t-1}$.

Following Pesaran et al. (1999) and Shin, Yu and Greenwood-Nimmo (2014), I construct my panel NARDL(*J, K, K*) model as:

$$\Delta D_{pt} = \alpha_0 + \sum_{j=1}^{J} \theta_{pj}\, \Delta D_{p,\, t-j} + \sum_{k=0}^{K} (\delta_{pk}^{+}\, \Delta GDPC_{p,t-k}^{+} + \delta_{pk}^{-} \Delta GDPC_{p,t-k}^{-}) + u_t + \omega_{pt} \tag{1.6}$$

The asymmetric first difference variables are similarly defined as in equations (1.3) and (1.4) in the NARDL model. A slight difference to equations (1.1) and (1.2) is to add the extra index p denoting the ten provinces. The deterministic trend used in the time series specification is replaced with time fixed effects to allow for a more flexible and general time trend.

One concern of the model specification in equations (1.5) and (1.6) is the independent variable of $D_{p,t-1}$ on the right-hand side might be correlated with the component of error term, $e_{p,t-1}$. In the empirical literature the generalised method of moments (GMM) estimator is commonly used for dynamic panel data model (Arellano & Bond, 1991; Blundell & Bond, 1998; Blundell et al., 2001; Bond et al., 2001; Baum et al., 2003), when there are a few time periods (small T) and a large number of cross-sectional units (large N) (Arellano & Bond, 1991). Specifically, GMM estimation is applied when the number of cross-sectional units is larger than 20 and the number of time periods varies between 8 and 19 (Wen & Yılmaz, 2020). In this model, I have 10 cross-sectional units across 25 years, thus GMM estimation is not an ideal choice. According to Roodman (2009), if the time dimension of a panel dataset is large, then the dynamic panel bias becomes insignificant, and the fixed-effects estimator has good properties. Several studies (Bond & Xing, 2015; Fatica, 2018) have avoided the need to account for dynamic small-sample bias by using a dataset with a sufficiently large time

[14] From 1997 to 2008, charities were required to report on the T3010 form the location of their activities. I have 118,065 charities in total and all of them indicate if their activities are 'international'. 77.4% of the charities report if their service locations are 'local' and/or 'national'. For the annulled charities before 1997 or the new entrants after 2008 this information is missing. In the end, I have 60% of charities providing local services in the robustness test.

dimension (e.g., more than 20 observations per cross-sectional unit). Jeanniton (2022) finds that if the time dimension of the dataset is greater than 20, the dynamic fixed effects (DFE) regression would be the method of choice since there would be no or an insignificant potential dynamic panel bias. Sample size also matters for the dynamic fixed-effects estimator, but in a different way than for GMM. While GMM relies on a large cross-sectional dimension, the performance of the dynamic fixed-effects estimator depends primarily on the length of the time dimension. In panels with a sufficiently large T, the dynamic panel bias associated with fixed effects becomes small (Roodman, 2009). Given the small number of cross-sectional units and the relatively long time dimension in this study, the dynamic fixed-effects estimator has favourable properties and is well suited to the data. As a consequence, I apply the dynamic fixed effects method to estimate panel ARDL and panel NARDL, and not the GMM method.

As with the ARDL and NARDL models, I conduct panel unit root tests to ensure that no variables are higher than *I(1)*. Then I report how the growth in provincial GDP per capita affect the corresponding value of donations per capita. There is no universally accepted cutoff in the literature for how large the cross-sectional dimension must be for panel unit root tests to be appropriate. Pesaran (2007) explicitly considers cases with small cross-sectional dimensions, including settings where N=10, and shows that the test remains valid in such configurations. In the Canadian context, the cross-sectional dimension is naturally limited by the number of provinces. Provincial-level analysis therefore implies a panel with ten cross-sectional units by construction, rather than by choice.

The results of the panel unit root tests for all variables in the panel ARDL and panel NARDL model are reported in table 1.11. In the panel unit root test, there are tests based on ADF and PP, but I choose not to use them, focusing, rather, on based on Breitung (2001), Levin, Lin, and Chu (LLC) (Levin et al. 2002), and Breitung and Das (2005). LLC (2002) recommend using their test with panels of "moderate" size, for instance, samples between 10 and 250 panels and 25 to 250 observations per panel. The Breitung test also has good power with small datasets, i.e., $N = 25$, $T = 25$. More information is provided in appendix 1.9B. From table 1.11, we see that in the IPS test, with or without a trend, no variable is integrated higher than *I(1).* In the Breitung test, with or without a trend, almost all variables are not integrated higher than *I(1),* except for Δ*ln(rgdpc_neg),* Δ*ln(rgdpc_pos),* which are stationary without a trend.

One limitation of the LLC and Breitung tests is that they assume cross section independence across provinces. This assumption may not hold in Canada because provinces face common national shocks such as monetary policy, federal fiscal policy, business cycles, and commodity price movements, which can induce correlated movements. To address this issue, I also apply the cross sectionally augmented IPS (CIPS) test proposed by Pesaran (2007), which accounts for common shocks by including cross section averages and has been shown to perform well in panels with small cross section dimensions, including cases with around ten units. The CIPS results confirm the conclusions about the order of integration.

To address heteroscedasticity and autocorrelation (see diagnostic tests in appendix 1.C, tables 1.7C and 1.8C), I cluster standard errors at the province level throughout the panel data analysis in this paper. This approach allows for heteroskedasticity and serial correlation within provinces over time, ensuring valid inference without requiring strong assumptions about the error structure (Cameron & Miller, 2015). While feasible generalised least squares (FGLS) can also address heteroskedasticity and autocorrelation, I do not use it due to its reliance on strong assumptions about the error structure and its sensitivity to model misspecification (Beck & Katz, 1995). For instance, if the model assumes an *AR(1)* error structure but the true process is *AR(2)*, non-linear, or varies across units, the resulting FGLS estimates may be biased, not just in standard errors but also in the coefficient estimates themselves.

Table 1.12 reports the panel ARDL results. The growth in real GDP per capita at time *t* is significantly and positively related to the growth in total giving, giving to Religion, and Arts per capita. Specifically, a one percentage point increase in real GDP per capita growth is associated with a 0.474 percentage point increase in the growth of total giving per capita and a 0.301 percentage point increase in giving to Religion per capita, but a 0.586 percentage point decline in giving to Arts per capita. The positive coefficient on total giving indicates that charitable giving is procyclical, while the negative coefficient for Arts suggests that faster economic growth is associated with weaker growth in arts-related donations. Overall, these results show that aggregate giving rises with economic growth, but the response varies substantially across subsectors.

Panel NARDL estimates are presented in table 1.13, allowing for asymmetric effects of economic expansions and contractions to private donations. During economic expansions, one percentage point increase in the growth of GDP is significantly associated with 0.406 percentage points increase in the growth of total giving and 0.291 percentage points increase in the growth of giving to Religion. In economic contractions, one percentage point decrease in the growth of GDP is significantly associated with 0.566 percentage points decrease in the growth of total giving, 0.313 percentage points decrease in the growth of giving to Religion, while 1.269 percentage points increase in the growth of giving to Relief of Poverty, suggesting countercyclicality of giving to this type of charity in downturns. These estimates are economically meaningful, indicating nontrivial changes in charitable giving in response to moderate macroeconomic fluctuations. Based on asymmetry tests, giving to Relief of Poverty is more responsive in bad times. To test the sensitivity of results to lags, in table 1.9C, I set lag equal to one in real GDP per capita in both the panel ARDL and NARDL models. I find that the growth of giving in total and by fields are not sensitive to lags, for two cases: giving to Education responds to negative GDP growth at time *t-1*, and giving to Community responds to positive GDP growth at time *t-1*.

In exploring the provincial differences in charitable donations as evidenced by the findings from the panel NARDL estimates, several factors emerge from the literature that could explain these variations. Drawing on research into spatial differences in donations for organ, blood, or disaster relief (Gill et al., 2008; Bekkers & Veldhuizen, 2008; Wei & Marinova, 2016), it is apparent that local contexts shape giving behaviours. First, variations in provincial laws may influence the ease with which charities can operate or the incentives for donors, impacting donation levels differently across provinces. Second, how resources are distributed among different fields of charitable services within a province can affect which sectors see growth in donations, as donors respond to visible needs and organisational effectiveness. Third, the governing political party's ideology (conservative vs. liberal) can influence public sentiment and policies regarding philanthropy, potentially affecting donations. For example, liberal administrations might promote social welfare programs more actively, thereby influencing private giving patterns. Fourth, the scale and intensity of economic fluctuations – reflected in the number of expansion and contraction cycles a province experiences and the severity of these shifts – can significantly influence charitable contributions. Regions experiencing more severe economic downturns might see increased donations to sectors like Relief of Poverty due to heightened need, while more stable regions might show different patterns of giving. These factors collectively contribute to the observed provincial differences in donation trends. Each province's unique economic, political, and legislative context creates a distinctive environment that influences how residents respond to calls for donations, particularly during varying economic conditions.

This subsection investigated the symmetric and asymmetric effects of the macroeconomic indicators real GDP per capita on provincial donations per capita in total and by fields of activities. I found a linear and non-linear relationship between macroeconomic conditions and provincial donations for charities operating within the national border. In the panel ARDL model, the growth rate of GDP at time *t* is significantly and positively related to the growth in total giving, giving to Religion, and Arts. Compared with the growth in GDP, it is indicated that the growth is generally smaller in the rest of charitable fields. In the panel NARDL model, three things are highlighted. First, in addition to the significant associations between the growth in giving variables and the growth in GDP as in panel ARDL model, the estimated coefficients of giving to Relief of Poverty become significant in the panel NARDL as opposed to the results in the panel ARDL. Second, the growth in total giving and giving to Religion are sensitive to both economic expansions and contractions. Giving to Relief of Poverty responds significantly to contractions, showing countercyclicality during contractions. Third, in terms of the change of magnitude, the estimated (absolute) coefficient of giving to Relief of Poverty is larger in bad times than in good times.

1.5.4 A Summary of Findings

Table 1.14 presents a summary of the main, statistically significant, findings from the ARDL and NARDL models using aggregate data, the panel ARDL and panel NARDL models, and models with per capita donations. In this table the symbols +/- reflect a statistically significant estimated coefficient of the noted variable of interest; I also indicate if the slopes differ when looking at the responses of the growth of donations (per capita) in periods of positive GDP (per capita) growth and negative growth, in (panel) NARDL models.

There are four main takeaways from this table. Firstly, when the estimated effects are significant, growth in GDP per capita is always associated with growth in giving per capita (it is significant usually for total giving and giving to Religion, at national and provincial level). Secondly, growth in total giving and giving to Religion per capita is always positively associated with growth in GDP; Thirdly, some fields of giving appear to be sensitive to negative changes in GDP per capita while insensitive to positive changes in GDP per capita, such as giving to Relief of Poverty. In comparison, total giving and donations to Religion respond to both positive and negative changes in GDP per capita, but the magnitude of the response does not differ substantially between the two. Additionally, more variables become significantly associated with GDP per capita growth in the panel NARDL model as opposed to non-significance in the panel ARDL model, suggesting that this specification better captures the underlying data structure.

1.6 Robustness

I check the robustness of my results by redoing the analysis in several ways: by applying different measurements of macroeconomic indicators, such as output gap used in the monetary policy report;[15] using the data set without recalculated receipted gifts (15.8% of the sample are dropped); by focusing on charities operating locally; by excluding hospitals and universities as these are largely government funded. All results are reported in appendix 1.C.

Table 1.10C reports the results using the output gap as the economic indicator. The findings closely resemble those of the full-sample panel NARDL model in table 1.10, particularly in the estimated values and signs of key coefficients. A slight difference is that no significant asymmetric relationship is found between charitable giving and positive or negative GDP growth.

Tables 1.11C and 1.12C present results based on a subsample that excludes observations with missing values in Line 4500, which accounts for 15.8% of the original private donation sample. The estimates are largely consistent with those from the full-sample panel ARDL and NARDL models in tables 1.12 and 1.13, in terms of the values and signs of key coefficients, as well as the significance of the asymmetry tests.

Table 1.13C presents results based on a restricted sample of locally operated charities, which account for approximately 60% of the full sample (see footnote 11 for details on program location reporting). Several results remain consistent with the main analysis. In particular, the growth in giving to Religion continues to exhibit significant responses to both positive and negative GDP per capita growth, with estimated coefficients similar in magnitude to those in the full sample. However, some differences emerge. The significance of total giving and giving to Relief of Poverty during expansions and contractions disappears. In contrast, the estimated coefficient for giving to Education in response to positive GDP growth becomes significant, whereas it was not in the full sample. These findings suggest that locally operated educational charities are more responsive to local economic conditions, while locally operated charities focused on poverty relief are not.

In addition, I also consider the cases where charities are primarily funded by governments, such as is the case for universities and hospitals. I exclude these charities from my sample. I have 112,271 non-international charities located in provinces, among which 2,008 charities (i.e., 1.7%) are hospitals or universities, accounting for 5.9% of total

[15] Defined as the percentage deviation of real GDP from potential GDP, as reported by the Bank of Canada (see table 1). Because the series is quarterly and national, I use the NARDL model and take the annual average. This measure captures declines in GDP that still occur above potential.

donations.[16] In appendix 1.C table 1.14C, the significance of the estimated coefficients remains consistent with my main results. In addition, giving to Education exhibits significant procyclicality during economic expansions. This finding suggests that private donations to educational charities are more responsive to increases in GDP, while remaining largely unresponsive during periods of GDP decline.

1.7 Discussion and Conclusion

I implement three approaches to the study of aggregate donations and macroeconomic conditions: L&P's 'descriptive' approach using aggregate level, applying time series models of ARDL and NARDL using aggregate data, and employing panel data ARDL and NARDL models at the provincial level. Taken together, these approaches reveal a clear pattern. Macroeconomic conditions shape private charitable donations in uneven ways. The relationship varies across charitable fields and differs between economic expansions and contractions, revealing clear patterns in how donors adjust their giving over economic fluctuations.

First, aggregate private giving responds to macroeconomic fluctuations in an asymmetric manner. Total donations rise with economic growth, but they respond more strongly during economic contractions than during expansions. This pattern suggests that private giving in Canada is not smooth over the cycle. Instead, donors adjust their contributions more sharply in bad times, contradicting the view that aggregate giving is largely sticky during downturns.

Second, donation responses differ markedly across charitable fields, reflecting differences in perceived need and donor priorities. Giving to Relief of Poverty is countercyclical, increasing more during economic contractions at both the national and provincial levels. In contrast, giving to Religion responds to both expansions and contractions with similar magnitudes, indicating relative stability over the cycle. Donations to Education and Health show greater sensitivity during downturns, while giving to Arts displays little response to macroeconomic conditions. These patterns indicate that donors reallocate support across causes as economic conditions change.

Some of my findings are consistent with L&P's. For example, the percentage change of real GDP (unemployment rate) is positively (negatively) correlated to total giving and giving by fields of charitable activities (except for Health). However, there are differences in my

[16] I search the key legal names of the charities, such as hospital, infirmary, medical institution, clinic, university and college. I exclude those charities from my full sample.

results with L&P. L&P find that the percentage change in lagged S&P 500 has the highest correlation with changes in Education donations, while in my paper, changes in the lagged S&P/TSX has the largest correlation with the percentage change in Religion while the lowest correlation with the percentage change in Health. What is more, the percentage change of total giving in the United States is sticky in bad times while this paper finds the contrary: the growth in total giving is more responsive in bad times than in good times. By further looking at giving by fields, I can refine this result. I find that giving to Education and Health are more responsive in bad times. Giving to Religion is sticky in bad times, while giving to Relief of Poverty, Community and Foundations are sticky in good times. Giving to Arts seems not to be responsive to economic fluctuations. Overall, therefore, I find some similarities between the growth of Canadian donations and macroeconomic conditions with those of the United States, but they are not the same.

In addition, I distinguish between private donations to regional and national causes. First, focusing on charities that operate locally, I find that the signs of the estimated coefficients are consistent with those in the full sample, particularly for giving to Religion. Moreover, giving to Education becomes responsive to GDP growth in this locally operated sample. Next, I turn to nationally operated charities and restrict the sample by excluding those affiliated with universities and hospitals. In this subsample, the estimated coefficients for giving to Education in response to GDP changes also become statistically significant. This pattern suggests that educational charities operating at the community or sectoral level – excluding large, institutionally complex recipients like universities – are more sensitive to macroeconomic conditions.

In the ARDL and NARDL models, I find evidence to support both a symmetric and asymmetric relationship between giving and economic fluctuations. The ARDL model shows that the growth in total giving, giving in Religion and Foundations respond to the growth in real GDP in a statistically significant manner. The NARDL model also indicates that the growth in total giving and giving to Foundations respond to GDP growth variations over expansions and contractions significantly. Giving to Relief of Poverty reacts countercyclically during downturns. Asymmetric effects of GDP to giving to Education is found in the aggregate data, implying that people cut their donations more in bad times than they increase them in good times.

In terms of the panel ARDL and NARDL models, I also find symmetric and asymmetric effects of macroeconomic indicators on private donations. In the panel ARDL model, the growth rate of per capita private donations – both in total and within the Religion and Arts categories – is significantly associated with the growth rate of GDP per capita. However, the estimated coefficients are below one, implying that private giving in those categories grows at a slower rate than GDP. The panel NARDL model reveals additional asymmetric effects. In addition to total and religious giving, donations to Relief of Poverty are significantly associated with negative changes in GDP. Notably, Relief of Poverty giving shows countercyclical behaviour at the provincial level, consistent with national-level patterns. While giving in total and Religion respond to both economic expansions and contractions, the size of their responses does not differ substantially. In contrast, giving to Relief of Poverty responds more strongly during downturns, as shown by larger absolute coefficients in periods of negative GDP growth.

Findings in this paper present a nuanced understanding of how macroeconomic fluctuations influence charitable donations, revealing both linear and nonlinear relationships across different sectors and economic conditions. To effectively link these findings to the existing literature, I will discuss specific connections and mechanisms suggested by the results and how they align with theoretical and empirical insights from previous studies.

In the ARDL and NARDL models, growth in total giving and giving to Foundations responds significantly to GDP growth variations, showing both symmetric and asymmetric relationships, with increased responsiveness in economic contractions. This finding can be linked to List and Peysakhovich (2011), who indicate that charitable giving tends to resist decreases during economic downturns due to societal pressures to maintain or even increase donation levels. In the panel ARDL model, giving to Religion and Arts is significantly associated with the growth rate of GDP per capita. This result aligns with Osili et al. (2019a), who suggest that households may reallocate donations across charitable categories based on perceived impact. In the panel NARDL model, giving to Relief of Poverty reacts countercyclically during downturns, reflecting an urgent response to heightened needs. This finding is consistent with Lombe et al. (2018) and Sard (2009), who document rising demand for basic necessities during economic contractions. List and Peysakhovich (2011) further suggest that donors perceive charitable giving as more valuable in downturns, leading to stronger support for essential services like poverty relief during these periods. While giving to Religion responds to both expansions and contractions, giving to Relief of Poverty is primarily sensitive to contractions. This pattern is consistent with Thaler's (1985) theory of mental accounting, where donors may prioritise certain types of giving over others depending on prevailing economic conditions.

This study has several limitations, especially concerning data constraints outlined in the data section. One concern is the fluid characteristics of private donations: people located in one province may donate to another province. As a consequence, the provincial economic conditions may not affect charities located in this province. This paper tries to address this issue by first excluding international charities in the analysis at the provincial level and then focusing on local charities that carry out their programs within one region or one province. This approach reduces the likelihood that donations cross provincial boundaries and helps better align local economic conditions with local giving patterns. The data set only provides information from the charity's perspective and not from the donor's perspective. This means that I cannot include donor characteristics in the analysis. Another approach would have been to use micro data on individual giving (GSS surveys on giving) but then I would have been severely limited in terms of my ability to look at macroeconomic conditions and giving, the main point of my paper.

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Table 1.1 Data Sources

Variables	Tables	Data Sources
Real GDP at market price (at 2017 constant prices), 1990-2021	36-10-0369-01	Statistics Canada
Current output gap published in monetary policy report (MPR), quarterly, 1990-2021		Bank of Canada
Real household final consumption expenditure (at 2017 constant prices), 1990-2021	36-10-0369-01	Statistics Canada
Consumer Price Index (2002 = 100), 1990-2021	18-10-0005-01	Statistics Canada
Real GDP by province (at 2017 constant prices), 1990-2021	36-10-0222-01	Statistics Canada
Unemployment rate in Canada and by province, both sex, 15 to 64 years, 1990-2021	14-10-0327-01	Statistics Canada
Estimates of population by province	17-10-0060-01	Statistics Canada
S&P/TSX Composite Index adjusted close price, monthly, 1990-2021		Yahoo Finance

Table 1.2 Variable Definitions

Variable Name and Related Tables	Variable Definitions
Tables 1.3	
GDP (%△)	The percentage change in annual real GDP of Canada
SP/TSX (%△)	The percentage change in annual real S&P/TSX Composite Index
Unemployment (%△)	The change in annual unemployment rate of Canada
Consumption expenditure (%△)	The percentage change in annual real consumption expenditure of Canada
Total giving (%△)	The percentage change in annual aggregate giving
Relief of poverty (%△)	The percentage change in annual giving to Relief of Poverty
Education (%△)	The percentage change in annual giving to Education
Religion (%△)	The percentage change in annual giving to Religion
Health (%△)	The percentage change in annual giving to Health
Community (%△)	The percentage change in annual giving to Community
Art (%△)	The percentage change in annual giving to Arts
Foundation (%△)	The percentage change in annual giving to Foundations
Other (%△)	The percentage change in annual giving to Other charities
Table 1.4	
Real GDP ($M)	Annual real GDP of Canada in million dollars by province
Real GDPC ($K)	Annual real GDP per capita in thousand dollars by province
Total ($)	Annual real total giving per capita to all charities in dollars by province
Poverty ($)	Annual real giving to charities of Relief of Poverty per capita in dollars by province
Education ($)	Annual real giving to charities of Education per capita in dollars by province
Religion ($)	Annual real giving to charities of Religion per capita in dollars by province
Health ($)	Annual real giving to charities of Health per capita in dollars by province
Community ($)	Annual real giving to charities of Community per capita in dollars by province
Art ($)	Annual real giving to charities of Arts per capita in dollars by province
Foundation ($)	Annual real giving to charities of Foundations per capita in dollars by province
Other ($)	Annual real giving to charities of Other per capita in dollars by province
Tables 1.5, 1.6, 1.7	
GDP_t(%△)	The percentage change in annual real GDP of Canada at time t
GDP_{t-1}(%△)	The percentage change of annual real GDP of Canada at time t-1
SP/TSX_t(%△)	The percentage change in annual real S&P/TSX Composite Index at time t
SP/TSX_{t-1}(%△)	The percentage change of annual real S&P/TSX Composite Index at time t-1
$Unemploy_t$(%△)	The change in annual unemployment rate of Canada at time t
$Unemploy_{t-1}$(%△)	The change in annual unemployment rate of Canada at time t-1
$Consump.exp_t$(%△)	The percentage change in annual real consumption expenditure of Canada at time t
$Consump.exp_{t-1}$(%△)	The percentage change of annual real consumption expenditure of Canada at time t-1
Total (%△)	The percentage change in annual real total giving to all charities; subgroups exclude international, university, and hospital charities, respectively.
Poverty (%△)	The percentage change in annual real giving to Relief of Poverty; subgroups exclude international, university, and hospital charities, respectively.
Edu (%△)	The percentage change in annual real giving to Education; subgroups exclude international, university, and hospital charities, respectively.
Religion (%△)	The percentage change in annual real giving to Religion; subgroups exclude international, university, and hospital charities, respectively.
Health (%△)	The percentage change in annual real giving to Health; subgroups exclude international, university, and hospital charities, respectively.
Comm (%△)	The percentage change in annual real giving to Community; subgroups exclude international, university, and hospital charities, respectively.
Art (%△)	The percentage change in annual real giving to Arts; subgroups exclude international, university, and hospital charities, respectively.
Found (%△)	The percentage change in annual real giving to Foundations; subgroups exclude international, university, and hospital charities, respectively.
Other (%△)	The percentage change in real Other giving; subgroups exclude international, university, and hospital charities, respectively.
Tables 1.8-1.10	
All analyses exclude international charities	
△ln(Total)	The first difference of natural logarithm of annual real total giving per capita
△ln(Poverty)	The first difference of natural logarithm of annual real giving to Relief of Poverty per capita
△ln(Edu)	The first difference of natural logarithm of real giving to Education per capita

$\triangle$ln(Religion)	The first difference of natural logarithm of annual real giving to Religion per capita
$\triangle$ln(Health)	The first difference of natural logarithm of annual real giving to Health per capita
$\triangle$ln(Comm)	The first difference of natural logarithm of annual real giving to Community per capita
$\triangle$ln(Art)	The first difference of natural logarithm of annual real giving to Arts per capita
$\triangle$ln(Found)	The first difference of natural logarithm of annual real giving to Foundations per capita
$\triangle$ln(Other)	The first difference of natural logarithm of annual real Other giving per capita
$\triangle$ln(RGDPC)	The first difference of natural logarithm of annual real GDP in Canada
$\triangle$ln(RGDPC_pos)	The first difference of natural logarithm of annual positive change in real GDP per capita in Canada
$\triangle$ln(RGDPC_neg)	The first difference of natural logarithm of annual negative change in real GDP per capita in Canada
Tables 1.11-1.13	
All analyses exclude international charities	
$\triangle$ln(total)	The first difference of natural logarithm of annual real total giving per capita by province to charities operating within the boarder
$\triangle$ln(poverty)	The first difference of natural logarithm of annual real giving to Relief of Poverty per capita by province to charities operating within the boarder
$\triangle$ln(edu)	The first difference of natural logarithm of annual real giving to Education per capita by province to charities operating within the boarder
$\triangle$ln(religion)	The first difference of natural logarithm of annual real giving to Religion per capita by province to charities operating within the boarder
$\triangle$ln(health)	The first difference of natural logarithm of annual real giving to Health per capita by province to charities operating within the boarder
$\triangle$ln(comm)	The first difference of natural logarithm of annual real giving to Community per capita by province to charities operating within the boarder
$\triangle$ln(art)	The first difference of natural logarithm of annual real giving to Arts per capita by province to charities operating within the boarder
$\triangle$ln(found)	The first difference of natural logarithm of annual real giving to Foundations per capita by province to charities operating within the boarder
$\triangle$ln(other)	The first difference of natural logarithm of annual real Other giving per capita by province to charities operating within the boarder
$\triangle$ln(rgdpc)	The first difference of natural logarithm of annual real GDP per capita by province
$\triangle$ln(rgdpc_pos)	The first difference of natural logarithm of annual positive change in real GDP per capita by province
$\triangle$ln(rgdpc_neg)	The first difference of natural logarithm of annual negative change in real GDP per capita by province

Table 1.3 Descriptive Statistics of Percentage Changes in Donation by Fields and Economic Indicators at the Aggregate Level, 1991-2021

Variable	Mean	SD	Min	Max
GDP (%△)	2.200	2.310	-4.930	5.520
SP/TSX (%△)	4.520	12.200	-21.500	32.540
Unemployment (%△)	0.820	16.670	-22.680	70.180
Consumption expenditure (%△)	0.640	2.190	-6.980	3.030
Total giving (%△)	2.280	3.530	-5.410	9.790
Relief of poverty (%△)	4.100	4.050	-2.340	12.800
Education (%△)	2.660	3.970	-8.520	8.410
Religion (%△)	0.950	2.540	-5.980	7.480
Health (%△)	1.220	5.200	-15.020	10.820
Community (%△)	2.460	6.240	-8.390	15.570
Art (%△)	0.990	8.420	-23.950	20.690
Foundation (%△)	5.410	10.420	-11.190	28.060
Other (%△)	7.220	13.960	-18.680	52.340

Note: Variables are percentage changes of real terms of GDP, S&P/TSX composite index, unemployment rate, consumption expenditures, total giving and giving by fields..

Table 1.4 Average values in Donation Per Capita by Areas and Economic Indicators at the Provincial Level, 1990-2021

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ON	AB	BC	NB	NL	NS	PE	QC	SK	MB
Real GDP ($M)	660,000	260,000	210,000	30,245	27,712	36,243	5,375	340,000	60,150	55,372
Real GDPC ($K)	50	70	50	40	50	40	40	40	60	40
Total ($)	281.03	280.18	240.78	201.79	161.17	171.18	183.48	104.44	220.60	269.86
Poverty ($)	15.69	14.91	11.39	7.65	4.61	6.53	7.75	7.13	9.86	13.94
Education ($)	32.04	22.73	29.51	13.88	2.59	17.97	11.72	16.98	16.23	25.90
Religion ($)	138.76	169.95	125.42	143.78	132.08	106.31	142.47	36.62	149.09	161.48
Health ($)	12.04	7.63	7.02	4.22	5.11	5.53	4.42	4.45	8.01	8.00
Community ($)	6.18	6.43	6.63	3.48	2.07	5.08	6.22	2.91	5.42	7.00
Art ($)	2.89	2.46	2.56	1.32	0.71	1.61	0.95	1.41	1.66	3.24
Foundation ($)	70.23	53.69	56.38	25.36	13.34	26.64	9.51	34.63	28.65	45.64
Other ($)	3.20	2.38	1.87	2.10	0.67	1.52	0.44	0.31	1.67	4.66
No. Charities	25093	7555	9551	2366	1017	3274	496	13063	3925	3966

Note: Real GDP denotes provincial values of real GDP (base year 2017) in million Canadian dollars. Total, Relief of Poverty, Education, Religion, Health, Community, Art, Foundation and Other represent the real donation per capita (base year 2017) in unit dollar in total and by field in 10 provinces. Real GDPC represents real GDP per capita (base year 2017) in thousand dollars.

Table 1.5 Correlations Between Changes in Charitable Giving and Changes in Macroeconomic Indicators (CA)

	Total (%△)	Poverty (%△)	Edu (%△)	Religion (%△)	Health (%△)	Comm (%△)	Art (%△)	Found(%△)	Other (%△)
GDP_t(%△)	0.558	-0.178	0.406	0.440	-0.100	0.293	0.060	0.557	-0.100
GDP_{t-1}(%△)	0.103	0.103	0.299	0.213	0.198	0.050	0.370	0.005	0.087
SP/TSX_t(%△)	0.572	0.191	0.174	0.304	-0.135	0.292	0.148	0.695	0.104
SP/TSX_{t-1}(%△)	0.217	0.113	0.222	0.324	0.055	0.264	0.292	0.097	-0.136
$Unemploy_t$(%△)	-0.538	0.213	-0.423	-0.440	0.098	-0.316	-0.099	-0.502	0.083
$Unemploy_{t-1}$(%△)	0.030	-0.039	-0.216	-0.040	-0.246	0.146	-0.325	0.072	-0.010
$Consump.exp_t$(%△)	0.557	-0.093	0.469	0.507	0.032	0.293	0.068	0.497	-0.346
$Consump.exp_{t-1}$(%△)	-0.022	-0.132	0.180	0.044	0.076	-0.148	0.316	-0.027	0.095

Note: The variables in the first row are: percentage changes of total giving, giving to Relief of Poverty, giving to Education, giving to Religion, giving to Health, giving to Community, giving to Arts, giving to Foundations, and Other giving to all charities registered in Canada, respectively. The variables in the first column are: percentage changes of real GDP, lag one real GDP, S&P/TSX Composite Index, lag one S&P/TSX Composite Index, unemployment rate, lag one unemployment rate, household final consumption expenditure, lag one household final consumption expenditure accordingly.

Table 1.6 Correlations Between Changes in Charitable Giving and Changes in Macroeconomic Indicators Without International Charities

Variables	Total (%△)	Poverty (%△)	Edu (%△)	Religion (%△)	Health (%△)	Comm (%△)	Art (%△)	Found(%△)	Other (%△)
GDP_t(%△)	0.571	-0.108	0.315	0.454	-0.088	0.278	0.076	0.549	-0.053
GDP_{t-1}(%△)	0.082	0.089	0.264	0.204	0.192	0.073	0.393	-0.006	0.033
SP/TSX_t(%△)	0.576	0.212	0.062	0.319	-0.111	0.278	0.150	0.678	0.135
SP/TSX_{t-1}(%△)	0.197	0.020	0.185	0.318	0.009	0.265	0.266	0.092	-0.139
$Unemploy_t$(%△)	-0.542	0.230	-0.324	-0.445	0.106	-0.310	-0.122	-0.493	0.043
$Unemploy_{t-1}$(%△)	0.053	-0.007	-0.203	-0.025	-0.252	0.120	-0.341	0.081	0.080
$Consump.exp_t$(%△)	0.555	-0.100	0.370	0.503	-0.023	0.279	0.063	0.501	-0.308
$Consump.exp_{t-1}$(%△)	-0.040	-0.184	0.168	0.035	0.110	-0.126	0.364	-0.047	0.015

Note: The difference to table 1.5 is the variables in the first row are: percentage changes of total giving, giving to Relief of Poverty, giving to Education, giving to Religion, giving to Health, giving to Community, giving to Arts, giving to Foundations, and Other giving to charities provide services within the boarder, respectively. See footnote one for definition to internationally operated charities.

Table 1.7 Correlations Between Changes in Charitable Giving and Changes in Macroeconomic Indicators Without International Charities, Universities and Hospitals

Variables	Total (%△)	Poverty (%△)	Edu(%△)	Religion (%△)	Health (%△)	Comm (%△)	Art (%△)	Found(%△)	Other (%△)
GDP_t(%△)	0.547	-0.108	0.212	0.453	-0.081	0.281	0.043	0.551	-0.053
GDP_{t-1}(%△)	0.103	0.086	0.430	0.204	0.289	0.076	0.390	-0.002	0.033
SP/TSX_t(%△)	0.576	0.208	0.131	0.320	-0.100	0.280	0.145	0.700	0.135
SP/TSX_{t-1}(%△)	0.228	0.020	0.264	0.317	0.093	0.266	0.268	0.127	-0.138
$Unemploy_t$(%△)	-0.520	0.229	-0.220	-0.445	0.086	-0.310	-0.072	-0.493	0.044
$Unemploy_{t-1}$(%△)	0.039	-0.002	-0.360	-0.025	-0.309	0.119	-0.335	0.080	0.080
$Consump.exp_t$(%△)	0.531	-0.100	0.196	0.503	-0.017	0.279	0.028	0.516	-0.308
$Consump.exp_{t-1}$(%△)	-0.023	-0.184	0.337	0.034	0.170	-0.123	0.364	-0.040	0.015

Note: The difference to table 1.5 is the variables in the first row are: percentage changes of total giving, giving to Relief of Poverty, giving to Education, giving to Religion, giving to Health, giving to Community, giving to Arts, giving to Foundations, and Other giving to sub-samples excluding universities and hospitals that provide services within the boarder, respectively.

Table 1.8 Unit Root Test for ARDL and NARDL Model at Aggregate Level

Method	PP		DFGLS		ADF		KPSS	
Variables	Intercept	Trend and intercept	Intercept	Trend and intercept	Intercept	Trend and intercept	Intercept	Trend and intercept
At level								
ln(RGDPC)	-1.183	-1.130	-0.732	-1.632	-1.907	-1.183	1.05***	0.253***
ln(Total)	-1.571	-0.937	-1.003	-1.700	-2.029	-0.803	0.636**	0.181**
ln(Poverty)	-1.113	-1.393	-0.530	-1.487	-1.335	-1.318	1.1***	0.252***
ln(Edu)	-2.521	-0.092	-1.146	-0.981	-2.816*	-0.905	0.678**	0.230***
ln(Religion)	-0.890	-0.271	-1.265	-1.190	-1.324	-0.232	0.454*	0.225***
ln(Health)	-2.245	-2.543	-2.331*	-2.657	-2.082	-2.393	0.375*	0.127*
ln(Comm)	-2.242	-1.584	-1.388	-1.862	-3.010**	-1.552	0.549**	0.220***
ln(Art)	-2.034	-1.794	-1.416	-1.485	-1.460	-1.221	0.240	0.236***
ln(Found)	-0.628	-2.704	-0.436	-2.466	-0.973	-1.749	1.11***	0.179**
ln(Other)	-1.610	-4.381**	1.366	-1.811	-0.479	-1.892	1.12***	0.187**
At first difference								
△ln(RGDPC)	-5.155***	-5.549***	-2.473**	-2.791	-3.843***	-4.550***	0.193	0.093
△ln(RGDPC_neg)	-6.078***	-6.458***	-1.978	-2.412	-3.514***	-3.781**	0.150	0.089
△ln(RGDPC_pos)	-3.852***	-3.863**	-3.319***	-3.206*	-3.749***	-4.082***	0.205	0.097
△ln(Total)	-6.300***	-6.845***	-2.476**	-2.759	-2.600*	-3.460**	0.317	0.095
△ln(Poverty)	-6.145***	-6.219***	-3.215***	-3.227*	-3.199**	-3.218*	0.198	0.103
△ln(Edu)	-3.918***	-5.641***	-1.666	-2.576	-	-2.954	0.553*	0.075
△ln(Religion)	-4.137***	-5.364***	-1.935	-2.569	-1.724	-3.066	0.515*	0.123
△ln(Health)	-5.752***	-5.672***	-	-3.589**	-3.566***	-3.518**	0.072**	0.058
△ln(Comm)	-7.577***	-9.441***	-3.162***	-3.149*	-	-3.595**	0.368*	0.078
△ln(Art)	-7.401***	-7.601***	-3.381***	-4.095***	-4.311***	-4.533***	0.239	0.057
△ln(Found)	-7.794***	-7.744***	-2.845***	-3.227*	-3.711***	-3.749**	0 .072	0.067
△ln(Other)	-10.688***	-	-1.530	-2.771	-4.356***	-4.212***	0.136	0 .085

Note: The tests conducted in a row are Phillips-Perron (PP), the augmented Dicky-Fuller (ADF), Dicky-Fuller Generalised Least Squares (DF-GLS), Kwiatkowski-Phillips-Schmidt-Shin (KPSS).The null hypothesis of the first three tests is: the variable has a unit root; The null hypothesis of the KPSS test is: the variable has no unit root.

Table 1.9 Bootstrapped ARDL Estimation to Aggregate Donations, 1990-2021

Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Found)	△ln(Other)
Trend	-0.001	-0.001	-0.002**	-0.001**	0.000	-0.003**	-0.003	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
△ln(Total)$_{t-1}$	-0.183								
	(0.148)								
△ln(Total)$_{t-2}$	0.383**								
	(0.171)								
△ln(Total)$_{t-3}$	-0.077								
	(0.181)								
△ln(RGDPC)$_t$	0.730***	-0.277	0.418	0.416**	-0.185	0.695	-0.469	2.562***	0.552
	(0.204)	(0.301)	(0.308)	(0.187)	(0.275)	(0.470)	(0.582)	(0.706)	(0.580)
△ln(Edu)$_{t-1}$			0.000						
			(0.195)						
△ln(Edu)$_{t-2}$			0.155						
			(0.139)						
△ln(Religion)$_{t-1}$				-0.092					
				(0.158)					
△ln(Religion)$_{t-2}$				0.217					
				(0.193)					
△ln(Comm)$_{t-1}$						-0.685***			
						(0.189)			
△ln(Comm)$_{t-2}$						0.033			
						(0.168)			
△ln(Art)$_{t-1}$							-0.428***		
							(0.121)		
△ln(Found)$_{t-1}$								-0.380***	
								(0.130)	
△ln(Other)$_{t-1}$									-0.453***

									(0.105)
Constant	0.012	0.056**	0.048**	0.014	0.001	0.067**	0.047	0.010	0.047
	(0.020)	(0.022)	(0.021)	(0.011)	(0.020)	(0.032)	(0.042)	(0.033)	(0.045)
Observations	28	31	29	29	31	29	30	30	30
Model	ARDL(3,0)	ARDL(0,0)	ARDL(2,0)	ARDL(2,0)	ARDL(0,0)	ARDL(2,0)	ARDL(1,0)	ARDL(1,0)	ARDL(1,0)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. All giving variables are real values. Macroeconomic indicator used is the real GDP per capita. Since trend is significant in the regression for giving to Education, Religion and Community, I assume that trend is non-linear to donation so that it is not cancelled out through first difference. The lag used in the analysis is the optimal lag based on Akaike Information Criterion (AIC). I conduct wild cluster bootstrap to take account of heteroskedasticity and auto-correlation. 95% of confidence interval of the estimated coefficient of real GDP per capita is reported right below the row of $\triangle \ln(\mathrm{RGDPC})_t$. In this test, I perform 10,000 of repetition with resample size 32. Cluster variable is year.

Table 1.10 Bootstrapped NARDL Estimation to Aggregate Donations, 1990-2021

Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Found)	△ln(Other)
Trend	-0.001	-0.001	-0.002**	-0.001**	0.000	-0.003**	-0.003	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
△ln(Total)$_{t-1}$	-0.184								
	(0.151)								
△ln(Total)$_{t-2}$	0.383**								
	(0.174)								
△ln(Total)$_{t-3}$	-0.076								
	(0.187)								
△ln(RGDPC_neg)$_t$	0.747**	-0.763**	1.105**	0.513	-0.122	0.308	0.274	2.455**	-0.142
	(0.287)	(0.353)	(0.411)	(0.344)	(0.338)	(0.652)	(0.778)	(1.124)	(0.616)
△ln(RGDPC_pos)$_t$	0.715**	0.206	-0.300	0.323	-0.248	1.062	-1.136	2.658**	1.174
	(0.336)	(0.589)	(0.393)	(0.241)	(0.688)	(0.780)	(0.966)	(1.139)	(1.298)
△ln(Edu)$_{t-1}$			-0.023						
			(0.197)						
△ln(Edu)$_{t-2}$			0.265						
			(0.159)						
△ln(Religion)$_{t-1}$				-0.107					
				(0.154)					
△ln(Religion)$_{t-2}$				0.222					
				(0.194)					
△ln(Comm)$_{t-1}$						-0.675***			
						(0.183)			
△ln(Comm)$_{t-2}$						0.023			
						(0.174)			
△ln(Art)$_{t-1}$							-0.428***		
							(0.120)		
△ln(Found)$_{t-1}$								-0.379***	

								(0.132)	
$\triangle\ln(\text{Other})_{t-1}$									-0.455***
									(0.109)
Constant	0.013	0.046**	0.059***	0.016	0.001	0.059	0.060	0.008	0.036
	(0.021)	(0.022)	(0.020)	(0.011)	(0.019)	(0.036)	(0.045)	(0.037)	(0.050)
Observations	28	31	29	29	31	29	30	30	30
Wald	0.00[0.94]	1.40[0.24]	4.69**[0.04]	0.17[0.68]	0.02[0.89]	0.47[0.50]	0.99[0.32]	0.01[0.90]	0.57[0.45]
Model	NARDL (3,0,0)	NARDL (0,0,0)	NARDL (2,0,0)	NARDL (2,0,0)	NARDL (0,0,0)	NARDL (2,0,0)	NARDL (1,0,0)	NARDL (1,0,0)	NARDL (1,0,0)

Note: Slight differences to table 1.9 include: negative and positive growth in real GDP per capita, such as $\triangle\ln(\text{RGDPC\_neg})_t$, $\triangle\ln(\text{RGDPC\_pos})_t$ and their corresponding 95% confidence intervals.

Table 1.11 Unit Root Test for Panel ARDL and Panel NARDL Model at Provincial Level

Method	Breitung		LLC	
Variables	Intercept	Trend and intercept	Intercept	Trend and intercept
At level				
ln(rgdpc)	0.808	0.630	-7.727***	-3.550***
ln(total)	0.291	0.902	-1.965**	-0.505
ln(poverty)	0.772	-0.233	-2.242**	-0.339
ln(edu)	-1.026	-1.288*	-2.107**	-1.135
ln(religion)	0.676	1.316	7.596	1.279
ln(health)	-2.131	-2.290**	-2.169**	-1.725**
ln(comm)	-1.403*	-0.705	-2.439***	-1.913**
ln(art)	-1.716**	0.450	-0.654	-0.202
ln(found)	0.425	-1.127	-2.886***	-2.311***
ln(other)	0.348	-0.736	-0.354	-1.770**
At first difference				
△ln(rgdpc)	-1.938**	-3.220***	-	-
△ln(rgdpc_neg)	-3.171***	-1.205	-6.849***	-5.818***
△ln(rgdpc_pos)	-1.656**	-0.256	-3.969***	-4.277***
△ln(total)	-5.110***	-3.404***	-	-5.512***
△ln(poverty)	-5.793***	-2.341***	-	-4.108***
△ln(edu)	-4.558***	-	-	-6.347***
△ln(religion)	-3.278***	-3.449***	-2.736***	-4.213***
△ln(health)	-4.382***	-	-	-
△ln(comm)	-	-2.996***	-	-
△ln(art)	-	-2.469***	-5.448***	-3.622***
△ln(found)	-4.603***	-2.980***	-	-
△ln(other)	-5.046***	-2.661***	-8.076***	-

Note: ***, ** and * denote that a series is stationary at 1%, 5% and 10% levels of significance, respectively.The lag used in the unit root test is one. Variables △ln(rgdpc_neg) and △ln(rgdpc_pos) denote the first difference of log of negative change in real GDP per capita at time t, the first differnce of the log of positive change in real GDP per capita at time t, respectively. The tests conducted in a row are Levin, Lin, and Chu (LLC) (Levin et al. 2002) and Breitung (2000; Breitung and Das (2005)) test. The null hypothesis of the tests is: panels contain unit roots. Both tests take account of cross-sectional correlation.

Table 1.12 Panel ARDL Estimation to Provincial Donations, 1990-2021

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(found)	△ln(other)
△ln(total)$_{t-1}$	-0.197***								
	(0.044)								
△ln(rgdpc)$_t$	0.474***	-0.214	0.882	0.301***	0.028	0.206	-0.586*	1.306	-1.159
	(0.124)	(0.255)	(0.485)	(0.072)	(0.291)	(0.606)	(0.312)	(0.962)	(1.183)
△ln(poverty)$_{t-1}$		-0.371***							
		(0.054)							
△ln(edu)$_{t-1}$			-0.306***						
			(0.055)						
△ln(religion)$_{t-1}$				-0.072**					
				(0.031)					
△ln(health)$_{t-1}$					-0.337***				
					(0.064)				
△ln(comm)$_{t-1}$						-0.310**			
						(0.109)			
△ln(art)$_{t-1}$							-0.256***		
							(0.026)		
△ln(found)$_{t-1}$								-0.365***	
								(0.056)	
△ln(other)$_{t-1}$									-0.481***
									(0.012)
Constant	0.020***	0.084***	0.073***	0.017***	-0.016	0.063*	0.084***	0.041	0.137**
	(0.005)	(0.015)	(0.016)	(0.003)	(0.019)	(0.030)	(0.020)	(0.028)	(0.043)
Observations	300	300	300	300	300	300	300	300	300

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. All giving variables are real donations per capita. Macroeconomic indicators used are real GDP per capita in each province. Trend term is significant to total giving, giving to Relief of Poverty, Education, Religion, and Community, indicating that trend is non-linear to donations at provincial level.The lag used in the analysis is the most common and optimal lag for each of province, based on AIC.

Table 1.13 Panel NARDL Estimation to Provincial Donations, 1990-2021

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(found)	△ln(other)
△ln(total)$_{t-1}$	-0.196***								
	(0.043)								
△ln(rgdpc_neg)	0.566**	-1.269**	0.361	0.313**	0.193	-0.545	-0.302	1.715	3.666
	(0.233)	(0.491)	(0.313)	(0.128)	(0.705)	(0.828)	(0.807)	(1.358)	(3.180)
△ln(rgdpc_pos)	0.406**	0.572	1.264	0.291***	-0.0940	0.764	-0.795	1.003	-4.743
	(0.177)	(0.361)	(0.856)	(0.0872)	(0.749)	(0.773)	(0.989)	(0.941)	(4.134)
△ln(poverty)$_{t-1}$		-0.386***							
		(0.052)							
△ln(edu)$_{t-1}$			-0.304***						
			(0.055)						
△ln(religion)$_{t-1}$				-0.072**					
				(0.031)					
△ln(health)$_{t-1}$					-0.337***				
					(0.065)				
△ln(comm)$_{t-1}$						-0.310**			
						(0.109)			
△ln(art)$_{t-1}$							-0.255***		
							(0.025)		
△ln(found)$_{t-1}$								-0.365***	
								(0.055)	
△ln(other)$_{t-1}$									-0.486***
									(0.015)
Constant	0.022***	0.067***	0.064**	0.017***	-0.013	0.050	0.089***	0.048	0.220*
	(0.007)	(0.020)	(0.024)	(0.004)	(0.024)	(0.030)	(0.026)	(0.028)	(0.109)
Wald	0.24[0.63]	7.51**[0.02]	0.83[0.36]	0.01[0.91]	1.91[0.17]	1.59[0.23]	0.30[0.58]	0.33[0.57]	1.34[0.27]
Observations	300	300	300	300	300	300	300	300	300

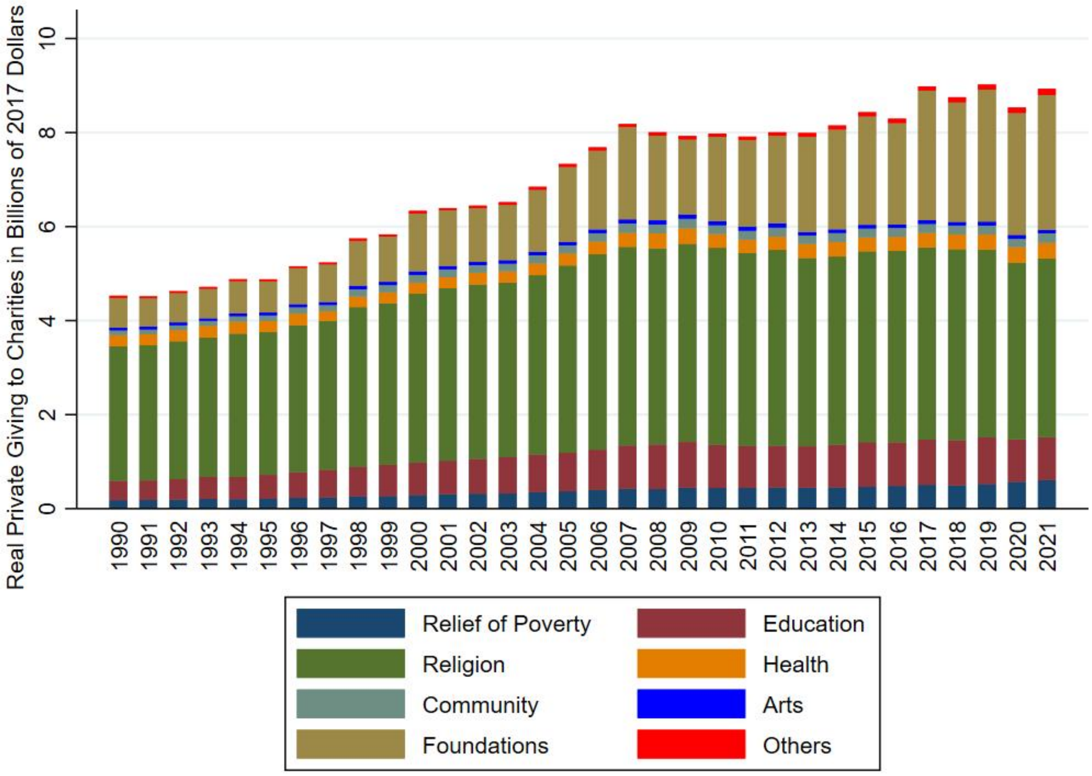
Note: Differences from table 1.12 include: △ln(rgdpc_neg) and △ln(rgdpc_pos) denote the first difference of the log of negative change in real GDP per capita at time t, the first difference of the log of positive change in real GDP per capita at time t, respectively

Table1.14 Summary of Significant Relationships Between Macroeconomic Indicators and Private Donations in ARDL, NARDL, Panel ARDL and Panel NARDL Model

<table>
<tr><th></th><th>Growth in GDP Per Capita</th><th>Positive Growth in GDP Per capita
vs.
Negative Growth in GDP Per Capita</th><th>Growth in Provincial GDP Per Capita</th><th>Positive Growth
in Provincial GDP Per Capita
vs.
Negative Growth in Provincial GDP Per Capita</th></tr>
<tr><td>ARDL</td><td>+ Total***
+ Religion*
+Foundation***</td><td></td><td></td><td></td></tr>
<tr><td>NARDL</td><td></td><td>+ Total** < + Total***
+ Poverty < |- Poverty|***
|- Education| < + Education***
+Foundation***>+Foundation**</td><td></td><td></td></tr>
<tr><td>Panel ARDL</td><td></td><td></td><td>+ total***
+ religion***</td><td></td></tr>
<tr><td>Panel NARDL</td><td></td><td></td><td></td><td>+ total**< + total**
+ poverty< |-poverty|**
+ religion*** < + religion**</td></tr>
</table>

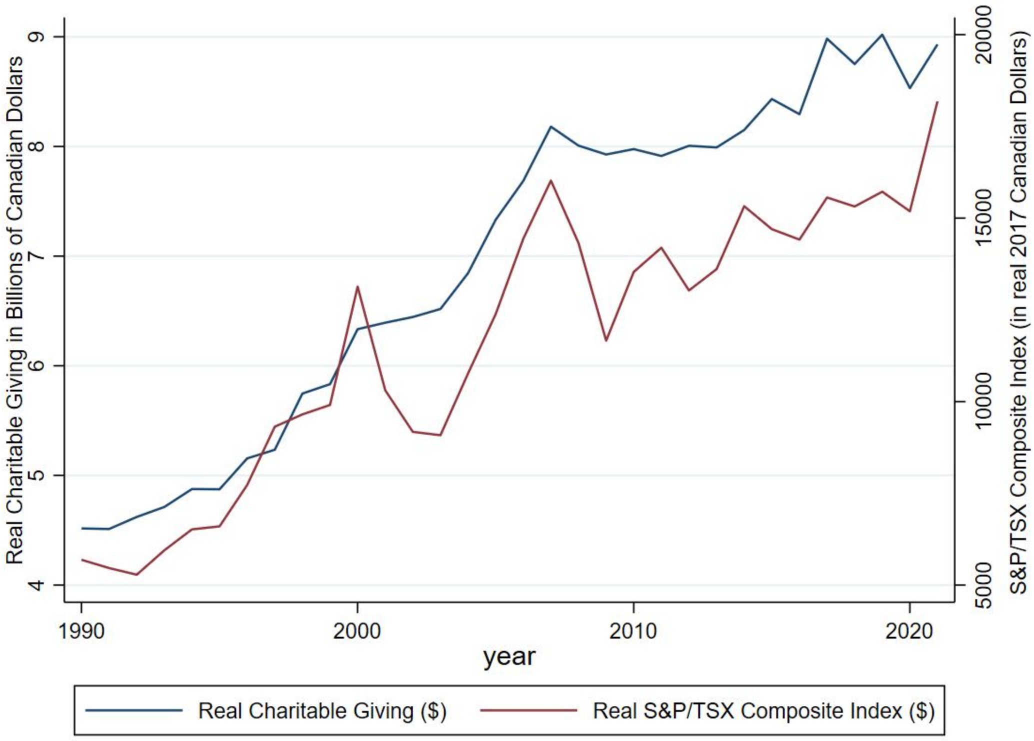
Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. The signs of "+" and "-" represent positive and negative relationships between the growth in macroeconomic indicators and the growth in private donations in the corresponding model, respectively. The signs of ">" and "<" denote the slope of giving in positive domain is larger or smaller than the slope in the negative domain. In the NARDL model, according to wald test, there is a significant asymmetry in growth of giving to Education in response to positive and negative changes in real GDP per capita. In the panel NARDL model, based on wald test, the change in total giving and giving to Relief of Poverty, Community and Foundation per capita is significantly asymmetric in response to changes in real GDP per capita. The last column compares the absolute value of slopes of giving to Relief of Poverty in response to positive and negative changes in current change in real GDP per capita.

Figure 1.1 Decomposition of Charitable Giving over Time (CA)



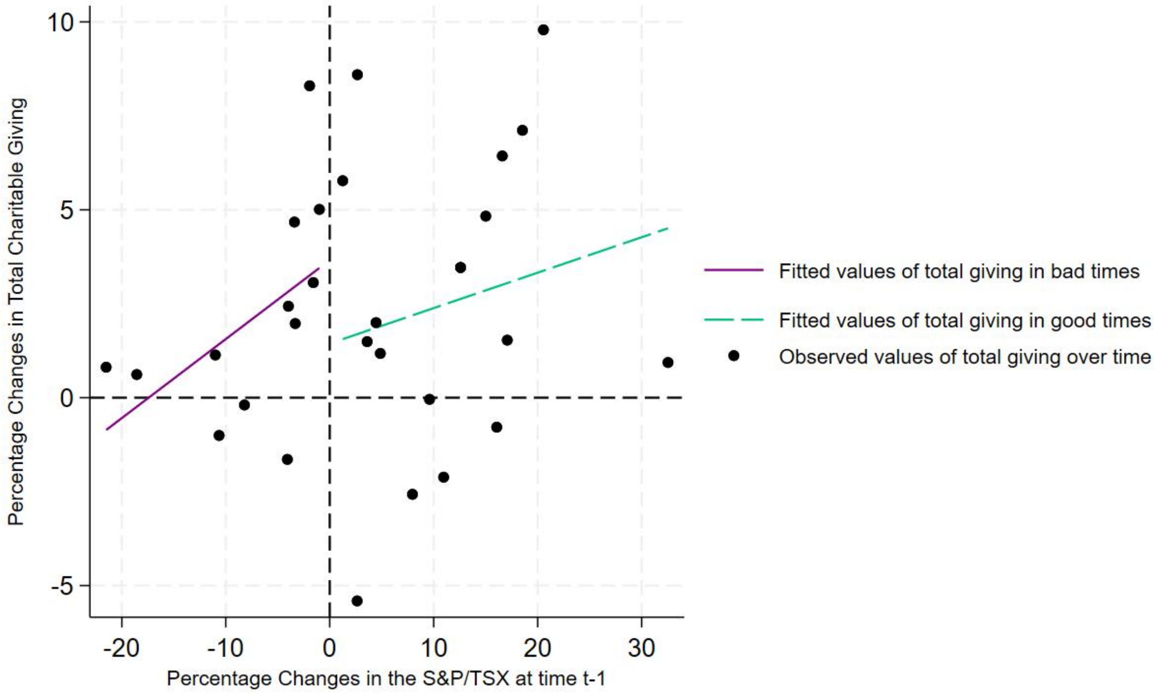
Source: author's calculations from the T3010 data base.

Figure 1.2 Real Charitable Giving and the S&P/TSX Index over Time (CA)



Source: author's calculations from the T3010 data base and stock market data (see table 1.1 for source).

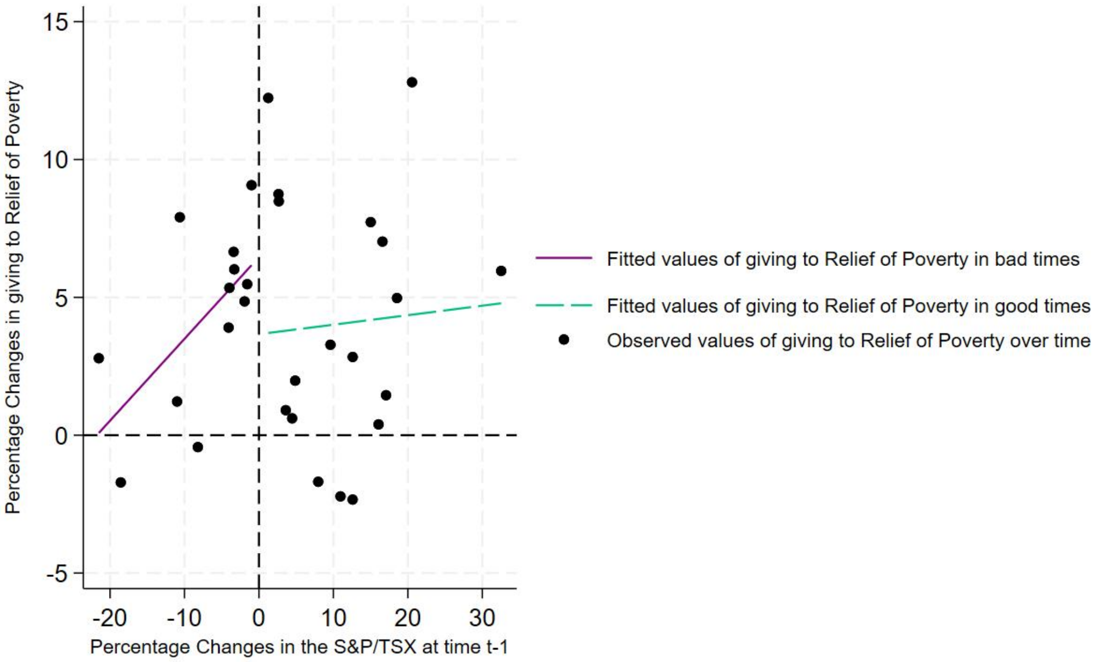
Figure 1.3 Changes in the S&P/TSX and Total Charitable Giving from 1992 to 2021 with Trendlines (CA)



Source: author's calculations from the T3010 data base and stock market data (see table 1.1 for source).

Note: I split the sample into observations with lagged sptsx < 0 and lagged sptsx > 0, and report separate slope estimates and bootstrap confidence intervals for each subsample. When lagged < 0, the slope of the fitted line is 0.21, with a 95% percentile bootstrap confidence interval of [0.05, 0.68], based on 10,000 replications of the original 12 observations. When lagged sptsx > 0, the slope is 0.09, with a bootstrap confidence interval of [−0.11, 0.49], based on 10,000 replications of the original 18 observations.

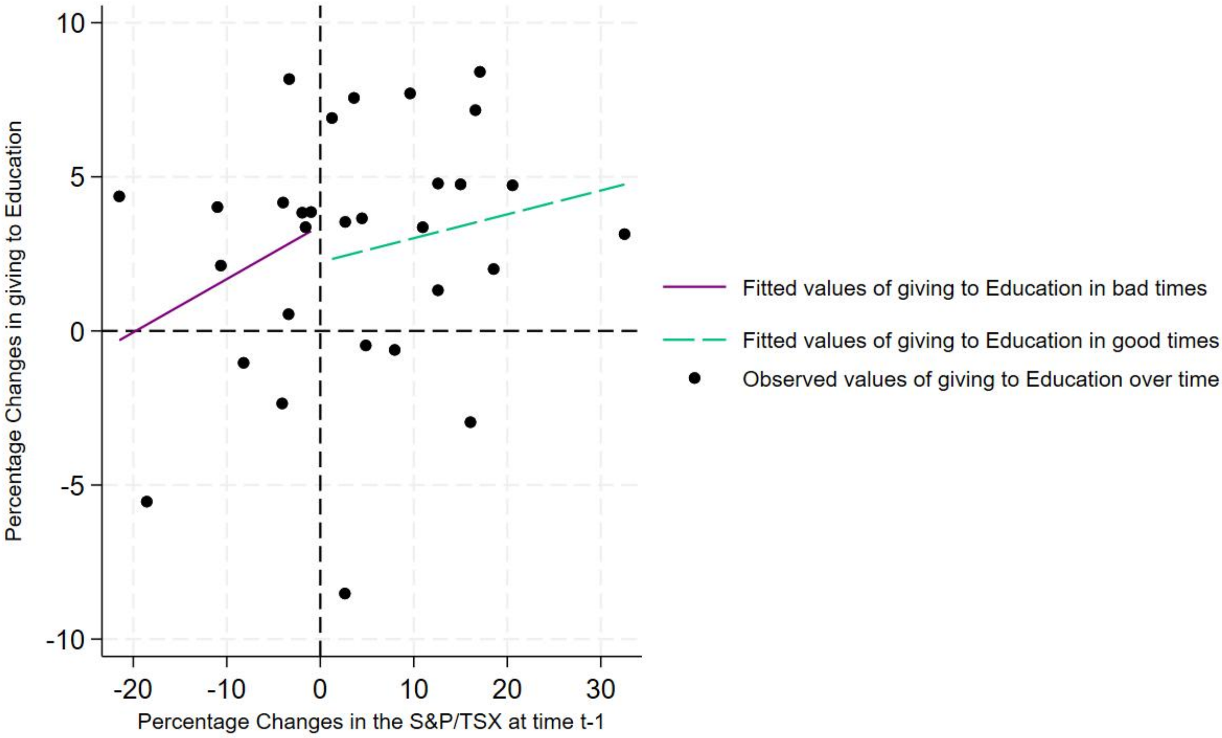
Figure 1.4 Changes in the S&P/TSX and Giving to Relief of Poverty from 1992 to 2021 with Trendlines (CA)



Source: author's calculations from the T3010 data base and stock market data (see table 1.1 for source).

Note: The difference from figure 1.3 is that when lagged sptsx < 0, the slope of the fitted line is 0.29, with a 95% percentile bootstrap confidence interval of [0.07, 0.65]. When lagged sptsx > 0, the slope is 0.03, with a bootstrap confidence interval of [−0.33, 0.36].

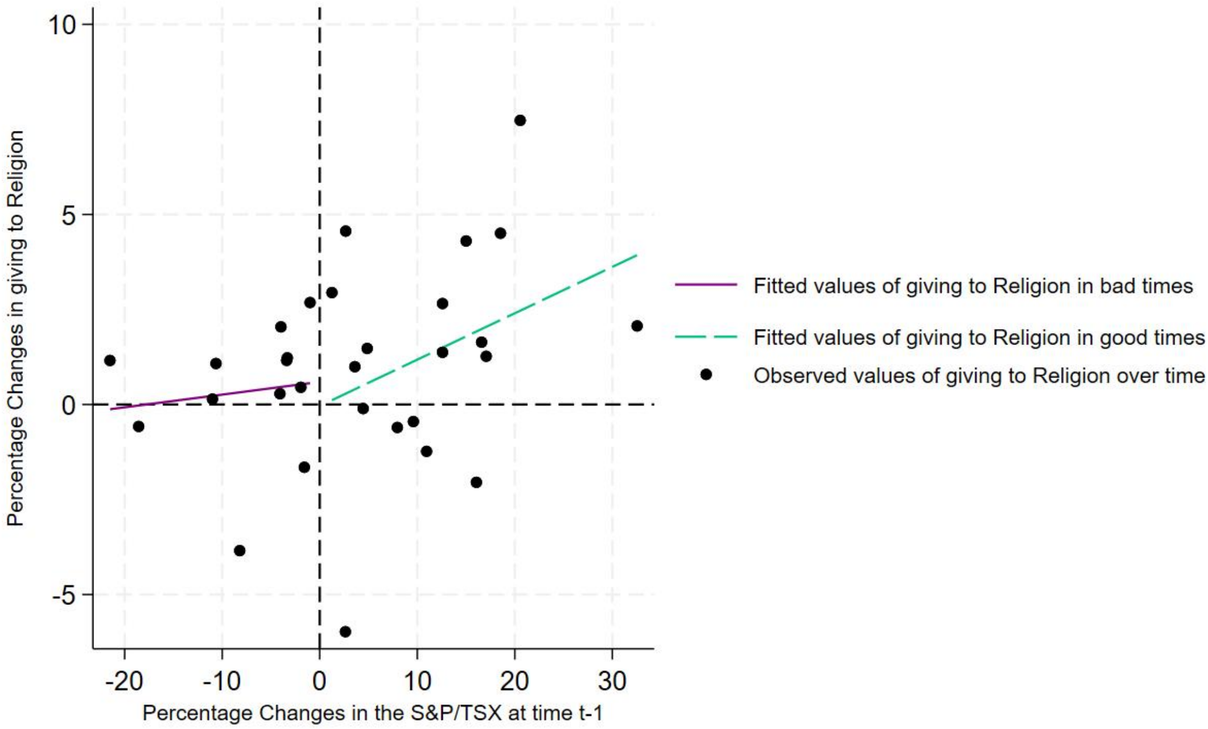
Figure 1.5 Percentage Changes in the S&P/TSX and Giving to Education from 1992 to 2021 with Trendlines (CA)



Source: author’s calculations from the T3010 data base and stock market data (see table 1.1 for source).

Note: The difference from figure 1.3 is that when lagged sptsx < 0, the slope of the fitted line is 0.17, with a 95% percentile bootstrap confidence interval of [−0.12, 0.59]. When lagged sptsx > 0, the slope is 0.07, with a bootstrap confidence interval of [−0.14, 0.42].

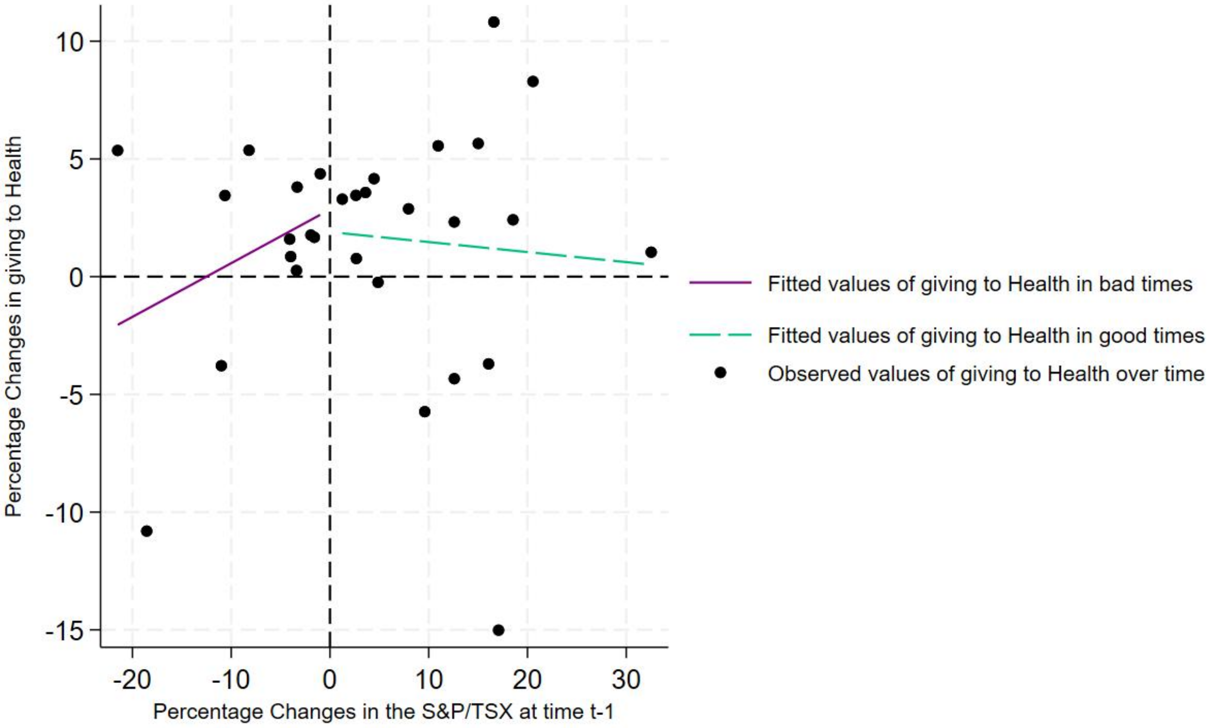
Figure 1.6 Percentage Changes in the S&P/TSX and Giving to Religion from 1992 to 2021 with Trendlines (CA)



Source: author's calculations from the T3010 data base and stock market data (see table 1.1 for source).

Note: The difference from figure 1.3 is that when lagged sptsx < 0, the slope of the fitted line is 0.03, with a 95% percentile bootstrap confidence interval of [−0.07, 0.27]. When lagged sptsx > 0, the slope is 0.12, with a bootstrap confidence interval of [−0.04, 0.39].

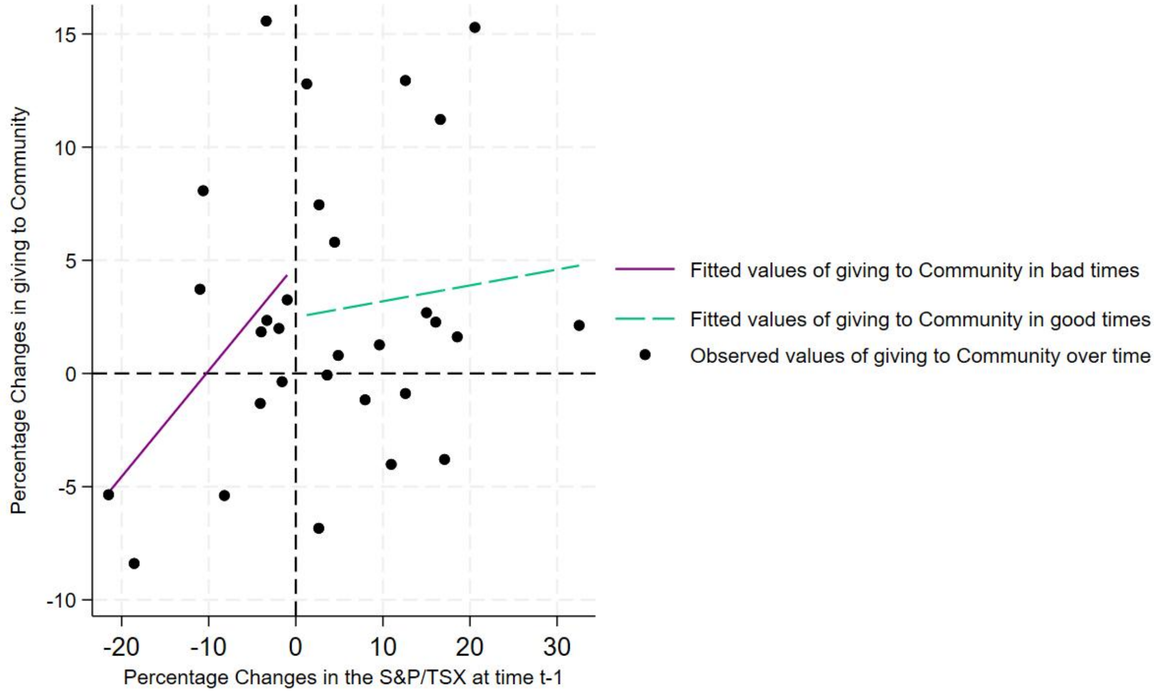
Figure 1.7 Percentage Changes in the S&P/TSX and Giving to Health from 1992 to 2021 with Trendlines (CA)



Source: author's calculations from the T3010 data base and stock market data (see table 1.1 for source).

Note: The difference from figure 1.3 is that when lagged sptsx < 0, the slope of the fitted line is 0.22, with a 95% percentile bootstrap confidence interval of [−0.21, 0.80]. When lagged sptsx > 0, the slope is -0.04, with a bootstrap confidence interval of [−0.45, 0.26].

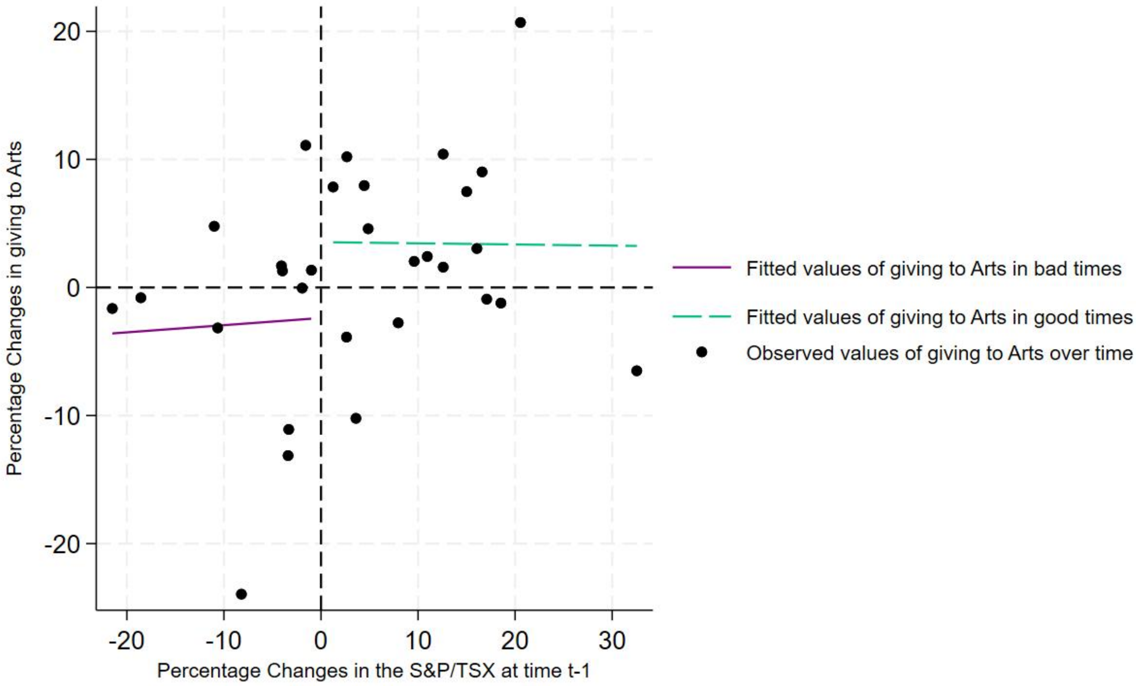
Figure 1.8 Percentage Changes in the S&P/TSX and Giving to Community from 1992 to 2021 with Trendlines (CA)



Source: author's calculations from the T3010 data base and stock market data (see table 1.1 for source).

Note: The difference from figure 1.3 is that when lagged sptsx < 0, the slope of the fitted line is 0.46, with a 95% percentile bootstrap confidence interval of [−0.32, 0.86]. When lagged sptsx > 0, the slope is 0.07, with a bootstrap confidence interval of [−0.30, 0.61].

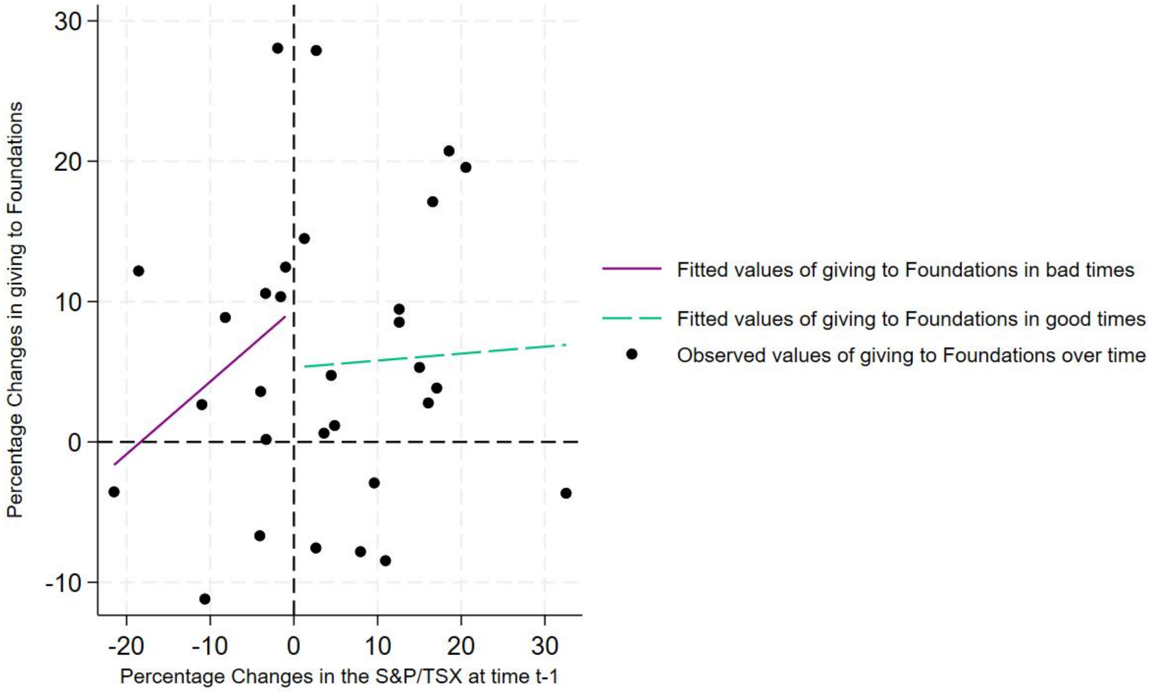
Figure 1.9 Percentage Changes in the S&P/TSX and Giving to Arts from 1992 to 2021 with Trendlines (CA)



Source: author's calculations from the T3010 data base and stock market data (see table 1.1 for source).

Note: The difference from figure 1.3 is that when lagged sptsx < 0, the slope of the fitted line is 0.05, with a 95% percentile bootstrap confidence interval of [−0.48, 1.43]. When lagged sptsx > 0, the slope is −0.01, with a bootstrap confidence interval of [−0.39, 0.83].

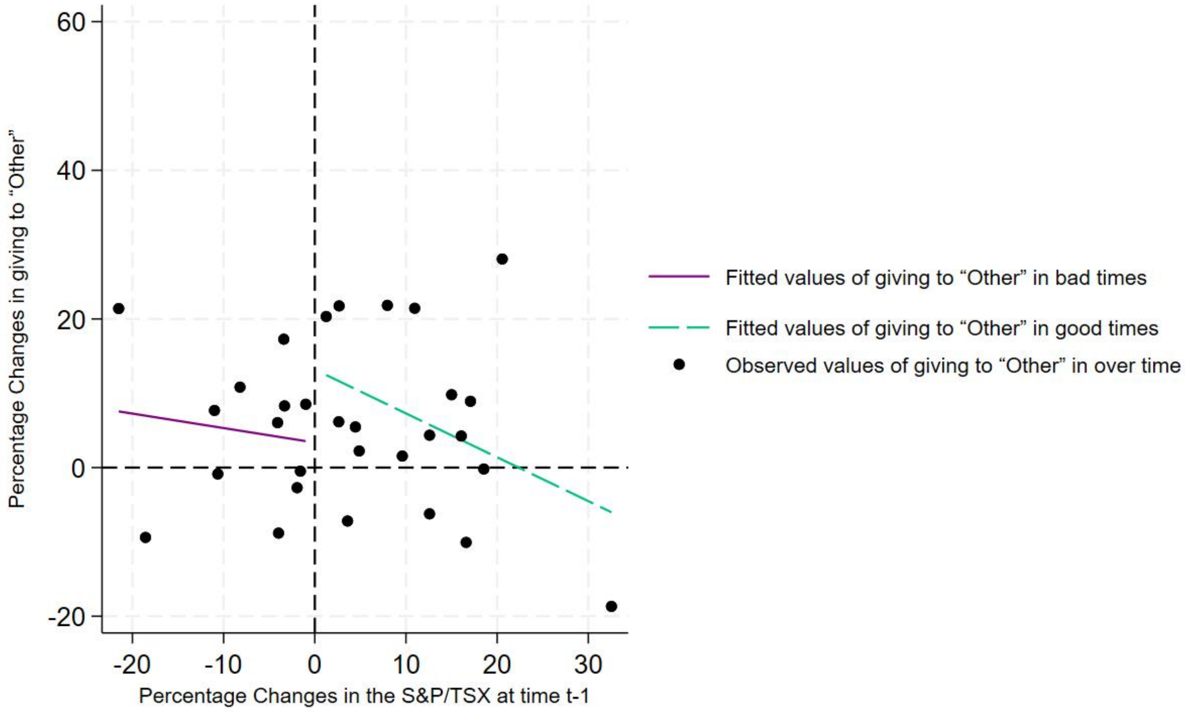
Figure 1.10 Percentage Changes in the S&P/TSX and Giving to Foundations from 1992 to 2021 with Trendlines (CA)



Source: author,s calculations from the T3010 data base and stock market data (see table 1.1 for source).

Note: The difference from figure 1.3 is that when lagged sptsx < 0, the slope of the fitted line is 0.51, with a 95% percentile bootstrap confidence interval of [−0.29, 2.22]. When lagged sptsx > 0, the slope is 0.04, with a bootstrap confidence interval of [−0.52, 1.13].

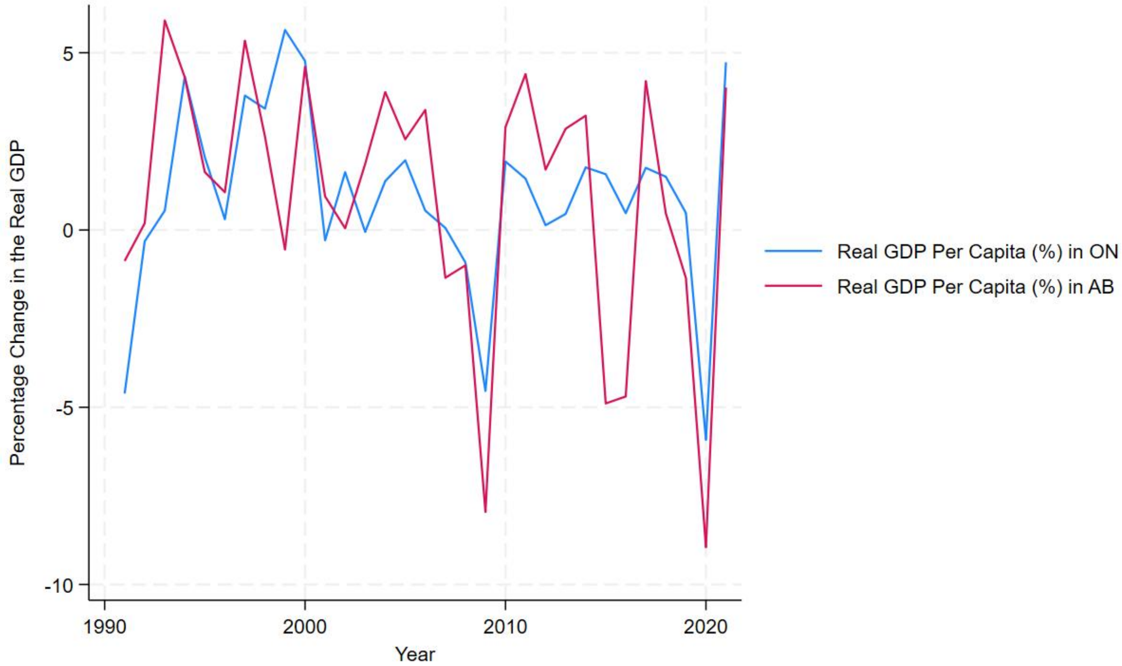
Figure 1.11 Percentage Changes in the S&P/TSX and Giving to "Other" from 1992 to 2021 with Trendlines (CA)



Source: author's calculations from the T3010 data base and stock market data (see table 1.1 for source).

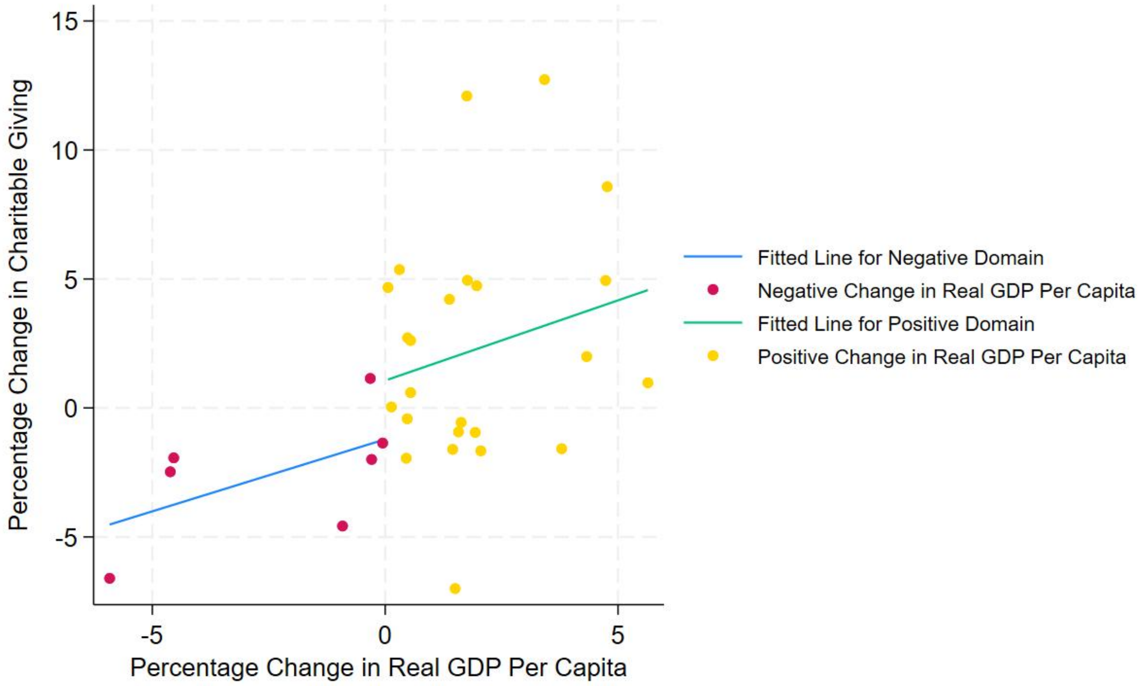
Note: The difference from figure 1.3 is that when lagged sptsx < 0, the slope of the fitted line is −0.19, with a 95% percentile bootstrap confidence interval of [−1.06, 0.96]. When lagged sptsx > 0, the slope is −0.59, with a bootstrap confidence interval of [−1.16, 0.59].

Figure 1.12 Percentage Changes in Real GDP in Ontario and Alberta from 1991 to 2021



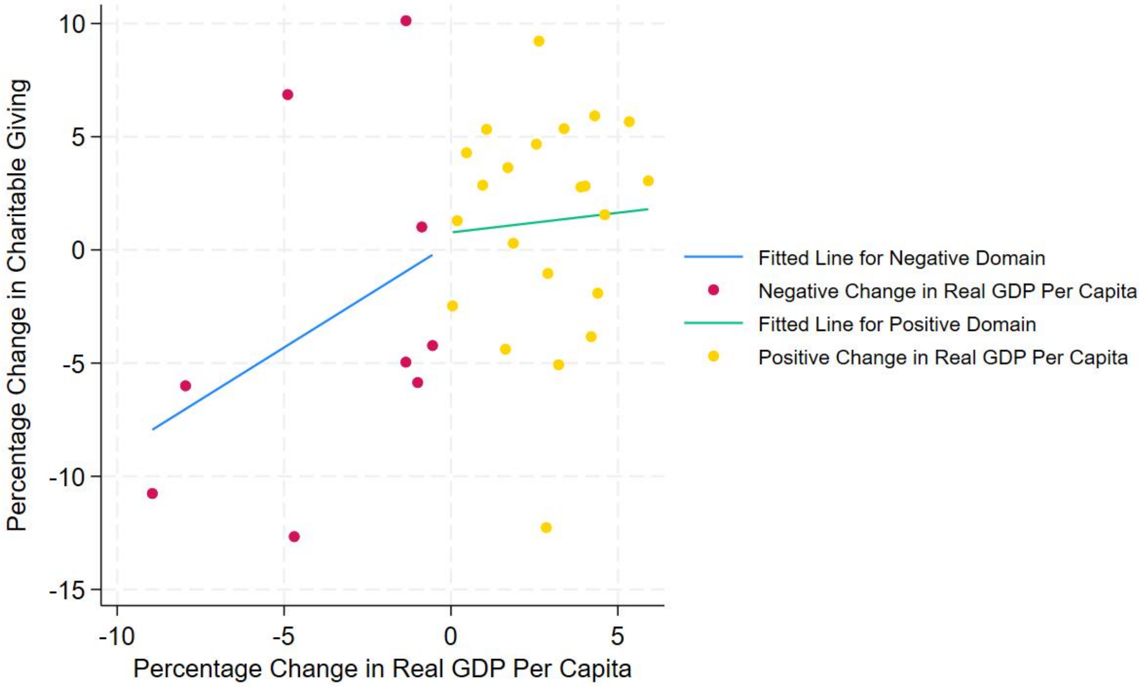
Source: author's calculations from the T3010 data base and GDP data (see table 1.1 for source).

Figure 1.13 Percentage Changes in Real GDP per capita and Real Charitable Giving per capita from 1991 to 2021 with Trendline (ON)



Source: author's calculations from the T3010 data base and GDP data (see table 1.1 for source)

Figure 1.14 Percentage Changes in Real GDP per capita and Real Charitable Giving per capita from 1991 to 2021 with Trendline (AB)



Source: author's calculations from the T3010 data base and GDP data (see table 1.1 for source).

APPENDIX 1.A: T3010 Data Problems and Solutions

1.1A Data Section

My sample period is from 1990 to 2021. The reason why I do not take year 2022 into account is that comparing to year 2021, year 2020 and year 2019 which have around 84 thousand charities in each year, year 2022 reports 75 thousand charities that might bias my analysis. In the following parts, I will present problems in T3010 and my solutions to tackle the problems.

Problem: Variable Consistency

The coding of the variables changes over the 32 years of my data set. After manually checking the copies of T3010 in each year, I conclude that the data structure can be generalized into four groups: 1990 to 1996, 1997 to 2002, 2003 to 2008, 2009 to 2021. The variables are coded the same within group but differently between groups. Taking the components of total revenue as an example, in the fiscal years of 1990 to 1996, line 100 denotes the amount of tax-receipted gift, excluding receipt from other registered charities, while from 1997 to 2002, line 100 represents the amount of tax-receipted gift, including receipts from other registered charities (line 101). Meanwhile, the same code means different things between different groups. For example, from 1994 to 1996, line 104 reports Investment and property income while from 1997 to 2002, line 104 shows federal grants. Starting from 2003, the variable codes become four-digit. Groups of 2003 to 2008, 2009 to 2021 have a slight difference in some of the variable codes, such as line 2000 in years of 2003 to 2008 means whether the domestic programs of the charity was carried out at the city level, province level or national level, however, the same line indicates whether the charity make gifts or transfer funds to qualified donees or other organizations in years of 2009 to 2021. Fortunately, the variables of interests have consistent codes for years 2003 to 2021. Also fortunately, I can render consistent all of the variables of interest by renaming codes, as I now discuss.

Solution

Referring to the coding rule and variable definitions after 2009 (as mentioned above, the data structure can be classified into four groups and 2009 to 2020 is the newest version of data structure), I rename line 100 (1994 to 1996) as line 4500 (the amount of tax-receipted gift for years 2003 to 2021) and the difference between line 100 and line 101 (1997 to 2002) as line 4500. For line 104 in 1994 to 1996, I rename it as line 4580, while for the same line in 1997 to 2002, I rename it as line 4540. As for line 2000, I keep it in years 2003 to 2008 while drop it in years 2009 to 2021, as I am interested in the locations of program activities not transfers to qualified donees.

Problem: Subordinate Status of Charities

From 1990 to 1996, information on whether the charity is a subordinate to an organization or a charity is not available. From 1997 to 2002 (2003 to 2008), there are two variables showing the subordinate status of a charity. For example, line 006 (line 1510) indicates whether the charity is an internal division of another charity and line 008 (line 1540) reports whether the charity is a subordinate to a provincial, national, or international organization. From 2009 to 2021, the two variables mentioned above are combined into one variable, that is line 1510, showing whether the charity is in a subordinate position to a parent organization.

Solution

For years 1997 to 2002 (2003 to 2008), I generate a variable _6_8 (_1510_1540) that equals to the value of line 006 (line 1510) or line 008 (line 1540) when either of them is not missing. When both lines are not missing, I take the value of line 008 (line 1540) as the value of newly generated variable _6_8 (_1510_1540), since its definition is closer to the definition of line 1510 after 2009. Then I rename variable _6_8 (_1510_1540) as line 1510.

There are 14.07% of charities in a subordinate position to a parent organization or charity: 11.98% of charities provide the business number of parent organizations that is different from the charity's own. In my analysis, I treat the subordinate charity and parent charity as independent ones, because I am interested in total donations to charities. I mention this issue only for the sake of completeness. If the parent organization transferred money to the subordinate charity, this would show up as another component of total revenues (transfers from other charities).

Problem: Missing Value in Tax-Receipted Gift (line 4500)

My initial usable sample size is 2,440,006. 15.8% of this sample does not report 'receipted gifts' (line 4500). As I am interested in receipted gifts (donations), I can back out this number using data on sources of revenue, as follows.

Solution

（1）Recalculate Line 4500 in the Non-missing Data of Line 4500

According to T3010, total revenue (line 4700) equals to the sum of tax-receipted gift (line 4500), total amount from other registered charities (line 4510), other gifts for which a tax receipt was not issued (line 4530), total revenue from governments (line 4570), non tax-receipted revenue from all sources outside Canada (line 4575), interest and investment income received or earned (line 4580), net proceeds from disposition of assets (line 4600), gross income received from rental of land and/or buildings (line 4610), revenues received for memberships, dues and association fees (line 4620), revenue from fundraising (line 4630), revenue from sale of goods and services (line 4640), other revenue (line 4650). Among which, line 4570 is composed of revenues from federal government (line 4540), from provincial/territorial governments (line 4550), or from municipal/regional governments (line 4560) (prior to 2009, total government grants are reported not by level of government). I am able to calculate line 4500 using total revenue and subtracting off all of the subcomponents just mentioned. I do this and then compare the 'estimated' receipted gifts with the 'actual' receipted gifts for the 84.2% of the sample which reports receipted gifts. The non-missing private donation data has 2,053,701 observations. Private donations denoted by tax-receipted gift is a portion of total revenue.

Of the 2,053,701 observations that report receipted gifts on line 4500, I drop observations that components of total revenues are all missing (25,387 observations), drop charities which never report any private donations every year (4,394 charities out of 128,498 in total), drop charities which always report negative private donations every year (one charity), drop charities filed twice (6,038 charities – likely because they changed their fiscal years). I initially have a **80.19%** match when I recalculate the receipted gifts by subtracting the components from total revenue.

For the 19.81% of the sample that does not match up, most of them (**11.5%** of total observations) are within **one hundred Canadian dollars** between the recalculated receipted gifts and the actual reported gifts. I replaced the original line 4500 with the recalculated one, since the minor difference might be caused by errors in reporting. For the remaining 8.5% of the sample where the recalculated receipted gifts do not line up with the reported receipted gifts, a small fraction (about 1.3% of the total sample) has to file schedule 6 which means that they are larger charities with revenue of $100,000 or more. For this group of larger charities, I assume that they are more likely to accurately report total revenues when compared to smaller charities, and hence I assume that my recalculated receipted gifts are accurate. In the end, I have **92.1%** of recalculated line 4500 matched with original line 4500. Then I generate a dummy variable _4500equal1 which equals to one when original line 4500 equals to recalculated line 4500.

All calculations are based on a comparison of reported receipted gifts with recalculated receipted gifts. More than 90 percent of the match between non-missing line 4500 and recalculated line 4500 validates that this method can be applied to the recalculation of the actual missing values in line 4500. Finally, I used the sample that excludes the 15.8% of the sample that did not report receipted gifts in one of my robustness checks. It did not affect my main results.

(2) Check Annual Reports of Charities with Missing Value in Line 4500

In addition to the above, I also checked the annual reports of some of the charities that failed to provide receipted gifts. I picked out some charities with annual reports that were readily available. In some annual reports, private donations are not provided. So, the only way to check if the recalculated line 4500 is accurate is to look at total revenues in the annual reports. I find that in cases when the recalculated line 4500 are positive or zero, the annual reports I refer to have consistent values in total revenue to T3010's (examples from Western Grain Research Foundation,[17] Manitoba Adolescent Treatment Centre Inc,[18] London Health Sciences Centre,[19] The Board of Education of School District No.59[20]). When the recalculated line 4500 are negative, it is highly likely that total revenues of the charity is misreported (see example from Atikokan General Hospital[21]). As for the negative recalculated line 4500, I drop them when the original line 4500 are missing.

Problem: Outliers in Data with Missing Value and Non-missing Value in Original Line 4500

Most of the missing values for the receipted gifts are for small charities. Based on Penner (2017) who uses one million and five million Canadian dollars of total revenue as cutoffs for small, medium and large charities. I find that 87.4% of the missing values in line 4500 are from 'small' charities (under $1m in total revenues), 8.25% from medium charities ($1m-5m), and 4.35% from large charities.

When my recalculated receipted gift estimate is three times larger than the historically largest non-missing gift, I consider these to be outliers. I have 0.16% observations as outliers for the recalculated gift. Outliers may exist in the non-missing values. In this case, I drop observations higher than 99 percentile of line 4500 by province, by year and by category of charities.

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17 FINAL-WGRF_2016AnnualReport_web.pdf
18 About Us - MATC
19 LHSC Publications | LHSC
20 Financial Information | School District 59 (sd59.bc.ca)
21 Reports - Hospital Annual Report - Atikokan General Hospital (aghospital.on.ca)

1.2A Local, National and International Charities

From 1997 to 2008, charities were required to report on the T3010 form the location of their activities. The definition to service locations changed throughout this period: from 1997 to 1998, location was defined as four groups (single municipality, within one province or territory, within more than one province or territory, and throughout Canada). From 1999 to 2002, location was defined as five groups: within a single municipality, within a region or metropolitan area, within one province or territory, within more than one province or territory, and throughout Canada. From 2003 to 2008, location was defined as three groups: in a single rural municipality, city, or metropolitan area, in one province or territory, or in more than one province or territory. I recalculated the location of activities throughout the 1997-2008 period into three groups: I define a charity as 'local' if its program was carried on in a single rural, city, or metropolitan area or provincially or territorially; and "national" if a charity's activities were carried out in more than one province or territory. The third group is "international" charities. Throughout the entire period of my data, 1990-2021, charities must report if more than 50% of total expenditures occur outside of Canada (information provided by email from the research director of Charity Intelligence, Greg Thomson).

I have 118,065 charities in total and all of them indicate if their activities are 'international'. 91,420 of charities (77.4% of total charities) report if their service locations are 'local' or 'national'. For the annulled charities before 1997 or the new entrants after 2008 this information is missing. In this paper, I removed those charities operating internationally when I conducted the time-series national aggregate analysis as well as provincial-based analysis. Overall, there are 4.91% international charities, on average accounting for 6.29% of total private donations. My final sample size is 2,236,318 observations.

In the robustness check, I consider charities providing local services in provincial data, since charities operating locally are more likely to be affected by provincial macroeconomic conditions. I checked if any charity changed its program location during the sample period, and found that 10,765 charities change between local and national, 2,399 charities change between local and international, 1,595 charities change between national and international. I dropped 14,759 charities that reported more than one location of activities over time. I also dropped 1,769 charities on charities that changed their names over the sample period. Because charities did not have to report the location of their activities after 2008 (except for international charities, which is defined based on expenditures outside of the country), I assumed that the location of activities in 2008 for the charity remained fixed for the rest of the sample. I have 60% of charities proving local services in robustness tests.

1.3A Categories of Charities

The T3010 data set requires charities to indicate their main area of activity. Before 2013, charities could choose from six areas: benefit to community, education, health, religion, welfare and other. From 2013 onwards, charities could choose from four general fields: relief of poverty, education, religion and other. (Until 2017, the T3010 data set provided information on six areas as there was an overlap during the transition from six to four fields of activity). In the latest version of the data set (1990 to 2022 although I only use until 2021), I decompose other fields into health, community, arts, Foundations and 'Other'. Altogether I have eight fields to reported.

I was able to render consistent the definitions of activities over time based on the mapping table provided by Revenue Canada of the old category codes (before 2012) and new category and sub-category code (after 2013). I was able to reclassify charities into four types referring to the category and subcategory codes provided by the CRA.

1.4A Schedule 6 Charities

From 2009 onwards, charities are required to fill in schedule 6 when one of following conditions applies:

(1) The charity's revenue exceeds $100,000;

(2) The amount of all property (for example, investments, rental properties) not used in charitable activities is more than $25,000;

(3) The charity has permission to accumulate funds during this fiscal period;

(4) The charity has spent or transferred enduring property during this fiscal period

This classification does not affect my analysis for this paper. I am providing this information for completeness.

APPENDIX 1.B: Model

1.1B ARDL Model and NARDL Model in the Error Correction Form

According to Philips (2018), the general time-series ARDL(p,q) model is specified as follows:

$$D_t = \alpha_0 + \tau t + \sum_{j=1}^{p} \alpha_j D_{t-j} + \sum_{j=0}^{q} \beta_j GDP_{t-j} + \varepsilon_t,\ \varepsilon_t \sim N(0, \sigma^2) \quad \text{(a1.1)}$$

Then transform equation (a1) in the error correction form as suggested by Philips (2018):

$$\Delta D_t = \alpha_0 + \tau t + \sum_{j=1}^{p-1} \theta_j \Delta D_{t-j} + \sum_{j=0}^{q-1} \delta_j \Delta GDP_{t-j} + \gamma_1 D_{t-1} + \varphi_1 GDP_{t-1} + \varepsilon_t$$

$$= \alpha_0 + \tau t + \sum_{j=1}^{p-1} \theta_j \Delta D_{t-j} + \sum_{j=0}^{q-1} \delta_j \Delta GDP_{t-j} + \gamma_1 (D_{t-1} - \beta_1 GDP_{t-1}) + \varepsilon_t$$

$$= \alpha_0 + \tau t + \sum_{j=1}^{p-1} \theta_j \Delta D_{t-j} + \sum_{j=0}^{q-1} \delta_j \Delta GDP_{t-j} + \gamma_1 ECT(-1) + \varepsilon_t \quad \text{(a1.2)}$$

where $\gamma_1 = \sum_{j=1}^{p} \alpha_j - 1$; $\theta_j = -\sum_{k=j+1}^{p} \alpha_k$, for j = 1,..., p-1; $\delta_j = -\sum_{k=j+1}^{q} \beta_j$ for j = 1, ..., q-1; $\delta_0 = \beta_0$; $\varphi_1 = \sum_{j=0}^{q} \beta_j$; $\beta_1 = -\varphi_1/\gamma_1$. $ECT(-1)$ denotes the error-correction term at time t-1. The existence of long-run relationship (cointegration) technically means a linear combination of two or more first-order nonstationary series generates a stationary series (Philips, 2018), for instance, the residual in the parenthesis of equation (a2) is stationary and D_t , GDP_t are integrated of order one *I(1).* The parameter γ_1 denotes the adjustment rate to equilibrium in the long-term dynamics. Only when γ_1 is negative and significant, donations converge to stabilization. β_1 indicates the long-run relationship between the changes in GDP_t and D_t. δ_j represent the estimated short-term coefficients linking real GDP growth with its past values and the growth in donations.

Following Shin, Yu and Greenwood-Nimmo (2014), NARDL model is written as:

$$D_t = \alpha_0 + \tau t + \sum_{j=1}^{p} \alpha_j D_{t-j} + \sum_{j=0}^{q} (\beta_j^+ GDP_{t-j}^+ + \beta_j^- GDP_{t-j}^-) + \varepsilon_t,\ \varepsilon_t \sim N(0, \sigma^2) \text{(a1.3)}$$

The error correction is then rewritten as:

$$\Delta D_t = \alpha_0 + \tau t + \sum_{j=1}^{p-1} \theta_j \Delta D_{t-j} + \sum_{j=0}^{q-1} (\delta_j^+ \Delta GDP_{t-j}^+ + \delta_j^- \Delta GDP_{t-j}^-) + \gamma_1 D_{t-1} + \varphi_1^+ GDP_{t-1}^+ + \varphi_1^- GDP_{t-1}^- + \varepsilon_t$$

$$= \alpha_0 + \tau t + \sum_{j=1}^{p-1} \theta_j \Delta D_{t-j} + \sum_{j=0}^{q-1} (\delta_j^+ \Delta GDP_{t-j}^+ + \delta_j^- \Delta GDP_{t-j}^-) + \gamma_1 (D_{t-1} - \beta_1^+ GDP_{t-1}^+ - \beta_1^- GDP_{t-1}^-) + \varepsilon_t$$

$$= \alpha_0 + \tau t + \sum_{j=1}^{p-1} \theta_j \Delta D_{t-j} + \sum_{j=0}^{q-1} (\delta_j^+ \Delta GDP_{t-j}^+ + \delta_j^- \Delta GDP_{t-j}^-) + \gamma_1 ECT(-1) + \varepsilon_t \quad \text{(a1.4)}$$

where $\gamma_1 = \sum_{j=1}^{p} \alpha_j - 1$; $\theta_j =- \sum_{k=j+1}^{p} \alpha_k$, for j = 1,..., p-1; $\delta_j^+ =- \sum_{k=j+1}^{q} \beta_j^+$ for j = 1, ..., q-1; $\delta_0^+ = \beta_0^+$; $\varphi_1^+ = \sum_{j=0}^{q} \beta_j^+$; $\beta_1^+ =- \varphi_1^+/\gamma_1$; $\delta_j^- =- \sum_{k=j+1}^{q} \beta_j^-$ for j = 1, ..., q-1; $\delta_0^- = \beta_0^-$; $\varphi_1^- = \sum_{j=0}^{q} \beta_j^-$; $\beta_1^- =- \varphi_1^-/\gamma_1$.

I define the asymmetric variables following Hansen (2000):

$$\Delta GDP_{t-j}^{+} = \Delta GDP_{t-j} I_{t-j}^{+}, where\ I_{t-j}^{+} = \begin{cases} 1, if\ \Delta GDP_{t-j} \geq 0 \\ 0, if\ \Delta GDP_{t-j} < 0 \end{cases} \quad \text{(a1.5)}$$

$$\Delta GDP_{t-j}^{-} = \Delta GDP_{t-j} I_{t-j}^{-}, where\ I_{t-j}^{-} = \begin{cases} 1, if\ \Delta GDP_{t-j} \leq 0 \\ 0, if\ \Delta GDP_{t-j} > 0 \end{cases} \quad \text{(a1.6)}$$

$$GDP_t^{+} = GDP_t I_t^{+}, where\ I_t^{+} = \begin{cases} 1, if\ \Delta GDP_t \geq 0 \\ 0, if\ \Delta GDP_t < 0 \end{cases} \quad \text{(a1.7)}$$

$$GDP_t^{-} = GDP_t I_t^{-}, where\ I_t^{-} = \begin{cases} 1, if\ \Delta GDP_t \leq 0 \\ 0, if\ \Delta GDP_t > 0 \end{cases} \quad \text{(a1.8)}$$

1.2B Derivation of Partial Sum Decomposition in the NARDL model

In Schorderet (2001)'s study, suppose that unemployment is a function of output and other determinants.

$$u_t = \beta y_t + \tau' z_t, \beta < 0 \quad \text{(a1.9)}$$

Since $u_t = u_0 + (u_t - u_{t-1}) + (u_{t-1} - u_{t-2}) + \ldots + (u_2 - u_1) + (u_1 - u_0) = u_0 + \sum_{i=1}^{t} \Delta u_i$

Then rewrite:

$$u_t = \alpha + \beta^+ y_t^+ + \beta^- y_t^- + \tau' z_t \quad \text{(a1.10)}$$

where $\alpha = u_0 - \tau' z_0$, $y_t^+ = \sum_{i=0}^{t} I(\Delta y_i > 0)\Delta y_i$, $y_t^- = \sum_{i=0}^{t} I(\Delta y_i < 0)\Delta y_i$

1.3B Panel ARDL Model and Panel NARDL Model in the Error Correction Form

Following Pesaran et al. (1999), I specify the panel ARDL(p, q) model as:

$$D_{it} = \alpha_0 + \sum_{j=1}^{p} \alpha_{ij} D_{i,t-j} + \sum_{j=0}^{q} \beta_{ij} GDP_{i,t-j} + \mu_i + \tau_t + \varepsilon_{it},\ \varepsilon_{it} \sim N(0, \sigma^2) \quad \text{(a1.11)}$$

I rewrite equation (a11) in the error-correction form:

$$\Delta D_{it} = \alpha_0 + \sum_{j=1}^{p-1} \theta_{ij} \Delta D_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij} \Delta GDP_{i,t-j} + \gamma_i D_{i,t-1} + \varphi_{1i} GDP_{i,t-1} + \mu_i + \tau_t + \varepsilon_{it}$$

$$= \alpha_0 + \sum_{j=1}^{p-1} \theta_{ij}\, \Delta D_{i,\,t-j} + \sum_{j=0}^{q-1} \delta_{ij}\, \Delta GDP_{i,\,t-j} + \gamma_i (D_{i,\,t-1} - \beta_{1i} GDP_{i,\,t-1}) + \mu_i + \tau_t + \varepsilon_{it}$$

$$= \alpha_0 + \sum_{j=1}^{p-1} \theta_{ij}\, \Delta D_{i,\,t-j} + \sum_{j=0}^{q-1} \delta_{ij}\, \Delta GDP_{i,\,t-j} + \gamma_i ECT(-1) + \mu_i + \tau_t + \varepsilon_{it} \quad \text{(a1.12)}$$

where D_{it} denotes aggregate donation in total and by area in province *i* at time *t;* μ_i represents the provincial fixed effect; α_{ij} and β_{ij} are scalars; *i* = 1, 2, ..., *N*; *t* = 1, 2, ..., *T*; *p* and *q* are time lags. The rest of denotations are similar to equation (a2) in the ARDL model.

Following Pesaran et al. (1999) and Shin, Yu and Greenwood-Nimmo (2014), I construct the panel NARDL(*p, q*) model as:

$$D_{it} = \alpha_0 + \sum_{j=1}^{p} \alpha_{ij}\, D_{i,\,t-j} + \sum_{j=0}^{q} \beta_{ij}\, (GDP_{i,t-1}^{+} + GDP_{i,t-1}^{-}) + \mu_i + \tau_t + \varepsilon_{it},\ \varepsilon_{it} \sim N(0, \sigma^2)$$

(a1.13)

Then rewrite equation (a13) as:

$$\Delta D_{it} = \alpha_0 + \sum_{j=1}^{p-1} \theta_{ij}\, \Delta D_{i,\,t-j} + \sum_{j=0}^{q-1} (\delta_{ij}^{+}\, \Delta GDP_{i,t-j}^{+} + \delta_{ij}^{-} \Delta GDP_{i,t-j}^{-}) + \gamma_i D_{i,\,t-1} +$$
$$\varphi_{1i}^{+} GDP_{i,t-1}^{+} + \varphi_{1i}^{-} GDP_{i,t-1}^{-} + \mu_i + \tau_t + \varepsilon_{it}$$

$$= \alpha_0 + \sum_{j=1}^{p-1} \theta_{ij}\, \Delta D_{i,\,t-j} + \sum_{j=0}^{q-1} (\delta_{ij}^{+}\, \Delta GDP_{i,t-j}^{+} + \delta_{ij}^{-} \Delta GDP_{i,t-j}^{-}) + \gamma_i (D_{i,\,t-1} - \beta_{1i}^{+} GDP_{i,t-1}^{+} -$$
$$\beta_{2i}^{-} GDP_{i,t-1}^{-}) + \mu_i + \tau_t + \varepsilon_{it}$$

$$= \alpha_0 + \sum_{j=1}^{p-1} \theta_{ij}\, \Delta D_{i,\,t-j} + \sum_{j=0}^{q-1} (\delta_{ij}^{+}\, \Delta GDP_{i,t-j}^{+} + \delta_{ij}^{-} \Delta GDP_{i,t-j}^{-}) + \gamma_i ECT(-1) + \mu_i + \tau_t$$
$$+ \varepsilon_{it} \quad \text{(a1.14)}$$

where denotations are similar to the equation (a1.14) in the NARDL model. GDP_{it} can be also be decomposed into $GDP_{it} = GDP_{i0} + GDP_{it}^{-} + GDP_{it}^{+}$. GDP_{it}^{-} and GDP_{it}^{+} separately capture negative and positive change in real GDP in province *i* at time *t*, around a threshold of zero. The asymmetric level and first difference variables are also defined based on studies from Hansen (2000), a slight difference to equations (a5), (a6), (a7) and (a8) is to add an extra index of individual province *i.*

To estimate equation (a1.14), generally three estimation methods are used: the mean-group (MG) developed by Pesaran and Smith (1995), pooled mean-group (PMG) developed by Pesaran et al. (1999), and the dynamic fixed effect (DFE) (Hsiao et al. 2002). Assumptions differ in three methods. The PMG approach allows estimated short-term coefficients, including intercepts and speed of adjustment (i.e., the estimated coefficient of *ECT(-1)*) to long-term equilibrium values, to be heterogeneous by province. Whereas the long-term slope of estimated coefficients are restricted to be homogeneous across provinces.

The MG technique allows for all estimated coefficients to vary and be heterogeneous in the long and short terms, based on a sufficiently large time-series dimension of the data. The DFE method restricts all but intercepts to be homogeneous across provinces.[22]

1.4B Assumptions in PMG, MG and DFE Methods in the Panel ARDL and Panel NARDL Model

Use the panel ARDL model specification as an example, since panel NARDL is analogous to panel ARDL. Under PMG, according to Pesaran et al. (1999), the estimated long-run coefficient in my analysis should be:

$$\widehat{\beta}_{1i} = \widehat{\beta}_1 = -\left\{\sum_{i=1}^{N} \frac{\hat{\gamma}_i^2}{\hat{\sigma}_i^2} GDP_{it}^2 H_{it}\right\}^{-1} \times \left\{\sum_{i=1}^{N} \frac{\hat{\gamma}_i^2}{\hat{\sigma}_i^2} GDP_{it} H_{it} (\Delta D_{it} - \hat{\gamma}_i D_{i,\,t-1})\right\} \quad \text{(a1.15)}$$

where $\hat{\gamma}_i = (\widehat{\omega}_{it}^2 H_{it})^{-1} \widehat{\omega}_{it} H_{it} \Delta D_{it}$; $\widehat{\sigma}_i^2 = T^{-1}(\Delta D_{it} - \hat{\gamma}_i \widehat{\omega}_{it}) H_{it} (\Delta D_{it} - \hat{\gamma}_i \widehat{\omega}_{it})$;

$\omega_{it}(\widehat{\beta}_{1i}) = D_{i,\,t-1} - \widehat{\beta}_{1i} GDP_{i,\,t-1}$;

$H_{it} = 1 - \pi_{it}(\pi_{it}^{'}\pi_{it})^{-1}\pi_{it}^{'}$;

$\pi_{it} = (\Delta D_{i,\,t-1}, \ldots, \Delta D_{i,\,t-p-1,}\, \Delta GDP_{it}, \Delta GDP_{i,\,t-1}, \ldots, \Delta GDP_{i,\,t-q+1})$;

π_{it} is a vector of $1 \times (p - 1 + q)$. Start with an initial value of $\widehat{\beta}_{1i}$, say $\widehat{\beta}_{1i}^0$, to estimate $\widehat{\gamma}_i$ and $\widehat{\sigma_i^2}$. Then re-estimate $\widehat{\beta}_{1i}$ and obtain a new value say $\widehat{\beta}_{1i}^1$. Repeat the steps until convergence is achieved. Under MG, I do not need to obtain the converged value of $\widehat{\beta}_1$, since $\widehat{\beta}_{1i} \neq \widehat{\beta}_1$. DFE method refer to the regular fixed effect model with lags.

1.5B Panel Unit Root Test: Breitung and LLC Test

For Breitung test, suppose that D_{it} is first-order autoregressive and expressed as:

$$D_{it} = \boldsymbol{Z}_{it}^{'} \beta_i + GDP_{it} \quad \text{(a1.16)}$$

where $GDP_{it} = \alpha_1 GDP_{i,t-1} + \alpha_2 GDP_{i,t-2} + \varepsilon_{it}$

where ε_{it} is the error term, under the nonrobust assumption, ε_{it} is uncorrelated across panels while under the robust assumption, ε_{it} is correlated with covariate matrix.

The null hypothesis of the unit root test is H_0: $\alpha_1 + \alpha_2 = 1$, for all provinces i, against the alternatives H_1: $\alpha_1 + \alpha_2 < 1$ (see Breitung (2000) and Breitung and Das (2005)).

[22] Note that Blackburne and Frank(2007) point out that when applying the *xtpmg* command for the DFE model in stata, it is equivalent to *xtreg, fe* command.

Equation (a17) specifies LLC:

$$\Delta D_{it} = \delta_i D_{i,\,t-1} + \sum_{L=1}^{P_i} \theta_{iL}\, \Delta D_{i,\,t-L} + \alpha_{mi} d_{mt} + \varepsilon_{it,}\, m = 1,2,3 \qquad \text{(a1.17)}$$

The null hypothesis $\mathrm{H_0}\text{:}\ \delta_\mathrm{i} = 0$, against the alternative $\mathrm{H_1}\text{:}\ \delta_\mathrm{i} < 0$. Levin et al. (2002) calculate an adjusted t-statistics (see p.8).

1.6B Panel Cointegration Test: Pedroni and Kao Test

I specify the following general model for the I(1) dependent variable for Pedroni and Kao test

$$D_{it} = \beta_{1i} GDP_{it} + \gamma_i + \mu_{it} \qquad \text{(a1.18)}$$

where β_{1i} denotes the cointegration relationship; γ_i represents the fixed effect. Since Kao (1999) does not allow for time trend, I thus exclude time trend in the general form. Pedroni (1999, 2004) instead relaxes this restriction.

For the PP t-test, the regression model is specified as:

$$\hat{\mu}_{it} = \rho_i \hat{\mu}_{i,t-1} + \varepsilon_{it} \qquad \text{(a1.19)}$$

H_0: $\rho_i = 1$ in the PP t-test versus H_0: $\rho_i - 1 = 0$ in the modified PP t-test.

The ADF regression introduces additional lags of residuals:

$$\hat{\mu}_{it} = \rho_i \hat{\mu}_{i,t-1} + \sum_{j=1}^{p} \rho_{ij}\, \Delta\hat{\mu}_{i,t-j} + \theta_{it} \qquad \text{(a1.20)}$$

The null hypothesis is H_0: $\rho = 1$

1.7B Wild Cluster Bootstrap

In social science research, it is typically assumed that the error terms in regression models exhibit correlation within distinct clusters, such as jurisdictions, villages, types of firms, classrooms, schools, or time periods (Roodman et al., 2019). Bootstrap methods for hypothesis testing involve generating numerous bootstrap samples that mirror the original sample, calculating the test statistic for each sample, and then evaluating the extremity of the original test statistic by comparing it to the distribution of bootstrap test statistics. This approach generally performs effectively. In some instances, it leads to an asymptotic refinement, indicating that the bootstrap distribution converges to the actual distribution more quickly than the traditional asymptotic distribution (such as the t or chi-squared distributions). This theoretical outcome is applicable to test statistics that are asymptotically pivotal, including most t-statistics (Roodman et al., 2019).

The wild cluster bootstrap, an advancement on the original wild bootstrap method introduced by Wu in 1986, was proposed by Cameron et al. (2008). This modification was designed to address models with heteroskedasticity and has been extended to accommodate cluster-level correlations. The wild bootstrap has demonstrated effectiveness in scenarios where cluster-robust standard errors, which typically assume standard normal critical values, fail to perform adequately.

APPENDIX 1.C: Tables

Table 1.1C Selection Critiria to Optimal lags in the Aggregate Data

Variables	AIC	HQIC	SBIC
△ln(RGDPC)	Lag = 0	Lag = 0	Lag = 0
△ln(RGDPC_neg)	Lag = 0	Lag = 0	Lag = 0
△ln(RGDPC_pos)	Lag = 0	Lag = 0	Lag = 0
△ln(Total)	Lag = 3	Lag = 3	Lag = 2
△ln(Poverty)	Lag = 0	Lag = 0	Lag = 0
△ln(Edu)	Lag = 2	Lag = 2	Lag = 2
△ln(Religion)	Lag = 2	Lag = 2	Lag = 0
△ln(Health)	Lag = 0	Lag = 0	Lag = 0
△ln(Comm)	Lag = 2	Lag = 2	Lag = 1
△ln(Art)	Lag = 1	Lag = 1	Lag = 0
△ln(Found)	Lag = 1	Lag = 1	Lag = 1
△ln(Other)	Lag = 1	Lag = 1	Lag = 1

Note: The optimal lags (up to 4) based on selection criteria such as Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQIC) and Schwarz Bayesian Information Criterion (SBIC) are reported in the table.

Table 1.2C ARDL Model Diagnostic Tests, in the Form of First Difference

Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Found)	△ln(Other)
Normality (Shapiro-Francia test)	0.68[0.25]	-0.78[0.78]	0.54[0.30]	0.31[0.38]	2.52***[0.01]	-1.11[0.87]	1.66**[0.05]	0.55[0.28]	-0.39[0.65]
Autocorrelation (Breusch-Godfrey LM test)	1.74[0.20]	0.65[0.43]	0.02[0.89]	0.32[0.58]	0.15[0.70]	0.64[0.43]	0.01[0.92]	2.64[0.12]	0.04[0.85]
Heteroscedasticity (Breusch-Pagan-Godfrey test)	0.80[0.37]	0.10[0.76]	1.10[0.29]	0.19[0.66]	4.51**[0.03]	1.96 [0.16]	0.53[0.47]	0.56[0.45]	0.01[0.91]
RESET (Ramsey test)	0.23[0.87]	1.45[0.25]	1.79[0.18]	0.77[0.52]	0.04[0.99]	0.13[0.94]	0.26[0.85]	1.25[0.32]	0.10[0.96]

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. Shapiro-Francia test for normality should be applied when observations are between 5 and 5000.. P-values are reported in the Normality test. F-statistics are reported in BG LM test and Ramsey test. Chi-square test is reported in the BPG test with p-values included in square brackets. The null hypothesis for Shapiro-Wilk test: the residual is normally distributed.. The null hypothesis for LM test: no serial correlation. The null hypothesis for BPG test: the residual is homoscedastic. The null hypothesis for Ramsey test: no omitted variable.

Table 1.3C NARDL Model Diagnostic Tests, in the Form of First Difference

Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Found)	△ln(Other)
Normality (Shapiro-Wilk test)	0.62[0.27]	-0.78[0.78]	1.13[0.13]	0.33[0.37]	2.52***[0.01]	-1.65[0.95]	2.22***[0.01]	0.40[0.34]	-0.72[0.76]
Autocorrelation (Breusch-Godfrey LM test)	1.77[0.20]	1.59[0.22]	0.33[0.57]	0.12[0.73]	0.15[0.70]	1.62[0.22]	0.06[0.81]	2.66[0.11]	0.15[0.71]
Heteroscedasticity (Breusch-Pagan-Godfrey test)	0.80[0.37]	0.06[0.81]	0.08[0.78]	0.08[0.77]	4.73**[0.03]	1.13[0.29]	0.08[0.78]	0.67[0.41]	0.02[0.88]
RESET (Ramsey test)	0.26[0.85]	1.48[0.24]	0.66[0.59]	0.83[0.49]	0.08[0.97]	0.34[0.79]	0.65[0.59]	1.32[0.29]	0.23[0.88]

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. Shapiro-Francia test for normality should be applied when observations are between 5 and 5000.. P-values are reported in the Normality test. F-statistics are reported in BG LM test and Ramsey test. Chi-square test is reported in the BPG test with p-values included in square brackets. The null hypothesis for Shapiro-Wilk test: the residual is normally distributed.. The null hypothesis for LM test: no serial correlation. The null hypothesis for BPG test: the residual is homoscedastic. The null hypothesis for Ramsey test: no omitted variable.

Table 1.4C Lag One in the Key Variable of Interest, ARDL and NARDL, Bootstrap

Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Found)	△ln(Other)
ARDL									
$\triangle\ln(\mathrm{RGDPC})_t$	0.840***	-0.419	0.439	0.440**	-0.277	0.708	-0.470	2.639***	0.557
	(0.228)	(0.332)	(0.327)	(0.212)	(0.276)	(0.467)	(0.409)	(0.651)	(0.588)
$\triangle\ln(\mathrm{RGDPC})_{t-1}$	0.330	0.090	0.326	0.137	0.544	0.095	1.456***	1.482***	0.087
	(0.273)	(0.392)	(0.439)	(0.200)	(0.482)	(0.648)	(0.486)	(0.511)	(1.099)
NARDL									
$\triangle\ln(\mathrm{RGDPC\_neg})_t$	0.744*	-1.160***	1.169***	0.440	-0.252	0.077	-0.092	2.342*	-0.038
	(0.382)	(0.273)	(0.404)	(0.391)	(0.295)	(0.754)	(0.850)	(1.263)	(0.620)
$\triangle\ln(\mathrm{RGDPC\_pos})_t$	0.797	-0.078	0.007	0.201	-0.043	0.566	-1.282	2.677***	1.403
	(0.548)	(0.594)	(0.501)	(0.282)	(1.012)	(0.729)	(0.908)	(0.897)	(1.641)
$\triangle\ln(\mathrm{RGDPC\_neg})_{t-1}$	0.178	-0.414	0.841	-0.237	0.971	-0.967	0.696	1.126	0.631
	(0.548)	(0.624)	(0.918)	(0.299)	(1.078)	(1.190)	(1.008)	(0.966)	(1.948)
$\triangle\ln(\mathrm{RGDPC\_pos})_{t-1}$	0.469	0.753	-0.322	0.438	0.060	1.258*	2.270	1.951*	-0.427
	(0.519)	(0.540)	(0.376)	(0.349)	(1.145)	(0.649)	(1.766)	(1.022)	(2.044)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. All variables are in real values. In the aggregate data, the key independent variable is real GDP per capita. Outcome variables are giving in total and by fields. I summarize the results of ARDL and NARDL in one table and report the estimated coefficients of real GDP per capita.

Table 1.5C Significant ARDL Estimation to Aggregate Donations, 1990-2021 vs. Provincial Donations, 1997-2021

	CA			AB	BC			MB	ON		
Variables	△ln(Total)	△ln(Religion)	△ln(Found)	△ln(found)	△ln(total)	△ln(religion)	△ln(found)	△ln(religion)	△ln(total)	△ln(religion)	△ln(found)
$\triangle\ln(\mathrm{RGDPC})_t$	0.730***	0.416*	2.562***								
	(0.185)	(0.205)	(0.794)								
$\triangle\ln(\mathrm{rgdpc})_t$				2.545**	1.680***	0.894***	5.102**	0.645***	0.957***	0.536**	2.352***
				(0.988)	(0.399)	(0.223)	(2.179)	(0.174)	(0.140)	(0.192)	(0.704)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. All variables are in real values. In the aggregate data, the key independent variable is real GDP per capita. Outcome variables are giving in total and by fields. In the provincial data, real GDP per capita by province is the key explanatory variable. Private donations per capita by province are the explained variables. Since trend is significant in some fields of donation, I assume that trend is non-linear to donation so that it is not cancelled out through first difference. The lag used in the aggregate data is based on Akaike Information Criterion (AIC), which is 3, 0, 2, 2, 0, 2, 1, 1, 1 for ln(RGDPC), ln(Total), ln(Poverty), ln(Edu), ln(Religion), ln(Health), ln(Comm), ln(Art), ln(Found), and ln(Other), respectively. The lag used in the provincial data is 0 and 1 for provincial GDP per capita and private donations, respectively. Provinces PE and SK also have significant response of giving to Foundation to GDP, due to the limited space, I do not report them all.

Table 1.6C Significant NARDL Estimation to Aggregate Donations, 1990-2021 vs. Provincial Donations, 1997-2021

	CA				ON			MB
Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Found)	△ln(total)	△ln(poverty)	△ln(found)	△ln(edu)
$\triangle\ln(\text{RGDPC\_neg})_t$	0.747***	-0.763*	1.105**	2.455**				
	(0.245)	(0.403)	(0.414)	(1.062)				
$\triangle\ln(\text{RGDPC\_pos})_t$	0.715**	0.206	-0.300	2.658***				
	(0.264)	(0.546)	(0.379)	(0.902)				
$\triangle\ln(\text{rgdpc\_neg})_t$					0.954***	-0.725*	2.403*	1.686*
					(0.265)	(0.382)	(1.167)	(0.954)
$\triangle\ln(\text{rgdpc\_pos})_t$					0.960***	0.720	2.305**	-2.373
					(0.310)	(0.536)	(0.881)	(1.575)

Note: The differences to table 1.5C are: The lag used in the aggregate data is based on AIC, which is 0, 0 for ln(RGDPC_neg) and ln(RGDPC_pos), respectively. The lag used in the provincial data is also 0, 0 for asymmetric macroeconomic indicators, respectively. Provinces AB/PE have significant reponse to GDP in total giving, and giving to Foundations. Provinces BC/NS/QC/SK have significant response to GDP in giving to Relief of Poverty. Due to limited space, I do not report them all.

Table 1.7C PARDL Model Diagnostic Tests, in the Form of First Difference

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(found)	△ln(other)
groupwise heteroskedasticity (chi2)	34.33***	635.08***	8296.10***	238.15***	3495.46***	446.92***	304.45***	280.78***	1534.60***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
contemporaneous correlations	73.15***	87.69***	55.82	146.90***	52.28	66.97**	101.53***	61.04*	56.24
	[0.01]	[0.00]	[0.13]	[0.00]	[0.21]	[0.02]	[0.00]	[0.06]	[0.12]
autocorrelation	0.78	0.18	1.95	2.15	0.09	0.10	0.33	0.71	0.52
	[0.38]	[0.67]	[0.16]	[0.14]	[0.77]	[0.76]	[0.56]	[0.40]	[0.47]

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. The diagnostic tests are conducted after the command of xtreg, fe. Null hypothesis of the groupwise heteroskedasticity: homoskedasticity; Null hypothesis of contemporaneous correlations: no contemporaneous correlations; Null hypothesis of autocorrelation: no serial correlation. The corresponding stata command for above tests is: xttest3, xttest2, xtqptest, lags(1).

Table 1.8C PNARDL Model Diagnostic Tests, in the Form of First Difference

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(found)	△ln(other)
groupwise heteroskedasticity (chi2)	33.67*** [0.00]	984.03*** [0.00]	7595.19*** [0.00]	271.81*** [0.00]	3287.82*** [0.00]	460.56*** [0.00]	300.79*** [0.00]	306.77*** [0.00]	1570.52*** [0.00]
contemporaneous correlations	70.88*** [0.01]	59.20* [0.08]	55.50 [0.14]	137.94*** [0.00]	51.80 [0.22]	66.34** [0.02]	100.95*** [0.00]	62.18** [0.05]	54.71 [0.15]
autocorrelation	0.02 [0.89]	0.16 [0.69]	0.63 [0.45]	0.73 [0.39]	0.15 [0.70]	0.23 [0.63]	0.28 [0.59]	0.73 [0.39]	0.97 [0.32]

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. The diagnostic tests are conducted after the command of xtreg, fe. Null hypothesis of the groupwise heteroskedasticity: homoskedasticity; Null hypothesis of contemporaneous correlations: no contemporaneous correlations; Null hypothesis of autocorrelation: no serial correlation. The corresponding stata command for above tests is: xttest3, xttest2, xtqptest, lags(1).

Table 1.9C Lag One in the Key Variable of Interest, Panel ARDL and Panel NARDL

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(found)	△ln(other)
Panel ARDL									
$\triangle\ln(\text{rgdpc})_t$	0.477***	-0.215	0.879	0.301***	0.030	0.212	-0.581*	1.309	-1.162
	(0.126)	(0.256)	(0.482)	(0.073)	(0.281)	(0.627)	(0.303)	(0.973)	(1.194)
$\triangle\ln(\text{rgdpc})_{t-1}$	0.151	-0.048	-0.154	0.029	0.150	0.821	0.371	0.236	-0.334
	(0.150)	(0.172)	(0.593)	(0.051)	(0.859)	(0.505)	(0.461)	(0.711)	(0.385)
Panel NARDL									
$\triangle\ln(\text{rgdpc\_neg})_t$	0.569**	-1.252**	0.445	0.315**	0.161	-0.608	-0.223	1.714	3.757
	(0.225)	(0.511)	(0.297)	(0.132)	(0.686)	(0.818)	(0.778)	(1.322)	(3.173)
$\triangle\ln(\text{rgdpc\_pos})_t$	0.419**	0.634*	1.576	0.297***	-0.210	0.578	-0.500	1.001	-4.462
	(0.171)	(0.296)	(0.931)	(0.089)	(0.824)	(0.896)	(0.945)	(0.822)	(4.112)
$\triangle\ln(\text{rgdpc\_neg})_{t-1}$	0.185	0.211	1.152***	0.045	-0.333	0.015	1.562	0.208	0.841**
	(0.111)	(0.463)	(0.281)	(0.124)	(1.181)	(0.853)	(1.151)	(0.818)	(0.372)
$\triangle\ln(\text{rgdpc\_pos})_{t-1}$	0.122	-0.269	-1.264	0.015	0.559	1.514*	-0.647	0.256	-1.389**
	(0.233)	(0.293)	(1.213)	(0.105)	(0.902)	(0.748)	(1.219)	(1.030)	(0.593)

Note: I summarise the results of Panel ARDL and Panel NARDL in one table and report the estimated coefficients of real GDP per capita.

Table 1.10C Bootstrapped NARDL Estimation to Aggregate Donations, Measured by Output Gap, 1990-2021

Variables	△(Total)	△(Poverty)	△(Edu)	△(Religion)	△(Health)	△(Comm)	△(Art)	△(Found)	△(Other)
Trend	-0.001	-0.000	-0.002**	-0.002***	0.001	-0.004**	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
$\triangle(\text{Total})_{t-1}$	-0.412**								
	(0.173)								
$\triangle(\text{Total})_{t-2}$	0.164								
	(0.215)								
$\triangle(\text{Total})_{t-3}$	-0.156								
	(0.169)								
$(\text{Outgap\_neg})_t$	1.252***	-0.853	1.306**	0.639	0.207	1.014	0.667	4.109***	-1.452
	(0.433)	(0.537)	(0.590)	(0.531)	(0.697)	(1.009)	(0.943)	(1.391)	(1.499)
$(\text{Outgap\_pos})_t$	1.568*	0.770	0.126	1.298***	1.654	0.108	2.323	5.117***	2.426
	(0.845)	(0.788)	(0.808)	(0.415)	(1.236)	(1.152)	(1.586)	(1.787)	(1.779)
$\triangle(\text{Edu})_{t-1}$			-0.017						
			(0.198)						
$\triangle(\text{Edu})_{t-2}$			0.177						
			(0.163)						
$\triangle(\text{Religion})_{t-1}$				-0.306*					
				(0.178)					
$\triangle(\text{Religion})_{t-2}$				-0.069					
				(0.222)					
$\triangle(\text{Comm})_{t-1}$						-0.711***			
						(0.210)			
$\triangle(\text{Comm})_{t-2}$						0.044			
						(0.178)			
$\triangle(\text{Art})_{t-1}$							-0.390***		
							(0.136)		
$\triangle(\text{Found})_{t-1}$								-0.609***	

								(0.160)	
$\triangle(\text{Other})_{t-1}$									-0.460***
									(0.107)
Constant	0.039**	0.034*	0.057***	0.033***	-0.009	0.090***	0.033	0.084***	0.074
	(0.017)	(0.018)	(0.020)	(0.012)	(0.025)	(0.032)	(0.033)	(0.030)	(0.046)
Observations	28	31	29	29	31	29	30	30	30
Wald	0.09[0.77]	1.96[0.17]	1.35[0.26]	0.92[0.35]	0.96[0.34]	0.26[0.61]	0.53[0.47]	0.18[0.68]	1.78[0.19]
Model	NARDL (3,0,0)	NARDL (0,0,0)	NARDL (2,0,0)	NARDL (2,0,0)	NARDL (0,0,0)	NARDL (2,0,0)	NARDL (1,0,0)	NARDL (1,0,0)	NARDL (1,0,0)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. All giving variables are real values. Trend is significant in the regression for giving to Education, Religion and Community. The lag used in the analysis is the optimal lag based on AIC. The key independent variable of interests is level variable, since the output gap data used in the monetary policy report available in Bank of Canada is in the form of percentage which captures volatility in productions. The rest of donation variables are described by the percent change not by the first difference of natural logarithm, since output gap has negative values.

Table 1.11C Panel ARDL Estimation to Provincial Donations, Non-missing Sample 1990-2021

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(found)	△ln(other)
△ln(total)$_{t-1}$	-0.197***								
	(0.044)								
△ln(rgdpc)$_t$	0.474***	-0.214	0.882	0.301***	0.028	0.206	-0.586*	1.306	-1.159
	(0.124)	(0.255)	(0.485)	(0.072)	(0.291)	(0.606)	(0.312)	(0.962)	(1.183)
△ln(poverty)$_{t-1}$		-0.371***							
		(0.054)							
△ln(edu)$_{t-1}$			-0.306***						
			(0.055)						
△ln(religion)$_{t-1}$				-0.072**					
				(0.031)					
△ln(health)$_{t-1}$					-0.337***				
					(0.064)				
△ln(comm)$_{t-1}$						-0.310**			
						(0.109)			
△ln(art)$_{t-1}$							-0.256***		
							(0.026)		
△ln(found)$_{t-1}$								-0.365***	
								(0.056)	
△ln(other)$_{t-1}$									-0.481***
									(0.012)
Constant	0.020***	0.084***	0.073***	0.017***	-0.016	0.063*	0.084***	0.041	0.137**
	(0.005)	(0.015)	(0.016)	(0.003)	(0.019)	(0.030)	(0.020)	(0.028)	(0.043)
Observations	300	300	300	300	300	300	300	300	300

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. All giving variables are real donations per capita. Macroeconomic indicators used are real GDP per capita in each province. Trend term is almost significant to all giving variables, indicating that trend is non-linear to donations at provincial level. The lag used in the analysis is the most common and optimal lag for each of province, based on AIC.

Table 1.12C Panel NARDL Estimation to Provincial Donations, Non-missing Sample 1990-2021

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(Religion)	△ln(health)	△ln(comm)	△ln(Art)	△ln(found)	△ln(other)
△ln(total)$_{t-1}$	-0.196***								
	(0.043)								
△ln(rgdpc_neg)$_t$	0.566**	-1.269**	0.361	0.313**	0.193	-0.545	-0.302	1.715	3.666
	(0.233)	(0.491)	(0.313)	(0.128)	(0.705)	(0.828)	(0.807)	(1.358)	(3.180)
△ln(rgdpc_pos)$_t$	0.406**	0.572	1.264	0.291***	-0.094	0.764	-0.795	1.003	-4.743
	(0.177)	(0.361)	(0.856)	(0.087)	(0.749)	(0.773)	(0.989)	(0.941)	(4.134)
△ln(poverty)$_{t-1}$		-0.386***							
		(0.052)							
△ln(edu)$_{t-1}$			-0.304***						
			(0.055)						
△ln(religion)$_{t-1}$				-0.072**					
				(0.031)					
△ln(health)$_{t-1}$					-0.337***				
					(0.065)				
△ln(comm)$_{t-1}$						-0.310**			
						(0.109)			
△ln(art)$_{t-1}$							-0.255***		
							(0.025)		
△ln(found)$_{t-1}$								-0.365***	
								(0.055)	
△ln(other)$_{t-1}$									-0.486***
									(0.015)
Constant	0.022***	0.067***	0.064**	0.017***	-0.013	0.050	0.089***	0.048	0.220*
	(0.007)	(0.020)	(0.024)	(0.004)	(0.024)	(0.030)	(0.026)	(0.028)	(0.109)
Wald	0.24[0.63]	7.51**[0.02]	0.02[0.89]	0.39[0.53]	0.83[0.36]	0.00[0.99]	1.49[0.22]	0.33[0.57]	1.34[0.27]
Observations	300	300	300	300	300	300	300	300	300

Note: Differences to table 1.11C include that variables △ln(rgdpc_pos)$_t$ and △ln(rgdpc_neg)$_t$ denote the first difference of the log of positive change in real GDP per capita at time t, the first difference of the log of negative change in real GDP per capita at time t, respectively.

Table 1.13C Panel NARDL Estimation to Provincial Donations, Local Sample 1990-2021

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(found)	△ln(other)
△ln(total)$_{t-1}$	-0.295***								
	(0.034)								
△ln(rgdpc_neg)$_t$	0.423	-0.690	-0.396	0.196**	1.458	-1.078	-0.579	0.689	5.800
	(0.388)	(0.791)	(1.013)	(0.075)	(1.185)	(1.261)	(1.527)	(2.390)	(4.109)
△ln(rgdpc_pos)$_t$	0.231	0.369	1.862**	0.211**	-0.505	1.330	-0.411	0.383	-6.709
	(0.192)	(0.337)	(0.812)	(0.088)	(0.783)	(0.980)	(0.977)	(0.842)	(5.082)
△ln(poverty)$_{t-1}$		-0.364***							
		(0.064)							
△ln(edu)$_{t-1}$			-0.312***						
			(0.066)						
△ln(religion)$_{t-1}$				-0.160**					
				(0.058)					
△ln(health)$_{t-1}$					-0.325***				
					(0.056)				
△ln(comm)$_{t-1}$						-0.275**			
						(0.115)			
△ln(art)$_{t-1}$							-0.243***		
							(0.023)		
△ln(found)$_{t-1}$								-0.369***	
								(0.047)	
△ln(other)$_{t-1}$									-0.494***
									(0.025)
Constant	0.016	0.050**	0.046	0.010	0.051	0.075	0.135*	-0.028	0.097
	(0.011)	(0.018)	(0.030)	(0.006)	(0.069)	(0.107)	(0.070)	(0.072)	(0.092)
Wald	0.11[0.73]	1.44[0.26]	5.21**[0.04]	0.04[0.84]	1.36[0.27]	2.95[0.12]	0.01[0.94]	0.01[0.91]	2.02[0.18]
Observations	300	300	300	300	300	300	300	300	300

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. See appendix 1.2A for local charities' definition.

Table 1.14C Panel NARDL Estimation to Provincial Donations, Without Universities and Hospitals 1990-2021

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(found)	△ln(other)
△ln(total)$_{t-1}$	-0.216***								
	(0.042)								
△ln(rgdpc_neg)$_t$	0.489*	-1.541***	0.434	0.313**	0.403	-0.566	-0.374	1.296	3.666
	(0.221)	(0.433)	(0.590)	(0.128)	(0.603)	(0.848)	(0.804)	(1.385)	(3.180)
△ln(rgdpc_pos)$_t$	0.469**	0.809**	1.736**	0.290***	0.107	0.922	-0.760	1.171	-4.743
	(0.183)	(0.254)	(0.655)	(0.088)	(0.531)	(0.730)	(0.990)	(1.074)	(4.134)
△ln(poverty)$_{t-1}$		-0.307***							
		(0.037)							
△ln(edu)$_{t-1}$			-0.406***						
			(0.031)						
△ln(religion)$_{t-1}$				-0.072**					
				(0.031)					
△ln(health)$_{t-1}$					-0.291***				
					(0.051)				
△ln(comm)$_{t-1}$						-0.321**			
						(0.114)			
△ln(art)$_{t-1}$							-0.257***		
							(0.026)		
△ln(found)$_{t-1}$								-0.387***	
								(0.071)	
△ln(other)$_{t-1}$									-0.486***
									(0.015)
Constant	0.022**	0.058***	0.060**	0.017***	0.013	0.046	0.088***	0.065	0.220*
	(0.007)	(0.015)	(0.020)	(0.004)	(0.023)	(0.028)	(0.026)	(0.038)	(0.109)
Wald	0.00[0.95]	27.58***[0.00]	2.68[0.13]	0.01[0.92]	0.08[0.80]	1.81[0.21]	0.05[0.83]	0.01[0.91]	1.34[0.27]
Observations	300	300	300	300	300	300	300	300	300

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively.

Chapter Two: Do Macroeconomic Conditions affect Government Funding to Charities? Evidence from Canada

2.1 Introduction

According to tax filing data from the CRA, there were 84,267 registered charities in Canada in 2021. Between 1990 and 2021, an average of 34.4% of registered charities received government funding in a given year. Over the same period, government transfers accounted for an average of 22.4% of total annual revenues across all charities, with the yearly share ranging from 17.5% to 26.7% (author's calculation). These figures are based on aggregate revenues, rather than the revenue share among only recipient charities, and they underscore the central role of government as a funding source for the charitable sector.

Previous studies have identified a mismatch between the supply of public services by charities and the demand for these services, especially during economic downturns (Salamon, 1987; Smith & Grønbjerg, 2006). During such periods, the need for essential services like food and housing increases (Sard, 2009; Lombe et al., 2018), yet the capacity of voluntary organisations to meet this rising demand often diminishes due to reduced income, particularly from government sources (Hastings et al., 2015). Ironically, recessions amplify the role of voluntary organisations in public service delivery, making them even more dependent on government funding (Smith & Lipsky, 1993; Allard, 2009).

This imbalance has spurred a small strand of literature on government funding to nonprofits or charities, particularly in the context of the Great Recession (Boris et al., 2010; Gordon, 2012; Pape et al., 2016). However, empirical evidence on how government funding to charities fluctuates over economic cycles remains scarce. The limited existing studies suggest a cumulative decline in total charity income, driven by policy austerity between 2008 and 2014 (Clifford, 2017). Moreover, total contributions to charities, including both donations and government funding, have been found to exhibit procyclical behaviour, aligning closely with business cycles (Exley et al., 2023). In Chapter One, my findings build on this by revealing that the growth of total giving and giving by fields – such as Education, Religion, Community, and Foundations – is significantly influenced by the growth in GDP per capita, further underscoring the procyclical nature of charitable contributions.

Organisations that aid individuals fulfill basic needs, such as food or housing, are generally expected to operate countercyclically. This expectation is based on survey findings indicating public support for US nonprofits during economic downturns (Exley et al., 2023), as food insecurity and homelessness rates tend to increase during such periods (Sard, 2009;

Lombe et al., 2018). However, there is limited evidence on whether charities, particularly those that the public expects to expand during economic downturns, actually operate in a countercyclical manner.

This paper seeks to address three unresolved questions: (1) Is government funding to charities procyclical or countercyclical? (2) Does government support to charities vary across different levels of government (municipal, provincial, or federal) during economic cycles? (3) Is there an asymmetry in government funding to charities during economic expansions and contractions?

Understanding how government funding to charities responds to macroeconomic conditions is crucial for both charities and policymakers. By examining the relationship between economic cycles and government funding across different types of charities, this study aims to contribute to a deeper understanding of the economics of public spending. Such insights can aid governments concerned about public good distributions during downturns. Understanding the cyclicality and asymmetry of government funding can help charitable organisations better strategize their efforts to secure government funds during economic fluctuations.

The most relevant studies to this paper are those by Boris et al. (2010), Clifford (2017), Kwak (2017), and Exley et al. (2023). However, this paper differentiates itself in at least four key ways: First, Clifford (2017) uses UK data, and Boris et al. (2010) and Exley et al. (2023) use US data, this study is the first to use Canadian data. Second, unlike Clifford (2017) and Exley et al. (2023), who do not disaggregate government money from total charitable income, this study achieves such a disaggregation. Third, while Clifford (2017) focuses on aggregate charitable income, and Exley et al. (2023) analyse data at the organisation-year level, this study investigates both national and provincial economic conditions, recognising that macroeconomic conditions may vary across Canadian jurisdictions. this study examines whether government funding to charities responds asymmetrically over the business cycle, an issue previously noted only by Kwak (2017) in the context of US public spending.

To explore these dynamics, I employ a time series ARDL model and a NARDL model for national aggregate government funding to charities. Additionally, a panel ARDL and a panel NARDL model are applied to analyse how government funding from federal and provincial levels responds to macroeconomic fluctuations.[23] The dataset, covering 1990 to 2021, includes three significant recessions in Canada, allowing for a comprehensive

[23] See sections 2.5.2 and 2.5.3 for a detailed discussion of all four estimation methods.

analysis.[24] A detailed definition of business cycles and recessions was provided in Section 1.3 of Chapter One.

The T3010 dataset used in this paper categorises the activities of registered charities into eight broad areas: Relief of Poverty, Education, Religion, Health, Community, Arts, Foundations, and "Other". This study examines the associations between government funding to these areas and business cycles both nationally and across the ten provinces. Funding to Foundations is excluded from the analysis due to their operational independence in their capacity, purpose, and intention from government actions (Mosley & Galaskiewicz, 2015). This independence is reflected in the fact that, in Canada on average, only 0.85% of Foundations received money from governments. Funding to Foundations accounts for 0.18% of total funding to charities. This study focuses specifically on charities, rather than the broader category of nonprofit organisations. In 2021, there were over 135,000 active nonprofits in Canada,[25] with registered charities making up approximately 62.42% of this total. However, comprehensive data on nonprofits in Canada remains difficult to access.

In this study, I begin by presenting figures that visualise the relationship between government spending and government funding to charities. I explore the correlations between the growth in government spending on general services and the growth in government funding to charities overall. Additionally, I examine the growth in government spending on education and its relationship to funding for educational charities, as well as the growth in spending on health and its impact on funding for health-related charities. My analysis reveals that the growth in funding to charities, both in total and by specific fields, exhibits greater volatility compared to the growth in government spending within corresponding categories. Furthermore, there appears to be no consistent pattern between government spending and funding to charities during periods of economic expansion and contraction. Notably, government funding to charities at the federal, provincial, and municipal levels was more volatile before the Great Recession (2008-2009) than in the years following, including during the Covid-19 recession. Since detailed funding data for charities are only available from 1997, variations in funding patterns during the 1990-1992 recession are not accessible. This trend suggests that Canadian governments may have responded to the Great Recession by stabilising their funding to charities.

[24] According to Cross and Bergevin (2012) and C.D. Howe Business Cycle Council (2021), four economic recessions have occurred since 1976: from the second quarter of 1981 to the fourth quarter of 1982, from the first quarter of 1990 to the second quarter of 1992, from the third quarter of 2008 to the second quarter of 2009, and from March to April 2020. Consequently, the dataset utilised in this study encompasses three of these recessions, in addition to other periods characterised by declining macroeconomic activity, which may not qualify as formal recessions under strict definitions.

[25] https://www150.statcan.gc.ca/n1/daily-quotidien/240212/dq240212c-eng.htm

To further analyse how government funds charities in Canada, I employ three approaches to study the relationship between aggregate government funding to charities and macroeconomic conditions: (1) simple correlations between aggregate funding to charities and macroeconomic indicators (an approach used by List and Peysakhovich (2011) in a different context), (2) time series models such as the ARDL and NARDL using aggregate data, and (3) panel data ARDL and NARDL models at the provincial level.

In analysing the correlations between government funding from federal, provincial, and municipal levels and economic fluctuations in Canada, I observed the following: First, the signs of the correlation coefficients between the percentage change in aggregate, federal, and municipal funding to charities and the percentage change in lagged macroeconomic indicators align with theoretical expectations. For example, the correlation coefficients between the percentage change in funding variables at time *t* and the percentage change in real GDP (or lagged unemployment rate) at time *t-1* are positive (or negative). In contrast, the percentage change in provincial funding to total charities, and in specific charitable fields, shows expected correlation coefficients with contemporaneous indicators such as real GDP (or unemployment rate). Second, the lagged S&P/TSX index significantly influences the correlation with the percentage change in aggregate funding/provincial funding to Community charities. Third, the countercyclicality of funding varies across government levels and charitable fields. For instance, aggregate government funding to Community and Arts is countercyclical, as is federal and provincial funding to religious charities, and municipal funding to health-related charities. Additionally, funding from the same level of government to the same charitable field may show different correlations with different macroeconomic indicators. For example, federal funding to Education exhibits a negative correlation with percentage changes in consumption expenditure, but a positive correlation with GDP growth. Lastly, when plotting the relationship between percentage changes in funding by charitable fields and percentage changes in the lagged S&P/TSX composite index, I observe a non-linear relationship for aggregate funding to total charities, Community, and Relief of Poverty in response to economic contractions and expansions, based on 95% confidence intervals obtained through bootstrapping.

Subsequently, I employ the bootstrapped ARDL and NARDL models to investigate symmetric and asymmetric relationships between the growth in real GDP per capita and the growth in aggregate funding to charities at the national level, as well as from federal, provincial, and municipal governments. Given that the correlation between the percentage change in real GDP and the percentage change in provincial funding to total charities is the highest among the macroeconomic indicators, I select real GDP per capita – adjusted for population in each province – as the key variable of interest. The ARDL and NARDL models yield several findings: Federal funding to religious charities is countercyclical during downturns, while municipal funding to health-related charities is cyclical during upturns, patterns that align with the aggregate funding to these fields. Meanwhile, provincial funding to Arts charities is countercyclical.

In the panel ARDL and NARDL models, I find both symmetric and asymmetric effects of macroeconomic indicators on aggregate funding to charities by province. In the panel ARDL model, growth in real GDP per capita is significantly and positively associated with growth in aggregate funding to Education but negatively associated with funding to Arts. In the panel NARDL model, significant relationships are found between GDP growth and aggregate funding to total charities, as well as to Education, Health, Community, and Arts. Specifically, funding to Education and Community is sensitive to economic expansions, while funding to Health and Arts is more responsive during contractions. These results indicate that aggregate funding to Health and Arts is countercyclical, whereas funding to Education and Community is cyclical. When examining asymmetric effects of real GDP per capita on aggregate funding per capita by charitable field, I find no significant difference in the magnitude of federal funding to Education between expansions and contractions. However, provincial funding to Health and Community does vary in magnitude across the cycle. Lastly, I control for the growth of private donations in the panel ARDL model to assess whether the effects of GDP remain significant. The results confirm that GDP growth continues to significantly affect funding in the Education and Arts sectors. I also find no evidence of crowd-in or crowd-out effects in Education but observe a crowding-out effect in the Arts sector, suggesting a substitution between government funding and private donations.

This paper contributes to four main areas: First, it provides the first analysis of government funding patterns across various fields of activity in Canada and their relationship with macroeconomic indicators, typically referred to as business cycles. Second, it is the first study to examine the role of provincial jurisdictions in the context of funding responses from federal and provincial governments during different phases of business cycles. Third, to the best of my knowledge, this research is the first to apply the ARDL and NARDL models to assess the symmetric and asymmetric responsiveness of aggregate funding to charities across business cycles. By exploring the interaction between economic cycles and government funding across different types of charities, this paper deepens the understanding of the economics of public funding. These insights can help governments distribute public goods more effectively during periods of need, while also enabling charitable organisations to maintain a competitive edge in securing funds or to refine their strategies in response to economic fluctuations. Finally, this paper provides insights into the relationship between private donations and government funding to charities by examining their dynamics under varying economic conditions.

The remainder of this chapter is structured as follows: Section 2.2 presents a brief literature review on government funding to charities, focusing on studies that examine recessions and business cycles; Section 2.3 discusses the dataset used (with further details provided in appendix 2.A); Section 2.4 describes the relationship between public spending and government funding to charities and outlines how government funds charities; Section 2.5 provides the empirical strategy and results; Section 2.6 discusses robustness; and Section 2.7 concludes.

2.2 Government Funding to Charities and Macroeconomic Conditions: Literature Review

This literature review examines five strands of research on government funding to charities and its relationship with macroeconomic conditions: (1) the cyclicality of government spending and its role in economic stabilisation; (2) asymmetric fiscal responses during expansions and recessions; (3) the impact of the Great Recession on public funding to nonprofits; (4) organisational factors that influence access to government support; and (5) how charitable funding varies across the business cycle. These strands offer a structured foundation for understanding how economic conditions shape public support for charities and highlight directions for future research.

2.2.1 Cyclicality and Stabilising Role of Government Spending

The behaviour of government spending over the business cycle has long been a focus of macroeconomic research. Fiscal reserves are widely seen as essential for maintaining stability across cycles (Hou, 2006; Hou & Moynihan, 2008; Thompson & Gates, 2008; Dothan & Thompson, 2009). A key mechanism is countercyclical fiscal policy, where governments increase spending during downturns and consolidate during expansions to smooth output fluctuations (Lane, 2003; Furceri, 2010; Fatás & Mihov, 2013).

Cross-country studies provide evidence of this stabilising role. Arreaza et al. (1999) show that social benefits absorb GDP shocks in OECD countries, while Afonso and Furceri (2008) find that both spending and revenue measures support macroeconomic stabilisation in the European Union. Advanced economies tend to adopt countercyclical strategies (Lane, 2003; Talvi & Vegh, 2005; Staehr, 2008), whereas many developing countries exhibit procyclical patterns, often due to fiscal or institutional constraints (Gavin et al., 1996; Talvi & Vegh, 2005; Diallo, 2009).

Within this broader context, health and labour-related expenditures act as automatic stabilisers. Unemployment benefits, labour market programmes, and family support schemes typically expand during recessions (Black et al., 2002; Ruhm & Black, 2002; Autor & Duggan, 2003; Coile & Levine, 2007). Health spending may rise in downturns due to increased need, but can also increase in booms owing to more workplace injuries, especially in high-risk sectors.

Economic contractions often reduce both household income and government health expenditure (Hopkins, 2006; Hou et al., 2013), compounding risks to population health. Scholars caution that cuts to government health expenditure during downturns may jeopardise access to essential services (Stuckler et al., 2010; Quaglio et al., 2013). These findings point to the importance of tracking not just total public spending but also funding allocated to charities that deliver frontline services.

The phase of the business cycle may also affect the impact of fiscal policy. Auerbach and Gorodnichenko (2012) show that fiscal multipliers are larger during recessions, when economic agents are more responsive to government action. While their analysis focuses on aggregate spending, it supports further investigation into the timing and sectoral composition of public funding, including support for charitable organisations.

2.2.2 Asymmetric Fiscal Responses Across the Business Cycle

Building on the study of fiscal cyclicality, Kwak (2017) investigates the asymmetric effects of cyclical revenue fluctuations on state fiscal adjustments using a panel dataset comprising 49 US states (excluding Alaska) over 19 fiscal years from 1992 to 2010. The study specifically examines whether the magnitude of spending increases during economic booms exceeds the magnitude of spending cuts during recessions. A central focus of Kwak's analysis is the "expenditure gap", which serves as one of the dependent variables. The key independent variables are the cumulative sum of increases and decreases in the tax base gap.[26] The concept of the tax base gap is closely related to the output gap, which represents the difference between actual and potential output. Similarly, the tax base gap is defined as

[26] For example, the level variables of positive versus negative tax base gap is defined as: $TBGAP_t^+ = \sum_{j=1}^{t} \Delta TBGAP_j^+ = \sum_{j=1}^{t} max(\Delta TBGAP_j, 0)$; $TBGAP_t^- = \sum_{j=1}^{t} \Delta TBGAP_j^- = \sum_{j=1}^{t} min(\Delta TBGAP_j, 0)$.

the cyclical component of the tax base, operationally measured as the difference between actual and potential tax base values. In essence, the tax base gaps are the residuals obtained from a regression of the tax base on time. Kwak's findings reveal that the procyclical effect of a decrease in the tax base gap on state-level spending is more pronounced than the effect of an increase in the tax base gap. This suggests that states are more likely to reduce spending in response to a shrinking tax base during economic downturns than they are to increase spending when the tax base expands during periods of growth.

One of the objectives of this paper is to explore government funding to charities in Canada during periods of economic expansion and contraction. By studying these dynamics, the paper aims to contribute to a better understanding of how fiscal policies are adjusted in response to economic cycles, particularly in the context of charitable funding.

2.2.3 Government Funding to Nonprofits During the Great Recession

Government funding to nonprofits is highly context-dependent, shaped by national fiscal conditions and policy choices. Bozio et al. (2015) examine six European countries during the global financial crisis and find that, except for Germany, most experienced sharp revenue declines. In response, France, Ireland, Italy, Spain, and the United Kingdom implemented tax increases and spending cuts. Yet, the extent of protection for essential services varied: health and education were largely shielded in France, Ireland, and the United Kingdom, but not in Italy and Spain.

A broader comparative analysis by Pape et al. (2016) explores how austerity affected nonprofit sectors in France, Germany, the Netherlands, Poland, and Spain. While voluntary organisations in Germany – such as sports clubs, cultural institutions, and senior services – were early targets of local budget cuts, Polish nonprofits showed greater resilience. In the Netherlands, subsectors like international aid, social services, and the arts saw substantial funding reductions. Spanish nonprofits, especially those reliant on government support, were hardest hit. French associations dependent on public funds also suffered notable losses.

Several studies highlight how education funding evolved during the crisis. Evans et al. (2019) trace shifts in K-12 school financing in the United States between 1970 and 2008. Over time, the state share of education funding increased, overtaking local contributions by 2008. During the Great Recession, the federal government temporarily raised its share from an average of 7.8% to 13% in 2010, before returning to historical norms.

Bhalla et al. (2017) compare New York and New Jersey during 2007-2009. New York received greater federal support, while New Jersey imposed deeper state-level cuts. Local revenue declined more sharply in New York, though differences in state and federal responses were more consequential. In both states, total education funding fell post-recession, with New Jersey experiencing a larger drop.

While education is only one component of the nonprofit sector, these studies illustrate broader patterns of how government support shifts in response to economic shocks. This paper extends the analysis to a wider range of charitable subgroups in Canada, contributing to a fuller understanding of fiscal policy's role across different nonprofit domains.

2.2.4 Which Nonprofits Receive Government Funding?

The likelihood of receiving government funding varies across nonprofit organisations depending on several organisational characteristics. Brown and Troutt (2004) and Cairns and Harris (2011) highlight the importance of clearly communicating mission and service alignment to funders. Governments are also more inclined to support nonprofits that engage in collaborative partnerships, which are often essential for tackling complex social challenges (Suárez, 2011).

Other factors such as bureaucratic orientation, alignment with policy priorities, and a history of receiving government support also play a role. Lu (2015) finds that organisations exhibiting these traits are more likely to secure contracts and grants. Recent work by Devlin and Planatscher (2023), based on Canada Revenue Agency T3010 data, shows that charities serving Indigenous communities are significantly more likely to receive public funding than their non-Indigenous counterparts. Similarly, Tafa (2018) identifies charity size, subsector, and geographic location (urban vs rural) as key determinants of government funding to registered charities in Canada.

Existing studies have yet to examine whether funding for specific types of charities remains stable across different phases of the economic cycle. Although charities fall under the broader category of nonprofit organisations, they are distinct in important legal and operational ways.[27] While funding patterns for charities may differ from those of nonprofits more broadly, much of the existing literature focuses on the nonprofit sector as a whole. This study draws from that literature while focusing specifically on the charitable subset.

[27] According to Canada's Income Tax Act ("ITA"), NPOs and charitable organisations distinguish from each other in the following aspects: Firstly, charitable organisations have to apply for and receive approval for registered charity status from the CRA to gain tax benefits from the ITA (CRA, 2016). A registered charity is described as an organisation established and operated exclusively for charitable purposes and activities (CRA, 2009), under four categories: relief of poverty, advancement of education, advancement of religion and certain other purposes beneficial to the community. Nonprofit organisations, however, do not need to be registered in order to receive the tax exemptions from the ITA. They need only meet specified eligibility requirements (CRA, 2016). Secondly, only registered charities are allowed to issue tax-receipts to donors, who in turn receive personal income tax benefits (Kitching, 2006; Manwaring and Valentine, 2010).

2.2.5 Research Gap and Contribution

Several studies provide valuable insights into how nonprofits and charities are funded during economic cycles. Boris et al. (2010), Clifford (2017), Kwak (2017), and Exley et al. (2023) are particularly relevant to the present study, though each leaves important gaps unaddressed.

Boris et al. (2010) examine public funding to nonprofits in the United States during the Great Recession, drawing on data across local, state, and federal levels. Their descriptive analysis identifies shifts in funding allocation across nonprofit fields in response to economic downturns. However, their focus on the broader nonprofit sector rather than charities specifically limits the direct applicability of their findings, given the institutional and regulatory differences between these groups.

Clifford (2017) offers rare longitudinal evidence on charities by tracking annual income trends for registered organisations in England and Wales between 1999 and 2014. The study finds a 13% cumulative decline in charitable income from 2008 to 2014 and shows heterogeneity by charity size, purpose, and location. However, it does not disaggregate income by source, making it difficult to isolate the effect of government funding from private donations or earned revenue. My study addresses this limitation by focusing explicitly on government support for charities.

Exley et al. (2023) take a different approach by constructing a Desired Countercyclicality Rating (DCR) for US nonprofits, based on whether survey respondents believe certain nonprofit types should expand services during downturns. They find that, despite normative expectations, many nonprofits exhibit procyclical financial patterns. While the study offers a rich dataset and considers both national and local economic shocks, its reliance on survey-derived DCRs raises concerns about sample selectivity and representativeness. Moreover, the authors assume linear responses to economic fluctuations.

Taken together, these studies underscore the importance of understanding how economic conditions shape nonprofit finances, but they leave several important questions open. There remains limited empirical work focusing on registered charities specifically, especially outside the US and UK contexts. Moreover, few studies isolate government funding as a distinct revenue source or consider the possibility of asymmetric responses across the business cycle, as highlighted in Kwak (2017).

This study aims to fill these gaps by examining government funding to registered charities in Canada over three decades. In doing so, it not only adds a new geographic and institutional context to the literature but also advances understanding of how different types of charities respond to economic conditions both in contractions and expansions.

2.3 Data Discussion

This chapter primarily uses administrative data from the CRA's T3010 filings for all registered charities from 1990 to 2021. As explained in Section 1.4, all registered charities in Canada are mandated to file a T3010 annual return with the CRA within six months of the end of their fiscal year to maintain their income tax-exempt status and the ability to issue tax receipts for donations. The T3010 return provides detailed information on charities' national and international activities, revenues, expenditures, liabilities, assets, and fields of activity. Non-compliance in submitting the information return can result in the revocation of a charity's status. The T3010 is the primary tool used by the CRA's Charities Directorate to verify that a registered charity meets its tax obligations.

As detailed in Chapter One, the T3010 dataset is increasingly valuable for researchers addressing various issues (Andreoni & Payne, 2011; Devlin, 2017; Brouard et al., 2021; Armstrong et al., 2023; Devlin & Planatscher, 2023). This dataset offers detailed information from the charity's perspective, including donations, government grants, expenditures, and fields of activity. However, it lacks data from the perspective of individual donors, which is a potential limitation. Since the dataset was originally designed for administrative rather than research purposes, multiple steps were required to prepare the data for this study. Appendix 1.A of Chapter One outlines the challenges encountered and the solutions applied.

In this chapter, I construct a measure of total government funding to charities by summing grants reported from federal, provincial, and municipal sources, based on detailed disclosures by individual charities (see appendix 2.1A). The data are organised at the province-year level, with funding totals further broken down by field of service. The final panel spans 32 years and includes 320 province-year observations.

In addition to the T3010 data, this chapter uses macroeconomic indicators – output gap, real GDP, unemployment rate, household consumption, and the S&P/TSX Composite Index – consistent with Chapter One. These variables help assess how economic fluctuations influence government funding to charities.

To express funding amounts and the S&P/TSX Index in real terms, I adjust for inflation using the Consumer Price Index (CPI), rebased from its original 2002 base to 2017 to align with the GDP series. The rebasing procedure follows the method outlined in Section 1.4.2 of Chapter One. For provincial analyses, I also include real GDP per capita and unemployment rates. All data sources are documented in table 2.1.

Table 2.2 defines all the variables used in the empirical analysis. Table 2.3 presents the percentage changes from time *t-1* to *t* in four macroeconomic indicators and aggregate government funding to charities, both in total and by specific fields. Simple correlations were applied to assess the impact of variables such as GDP, the S&P/TSX Composite Index, unemployment, and consumer expenditure on government funding to charities. Notably, the average percentage change in real GDP over the sample period was 2.20%, while the unemployment rate change averaged -0.02%. The S&P/TSX Composite Index exhibited the largest change among the four macroeconomic indicators. Among the seven categories of charitable funding, the mean percentage change in funding to religious charities was the highest,[28] followed by government funding to "Other" charities.

Table 2.4 presents the average values by province for the 32-year panel (1990-2021), including funding from all levels of government to charities located in each province. Despite being averaged over 32 years, significant differences across provinces are evident for most variables. Ontario leads in real GDP, averaging 660 billion dollars, followed by Quebec with 350 billion dollars. Prince Edward Island has the lowest real GDP at approximately 5 billion dollars. Alberta ranks highest in real GDP per capita, with 70 thousand dollars. In terms of real funding to charities per capita, column (1) shows that charities registered in Ontario received an average of $1,119.19 from all levels of government. Saskatchewan received the highest per capita funding, followed by Manitoba and Ontario. Across all provinces, funding for Health and Education per capita accounts for the largest proportion, except in New Brunswick and Prince Edward Island, where other categories dominate. Conversely, funding for "Other" charities has the smallest share across all provinces.

2.4 Government Funding to Charities

In this section, I first provide descriptive information on public spending and government funding to charities. This is followed by an examination of the funding sources for charities, specifically from federal, provincial, and municipal governments. Finally, I describe how government funding to nonprofits is managed in Canada, focusing on application processes and funding requirements.

2.4.1 Public Spending and Government Funding to Charities

Governments rely on nonprofits, including charities, to deliver public services such as employment training, education, and health programs (Laforest, 2011). As of 2021, registered

[28] In 1997, the growth in funding to Religion is 1351.72%. I tried to drop the highest 2% of funding to Religion in this year, the growth is still as large as 1025.68%. On average (1990-2021), funding to Religion accounts for 0.31% of total funding to charities. In this case, I decide to keep the sample which drops the highest 1% of funding to Religion, by year, by province, even though the variance is large. The reason is government only funds religious charities when they give money to communities.

charities comprised two-thirds of all nonprofits in Canada (see footnote 25). Due to limited availability of data on nonprofits, this paper focuses specifically on registered charities. Government support plays an important role in their financing: between 1990 and 2021, an average of 34.4% of charities received government funding in a given year. In revenue terms, transfers accounted for about 19% of total charitable revenues in 2021, compared with a historical average of 22.4% over 1990-2021. These figures are calculated at the aggregate level and do not represent the revenue share among only those charities that received government funding. Following Boris et al. (2010), charities are classified by total revenues into three groups: large (over $1 million), medium ($250,000-$999,999), and small ($249,999 or less). To avoid misclassification based on a single year, each charity is assigned to a size category using its average revenue over 1990-2021. On this basis, 9% of charities are classified as large, 16% as medium, and 75% as small. Among these, 7.36% of large charities, 12.21% of medium charities, and 44.15% of small charities report receiving government funding at least once during the sample period.

Government support to charities in core service areas can be assessed relative to overall public spending in those sectors. In 2021, transfers from the consolidated Canadian general government to educational charities represented 19.90% of total public education spending, while transfers to health-related charities accounted for 6.59% of total public health spending.[29] Looking across 1990-2021, the corresponding averages are 14.10% for education and 12.68% for health. These figures highlight the consistent role of charities as complementary providers in education and health, two areas that together account for more than 70% of total government funding to charities, with Education receiving an average of 35.39% and Health 42.48%.[30]

Before turning to the effects of macroeconomic conditions on government funding to charities, it is useful to compare trends in government spending and charity funding. This comparison helps clarify whether funding to charities co-moves with the government's budget or diverges from broader spending patterns. Although both reflect public resource allocation, government spending is typically less discretionary and more stable, while funding to charities is often more flexible and responsive to short-term fiscal or political

[29] Statistics Canada defines "consolidated Canadian general government" as the combined financial accounts of all levels of government (federal, provincial/territorial, and local), after removing internal transactions within the public sector. To illustrate consolidation, consider a case where one provincial government holds a bond issued by another provincial government. For each institution, the bond appears as an asset (the holder) and a liability (the issuer). However, when these two units are consolidated, the bond is eliminated from the aggregate accounts – treated as if it does not exist – because it represents a financial claim within the public sector. This process does not directly affect measures of government spending or revenue, but it ensures that aggregate fiscal indicators are not inflated by internal flows.

[30] According to the CRA's category classifications, charities of Education include Teaching Institutions, Support of Schools and Education, Education in the Arts, Research, and Foundations Advancing Education. Health charities include Core Health Care, Supportive Health Care, Protective Health Care, Health Care Products, Complementary or Alternative Health Care, and Relief of the Aged.

pressures. As such, observing greater volatility in charity funding relative to overall spending is expected. However, documenting this difference is important for understanding whether charity funding moves in proportion to public spending or follows a distinct trajectory – especially in response to macroeconomic changes.

Figure 2.1 shows the relationship between changes in general government spending (from all levels) and aggregate government funding to charities. The shaded areas indicate recessionary periods, defined by Cross and Bergevin (2012) and the C.D. Howe Business Cycle Council (2021): Q1 1990 – Q2 1992, Q3 2008 – Q2 2009, and March – April 2020. The figure illustrates that growth in government spending on general services and growth in government funding to charities are highly volatile, with government funding to charities showing greater volatility than general government spending. Moreover, no consistent pattern emerges between changes in these two variables. For instance, during the 1990-1992 recession, aggregate government funding to charities initially increased and then decreased, while government spending on general services consistently declined. Similar unaligned trends are observed during other recessionary periods.

Figures 2.2 and 2.3 further explore relationship between percentage changes in government spending on education and health (from all levels of government) and corresponding changes in aggregate government funding to charities operating in these sectors. The data reveal that government funding to Education and Health charities is generally more volatile than overall government spending in these sectors. No consistent trend is evident between the growth rates of government funding to these charities and the growth rates of government spending in the respective sectors. Specifically, as shown in figure 2.2, during the recessionary periods of 1990-1992 and 2020, the growth of government funding to Education aligned with the trend in government spending on education. However, this alignment was absent during the 2008-2009 recession and in non-recessionary periods. Similarly, in figure 2.3, government funding to Health followed a comparable trend to government health spending during the 1990-1992 and 2008-2009 recessions, yet this trend diverged in 2020.

Figures 2.1, 2.2, and 2.3 show that government funding from all three levels to charities – both in aggregate and within the Health and Education sectors – exhibits greater year-to-year volatility than corresponding government spending on general services, health, and education. This pattern is not unexpected. Government spending on core public services typically involves large base budgets and multi-year commitments, which smooth fluctuations over time. In contrast, government transfers to charities are smaller in scale and more discretionary, making them more sensitive to short-term fiscal or policy changes.

Part of the observed volatility also reflects the difference in scale: percentage changes in charity funding appear larger simply because they are calculated over a much smaller base. For example, an increase in charity funding from \$10 to \$15 represents a 50% change, whereas a similar \$5 increase in a \$1,000 education budget results in only a 0.5% change. These differences in magnitude must be kept in mind when comparing growth rates across categories. Notably, there is no consistent pattern linking the growth rates of government spending in a sector with the growth rates of funding to charities operating in that sector, suggesting that charity funding does not move proportionally with overall service budgets.

2.4.2 Funding from Different Government Levels

In 2021, federal transfers represented 6.5% of total government funding to charities, compared with 87.5% from provincial governments and 6% from municipal governments. These figures are based on the annual aggregation of all three funding sources. Looking across 1997 to 2021,[31] the average shares were 5.7% federal, 85.6% provincial, and 8.7% municipal. Thus, while provincial governments consistently account for most government support to charities, the federal and municipal contributions remain relatively stable over time. Among charities that report details on government funding sources, an average of 31.55% received grants from at least one level of government between 1990 and 2021, with yearly values ranging from 27.80% to 37.84%. This measure is calculated by identifying, for each year, the number of charities reporting positive federal, provincial, or municipal funding and dividing it by the total number of charities.

Figure 2.4 illustrates the percentage change in government funding to charities from the three levels of government. The growth in federal and provincial funding appears more volatile in the pre-recession period (before 2008) than in the post-recession years. This volatility might be explained by the federal and provincial governments learning from the Great Recession and attempting to stabilise their funding to charities. Overall, the growth in municipal funding to charities is the least volatile, followed by provincial funding.

During the 2008-2009 period, provincial and municipal funding to charities exhibited an N-shaped growth pattern, while federal funding followed a U-shaped pattern. In 2020, the trends diverged: federal funding to charities continued to increase, while provincial funding

[31] From 1997 to 2008, all charities provide details in funding sources. Starting from 2009, only charities meeting some conditions provide details by filling in schedule 6. About 50.23% of charities fill in schedule 6 after 2009. See appendix 2.A for explanations.

decreased, and municipal funding initially decreased before rising again. These observations suggest the need for further examination to differentiate aggregate funding to charities from federal, provincial, and municipal sources.

2.4.3 Procuring Government Funds for Charities

Obtaining government funding can be a complicated procedure for charities. The process involves application procedures, matching requirements, and reporting formats for contracts and grants at the federal, provincial, and local levels. This subsection relies on information from Charity Village, a leading online platform for the Canadian nonprofit sector.[32]

Most government funding programs for nonprofits require an application process which verifies that recipient organisations meet specific criteria and will use the funds appropriately. Typically, the application involves providing detailed information about the organisation's mission, financial status, and planned use of the funds. However, nonprofits might receive funds without going through a traditional application process. For example, as noted on Charity Village, during emergencies or crises, government agencies may directly allocate funds to organisations they know can provide immediate assistance. Additionally, some programs offer automatic funding to eligible organisations based on specific criteria, such as formula grants from the federal government to provincial and territorial governments in the fields of health and education.[33] Charities operating in these sectors often collaborate with government agencies during the fund allocation process at the provincial level. Moreover, nonprofits that have established relationships with government agencies might receive funding as part of ongoing cooperative agreements, particularly if they are viewed as extensions of the agency's own efforts.

Government contracts and grants often require or encourage charities to match the support they receive with other funding sources, such as donations (in cash, labour, materials, or services), or to explicitly share program costs. Charity Village outlines that eligible matching contributions must be directly related to the project. The required matching ratios can vary, with applicants typically needing to contribute an amount equal to or exceeding the grant request. In some cases, the matching ratios may differ between Indigenous and

[32] See https://charityvillage.com/funding-programs-for-nonprofits-directory/

[33] Here are a few examples of formula-based funding programs in Canada: (1) Canada Health Transfer (CHT). This is one of the largest federal transfer programs. It provides long-term predictable funding for health services to provinces and territories. The allocation is primarily based on population and adjusted for demographic factors (See Canada Health Transfer - Canada.ca); (2) Canada Social Transfer (CST). This formula-based funding supports provinces and territories in providing post-secondary education, social assistance, and social services, including early childhood development and childcare. It's also allocated based on population (See Canada Social Transfer - Canada.ca).

non-Indigenous applicants. Matching requirements are commonly associated with federal and provincial funding to charities.[34]

Regardless of the level of government funding, reporting is an essential part of the process. Failure to submit a required report may disqualify the grantee from receiving further financial support from the program.[35] Understanding the reporting requirements sheds light on the effort charities must exert to secure and maintain government funding.

2.5 Empirical Strategy

I employ three approaches to examine how government funding to charities responds to macroeconomic fluctuations.

2.5.1 Correlations

This subsection investigates how government funding to charities relates to broader macroeconomic conditions. I examine correlations between percentage changes in funding – by government level and charitable field – and lagged economic indicators. To capture possible asymmetric patterns and regional variation, I further analyse funding dynamics across fields and conduct provincial case studies of Alberta and Ontario.

Figure 2.5 illustrates a substantial increase in real aggregate government funding to charities over the sample period, rising from approximately \$15 billion in the 1990s to around \$45 billion by 2021. Within this overall trend, government funding to educational charities has grown dramatically, more than four times larger compared to the 1990s. In contrast, funding to religious organisations, arts charities, and the "Other" category has remained relatively stable and small. Funding to charities focused on Relief of Poverty and Community has also increased, though not as significantly as funding to Health and Education.

Table 2.5 presents correlations between changes in aggregate government funding to charities and specific fields and changes in various macroeconomic indicators. The findings reveal several key points: First, the correlation coefficients between macroeconomic indicators at time *t-1* (e.g., unemployment rate, S&P/TSX Index, and real consumption expenditure) and percentage changes in aggregate funding to total charities and most fields are negative. In contrast, correlations with macroeconomic indicators at time t vary in sign across funding categories. Second, the percentage change in SP/TSX_{t-1} shows the strongest

[34] Examples of matching grant programs at federal and provincial levels are available at: https://www.canada.ca/en/environment-climate-change/services/environmental-funding/programs/aboriginal-fund-species-risk.htm; https://www.alberta.ca/cip-project-based-grant#jumplinks-2

[35] An extra example of reporting obligations at local government funding level is available at: https://www.york.ca/business/assistance-non-profits/community-investment-fund

negative correlation (-0.594) with changes in funding to Community charities, and the weakest negative correlation (-0.070) with changes in funding to those in Arts. Conversely, the percentage change in funding to Health exhibits the most substantial positive correlation with the change in GDP_t (0.126), indicating a positive response to economic growth. The strongest negative correlation is observed between the percentage change in funding to Community charities and the change in GDP_t (-0.237), suggesting that funding to this field increases significantly during economic downturns. Additionally, the change in $Unemployment_{t-1}$ correlates strongly with changes in funding to Arts (0.507), reflecting government support for the arts during challenging economic periods.

I also disaggregated government funding into three levels: federal, provincial, and municipal. Tables 2.6, 2.7, and 2.8 provide correlations using these respective funding sources. As shown in table 2.6, the correlation coefficients between percentage changes in federal funding to charities, both in total and by field, and percentage changes in macroeconomic indicators at time *t* are generally negative. The strongest negative correlation (-0.687) is observed between the change in consumption expenditure $Consump.exp_t$ and federal funding to religious charities, while the smallest negative correlation (-0.016) is with federal funding to those in Education. The percentage change in federal funding to Education shows the most positive correlation with GDP_t (0.177), while the strongest negative correlation is with funding to religious charities and GDP_t (-0.490). The change in $Unemployment_t$ is strongly correlated with federal funding to religious charities (0.540), suggesting that the federal government tends to support religious charities during economic downturns.

Table 2.7 indicates that the correlation coefficients between the percentage changes in provincial funding to charities – both in total and by field – and macroeconomic indicators at time *t* are generally positive. The percentage change in provincial funding to Arts shows the most substantial positive correlation with changes in GDP_t (0.301), while the strongest negative correlation is between the percentage change in provincial funding to religious charities and changes in GDP_{t-1} (-0.186). The correlation with $Unemployment_{t-1}$ is particularly strong for provincial funding to religious charities (0.338), indicating provincial government responsiveness to religious charitable activities during economic downturns.

Table 2.8 reveals that the correlation coefficients between the percentage changes in municipal funding to charities – both in total and by field – and macroeconomic indicators at time *t* are generally positive, mirroring the pattern observed in provincial funding. The percentage change in municipal funding to Education shows the strongest positive correlation with changes in GDP_{t-1}(0.382), while the strongest negative correlation is with changes in GDP_{t-1} and municipal funding to Health (-0.325). The change in $Unemployment_{t-1}$ is strongly correlated with municipal funding to Health (0.466), suggesting that municipal governments support health-related charities during difficult economic times.

Tables 2.5, 2.6, 2.7, and 2.8 reveal several notable patterns in the correlations between government funding to charities and macroeconomic indicators. A key pattern is the consistently negative correlation between percentage changes in aggregate and federal funding to total charities and specific fields, and macroeconomic indicators at time *t-1*. Additionally, the percentage change in SP/TSX_{t-1} consistently shows the strongest negative correlation with the percentage change in aggregate funding, federal funding, and provincial funding to charities particularly in community services.

However, differences are also evident. Unlike the consistently negative correlation sign observed between aggregate government funding and federal funding to charities and lagged macroeconomic indicators, provincial funding and municipal funding to total charities and certain charitable fields exhibits a consistently positive correlation with contemporaneous indicators. Moreover, the countercyclicality of government funding varies across different levels of government and charitable fields. For instance, while aggregate government funding to Community and Arts is countercyclical, federal and provincial funding to religious charities, as well as municipal funding to the health sector, also show countercyclical patterns.

Furthermore, funding from the same level of government to the same charitable field can exhibit different signs of correlation coefficients with different macroeconomic indicators. For example, federal funding to Education has a negative correlation with percentage changes in consumption expenditure but a positive correlation with GDP growth. These observations highlight the need for a more precise examination of the significance of these correlations to gain a deeper understanding of the underlying dynamics.

Figure 2.6 illustrates the levels of aggregate government funding to charities alongside the S&P/TSX Composite Index in Canada from 1990 to 2021. The percentage change in aggregate government funding to charities closely mirrors the S&P/TSX Composite Index, with moderate variance, except for a notable two-year decline in funding during 1997 and 1998.

Figures 2.7 to 2.14 further explore the asymmetric relationship between aggregate government funding to charities both in total and by field, and economic conditions. I split the sample based on whether the percentage change in the S&P/TSX Composite Index is below or above zero and estimate separate slope coefficients for each subsample. For each coefficient, I report 95% confidence intervals based on 10,000 bootstrap replications. Since table 2.5 indicates that the percentage change in the S&P/TSX at time *t-1* shows the strongest correlation with the percentage change in aggregate funding to charities, this lagged index is used as the key variable for analysing economic fluctuations.

Figure 2.7 plots the relationship between the percentage change in the lagged S&P/TSX Composite Index and the percentage change in aggregate government funding to charities. In the negative domain, funding appears largely unresponsive to declines in the S&P/TSX, while in the positive domain, a negative slope emerges – suggesting that funding tends to decrease when the index rises. However, the 95% confidence intervals indicate that aggregate funding to total charities remains statistically insensitive to both expansions and contractions.

Consistent with this pattern, figures 2.8, 2.9, 2.10, 2.11, 2.13, and 2.14 show that aggregate funding to Relief of Poverty, Education, Religion, Health, Arts, and "Other" charities is generally unresponsive to economic fluctuations. By contrast, figure 2.12 reveals that funding to community services is more sensitive to economic expansions than downturns, as reflected in confidence intervals that lie below zero in the positive domain. These patterns suggest a potential asymmetry in how macroeconomic conditions shape government funding to charities, warranting further investigation at both the aggregate and sectoral levels.

Canada's regional economic diversity means that national-level data can obscure provincial differences. As in Chapter One, Alberta and Ontario are again examined as case studies to highlight variations in government funding and business cycles across provinces. The analysis considers the percentage changes in aggregate funding per capita to charities and real GDP per capita, accounting for population differences. Since table 2.7 identifies the correlation coefficient between provincial funding to total charities and GDP as the most significant among other indicators, real GDP per capita is used for this analysis. Figure 2.15 shows that real GDP per capita fluctuates more in Alberta than in Ontario, with Alberta experiencing five periods of economic contraction (1991, 1999, 2007-2009, 2015-2016, and 2019-2020) and Ontario undergoing contractions during different time frames (1991-1992, 2001, 2003, 2008-2009, and 2020).

In figure 2.16, the change in aggregate funding to total charities per capita in Ontario does not appear correlated with changes in real GDP per capita. In contrast, figure 2.17 shows a slightly downward-sloping fitted line in Alberta, with a coefficient of -0.26, compared to

Ontario's -0.13. These figures highlight the need for further examination of aggregate funding to charities by province during economic expansions and contractions.

Analysing correlations between funding from different levels of government to charities during economic fluctuations reveals several key findings. First, the sign of the correlation coefficients between the percentage changes in government funding to total charities (and by field) and the percentage changes in contemporaneous or lagged macroeconomic indicators is consistent, depending on the level of government. For example, there is a consistently negative sign of correlation between aggregate government funding and federal funding to charities and lagged indicators. In contrast, provincial funding as well as municipal funding to total charities and certain charitable fields shows a consistently positive correlation with contemporaneous indicators. Second, the countercyclicality of government funding varies across different levels of government and charitable fields. Additionally, funding from the same level of government to the same charitable field may exhibit different signs of correlation coefficients with different macroeconomic indicators. Finally, an asymmetric relationship is observed in aggregate funding to Community in response to economic contractions and expansions, as indicated by 95% confidence intervals using bootstrapping.

2.5.2 Time Series ARDL and NARDL Models

The ARDL and NARDL models help to further explore the links between macroeconomic indicators and aggregate government funding to charities, both in total and by specific fields of charitable activities. Given that 32 years of annual data constitutes a relatively short time series, the results from these models offer suggestive insights into the relationships between macroeconomic conditions and government funding to charities, complementing the findings from the earlier graphical and correlation analyses. As shown in table 2.7, real GDP is strongly correlated with provincial government funding to total charities. To account for population differences across provinces, I select real GDP per capita as the key variable of interest among the macroeconomic indicators in both the time series and provincial data analyses.

The ARDL model, developed by Pesaran et al. (2001), is widely used with time-series data (Kelly & Enns, 2010; Volscho & Kelly, 2012; Kharusi & Ada, 2018). In the ARDL framework, all regressors should be either purely stationary *I(0)*, purely integrated of order one *I(1)*, or a combination of both (Pesaran et al., 2001). This paper focuses on the short-run relationships between economic conditions and funding to charities, which are captured by the first differences of (lagged) variables in the ARDL model. The decision not to estimate long-run coefficients is due, in part, to the ambiguity in the literature regarding the definition of the long run in the context of the ARDL model (Pesaran et al., 2001; Kelly & Enns, 2010; Volscho & Kelly, 2012; Kharusi & Ada, 2018; Philips, 2018). Additionally, this paper does not aim to explore how government funding to charities converges to equilibrium (de Boef & Keele, 2008).

The NARDL model is similar to the ARDL model, with the key difference being its ability to capture asymmetry between the dependent and independent variables. Although other specifications, such as the quadratic form of GDP, can define asymmetric relationships, the NARDL model is derived from the ARDL to maintain consistency in measurement. The NARDL model was first proposed by Shin and Yu (2004) and further developed by Shin, Yu, and Greenwood-Nimmo (2014). The NARDL model allows for asymmetric effects of economic fluctuations, treating positive and negative changes in GDP as differing in magnitude. It is therefore preferred in this study.

According to Pesaran et al. (2001) and Philips (2018), the general time-series short run ARDL(*J,K*) model is specified as follows, corresponding to the description provided in Subsection 1.5.2 of Chapter One:

$$\Delta F_t = \alpha_0 + Trend + \sum_{j=1}^{J} \theta_j \, \Delta F_{t-j} + \sum_{k=0}^{K} \delta_k \, \Delta GDPC_{t-k} + \mu_t \qquad (2.1)$$

where $t = 1, 2, ..., T$ is the time; j is the number of lags; ΔF_t represents the first difference of natural logarithm of government funding to total charities and by fields at time t; $\Delta GDPC_t$ is the first difference of natural logarithm of GDP per capita at time t; μ_t is the identically distributed error term; J and K are the optimal lag length for ΔF_t and $\Delta GDPC_t$. All variables are in the real values with the base year of 2017. As in Chapter One, I allow for the possibility of a non-linear trend by including both a time trend and a constant in the regression. The constant captures the average growth in funding to charities, conditional on other factors.

I am assuming aggregate government funding available to the charitable sector to be exogenous. While individual charities submit grant applications and hence affect their own likelihood of funding, the analysis in this chapter operates at the aggregate level and examines total government funding to the charitable sector. At this level of aggregation, observed funding primarily reflects government budget decisions and fiscal priorities, which plausibly respond to macroeconomic conditions rather than to the actions of individual charities.

Following Shin, Yu, and Greenwood-Nimmo (2014), I construct the NARDL model, which is similar to the model outlined in Subsection 1.5.2 of Chapter One, with the primary difference being the dependent variable:

$$\Delta F_t = \alpha_0 + Trend + \sum_{j=1}^{J} \theta_j \Delta F_{t-j} + \sum_{k=0}^{K} (\delta_k^+ \Delta GDPC_{t-k}^+ + \delta_k^- \Delta GDPC_{t-k}^-) + \mu_t \quad (2.2)$$

As explained in Chapter One, Borenstein and Shepard (1996), Borenstein et al. (1997), Hansen (2000), Lee (2000), Virén (2001), and Shin, Yu, and Greenwood-Nimmo (2014) reach an agreement on the construction of asymmetric first difference variables. I thus define the asymmetric first difference variables based on their studies as follows:

$$\Delta GDPC_t^+ = \Delta GDPC_t I_t^+, \text{ where } I_t^+ = \begin{cases} 1, if\ \Delta GDPC_t \geq 0 \\ 0, if\ \Delta GDPC_t < 0 \end{cases} \quad (2.3)$$

$$\Delta GDPC_t^- = \Delta GDPC_t I_t^-, \text{ where } I_t^- = \begin{cases} 1, if\ \Delta GDPC_t \leq 0 \\ 0, if\ \Delta GDPC_t > 0 \end{cases} \quad (2.4)$$

The basic idea behind equations (2.3) and (2.4) is to achieve piecewise linearisation by introducing an indicator function, which serves as a switching mechanism (Hansen, 2000; Tong, 2011). This "threshold approach" is intuitive: a first-difference variable $\Delta GDPC_t^+$ is classified as "positive" if there is a positive change in GDP per capita at time *t*; otherwise, it is set to zero.

The performance of lags in small samples was discussed in Subsection 1.5.2 of Chapter One. To determine the optimal lag length, I applied traditional selection criteria, including the AIC, HQIC, and SBIC, also known as the BIC. These criteria, which are reported in table 2.1B, were used to select the optimal lags, with a maximum of four lags considered. The general rule is that the smaller the value, the better the model fit. As shown in table 2.1B, the optimal lag length for each variable is consistently zero across all three criteria in most cases, suggesting that the model reduces to a simple linear regression without autoregressive terms.

Before estimating the ARDL and NARDL models, I conducted a unit root test to ensure that none of the dependent or independent variables were integrated at a level higher than order one, *I(1)*. The results from four unit-root tests are presented in table 2.9, where I report the tests for both dependent and independent variables in the models. The tests conducted include the PP test (Phillips & Perron, 1988), the ADF test, the DF-GLS test, and the KPSS test (Kwiatkowski et al., 1992). Variables were tested both with and without a trend. The results indicate that, after including a trend, all variables are *I(1)* in the PP, ADF, and KPSS tests, except for ln(Art), which is *I(1)* without a trend in the PP test. This outcome satisfies the requirement that no variables are integrated at an order higher than *I(1)*. Since small-sample adjusted critical values are not available for these unit root tests, I rely on the four tests to confirm that the variables are indeed integrated at most at order *I(1)*.

As indicated in Chapter One, I conducted diagnostic tests to assess normality, heteroskedasticity, autocorrelation, and model specification. These tests are essential as violations of the first three assumptions render the *t*-test and *F*-test invalid, while issues with model specification, such as omitted variables, result in biased and inconsistent estimates. The Shapiro-Francia normality test, suitable for sample sizes ranging from 5 to 5,000 observations (Shapiro & Francia, 1972), was again employed for this analysis. According to the results detailed in appendix 2.B, table 2.2B, no issues with autocorrelation or model specification were detected. However, heteroskedasticity was observed in government funding variables for total charities and those specific to Education, Health, and Arts. To address this, and in consideration of the small sample size, I applied wild cluster bootstrap methods, as outlined in appendix 1.6B of Chapter One. Each estimation involved 10,000 bootstrap replications.

Table 2.10 presents the symmetric effects of changes in real GDP per capita on the growth of aggregate government funding to charities per capita, estimated using an ARDL model with wild cluster bootstrapping. As noted above, the optimal lag length is zero, so the model simplifies to a linear regression. The estimated effects are characterised by Δ*ln(RGDPC),* representing the impact of real GDP per capita changes on funding growth at lags *k*=0, ..., *K,* where the optimal lag length is selected using the Akaike Information Criterion (AIC) following Pesaran et al. (2001). The results indicate that, except for funding to Arts, the optimal lag for funding to total charities and various fields is zero. Moreover, no significant effects of Δ*ln(RGDPC)* on aggregate funding to total charities or specific fields of activity were found, with the exception that a one percentage point increase in real GDP at time *t* is significantly associated with a 1.682 percentage point decrease in funding growth for "Other" charities.

Table 2.11 examines the asymmetric effects of real GDP per capita on aggregate government funding to charities using a NARDL model.[36] As with the previous table, the zero optimal lag length reduces the model to a linear specification. Wald tests for asymmetry are conducted on the variables Δ*ln(RGDPC_pos)* and Δ*ln(RGDPC_neg)* to assess differential responses to positive and negative GDP changes. In contrast to the symmetric ARDL results, the NARDL estimates reveal that funding to charities in Relief of Poverty, Religion, and Arts

[36] Diagnostic tests are conducted in the appendix 2.B table 2.3B.

increases during economic downturns, while funding to Health decreases in response to falling GDP. Specifically, during economic contractions, a one percentage point decrease in GDP at time t is significantly and negatively associated with a 1.097 percentage point increase in government funding to Relief of Poverty, a 19.11 percentage point increase in funding to Religion, and a 1.695 percentage point increase in funding to Arts, indicating that funding to these fields is countercyclical during downturns. Conversely, aggregate funding to Health is procyclical, with a one percentage point decrease in real GDP per capita associated with a 1.081 percentage point decrease in Health funding. Significant asymmetry was found in funding to Religion and Arts, as evidenced by the Wald test, suggesting that government funding to Religion is more responsive during downturns, whereas funding to Arts is more responsive during expansions. These findings align with the understanding that government support for religious charities is more likely during periods of economic contraction, particularly when these charities assist communities in need.

The NARDL model findings indicate an asymmetric relationship between aggregate government funding to the Relief of Poverty and economic fluctuations, with funding being countercyclical during economic contractions. This aligns with the argument for countercyclical fiscal policies aimed at macroeconomic stabilisation (Lane, 2003; Furceri, 2010; Fatás & Mihov, 2013).

To further test the sensitivity of results to lags, table 2.4B sets the lag equal to one for the dependent variables in both the ARDL and NARDL models. When introducing lagged growth in funding by charitable fields in the ARDL model, only the growth in aggregate funding to "Other" charities remains significantly responsive to the growth in real GDP per capita. The significance and magnitude of the parameters are consistent with the results obtained without including lagged dependent variables. In the NARDL model, adding lags to the dependent variables does not substantially alter the main results, indicating that both the ARDL and NARDL models are robust to the inclusion of lags in the dependent variables. Additionally, in table 2.5B, the lag is set to one for the growth of real GDP per capita in both models. The findings suggest that in the ARDL model, the growth of aggregate government funding to total charities and specific fields is slightly sensitive to lags in GDP growth. When introducing lagged GDP growth, funding to Education and Community becomes significantly and negatively responsive to the lagged indicator in the ARDL model. In the NARDL model, the previously significant parameters, such as the growth in aggregate funding to Relief of Poverty and Arts, remain significant in response to both contemporaneous and lagged macroeconomic indicators, with the magnitude of change remaining similar to the main results. A slight difference observed is that funding to Education becomes negatively associated with the growth in lagged GDP per capita. Overall, lags in the dependent variables do not significantly affect the estimated results, and lags in the growth of GDP per capita have little impact on the significance and magnitude of the estimated coefficients.

The NARDL model captures the asymmetric responsiveness of aggregate government funding to charities relative to GDP per capita; I therefore use it to explore the asymmetric relationships between government funding from federal, provincial, and municipal levels to charities and GDP per capita. Tables 2.12, 2.13, and 2.14 present the NARDL estimations for government funding to charities at these different levels from 1997 to 2021. Table 2.12 shows that federal funding to Religious and "Other" charities responds countercyclically to negative GDP growth. However, the Wald test indicates that the difference between responses during economic expansions and contractions is not statistically significant. Table 2.13 shows that provincial funding to Arts charities is procyclical during economic downturns. However, no significant asymmetric effects are found between provincial funding to charities (by field) and GDP growth. In table 2.14, municipal funding to Health is found to be more responsive to economic expansions than contractions, with a one percentage point increase in real GDP per capita leading to a 16.27 percentage point increase in municipal funding to Health. However, the Wald test does not provide evidence of statistically significant asymmetry between responses in expansions and contractions.

The results in tables 2.11, 2.12, 2.13, and 2.14 reveal some similarities: both aggregate funding and federal funding to religious charities are countercyclical during downturns, while aggregate funding and municipal funding to Health are procyclical.

The ARDL and NARDL models, when using aggregate data, cannot accommodate provincial dummies and therefore do not capture provincial differences. To enable cross-province comparison, I applied ARDL(0,0) and NARDL(0,0,0) models – both of which reduce to linear regressions – to data from each of the ten provinces (tables 2.6B and 2.7B in appendix 2.B). The optimal lag for the independent variable in each province is based on the aggregate-level model, which is zero, while the lag for the dependent variable is selected based on the common lag in each province, which is one, according to the AIC.

In the ARDL(0,0) model, the key independent variable is real GDP per capita in each province. The results show that in Alberta, the growth in real GDP per capita at time *t* is negatively associated with the growth in aggregate funding per capita to total charities. Additionally, in Alberta and Manitoba, GDP per capita growth is negatively associated with funding to Relief of Poverty, while in New Brunswick, Newfoundland, Prince Edward Island,

and Quebec, it is negatively related to funding to religious charities. In Ontario and Nova Scotia, the growth in funding to "Other" charities is also negatively associated with GDP per capita growth. In the NARDL(0,0,0) estimation, significant asymmetric responses to economic fluctuations are found in provinces such as British Columbia, Manitoba, New Brunswick, Ontario, and Prince Edward Island. The NARDL model also reveals that funding to Relief of Poverty in British Columbia, Prince Edward Island, and Quebec; funding to Education in Alberta, British Columbia, and Quebec; funding to Religion in Alberta, Manitoba, New Brunswick, Nova Scotia, Ontario, Prince Edward Island, and Quebec; funding to Health in Ontario and Prince Edward Island; funding to Community in British Columbia, Newfoundland, and Prince Edward Island; and funding to Arts in Alberta, British Columbia, New Brunswick, Prince Edward Island, and Quebec exhibits significant asymmetric responses to expansions and contractions.

This subsection examined the symmetric and asymmetric effects of GDP on aggregate funding to total charities and specific fields of activity. The ARDL model indicates that only aggregate funding to "Other" charities shows a significant short-run response to changes in real GDP per capita. In contrast, the NARDL model reveals that the growth of aggregate funding to Relief of Poverty, Religion, Health, and Arts responds significantly to contractions in GDP. Specifically, funding to Relief of Poverty, Religion, and Arts is countercyclical during downturns, while funding to Health is procyclical. The NARDL model was then applied to assess the asymmetric relationships between government funding from federal, provincial, and municipal levels and GDP per capita. Some findings are consistent with the results for aggregate funding to charities; for example, federal funding to religious charities is countercyclical during downturns, and municipal funding to Health is procyclical during upturns. However, differences emerge, such as aggregate funding to Religion being countercyclical, while at the provincial level, it is procyclical. When applying the ARDL and NARDL models to each province, significant symmetric and asymmetric relationships between aggregate funding to charities per capita and provincial GDP per capita were identified. These results suggest that estimating panel ARDL and panel NARDL models would be a valuable next step.

2.5.3 Panel ARDL and NARDL Models

I use provincial panel data to explore the symmetric and asymmetric relationships between growth in real GDP per capita and growth in government funding to charities per capita. By applying the panel ARDL and NARDL models, I can examine how economic fluctuations impact aggregate government funding at the provincial level, addressing concerns that national aggregate data might obscure regional differences.

Building on the time-series models, the panel approach enhances the analysis in two important ways: it improves statistical power by exploiting variation across provinces and years, and it accounts for unobserved provincial heterogeneity through fixed effects. The panel NARDL specification further allows differential responses to positive and negative GDP shocks, making it especially useful for testing asymmetries in funding behaviour over the business cycle.

There has been very little work on provincial funding to charities in Canada. Previous research has primarily focused on federal government funding to nonprofits (Pal, 1995; Brodie, 1997, 2008; Phillips, 2000; Beres et al., 2009). Clément (2019) provides one of the few studies addressing changes in provincial policy, funding trajectories, patterns, and the types of organisations that have received provincial funding in British Columbia since 1960. Clément's work examines funding for nonprofits in four sectors: Aboriginal peoples, the environment, human rights, and women. Masson (1999, 2012) focuses on state funding to women's organisations in Quebec. My research will expand the scope to include federal, provincial, and municipal funding to charities within each province, addressing the broader landscape of funding structures.

Following Pesaran et al. (1999), I specify my panel ARDL(*J, K*) model as follows, which is similar to the model outlined in Subsection 1.5.3 of Chapter One:

$$\Delta F_{pt} = \alpha_0 + \sum_{j=1}^{J} \theta_{pj}\, \Delta F_{p,\,t-j} + \sum_{k=0}^{K} \delta_{pk}\, \Delta GDPC_{p,\,t-k} + u_t + \omega_{pt} \tag{2.5}$$

where all variables are in the form of natural logarithm of real values, ΔF_{pt} denotes the growth of government funding to charities per capita in total and by fields in province p at time *t;* $\Delta GDPC_{pt}$ is the growth of GDP per capita in province p at time *t*; θ_{pj} and δ_{pk} are scalars; p = 1, 2, ..., *N*; *t* = 1, 2, ..., *T*; *J* and *K* are time lags; u_t represents year fixed effects; $\omega_{pt} = e_{p,t} - e_{p,t-1}$.

Building on the work of Pesaran et al. (1999) and Shin, Yu, and Greenwood-Nimmo (2014), I develop my panel NARDL(*J, K, K*) model, similar to the model detailed in Subsection 1.5.3 of Chapter One:

$$\Delta F_{pt} = \alpha_0 + \sum_{j=1}^{J} \theta_{pj}\, \Delta F_{p,\,t-j} + \sum_{k=0}^{K} (\delta_{pk}^{+}\, \Delta GDPC_{p,t-k}^{+} + \delta_{pk}^{-} \Delta GDPC_{p,t-k}^{-}) + u_t + \omega_{pt} \tag{2.6}$$

where $\omega_{pt} \sim N(0, \sigma^2)$, the asymmetric first difference variables are similarly defined as in equations (2.3) and (2.4) in the NARDL model. A slight difference to equations (2.1) and (2.2) is to add the extra index p denoting the ten provinces, and the replacement of the deterministic trend with time fixed effects.

One concern of the model specification in equations (2.5) and (2.6) is the independent variable $F_{p,t-1}$ on the right-hand side might be correlated with the component of error term, $e_{p,t-1}$. As discussed in Subsection 1.5.3 of Chapter One, the dynamic fixed effects (DFE) method is appropriate for addressing dynamic small-sample bias when the time dimension of the dataset exceeds 20 (Roodman, 2009; Bond & Xing, 2015; Fatica, 2018; Jeanniton, 2022). In this study, with 10 cross-sectional units observed over 32 years, the DFE method is the most suitable choice. Conversely, the generalised method of moments (GMM) is typically applied when there are few time periods (small T) and a large number of cross-sectional units (large N) (Arellano & Bond, 1991; Blundell & Bond, 1998; Blundell et al., 2001; Baum et al., 2003; Wen & Yilmaz, 2020). Since this does not align with the characteristics of my dataset, GMM is not considered for this analysis.

As with the ARDL and NARDL models, I conduct panel unit root tests to ensure that no variables are higher than *I(1)*. Then I report how the growth in provincial GDP per capita affect the corresponding value of government funding to charities per capita. The results of the panel unit root tests for all variables in the panel ARDL and NARDL models are reported in table 2.15. In conducting the panel unit root test, although there are tests based on ADF and PP methods, I opted to focus on tests based on Levin, Lin, and Chu (LLC) (Levin et al., 2002), as well as Breitung (2001) and Breitung and Das (2005). The reason for choosing these tests is similar to the rationale provided in Subsection 1.5.3 of Chapter One: both the LLC and Breitung tests are known for their good power with small datasets. This makes them particularly well-suited for the panel data structure in this study. As shown in table 2.15, the LLC test results indicate that no variable is integrated higher than *I(1)*, regardless of whether a trend is included. Similarly, the Breitung test results, without a trend, confirm that all variables are integrated at most at order *I(1)*.

To account for heteroskedasticity and serial correlation within provinces, as indicated by diagnostic tests (Appendix 2.B, tables 2.8B and 2.9B), I cluster standard errors at the province level throughout the panel data analysis, as discussed in Section 1.5.3 of Chapter One (Beck & Katz, 1995; Cameron & Miller, 2015). Table 2.16 presents the panel ARDL estimation results. The growth in real GDP per capita at time *t* is significantly associated with changes in aggregate funding for Education and Arts. Specifically, a one percentage point increase in GDP per capita growth is linked to a 3.410 percentage point increase in funding growth for Education, while it is associated with a 1.058 percentage point decrease in funding growth for Arts. Taken together, these results suggest that government funding reallocates across subsectors over the business cycle, expanding support for Education during economic upturns while shifting resources away from Arts. The magnitudes imply economically meaningful shifts in funding composition in response to macroeconomic conditions.

Panel NARDL estimation results are reported in table 2.17. More charitable fields show significant responses to economic fluctuations when GDP growth is separated into positive and negative components, supporting the use of the panel NARDL model. Consistent with the panel ARDL results, funding for Education and Arts remains significantly associated with GDP growth. Aggregate funding to total charities and funding to Education appear procyclical, while funding to Health and Arts is countercyclical. Specifically, a one percentage point decrease in real GDP per capita is associated with a 4.999 percentage point increase in funding for Education and a 0.958 percentage point increase in funding for Community. Similarly, a one percentage point decrease in real GDP per capita corresponds to a 5.716 percentage point increase in funding for Health and a 1.586 percentage point increase in funding for Arts. These findings indicate asymmetric relationships between GDP and funding for total charities, Education, Health, and Community: funding to total charities and Education is more responsive to economic expansions, whereas funding to Health is more responsive to economic contractions. Finally, I test the sensitivity of the results to the inclusion of lags, as shown in table 2.10B, where the lag for the growth of real GDP per capita is set to one in the panel ARDL and NARDL models. The results remain robust to the inclusion of lags in the independent variables.

The panel ARDL model reveals that Education funding is procyclical. The panel NARDL model further shows that funding to Education is sensitive to economic expansions, adding a new dimension to our understanding of how these fields respond to macroeconomic changes (Bhalla et al., 2017; Evans et al., 2019). The observed asymmetric effects in the panel NARDL model, particularly the sensitivity of educational funding to economic contractions and expansions respectively, align with the notion of differential government spending responses across economic cycles (Kwak, 2017).

I further examine federal and provincial funding to charities at the provincial level using the panel NARDL model. Table 2.18 shows that federal funding to Education is sensitive to economic expansions and exhibits procyclical behaviour, while federal funding to Community is more responsive during economic contractions, indicating countercyclical behaviour. In addition, Wald tests confirm a significant asymmetric relationship between expansions and contractions in the case of federal funding to Community.

Table 2.19 shows that provincial funding for Health is sensitive to economic contractions and exhibits countercyclical behaviour, while funding for Community becomes more stable during downturns. Additionally, provincial funding to total charities is negatively associated with contractions. Wald tests indicate significant asymmetries in all three cases, suggesting that provincial governments allocate more – or at least maintain – funding to these charitable fields during economic downturns compared to periods of expansion.

Tables 2.18 and 2.19 reveal both similarities and differences in how federal and provincial funding to charities respond to economic conditions. At both levels of government, funding for Community exhibits significant asymmetric responses to expansions and contractions, showing countercyclical patterns overall. However, the direction of responsiveness differs: federal funding for Community increases during economic downturns but remains stable during expansions, while provincial funding increases during expansions and remains stable during downturns. A similar contrast appears in the Education sector – federal funding is procyclical, increasing during economic expansions, whereas provincial funding remains stable. Additionally, provincial funding for Health is countercyclical, rising during contractions, while federal funding to Health appears unaffected by changes during economic fluctuations.

This subsection examines the symmetric and asymmetric effects of real GDP per capita on aggregate government funding to charities per capita, both in total and across specific fields of activity. The analysis reveals that macroeconomic conditions influence charitable funding in both symmetric and asymmetric ways, with the asymmetric specification capturing more nuanced fluctuations. In the panel ARDL model, GDP growth at time *t* is significantly and positively associated with funding to Education but negatively associated with funding to Arts. The panel NARDL model yields three key findings. First, in addition to confirming the significant effects identified in the ARDL model, it reveals new significant associations: funding to Health and Community becomes significantly related to GDP movements under the asymmetric specification, despite being insignificant in the ARDL results. Second, the growth in aggregate funding to Arts is particularly sensitive to economic contractions, whereas the growth in funding to Education is more responsive to economic expansions. Finally, I examined the asymmetric effects of real GDP per capita on both federal and provincial funding per capita, in total and by fields of activity. Some similarities were observed between federal and provincial funding, particularly in the field of Community.

However, differences were also noted: more variables were significantly associated with positive or negative changes in the growth of real GDP per capita at the provincial level compared to the federal level. Additionally, the patterns of funding to Health and Education differ between federal and provincial levels.

2.5.4 Government Funding, Private Donation and Macroeconomic Conditions

In Chapter One, I find that the growth of aggregate giving, as well as giving by specific fields such as Education and Religion significantly responds to growth in GDP per capita. Given that both government funding and private donations to Education and Religion are responsive to changes in GDP per capita, it raises the question of whether government funding to charities interacts with private donations.

The dynamics between government funding to charities and charitable donations have been well studied, particularly in terms of crowding-in (positive correlation) and crowding-out (negative correlation) effects (de Wit & Bekkers, 2017; de Wit et al., 2017; de Wit & Bekkers, 2020). For example, in the Netherlands, charitable donations partially offset reductions in government funding to nonprofits when information about budget cuts is clearly communicated to the public (de Wit and Bekkers, 2020). In a systematic review, de Wit and Bekkers (2017) find that the evidence on crowding-out is significantly influenced by research methods: experimental studies often reveal crowding-out between government support and donations, whereas analyses using nonexperimental data tend to find a crowding-in relationship. Moreover, responses of donations to public funding vary by nonprofit sector. Even in sectors more prone to crowding out, increases in donations do not fully compensate for decreases in government support (de Wit et al., 2017).

In these studies, government funding is typically considered an explanatory variable. In my study, government funding is the outcome variable, which could introduce concerns about reverse causality. Nevertheless, as the primary aim is to examine the association between donations and funding and to observe how government funding responds when donations are controlled for, reverse causality should not pose a significant issue.

I investigate the relationship between private donations and government funding to charities in Canada, as well as the joint effects of macroeconomic fluctuations and private donations on funding to charities. The equations are as follows:

$$\Delta F_{pt} = \alpha_0 + \sum_{j=1}^{J} \theta_{pj}\, \Delta F_{i,\,t-j} + \sum_{k=0}^{K} \delta_{pk}\, \Delta Donation_{p,\,t-k} + u_t + \omega_{pt} \qquad (2.7)$$

$$\Delta F_{pt} = \alpha_0 + \sum_{j=1}^{J} \theta_{pj}\, \Delta F_{p,\,t-j} + \sum_{k=0}^{K} \delta_{pk}\, \Delta GDPC_{p,\,t-k}$$

$$+ \textstyle\sum_{k=0}^{K} \gamma_{pk}\, \Delta Donation_{p,\,t-k} + u_t + \omega_{pt} \qquad (2.8)$$

Equation (2.7) is a modified version of equation (2.5), where GDP is replaced with donations. In equation (2.8), I introduce an additional variable to equation (2.7) to estimate the separate effects of GDP per capita growth and donations per capita growth on the growth of funding to charities per capita.

Compared with table 2.16, which presents the impact of GDP per capita on aggregate government funding to charities, table 2.20 examines the effects of charitable donations on government funding patterns. The findings are as follows. First, charitable sectors except Arts and "Other" that do not respond to GDP growth also show no response to changes in private donations, suggesting that donations do not significantly relate to government funding in those fields. Second, government funding to Arts is positively associated with changes in private donations, indicating an indirect role of private donations in shaping public support for this sector.

It is possible that the coefficients in table 2.16 reflect indirect effects of private donations, which may lead to over- or underestimation. To address this, I include both private donations and GDP in the analysis. Table 2.21 shows that the association between funding growth and GDP growth – particularly in fields such as Education and Arts – remains even after controlling for donations per capita. Taking the positive sign in Education as an example, the coefficient is close in magnitude to that in table 2.16, suggesting that excluding private donations does not substantially overstate the effect of GDP in this field. In other fields, the differences are minimal, providing little evidence of systematic over- or underestimation.

In summary, including private donations does not alter the significance of GDP for government funding across charitable fields. After controlling for donations, crowding-in effects appear in Arts and "Other," while no significant crowding-out is observed in other sectors. This contrasts with de Wit et al. (2017), who found crowding-out in Health in the Netherlands. The difference likely reflects institutional context: Canada's health sector is financed almost entirely through public budgets, leaving little margin for private donations to adjust, whereas in the Netherlands charitable giving plays a more complementary role in health provision and is thus more responsive to changes in government spending.

To assess potential multicollinearity between GDP and donations, I calculate the Variance Inflation Factor (VIF) and present results in table 2.11B. While Chapter One demonstrates a significant economic relationship between GDP and donations, the low VIF values (mostly close to 1) indicate that GDP and donations do not exhibit statistical multicollinearity in this context. VIF assesses whether independent variables (e.g., GDP and donations) are highly correlated in the same model, which could inflate standard errors and reduce the reliability of coefficient estimates. Even if GDP and donations are related, their individual effects on government funding to charities are sufficiently distinct, which is why VIF values remain low.

2.5.5 A Summary of Findings

Table 2.22 provides a summary of the key statistically significant findings from the ARDL and NARDL models using both aggregate data and the panel ARDL and panel NARDL models. In this table, the symbols +/- indicate a statistically significant estimated coefficient for the variable of interest. Additionally, the table highlights differences in the slopes when examining the responses of the growth of government funding to charities (per capita) during periods of positive versus negative GDP (per capita) growth in the (panel) NARDL models.

This table yields five main takeaways. First, compared to the (panel) ARDL model, the (panel) NARDL model better captures significant responses of government funding to GDP changes, both in total and by field. Second, aggregate funding to Religion is significantly associated with GDP growth at the national level but not across provinces, while the reverse is true for Education, Health, and Community. Third, some sectors are more sensitive to negative GDP changes than to positive ones – for example, aggregate funding to Health, primarily driven by provincial funding. In contrast, funding to Education and Community is more responsive to positive GDP changes but not to contractions. Fourth, the panel NARDL model reveals contrasting dynamics in Community funding: federal funding is more responsive to downturns, while provincial funding reacts more to expansions. Finally, controlling for private donations does not alter the significance of GDP's relationship with government funding across fields.

2.6 Robustness

I checked the robustness of my results in several ways. First, I applied different measurements of macroeconomic indicators, such as the output gap used in the monetary policy report and the unemployment rate.[37] Second, I used the dataset without the

[37] Defined the percentage deviation of real GDP from potential GDP, reported by the Bank of Canada (see table 2.1). Given the quarterly national series, I use a time series NARDL model and take the unweighted annual average. This measure allows GDP to fall while remaining above potential.

recalculated aggregate funding to charities (noting that 14.31% of the original line 4570 entries did not match the recalculated values) to assess whether recalculation improves data accuracy. Third, I interact GDP changes with province fixed effects to capture heterogeneity in how provinces respond to economic cycles. Fourth, I restrict the sample to charities that operate primarily at the regional or provincial level to address potential mismatches between a charity's registered location and its actual service area. Lastly, I report the combined effects of GDP and donations using Principal Components Analysis (PCA). All these results are reported in appendix 2.B.

Table 2.12B presents the findings when the output gap from the monetary policy report is used. The growth in aggregate funding to Relief of Poverty responds significantly to a negative output gap. Specifically, a one percentage point decrease in the output gap is associated with a 1.47 percentage point increase in aggregate funding to Relief of Poverty. The other variables are not significantly associated with positive or negative changes in the output gap.

Table 2.13B suggests that when using the sample without recalculation of total government funding to charities, the significance of the estimates weakens. Only the growth in aggregate funding to Arts responds significantly to positive changes in real GDP per capita, highlighting the importance of recalculating line 4570.

Table 2.14B presents the findings when using an alternative measure of macroeconomic fluctuations – the unemployment rate. Similar to the results in the panel NARDL model (table 2.17), table 2.14B indicates that funding to the Education category becomes increasingly procyclical as the unemployment rate rises. Specifically, a one percentage point increase in the unemployment rate is associated with a 4.601 percentage point decline in average aggregate funding to educational charities. Unlike the main results, aggregate funding to Relief of Poverty is significantly associated with decreases in the unemployment rate, but remains unresponsive to provincial GDP changes.

To address the concern that provinces may respond differently to economic fluctuations, I include an interaction term between provincial dummies (with Ontario as the reference group) and GDP variations. Table 2.15B shows that, after including this term, funding to Education remains statistically significant, consistent with the panel ARDL results in table 2.16. In addition, more categories – such as aggregate funding to Relief of Poverty, Religion, and Community – become significant, suggesting that the interaction term improves model fit and captures meaningful regional heterogeneity.

A charity headquartered in Ontario may operate nationally, so Ontario's economic conditions may not directly affect the aggregate government's funding to that organisation. To address this concern, I exclude charities with national or international service scopes, focusing only on those providing local services (as noted in Chapter One, Section 1.2A, approximately 60% of charities serve local areas). Table 2.16B reports the relationship between provincial GDP fluctuations and aggregate funding to locally operating charities. The signs and significance of the coefficients for Education and Community remain consistent with the main results, lending support to the robustness of the findings.

Table 2.17B presents the joint effects of GDP and donations on government funding to charities, using a principal component derived from the two series: real GDP per capita and total charitable donations per capita. Although PCA is typically applied to larger sets of variables, applying it to these two allows for a formal summary of their shared variation in a single index capturing broad economic climate. Since both variables fluctuate with economic cycles, their common pattern likely reflects underlying economic conditions. The results show that this joint component is significantly associated with funding growth in the field of Education. This finding is consistent with table 2.21, where GDP per capita growth is also significantly related to funding in this field, suggesting that macroeconomic changes, particularly through GDP, play a key role in driving funding patterns in Education. Additionally, the impact of private donations on funding is limited to Arts and "Other" charities, which collectively account for a small and general portion of total funding to charities (as shown in figure 2.5), highlighting the dominant role of macroeconomic conditions in driving funding patterns.

2.7 Discussion and Conclusion

Macroeconomic conditions appear to influence government funding to charities. However, the relationship is complicated, varying with the level of government, the field of the charity, and whether the economy is in expansion or contraction.

Government funding to charities exhibits distinct patterns depending upon whether the funding comes from federal, provincial, or municipal governments. Federal funding is normally countercyclical, increasing during economic downturns and remaining stable during growth periods, to stabilise the critical sectors like Relief of Poverty and Religion and ensure continuity in essential services. In contrast, provincial and municipal funding is for the most part procyclical, rising during economic expansions but not falling during downturns, addressing immediate local needs in fields such as Community and Health. These patterns, in general, reflect broader governmental roles: federal funding focuses on stabilisation and equity, while provincial and municipal funding aligns more closely with current economic conditions.

Government funding also varies by charitable field. Aggregate funding to charities in Education and Health exhibits greater growth volatility compared to corresponding government expenditures in these sectors. Aggregate funding to Community is broadly procyclical across government levels, increasing during upturns and stabilising in downturns, underscoring its consistent prioritisation for societal stability. Education funding also exhibits a procyclical pattern, rising during economic growth and stabilising during contractions. Its strong alignment with GDP growth, even after controlling for changes in donations, suggests that Education funding is closely tied to overall economic performance. This pattern is consistent with governments partially offsetting weaker growth in private donations through increased grant funding, particularly in Education. This interpretation aligns with Hickey et al. (2025), who document that private donations have remained flat since the mid-2000s, alongside a declining share of donors and increasing concentration of giving among high-income households. As charitable giving becomes flatter and less broad-based, government funding to charities may play a more important stabilising role in specific sectors. In contrast, Religion funding is countercyclical at the national level: it tends to increase during downturns and remain stable during upturns. This pattern highlights the sector's role in promoting social cohesion during times of economic stress. The fact that it is only religious charities that provide social services that receive government funds, lends further support to the importance placed on these activities. Arts funding generally increases during economic contractions and remains constant during expansions, reflecting a strategy to sustain cultural institutions during downturns while preserving fiscal capacity for investment in better times. A crowding-out effect in the Arts category suggests a substitution between government funding and private donations.

Economic cycles engender asymmetric patterns in government funding to charities, with differentiated responses during expansions and contractions. Moderately countercyclical funding, such as that for Religion and Health, rise during downturns but stabilise in upturns. Moderately procyclical funding, as seen in Education and Community, increase during growth phases while remaining stable during contractions. These asymmetric responses highlight how funding priorities shift dynamically to address varying economic contexts across sectors, complementing findings on field-specific variations.

The findings of this study advance our understanding of how government funding to charities responds to macroeconomic conditions, adding depth to the existing literature on fiscal policy and economic stabilisation. By differentiating funding sources, fields, and economic phases, this research captures the nuanced dynamics underlying these relationships. The integration of diverse econometric models enriches the analysis, uncovering both symmetric and asymmetric effects that have received limited attention in prior research. The results reveal both countercyclical and procyclical behaviours, suggesting that funding the charitable sector is a firm government priority. Such funding comprises a very small portion of total government spending, which helps further explain its strength even in times of economic downturn. These insights contribute to broader theories of government expenditure behaviour over business cycles, fiscal policy roles, and sector-specific impacts, enhancing our understanding of resource allocation in response to economic fluctuations.

This study has limitations. The dataset used has inherent constraints, as discussed in the data section. One concern is the small sample size in the ARDL and NARDL models, which weakens the *t*-test assumptions based on the standard normal distribution. I addressed this issue by applying the wild cluster bootstrap test with 10,000 repetitions of replaced resampling. Another concern is the potential endogeneity problem in the panel ARDL and panel NARDL models after introducing the lagged dependent variable as one of the independent variables. To address the potential bias in the estimations, I employed the Dynamic Fixed Effects method. Moreover, there may be reverse causality when examining the relationship between government funding and private donations. However, this paper aims to explore the correlation between funding and donations, focusing on how funding responds to GDP after controlling for donations, so reverse causality should not pose a significant issue. Finally, the analysis is based on aggregate funding to charities across the country and by province, which limits the types of charity characteristics that can be included in the analysis. This trade-off was necessary to maintain focus on the main point of the paper: examining the relationship between macroeconomic conditions and government funding to charities.

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Table 2.1 Data Sources

Variables	Tables	Data Sources
Real GDP at market price (at 2017 constant prices), 1990-2021	36-10-0369-01	Statistics Canada
Current output gap published in monetary policy report (MPR), quarterly, 1990-2021		Bank of Canada
Real household final consumption expenditure (at 2017 constant prices), 1990-2021	36-10-0369-01	Statistics Canada
Consumer Price Index (2002 = 100), 1990-2021	18-10-0005-01	Statistics Canada
Real GDP by province (at 2017 constant prices), 1990-2021	36-10-0222-01	Statistics Canada
Unemployment rate in Canada and by province, both sex, 15 to 64 years, 1990-2021	14-10-0327-01	Statistics Canada
Estimates of population by province	17-10-0060-01	Statistics Canada
S&P/TSX Composite Index adjusted close price, monthly, 1990-2021		Yahoo Finance
Consolidated federal, provincial, territorial and local government expenditures	10-10-0039-01 (formerly CANSIM 385-0001)	Statistics Canada
Canadian Classification of Functions of Government (CCOFOG) by consolidated government component	10-10-0005-01 (formerly CANSIM 385-0041)	Statistics Canada

Table 2.2 Variable Definitions

Variable Name and Related Tables	Variable Definitions
Table 2.3	
GDP (%△)	The percentage change in annual real GDP of Canada
SP/TSX (%△)	The percentage change in annual real S&P/TSX Composite Index
Unemployment (%△)	The change in annual unemployment rate of Canada
Consumption expenditure (%△)	The percentage change in annual real consumption expenditure of Canada
Total funding (%△)	The percentage change in annual aggregate government funding to charities
Relief of poverty (%△)	The percentage change in annual funding to charities for Relief of Poverty
Education (%△)	The percentage change in annual funding to charities for Education
Religion (%△)	The percentage change in annual funding to charities for Religion
Health (%△)	The percentage change in annual funding to charities for Health
Community (%△)	The percentage change in annual funding to charities for Community
Art (%△)	The percentage change in annual funding to charities for Arts
Foundation (%△)	The percentage change in annual funding to charities for Foundations
Other (%△)	The percentage change in annual funding to Other charities
Table 2.4	
Real GDP ($M)	Annual real GDP of Canada in million dollars by province
Real GDPC ($K)	Annual real GDP per capita in thousand dollars by province
Total ($)	Annual real total funding per capita to all charities in dollars by province
Poverty ($)	Annual real funding to charities of Relief of Poverty per capita in dollars by province
Education ($)	Annual real funding to charities of Education per capita in dollars by province
Religion ($)	Annual real funding to charities of Religion per capita in dollars by province
Health ($)	Annual real funding to charities of Health per capita in dollars by province
Community ($)	Annual real funding to charities of Community per capita in dollars by province
Art ($)	Annual real funding to charities of Arts per capita in dollars by province
Foundation ($)	Annual real funding to charities of Foundations per capita in dollars by province
Other ($)	Annual real funding to charities of Other per capita in dollars by province
Tables 2.5-2.8	
GDP_t(%△)	The percentage change in annual real GDP of Canada at time t
GDP_{t-1}(%△)	The percentage change of annual real GDP of Canada at time t-1
SP/TSX_t(%△)	The percentage change in annual real S&P/TSX Composite Index at time t
SP/TSX_{t-1}(%△)	The percentage change of annual real S&P/TSX Composite Index at time t-1
$Unemploy_t$(%△)	The change in annual unemployment rate of Canada at time t
$Unemploy_{t-1}$(%△)	The change in annual unemployment rate of Canada at time t-1
$Consump.exp_t$(%△)	The percentage change in annual real consumption expenditure of Canada at time t
$Consump.exp_{t-1}$(%△)	The percentage change of annual real consumption expenditure of Canada at time t-1
Total (%△)	The percentage change in annual real funding to total charities, as well as separate funding sources from federal/provincial/municipal government, respectively
Poverty (%△)	The percentage change in annual real funding to charities of Relief of Poverty, as well as separate funding sources from federal/provincial/municipal government, respectively
Edu (%△)	The percentage change in annual real funding to charities of Education, as well as separate funding sources from federal/provincial/municipal government, respectively
Religion (%△)	The percentage change in annual real funding to charities of Religion, as well as separate funding sources from federal/provincial/municipal government, respectively
Health (%△)	The percentage change in annual real funding to charities of Health, as well as separate funding sources from federal/provincial/municipal government, respectively
Comm (%△)	The percentage change in annual real funding to charities of Community, as well as separate funding sources from federal/provincial/municipal government, respectively
Art (%△)	The percentage change in annual real funding to charities of Arts, as well as separate funding sources from federal/provincial/municipal government, respectively
Other (%△)	The percentage change in annual real funding to charities of Other, as well as separate funding sources from federal/provincial/municipal government, respectively
Tables 2.9-2.14	

△ln(Total)	The first difference of natural logarithm of annual real funding to total charities per capita; subgroups include funding sources from federal/provincial/municipal government, respectively
△ln(Poverty)	The first difference of natural logarithm of annual real funding to Relief of Poverty charities per capita; subgroups include funding sources from federal/provincial/municipal government, respectively
△ln(Edu)	The first difference of natural logarithm of annual real funding to Education charities per capita; subgroups include funding sources from federal/provincial/municipal government, respectively
△ln(Religion)	The first difference of natural logarithm of annual real funding to Religion charities per capita; subgroups include funding sources from federal/provincial/municipal government, respectively
△ln(Health)	The first difference of natural logarithm of annual real funding to Health charities per capita; subgroups include funding sources from federal/provincial/municipal government, respectively
△ln(Comm)	The first difference of natural logarithm of annual real funding to Community charities per capita; subgroups include funding sources from federal/provincial/municipal government, respectively
△ln(Art)	The first difference of natural logarithm of annual real funding to Arts charities per capita; subgroups include funding sources from federal/provincial/municipal government, respectively
△ln(Other)	The first difference of natural logarithm of annual real funding to Other charities per capita; subgroups include funding sources from federal/provincial/municipal government, respectively
△ln(RGDPC)	The first difference of natural logarithm of annual real GDP in Canada
△ln(RGDPC_pos)	The first difference of natural logarithm of annual positive change in real GDP per capita in Canada
△ln(RGDPC_neg)	The first difference of natural logarithm of annual negative change in real GDP per capita in Canada
Tables 2.15-2.19	
△ln(total)	The first difference of natural logarithm of annual real funding to total charities per capita by province; subgroups include funding sources from federal/provincial government, respectively
△ln(poverty)	The first difference of natural logarithm of annual real funding to Relief of Poverty charities per capita by province; subgroups include funding sources from federal/provincial government, respectively
△ln(edu)	The first difference ofnatural logarithm of annual real funding to Education charities per capita by province; subgroups include funding sources from federal/provincial government, respectively
△ln(religion)	The first difference of natural logarithm of annual real funding to Religion charities per capita by province; subgroups include funding sources from federal/provincial government, respectively
△ln(health)	The first difference of natural logarithm of annual real funding to Health charities per capita by province; subgroups include funding sources from federal/provincial government, respectively
△ln(comm)	The first difference of natural logarithm of annual real funding to Community charities per capita by province; subgroups include funding sources from federal/provincial government, respectively
△ln(art)	The first difference of natural logarithm of annual real funding to Art charities per capita by province; subgroups include funding sources from federal/provincial government, respectively
△ln(Other)	The first difference of natural logarithm of annual real funding to Other charities per capita by province; subgroups include funding sources from federal/provincial government, respectively
△ln(rgdpc)	The first difference of natural logarithm of annual real GDP per capita by province
△ln(rgdpc_pos)	The first difference of natural logarithm of annual positive change in real GDP per capita by province
△ln(rgdpc_neg)	The first difference of natural logarithm of annual negative change in real GDP per capita by province
Tables 2.20-2.21	
$\triangle\ln(x)_{d,t}$	The first difference of natural logarithm of annual real donations at time t, where x denotes donations in total and by fields of Relief of Poverty, Education, Religion, Health, Community, Arts, and “Other”
$\triangle\ln(y)_{g}$	The first difference of natural logarithm of annual real funding to charities at time t, where y denotes funding to charities in total and by fields of Relief of Poverty, Education, Religion, Health, Community, Arts, and “Other”

Table 2.3 Descriptive Statistics of Percentage Changes in Government Funding by Fields and Economic Indicators at the Aggregate Level, 1991-2021

Variable	Mean	SD	Min	Max
GDP (%△)	2.200	2.310	-4.930	5.520
SP/TSX (%△)	4.520	12.200	-21.500	32.540
Unemployment (%△)	-0.020	1.120	-2.200	4.000
Consumption expenditure (%△)	0.640	2.190	-6.980	3.030
Total funding (%△)	4.410	8.140	-14.500	23.650
Relief of poverty (%△)	5.110	8.770	-10.850	36.900
Education (%△)	7.320	12.120	-12.360	42.280
Religion (%△)	54.660	249.990	-84.520	1,351.720
Health (%△)	2.380	10.520	-17.010	19.640
Community (%△)	4.950	6.320	-8.610	23.850
Art (%△)	3.140	7.700	-19.440	29.780
Foundations (%△)	9.890	42.050	-29.090	215.020
Other(%△)	8.490	27.290	-26.710	130.920

Note: Variables are percentage changes of real terms of GDP, S&P/TSX, consumption expenditures, government funding to total charities and by fields of charitable services. Unemployment rate change is also considered. In 1997, the growth in funding to Religion is 1351.72%. I tried drop the highest 2% of funding to Religion in this year, the growth is still as large as 1025.68%. On average (1990-2021), funding to Religion accounts for 0.31% of total funding to charities. I then keep the observations of 99 percentile of funding to religious charities, since it has economic meaning, i.e., government only funds religious charities when they give money to communities.

Table 2.4 Provincial Averages of Aggregate Government Funding to Charities Per Capita by Field and Key Economic Indicators, 1990-2021

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ON	AB	BC	NB	NL	NS	PE	QC	SK	MB
Real GDP ($M)	660,000.00	250,000.00	210,000.00	31,359.00	27,733.00	37,918.00	5,442.00	350,000.00	64,710.00	56,320.00
Real GDPC ($K)	50.00	70.00	50.00	40.00	50.00	40.00	40.00	40.00	60.00	50.00
Total ($)	1,119.19	1,075.03	824.34	578.51	894.60	987.01	304.53	985.91	1,710.56	1,267.32
Poverty ($)	168.78	97.13	132.73	183.54	103.25	167.82	63.33	87.91	154.81	234.06
Education ($)	297.34	726.85	368.19	56.44	186.78	416.41	144.79	371.57	752.93	432.45
Religion ($)	2.82	3.00	3.87	4.02	4.16	2.78	4.01	1.72	3.36	4.20
Health ($)	586.02	200.12	240.40	293.40	571.54	345.15	61.30	477.43	738.75	526.27
Community ($)	55.58	39.55	70.22	33.68	26.02	47.39	26.38	34.79	51.37	57.90
Art ($)	7.64	7.24	7.37	5.72	2.58	6.88	3.28	12.07	8.20	10.41
Other($)	1.01	1.15	1.56	1.72	0.26	0.57	1.44	0.43	1.13	2.03

Note: Real GDP denotes provincial values of real GDP (base year 2017) in million Canadian dollars. Total, Relief of Poverty, Education, Religion, Health, Community, Art, and Other represent the real government funding to charities per capita (base year 2017) in unit dollar in total and by field in 10 provinces. Real GDPC represents real GDP per capita (base year 2017) in thousand dollars.

Table 2.5 Correlations Between Changes in Aggregate Government Funding to Charities and Macroeconomic Indicators (CA)

	Total (%△)	Poverty (%△)	Edu (%△)	Religion (%△)	Health (%△)	Comm (%△)	Art (%△)	Other (%△)
GDP_t(%△)	0.030	-0.201	0.054	0.020	0.126	-0.237	-0.037	-0.193
GDP_{t-1}(%△)	-0.065	-0.094	-0.074	-0.058	-0.002	-0.201	-0.399	-0.019
SP/TSX_t(%△)	-0.037	-0.227	-0.074	0.218	0.070	-0.254	-0.093	-0.169
SP/TSX_{t-1}(%△)	-0.225	-0.338	-0.223	0.187	-0.082	-0.594	-0.070	-0.334
$Unemploy_t$(%△)	0.058	0.213	0.070	0.107	-0.077	0.204	0.066	0.160
$Unemploy_{t-1}$(%△)	0.183	0.276	0.198	-0.003	0.079	0.208	0.507	0.007
$Consump.exp_t$(%△)	-0.051	-0.327	-0.075	0.003	0.106	-0.184	-0.186	-0.121
$Consump.exp_{t-1}$(%△)	-0.239	-0.209	-0.144	0.015	-0.209	-0.158	-0.514	0.004

Note: The variables in the first row are: percentage changes of total government funding to charities, funding to Relief of Poverty, funding to Education, funding to Religion, funding to Health, funding to Community, funding to Art, and Other funding to all charities registered in Canada, respectively. The variables in the first column are: percentage changes of real GDP, lag one real GDP, S&P/TSX Composite Index, lag one S&P/TSX Composite Index, unemployment rate, lag one unemployment rate, household final consumption expenditure, lag one household final consumption expenditure accordingly.

Table 2.6 Correlations Between Changes in Federal Funding to Charities And Macroeconomic Indicators

Variables	$Total_f$(%△)	$Poverty_f$(%△)	Edu_f(%△)	$Religion_f$(%△)	$Health_f$(%△)	$Comm_f$(%△)	Art_f(%△)	$Other_f$(%△)
GDP_t (%△)	-0.075	-0.152	0.177	-0.490	-0.002	0.011	0.038	-0.334
GDP_{t-1} (%△)	-0.007	-0.071	-0.029	-0.026	0.099	-0.266	-0.308	0.118
SP/TSX_t (%△)	-0.097	-0.206	-0.070	-0.157	-0.093	0.003	0.074	-0.254
SP/TSX_{t-1} (%△)	0.381	-0.152	-0.041	-0.192	0.474	-0.239	-0.191	0.116
$Unemploy_t$ (%△)	0.051	0.188	-0.120	0.540	-0.045	0.116	0.009	0.395
$Unemploy_{t-1}$ (%△)	0.102	0.198	0.154	0.128	-0.018	0.130	0.309	-0.144
$Consump.exp_t$ (%△)	-0.163	-0.334	-0.016	-0.687	0.051	-0.048	-0.108	-0.234
$Consump.exp_{t-1}$ (%△)	-0.157	-0.085	-0.052	-0.069	-0.120	-0.119	-0.380	0.153

Note: The only difference to table 2.5 is the variables in the first row are: percentage changes of total federal government funding to charities, federal funding to Education, federal funding to Religion, federal funding to Health, federal funding to Community, federal funding to Art, and Other federal funding to all charities registered in Canada, respectively.

Table 2.7 Correlations Between Changes in Provincial Funding to Charities and Macroeconomic Indicators

Variables	$Total_p$(%△)	$Poverty_p$(%△)	Edu_p(%△)	$Religion_p$(%△)	$Health_p$(%△)	$Comm_p$(%△)	Art_p(%△)	$Other_p$(%△)
GDP_t (%△)	0.196	0.175	0.220	0.240	0.200	-0.168	0.301	-0.034
GDP_{t-1} (%△)	0.052	0.064	0.082	-0.186	0.071	-0.031	0.035	0.058
SP/TSX_t (%△)	-0.086	-0.193	-0.078	0.125	0.062	-0.203	0.392	-0.080
SP/TSX_{t-1} (%△)	-0.182	-0.009	-0.161	-0.062	-0.246	-0.531	0.190	-0.079
$Unemploy_t$ (%△)	-0.065	-0.049	-0.083	-0.322	-0.079	0.250	-0.312	-0.026
$Unemploy_{t-1}$ (%△)	-0.061	-0.063	-0.048	0.338	-0.079	0.015	0.144	-0.124
$Consump.exp_t$ (%△)	0.141	0.094	0.241	0.166	0.081	-0.121	0.225	0.052
$Consump.exp_{t-1}$ (%△)	0.104	0.048	0.084	-0.181	0.151	0.012	0.039	0.154

Note: The only difference to table 2.5 is the variables in the first row are: percentage changes of total provincial government funding to charities, provincial funding to Relief of Poverty, provincial funding to Education, provincial funding to Religion, provincial funding to Health, provincial funding to Community, provincial funding to Art, and Other provincial funding to all charities registered in Canada, respectively.

Table 2.8 Correlations Between Changes in Municipal Funding to Charities and Macroeconomic Indicators

Variables	$Total_m(\%\triangle)$	$Poverty_m(\%\triangle)$	$Edu_m(\%\triangle)$	$Religion_m(\%\triangle)$	$Health_m(\%\triangle)$	$Comm_m(\%\triangle)$	$Art_m(\%\triangle)$	$Other_m(\%\triangle)$
GDP_t (%△)	0.100	-0.090	0.159	0.020	0.283	0.103	-0.236	-0.144
GDP_{t-1} (%△)	0.167	0.085	0.382	0.065	-0.325	0.052	-0.082	-0.029
SP/TSX_t (%△)	0.065	0.034	-0.116	0.287	0.227	0.015	-0.215	-0.103
SP/TSX_{t-1} (%△)	0.584	-0.146	0.367	0.047	0.102	0.172	0.251	-0.490
$Unemploy_t$ (%△)	-0.124	0.208	-0.033	-0.014	-0.335	-0.114	0.073	0.135
$Unemploy_{t-1}$ (%△)	-0.020	-0.088	-0.333	-0.074	0.466	-0.009	-0.017	0.050
$Consump.exp_t$ (%△)	-0.098	-0.086	-0.035	0.140	0.098	0.081	0.111	0.029
$Consump.exp_{t-1}$ (%△)	-0.075	0.015	0.261	0.097	-0.552	0.044	-0.196	0.054

Note: The only difference to table 2.5 is the variables in the first row are: percentage changes of total municipal government funding to charities, municipal funding to Relief of Poverty, municipal funding to Education, municipal funding to Religion, municipal funding to Health, municipal funding to Community, municipal funding to Art, and Other municipal funding to all charities registered in Canada, respective

Table 2.9 Unit Root Test for ARDL and NARDL Models at Aggregate Level

Method	PP		DFGLS		ADF		KPSS	
Variables	Intercept	Trend & intercept	Intercept	Trend & intercept	Intercept	Trend & intercept	Intercept	Trend & intercept
At level								
ln(RGDPC)	-1.183	-1.130	-0.457	-1.632	-1.907	-1.183	1.05***	0.253***
ln(Total)	-2.735*	-1.551	-0.363	-1.175	-2.456	-1.603	0.968***	0.235***
ln(Poverty)	-2.117	-2.273	0.060	-1.866	-1.428	-2.151	1.04***	0.19***
ln(Edu)	-3.328**	-1.865	-0.055	-0.988	-3.366**	-2.050	1.04***	0.268***
ln(Religion)	-2.108	-2.100	-2.071	-2.194	-2.225	-2.186	0.11	0.237***
ln(Health)	-2.041	-1.033	-1.039	-0.976	-1.951	-0.938	0.457*	0.217***
ln(Comm)	0.085	-1.932	0.791	-2.477	0.226	-2.362	1.13***	0.178**
ln(Art)	-1.002	-1.642	-0.494	-2.078	-0.834	-1.731	0.584**	0.146**
ln(Other)	0.219	-1.691	0.127	-1.462	0.260	-1.578	0.903***	0.252***
At first difference								
△ln(RGDPC)	-5.155***	-5.549***	-2.473**	-2.791	-3.843***	-4.550***	0.198	0.092
△ln(RGDPC_neg)	-6.078***	-6.458***	-1.978	-2.412	-3.514***	-3.781**	0.150	0.089
△ln(RGDPC_pos)	-3.852***	-3.863**	-3.319***	-3.206*	-3.749***	-4.082***	0.205	0.097
△ln(Total)	-	-5.032***	-3.283***	-4.120***	-3.627***	-3.966***	0.502*	0.062
△ln(Poverty)	-4.371***	-4.288***	-2.529**	-3.358**	-3.741***	-3.619**	0.253	0.073
△ln(Edu)	-	-6.355***	-3.963***	-4.618***	-	-3.608**	0.48**	0.054
△ln(Religion)	-5.225***	-5.137***	-3.926***	-3.926***	-3.920***	-3.838**	0.093	0.092
△ln(Health)	-4.984***	-5.674***	-2.956***	-3.742**	-3.285**	-3.715**	0.417*	0.073
△ln(Comm)	-4.552***	-4.585***	-4.060***	-4.506***	-4.656***	-4.834***	0.114	0.056
△ln(Art)	-3.102**	-2.977	-1.384	-1.587	-1.497	-1.361	0.154	0.117
△ln(Other)	-5.723***	-6.050***	-3.649***	-4.380***	-3.792***	-4.279***	0.312	0.060

Note: ***, ** and * denote that a series is stationary at 1%, 5% and 10% levels of significance, respectively. The lag used in the unit root test is the optimal lag based on Akaike Information Criterion (AIC). If the optimal lag is zero, I use lag one in the unit root test. In my study, the optimal lags for ln(RGDPC), ln(Total), ln(Poverty), ln(Education), ln(Religion), ln(Health), ln(Community), ln(Art), and ln(Other) are 0, 0, 0, 0, 0, 0, 0, 2, and 0, respectively. The tests conducted in a row are Phillips-Perron (PP), the augmented Dicky-Fuller (ADF), Dicky-Fuller Generalised Least Squares (DF-GLS), Kwiatkowski-Phillips-Schmidt-Shin (KPSS).The null hypothesis of the first three tests is: the variable has a unit root; The null hypothesis of the KPSS test is: the variable has no unit root.

Table 2.10 Bootstrapped ARDL Estimation to Aggregate Government Funding to Charities, 1990-2021

Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Other)
Trend	-0.003**	-0.002*	-0.005**	0.001	-0.004**	0.001	0.001	0.005
	(0.001)	(0.001)	(0.002)	(0.011)	(0.002)	(0.001)	(0.002)	(0.003)
△ln(RGDPC)$_t$	-0.115	-0.811	-0.092	-4.905	0.310	-0.559	-0.060	-1.682**
	(0.487)	(0.508)	(0.682)	(5.920)	(0.588)	(0.333)	(0.713)	(0.786)
Constant	0.088***	0.087***	0.136***	0.121	0.075*	0.033	0.001	-0.018
	(0.029)	(0.031)	(0.048)	(0.249)	(0.040)	(0.020)	(0.035)	(0.057)
Observations	31	31	31	31	31	31	29	31
Model	ARDL(0,0)	ARDL(0,0)	ARDL(0,0)	ARDL(0,0)	ARDL(0,0)	ARDL(0,0)	ARDL(2,0)	ARDL(0,0)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. All government funding variables are real values. Macroeconomic indicator used is the real GDP per capita. Since trend is significant in the regression for funding to total charities, Poverty, Education, and Health, I assume that trend is non-linear to government funding to charities so that it is not cancelled out through first difference. The lag used in the analysis is the optimal lag based on Akaike Information Criterion (AIC). I conduct diagnostic tests and the results indicate that there is no autocorrelation and mis-specification problem. However, government funding to total charities, Education, Health and Arts has heteroskedasticity. To address this, I apply wild cluster bootstrap methods, clustering by year. For each sample, I perform 10,000 bootstrap replications.

Table 2.11 Bootstrapped NARDL Estimation to Aggregate Government Funding to Charities, 1990-2021

Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Other)
Trend	-0.003**	-0.002*	-0.005**	0.000	-0.004**	0.001	0.001	0.005
	(0.001)	(0.001)	(0.002)	(0.011)	(0.002)	(0.001)	(0.002)	(0.003)
△ln(RGDPC_neg)$_t$	0.016	-1.097*	-0.238	-19.113**	1.081*	-0.626	-1.695***	-1.516
	(0.417)	(0.586)	(0.679)	(6.955)	(0.627)	(0.590)	(0.600)	(1.739)
△ln(RGDPC_pos)$_t$	-0.246	-0.526	0.054	9.222	-0.457	-0.492	1.566	-1.847
	(1.316)	(1.239)	(1.839)	(10.293)	(1.592)	(0.754)	(1.345)	(1.904)
Constant	0.091***	0.081**	0.133**	-0.168	0.091**	0.032	-0.032	-0.014
	(0.032)	(0.038)	(0.055)	(0.236)	(0.043)	(0.023)	(0.045)	(0.069)
Observations	31	31	31	31	31	31	29	31
Wald	0.04[0.84]	0.18[0.67]	0.02[0.88]	3.67*[0.06]	0.66[0.42]	0.02[0.87]	3.51*[0.07]	0.02[0.90]
Model	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (2,0,0)	NARDL (0,0,0)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. All government funding variables are real values. Macroeconomic indicator used is the real GDP per capita. Trend is significant in the regression for funding to total charities, Poverty, Education, and Health as in the ARDL model. The lag used in the analysis is the optimal lag based on Akaike Information Criterion (AIC). I apply wild cluster bootstrap methods, clustering by year. For each sample, I perform 10,000 bootstrap replications using a resample size of 31.

Table 2.12 Bootstrapped NARDL Estimation to Federal Government Funding to Charities, 1997-2021

Variables	$\triangle\ln(Total)_f$	$\triangle\ln(Poverty)_f$	$\triangle\ln(Edu)_f$	$\triangle\ln(Religion)_f$	$\triangle\ln(Health)_f$	$\triangle\ln(Comm)_f$	$\triangle\ln(Art)_f$	$\triangle\ln(Other)_f$
Trend	0.001	-0.001	-0.002	-0.001	0.011	0.002	0.003	-0.000
	(0.006)	(0.005)	(0.003)	(0.009)	(0.023)	(0.007)	(0.003)	(0.014)
$\triangle\ln(RGDPC\_neg)_t$	-0.406	-2.556	-0.047	-12.362*	2.872	-0.171	-0.982	-12.950***
	(1.229)	(2.060)	(0.851)	(6.000)	(3.561)	(3.410)	(1.421)	(3.949)
$\triangle\ln(RGDPC\_pos)_t$	-0.102	0.726	1.171	-0.065	-1.992	1.037	1.947	0.608
	(2.592)	(2.673)	(1.932)	(4.037)	(8.883)	(2.662)	(1.401)	(7.990)
Constant	0.011	0.036	0.051	0.061	-0.121	-0.017	-0.039	0.024
	(0.132)	(0.105)	(0.065)	(0.234)	(0.481)	(0.154)	(0.056)	(0.240)
Observations	24	24	24	24	24	24	24	24
Wald	0.01[0.94]	0.62[0.44]	0.20[0.66]	1.99[0.17]	0.24[0.63]	0.09[0.76]	1.74[0.20]	1.40[0.24]
Model	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)

Note: Differences to table 2.11 are: First, the funding source for charities is from federal government. Trend is nonsignificant in the regression for federal funding to charities, suggesting a potential linear relationship between federal funding variables and years. Second, the time span of observations is from 1997 to 2021, since the year 1997 is the earliest time that charities are required to provide details of funding sources. From 2009 onwards, only charities that need to fill in schedule 6 are required to report funding sources in detail (see appendix A for explanations).

Table 2.13 Bootstrapped NARDL Estimation to Provincial Government Funding to Charities, 1997-2021

Variables	$\triangle \ln(Total)_p$	$\triangle \ln(Poverty)_p$	$\triangle \ln(Edu)_p$	$\triangle \ln(Religion)_p$	$\triangle \ln(Health)_p$	$\triangle \ln(Comm)_p$	$\triangle \ln(Art)_p$	$\triangle \ln(Other)_p$
Trend	-0.004	-0.007	-0.003	0.002	-0.004	-0.001	-0.001	-0.007
	(0.003)	(0.009)	(0.003)	(0.009)	(0.004)	(0.003)	(0.003)	(0.007)
$\triangle \ln(RGDPC\_neg)_t$	-0.009	-2.254	0.029	2.581	0.316	-1.376	1.512*	0.447
	(0.970)	(2.797)	(0.651)	(1.863)	(1.334)	(0.870)	(0.780)	(2.603)
$\triangle \ln(RGDPC\_pos)_t$	0.693	2.096	0.702	2.333	0.573	0.148	0.751	-3.026
	(2.427)	(8.496)	(1.825)	(3.645)	(1.937)	(0.986)	(1.817)	(3.723)
Constant	0.086**	0.075	0.073**	-0.001	0.098	0.041	0.010	0.267*
	(0.040)	(0.065)	(0.028)	(0.147)	(0.063)	(0.045)	(0.047)	(0.152)
Observations	24	24	24	24	24	24	24	24
Wald	0.12[0.73]	0.51[0.48]	0.20[0.66]	0.00[0.95]	0.01[0.92]	2.02[0.17]	0.15[0.71]	0.86[0.37]
Model	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)

Note: A slight difference to table 2.11 is the funding source for charities is from provincial government. Trend is nonsignificant in the regression for federal funding to charities, suggesting a potential linear relationship between provincial funding variables and years.

Table 2.14 Bootstrapped NARDL Estimation to Municipal Government Funding to Charities, 1997-2021

Variables	$\triangle\ln(\text{Total})_m$	$\triangle\ln(\text{Poverty})_m$	$\triangle\ln(\text{Edu})_m$	$\triangle\ln(\text{Religion})_m$	$\triangle\ln(\text{Health})_m$	$\triangle\ln(\text{Comm})_m$	$\triangle\ln(\text{Art})_m$	$\triangle\ln(\text{Other})_m$
Trend	0.001	0.004	-0.005	0.002	0.033*	-0.004	-0.000	-0.001
	(0.002)	(0.007)	(0.004)	(0.004)	(0.017)	(0.018)	(0.004)	(0.007)
$\triangle\ln(\text{RGDPC\_neg})_t$	0.402	-0.421	-0.124	0.349	-0.377	1.420	-0.384	-1.325
	(0.724)	(0.996)	(1.483)	(2.266)	(3.636)	(3.664)	(1.407)	(2.713)
$\triangle\ln(\text{RGDPC\_pos})_t$	0.579	-0.597	0.530	-0.393	16.265**	-4.535	-1.752	-2.168
	(1.280)	(2.060)	(2.488)	(3.454)	(7.316)	(10.120)	(1.886)	(2.631)
Constant	-0.035	-0.053	0.057	0.013	-0.739**	0.135	0.033	0.104
	(0.051)	(0.115)	(0.058)	(0.060)	(0.286)	(0.221)	(0.084)	(0.153)
Observations	24	24	24	24	24	24	24	24
Wald	0.02[0.90]	0.01[0.93]	0.05[0.82]	0.04[0.85]	2.72[0.11]	0.44[0.52]	0.45[0.51]	0.06[0.81]
Model	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)

Note: A slight difference to table 2.11 is the funding source for charities is from municipal government. Trend is significant in the regression for municipal funding to Health, suggesting a potential nonlinear relationship between municipal funding variables and years.

Table 2.15 Unit Root Test for Panel ARDL and Panel NARDL Models at Provincial Level

Method	Breitung		LLC	
Variables	Intercept	Trend and intercept	Intercept	Trend and intercept
At level				
ln(rgdpc)	1.331	0.980	-0.479	-0.558
ln(total)	-0.959	-1.742**	-2.877***	-2.212**
ln(poverty)	1.204	-0.818	-0.958	-0.852
ln(education)	-1.051	-2.048**	-3.592***	-2.851***
ln(religion)	-0.798	-0.847	-2.949***	-1.345*
ln(health)	-2.274**	-1.582*	-2.318***	-1.962**
ln(community)	2.526	0.310	-2.082**	-2.953***
ln(art)	-0.179	-0.769	-2.801***	-2.887***
ln(other)	-0.814	-1.236	-1.889**	-2.699***
At first difference				
△ln(rgdpc)	-2.759***	-1.753**	-6.287***	-5.784***
△ln(rgdpc_neg)	-3.037***	-0.815	-4.009***	-2.411***
△ln(rgdpc_pos)	-2.948***	-1.306*	-5.172***	-4.703***
△ln(total)	-7.068***	-	-	-
△ln(poverty)	-4.040***	-4.244***	-7.776***	-6.571***
△ln(education)	-6.116***	-	-	-
△ln(religion)	-4.306***	-2.932***	-	-
△ln(health)	-	-	-	-
△ln(community)	-3.702***	-6.167***	-	-
△ln(art)	-1.467*	-0.881	-	-
△ln(other)	-3.335***	-4.458***	-	-

Note: ***, ** and * denote that a series is stationary at 1%, 5% and 10% levels of significance, respectively.The lag used in the unit root test is one. Variables in the table, △ln(rgdpc_neg) and △ln(rgdpc_pos) denote the first difference of log of negative change in real GDP per capita at time t, the first differnce of the log of positive change in real GDP per capita at time t, respectively. The tests conducted in a row are Levin,Lin, and Chu (LLC) (Levin et al. 2002) and Breitung (2000; Breitung and Das (2005)) test. The null hypothesis of the tests is: panels contain unit roots. Both tests take account of cross-sectional correlation.

Table 2.16 Panel ARDL Estimation to Aggregate Government Funding to Charities by Province, 1990-2021

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(other)
△ln(Total)$_{t-1}$	-0.348***							
	(0.041)							
△ln(rgdpc)$_t$	0.530	-0.087	3.410***	-0.267	-0.012	0.251	-1.058*	-2.025
	(1.093)	(0.379)	(0.793)	(0.699)	(2.847)	(0.157)	(0.503)	(1.174)
△ln(Poverty)$_{t-1}$		-0.147**						
		(0.056)						
△ln(Edu)$_{t-1}$			-0.289***					
			(0.021)					
△ln(religion)$_{t-1}$				-0.166**				
				(0.055)				
△ln(health)$_{t-1}$					-0.203*			
					(0.094)			
△ln(comm)$_{t-1}$						-0.101		
						(0.073)		
△ln(art)$_{t-1}$							-0.152**	
							(0.065)	
△ln(other)$_{t-1}$								-0.308***
								(0.040)
Constant	0.093*	0.085*	0.162**	0.089	0.073	0.032	0.188	-0.183
	(0.046)	(0.044)	(0.057)	(0.057)	(0.091)	(0.037)	(0.138)	(0.172)
Observations	300	300	300	300	300	300	300	300

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. All government funding variables are real value per capita. Macroeconomic indicators used are real GDP per capita in each province. Trend term is significant to total funding, funding to Religion, Health and Arts, indicating that trend is non-linear to government funding to charities at provincial level.The lag used in the analysis is the most common and optimal lag for each of province, based on Akaike Information Criterion (AIC).

Table 2.17 Panel NARDL Estimation to Aggregate Government Funding to Charities by Province, 1990-2021

Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Other)
△ln(Total)$_{t-1}$	-0.352***							
	(0.044)							
△ln(rgdpc_neg)$_t$	-2.613	0.335	0.0277	0.493	-5.716*	-1.237	-1.586***	-3.215
	(1.783)	(0.468)	(1.329)	(1.898)	(2.605)	(0.683)	(0.385)	(3.926)
△ln(rgdpc_pos)$_t$	2.008*	-0.285	4.999**	-0.621	2.675	0.950**	-0.814	-1.467
	(1.089)	(0.738)	(1.578)	(1.249)	(3.366)	(0.410)	(0.730)	(1.564)
△ln(Poverty)$_{t-1}$		-0.146**						
		(0.055)						
△ln(Edu)$_{t-1}$			-0.290***					
			(0.023)					
△ln(Religion)$_{t-1}$				-0.167**				
				(0.057)				
△ln(Health)$_{t-1}$					-0.206*			
					(0.097)			
△ln(Comm)$_{t-1}$						-0.104		
						(0.074)		
△ln(Art)$_{t-1}$							-0.150*	
							(0.067)	
△ln(Other)$_{t-1}$								-0.308***
								(0.041)
Constant	0.060	0.089*	0.127*	0.097	0.014	0.017	0.182	-0.196
	(0.058)	(0.047)	(0.058)	(0.073)	(0.103)	(0.036)	(0.139)	(0.184)
Wald	6.79**[0.02]	0.29[0.60]	3.40*[0.09]	0.16[0.70]	6.91**[0.02]	4.30*[0.06]	0.80[0.39]	0.85[0.82]
Observations	300	300	300	300	300	300	300	300

Note: Differences to table 2.16 include: △ln(rgdpc_neg) and △ln(rgdpc_pos) denote the first difference of the log of negative change in real GDP per capita at time t, the first difference of the log of positive change in real GDP per capita at time t, respectively

Table 2.18 Panel NARDL Estimation to Federal Funding to Charities, 1997-2021

Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Other)
△ln(Total)$_{t-1}$	-0.445***							
	(0.049)							
△ln(rgdpc_neg)$_t$	1.396	2.042	-1.156	2.859	7.093	-3.872***	4.344	-5.037
	(1.401)	(1.692)	(1.001)	(1.655)	(7.633)	(1.169)	(4.112)	(3.540)
△ln(rgdpc_pos)$_t$	-1.013	0.105	1.604**	0.244	-1.988	1.930	0.259	-2.968
	(0.739)	(0.984)	(0.682)	(1.223)	(3.841)	(1.601)	(1.057)	(2.828)
△ln(Poverty)$_{t-1}$		-0.331***						
		(0.074)						
△ln(Edu)$_{t-1}$			-0.294**					
			(0.098)					
△ln(Religion)$_{t-1}$				-0.267***				
				(0.077)				
△ln(Health)$_{t-1}$					-0.412***			
					(0.041)			
△ln(Comm)$_{t-1}$						-0.368***		
						(0.066)		
△ln(Art)$_{t-1}$							-0.373***	
							(0.036)	
△ln(Other)$_{t-1}$								-0.316***
								(0.042)
Constant	0.153*	0.306**	0.216	0.077	-0.081	-0.154	0.036	0.529
	(0.078)	(0.114)	(0.126)	(0.158)	(0.367)	(0.187)	(0.134)	(0.315)
Wald	2.63[0.11]	1.24[0.29]	0.13[0.72]	2.85[0.12]	0.88[0.37]	5.48**[0.04]	0.97[0.35]	0.23[0.64]
Observations	230	230	230	230	230	230	230	230

Note: Differences to table 2.17 include: the time span of observations is from 1997 to 2021, since the year 1997 is the earliest time that charities are required to provide details of funding sources. From 2009 onwards, only charities that need to fill in schedule 6 are required to report funding sources in detail (see appendix 2.A for explanations).

Table 2.19 Panel NARDL Estimation to Provincial Funding to Charities, 1997-2021

Variables	$\triangle\ln(total)_p$	$\triangle\ln(poverty)_p$	$\triangle\ln(edu)_p$	$\triangle\ln(religion)_p$	$\triangle\ln(health)_p$	$\triangle\ln(comm)_p$	$\triangle\ln(art)_p$	$\triangle\ln(other)_p$
$\triangle\ln(total)_{p, t-1}$	-0.330***							
	(0.073)							
$\triangle\ln(rgdpc\_neg)_t$	-3.216**	-0.184	-0.517	8.046	-6.033**	-0.378	0.994	-1.279
	(1.366)	(0.396)	(0.460)	(4.831)	(2.513)	(0.352)	(1.486)	(2.141)
$\triangle\ln(rgdpc\_pos)_t$	0.984	0.634	0.846	0.495	1.174	1.131***	-1.325	1.832
	(0.654)	(0.977)	(0.604)	(0.849)	(1.613)	(0.316)	(0.960)	(3.293)
$\triangle\ln(poverty)_{p, t-1}$		-0.398***						
		(0.075)						
$\triangle\ln(edu)_{p, t-1}$			-0.336***					
			(0.052)					
$\triangle\ln(religion)_{p, t-1}$				-0.205***				
				(0.054)				
$\triangle\ln(health)_{p, t-1}$					-0.174			
					(0.123)			
$\triangle\ln(comm)_{p, t-1}$						-0.269***		
						(0.050)		
$\triangle\ln(art)_{p, t-1}$							-0.317***	
							(0.059)	
$\triangle\ln(other)_{p, t-1}$								-0.102
								(0.110)
Constant	0.268***	0.106	0.230***	0.139	0.344***	0.0568*	0.00373	0.235
	(0.040)	(0.192)	(0.064)	(0.128)	(0.095)	(0.029)	(0.054)	(0.287)
Wald	9.70**[0.01]	0.45[0.52]	2.01[0.18]	1.91[0.20]	6.16**[0.03]	13.32***[0.01]	1.96[0.16]	0.67[0.43]
Observations	230	230	230	230	230	230	230	230

Note: Differences to table 2.17 include: the time span of observations is from 1997 to 2021, since the year 1997 is the earliest time that charities are required to provide details of funding sources. From 2009 onwards, only charities that need to fill in schedule 6 are required to report funding sources in detail (see appendix 2.A for explanations).

Table 2.20 Panel ARDL Estimation to Aggregate Government Funding to Charities by Province, using Private Donations as the Independent Variable, 1990-2021

Variables	$\triangle \ln(\text{Total})_g$	$\triangle \ln(\text{poverty})_g$	$\triangle \ln(\text{edu})_g$	$\triangle \ln(\text{religion})_g$	$\triangle \ln(\text{health})_g$	$\triangle \ln(\text{comm})_g$	$\triangle \ln(\text{art})_g$	$\triangle \ln(\text{other})_g$
$\triangle \ln(\text{total})_{d,t}$	0.233							
	(0.041)							
$\triangle \ln(\text{poverty})_{d,t}$		-0.051						
		(0.098)						
$\triangle \ln(\text{edu})_{d,t}$			0.140					
			(0.151)					
$\triangle \ln(\text{religion})_{d,t}$				0.042				
				(0.515)				
$\triangle \ln(\text{health})_{d,t}$					-0.066			
					(0.526)			
$\triangle \ln(\text{comm})_{d,t}$						0.033		
						(0.029)		
$\triangle \ln(\text{art})_{d,t}$							0.245***	
							(0.066)	
$\triangle \ln(\text{other})_{d,t}$								0.119***
								(0.029)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. The columns are government funding to charities in total and by fields. The rows are private donations to charities in total and by fields. All variables are real value per capita. The lag used in the analysis is the most common and optimal lag for each of province, based on Akaike Information Criterion (AIC), that is, (1,0,0) for all columns. I only report the key variables of interest to compare with results in table 2.16. Trend term and lagged terms of funding in total and by fields are not reported.

Table 2.21 Panel ARDL Estimation to Aggregate Government Funding to Charities by Province, the Joint Effects of Donations and Macroeconomic Indicators, 1990-2021

Variables	$\triangle\ln(total)_g$	$\triangle\ln(poverty)_g$	$\triangle\ln(edu)_g$	$\triangle\ln(religion)_g$	$\triangle\ln(health)_g$	$\triangle\ln(comm)_g$	$\triangle\ln(art)_g$	$\triangle\ln(other)_g$
$\triangle\ln(rgdpc)_t$	0.386	0.173	3.277***	-0.167	-0.426	0.193	-1.080*	-1.894
	(1.107)	(0.306)	(0.856)	(0.771)	(2.823)	(0.159)	(0.541)	(1.169)
$\triangle\ln(total)_{d,t}$	0.199							
	(0.400)							
$\triangle\ln(poverty)_{d,t}$		-0.051						
		(0.099)						
$\triangle\ln(edu)_{d,t}$			0.126					
			(0.134)					
$\triangle\ln(religion)_{d,t}$				0.059				
				(0.523)				
$\triangle\ln(health)_{d,t}$					-0.065			
					(0.532)			
$\triangle\ln(comm)_{d,t}$						0.032		
						(0.029)		
$\triangle\ln(art)_{d,t}$							0.243***	
							(0.065)	
$\triangle\ln(other)_{d,t}$								0.117***
								(0.029)

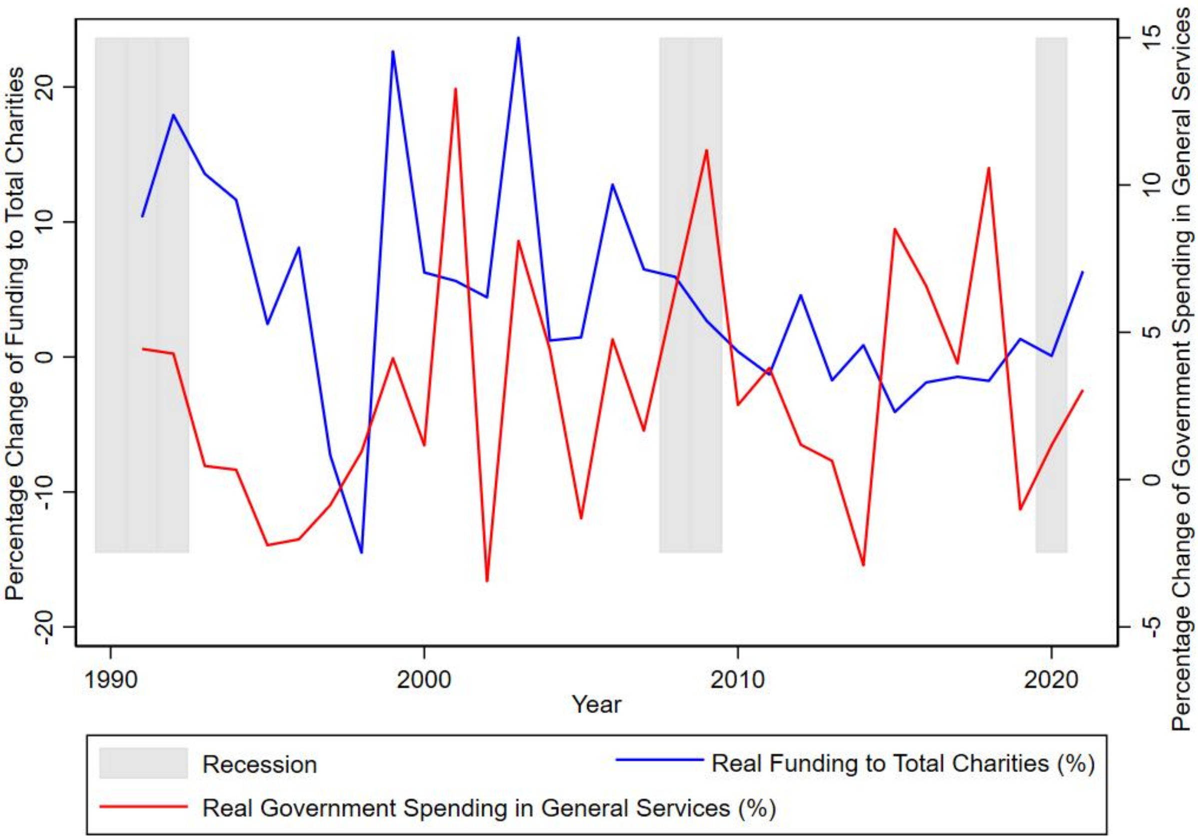
Note: The difference to table 2.20 is adding the macroeconomic variable of GDP per capita.

Table 2.22 Summary of Significant Relationships Between Macroeconomic Indicators and Government Funding to Charities in ARDL, NARDL, Panel ARDL and NARDL Models

	Growth in GDP	Positive Growth in GDP vs. Negative Growth in GDP	Growth in Provincial GDP	Positive Growth in Provincial GDP vs. Negative Growth in Provincial GDP	Growth in Provincial Donations vs. Growth in Provincial GDP
Aggregate ARDL	-Other***				
Aggregate NARDL		+Religion < |-Religion|** +Arts < |-Arts|***			
Federal NARDL		|-Religion| < |-Religion|* +Other < |-Other|***			
Provincial NARDL		+Arts < |-Arts|*			
Municipal NARDL		+Health***> |-Health|			
Aggregate Panel ARDL			+ education*** - arts***		+art***> |-art|* +Other***<|-Other|
Aggregate Panel NARDL				+total** < |-total| +education*** > |-education| + health < |- health|*** +community** > |-community| +arts<|-arts|***	
Federal Panel NARDL				+education** > |-education| +community < |-community|***	
Provincial Panel NARDL				+total < |-total|** +health < |-health|** +community*** > |-community|	

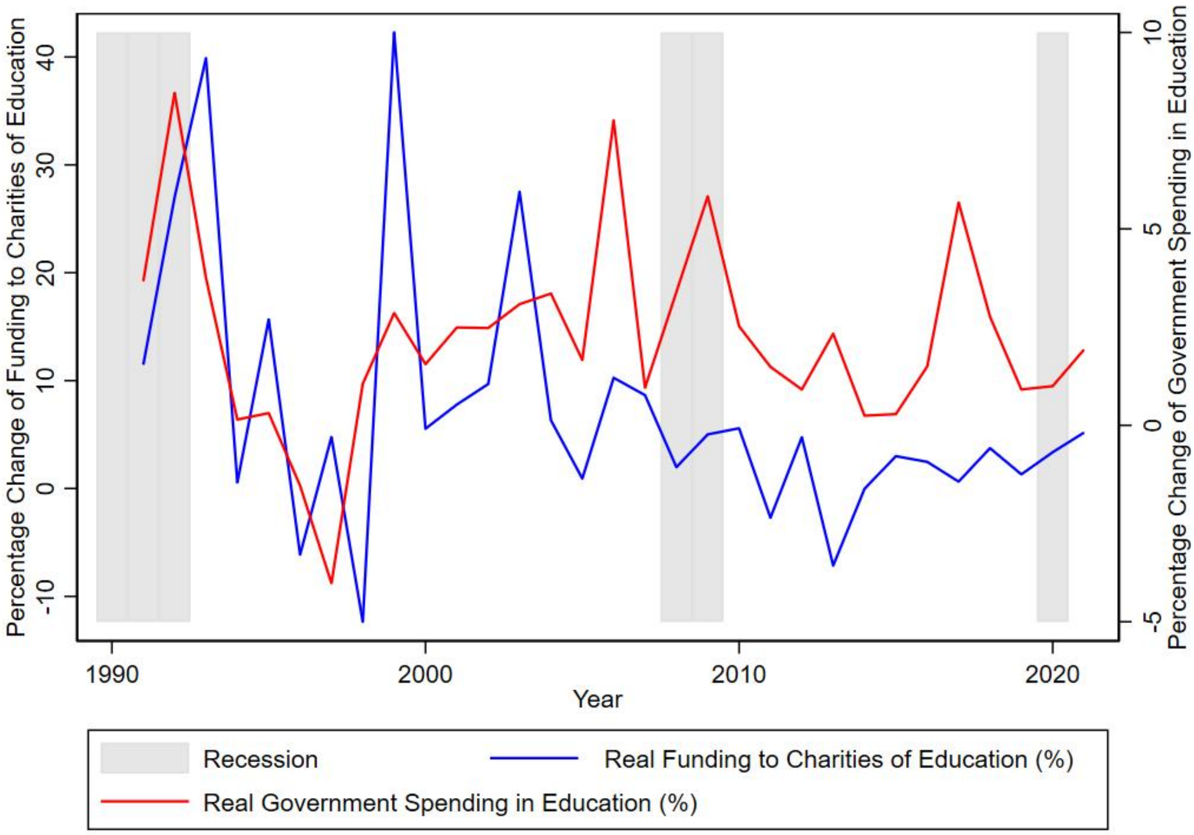
Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. The signs of “+” and “-” represent positive and negative relationships between the growth in macroeconomic indicators and the growth in government funding to charities in the corresponding model, respectively. The signs of “>” and “<” denote the slope of government funding in positive domain is larger or smaller than the slope in the negative domain.

Figure 2.1 Percentage Change of Government Spending of All Levels in General Services and Percentage Change of Aggregate Funding to Charities



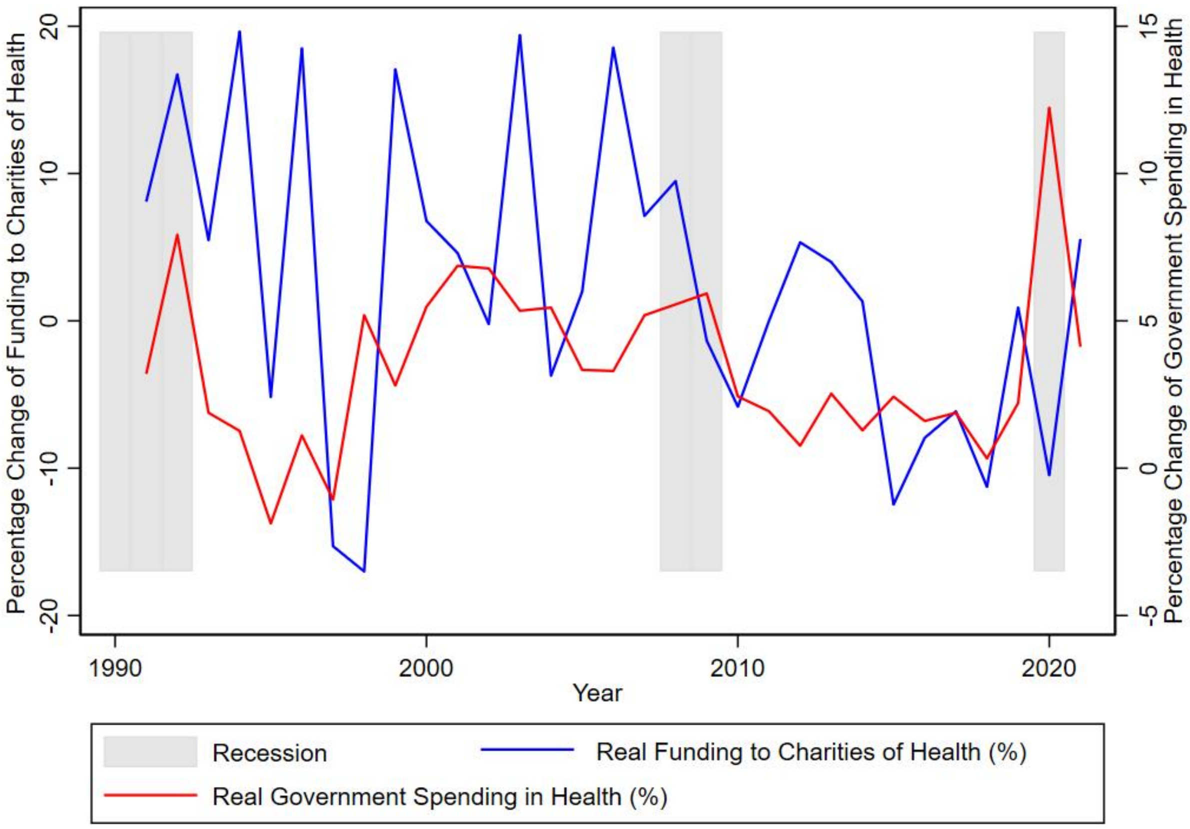
Source: author's calculations from the T3010 data base and government expenditure data (see table 2.1 for source).

Figure 2.2 Percentage Change of Government Spending of All Levels in Education and Percentage Change of Aggregate Funding to Charities of Education



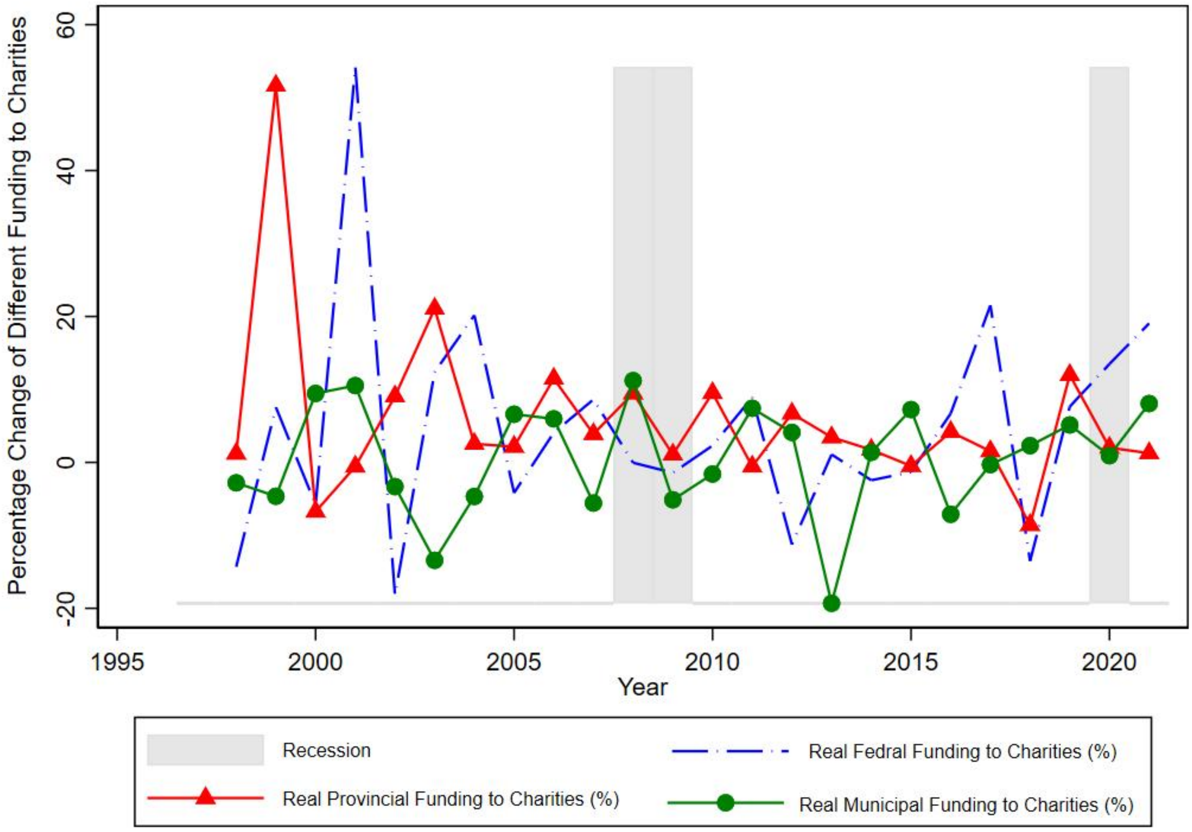
Source: author's calculations from the T3010 data base and government expenditure data (see table 2.1 for source).

Figure 2.3 Percentage Change of Government Spending of All Levels in Health and Percentage Change of Aggregate Funding to Charities of Health



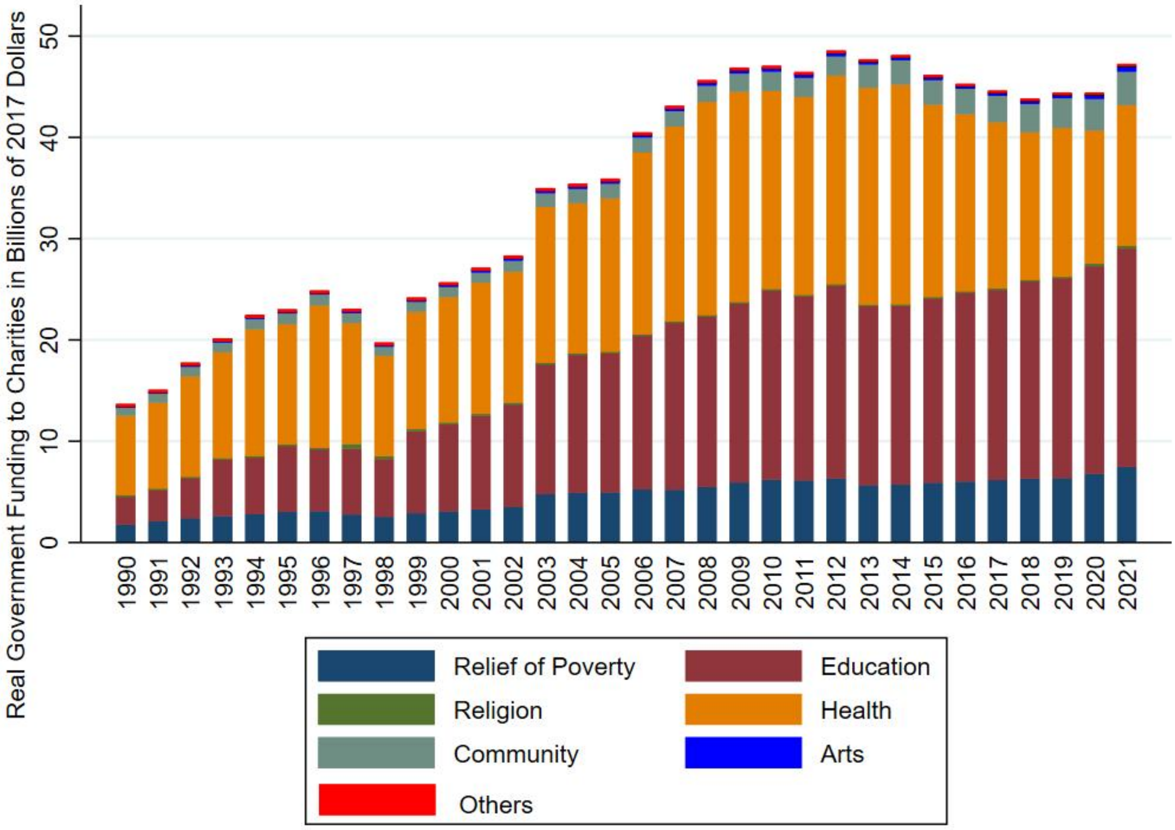
Source: author's calculations from the T3010 data base and government expenditure data (see table 2.1 for source).

Figure 2.4 Percentage Change of Federal, Provincial, and Municipal Government Funding to Charities



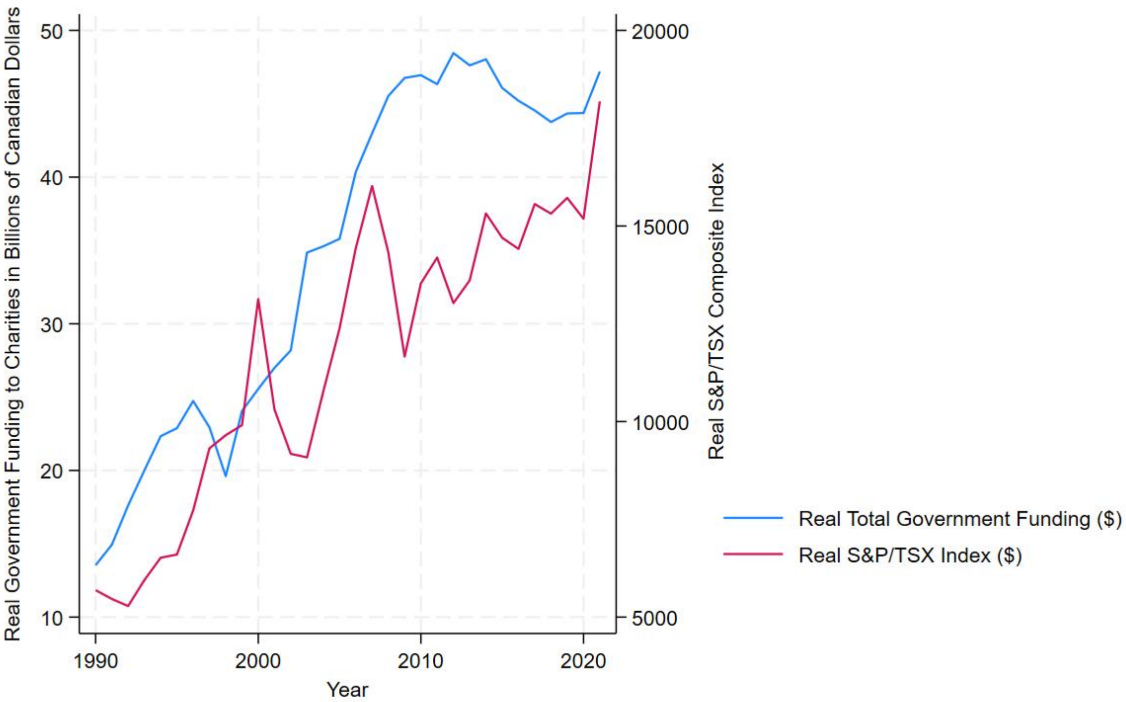
Source: author's calculations from the T3010 data base.

Figure 2.5 Decomposition of Aggregate Government Funding to Charities over Time (CA)



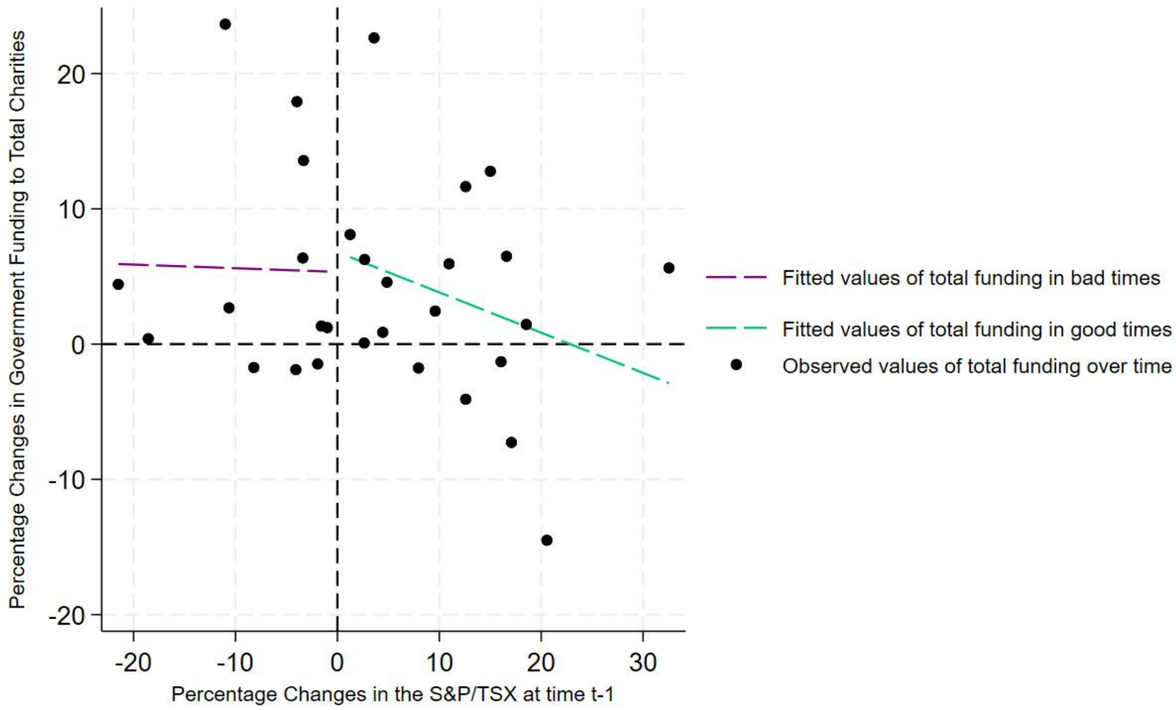
Source: author's calculations from the T3010 data base.

Figure 2.6 Real Aggregate Funding to Charities and the S&P/TSX Index over Time (CA)



Source: author's calculations from the T3010 data base and stock market data (see table 2.1 for source).

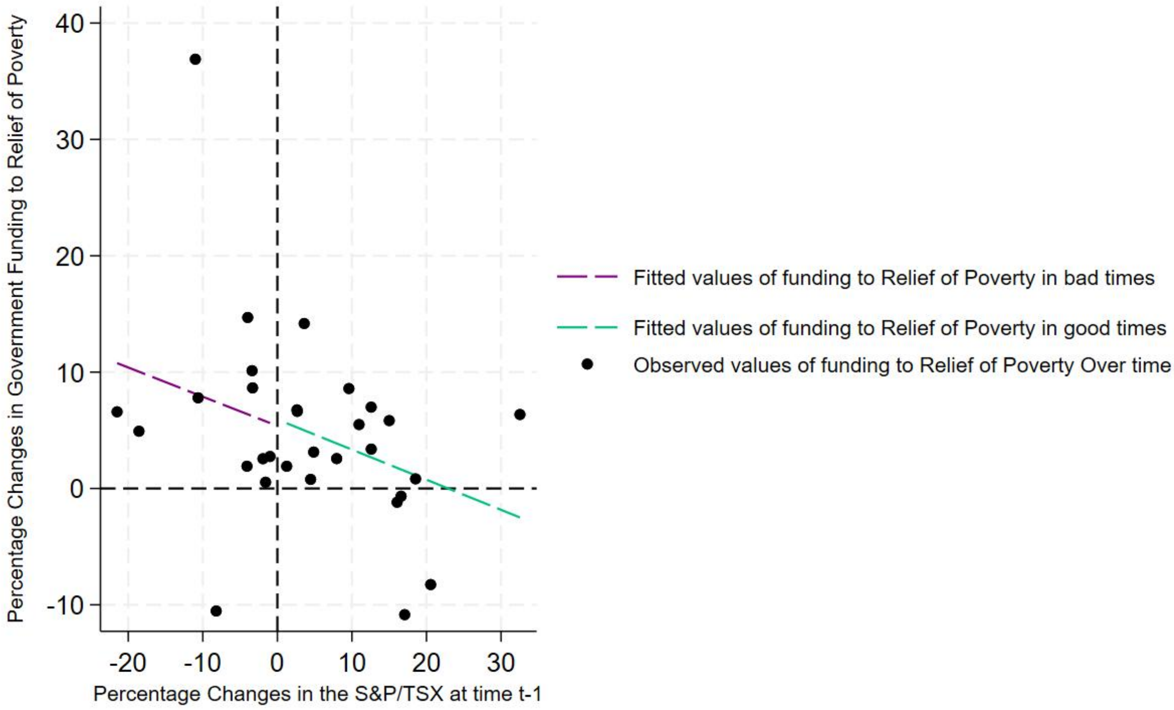
Figure 2.7 Changes in the S&P/TSX and Aggregate Government Funding to Charitiesfrom 1992 to 2021 with Trendlines (CA)



Source: author's calculations from the T3010 data base and stock market data (see table 2.1 for source).

Note: I split the sample into observations with lagged sptsx < 0 and lagged sptsx > 0, and report separate slope estimates and bootstrap confidence intervals for each subsample. When lagged sptsx < 0, the slope of the fitted line is −0.03, with a 95% percentile bootstrap confidence interval of [−1.43, 0.49], based on 10,000 replications of the original 12 observations. When lagged sptsx > 0, the slope is −0.30, with a bootstrap confidence interval of [−1.04, 0.08], based on 10,000 replications of the original 18 observations.

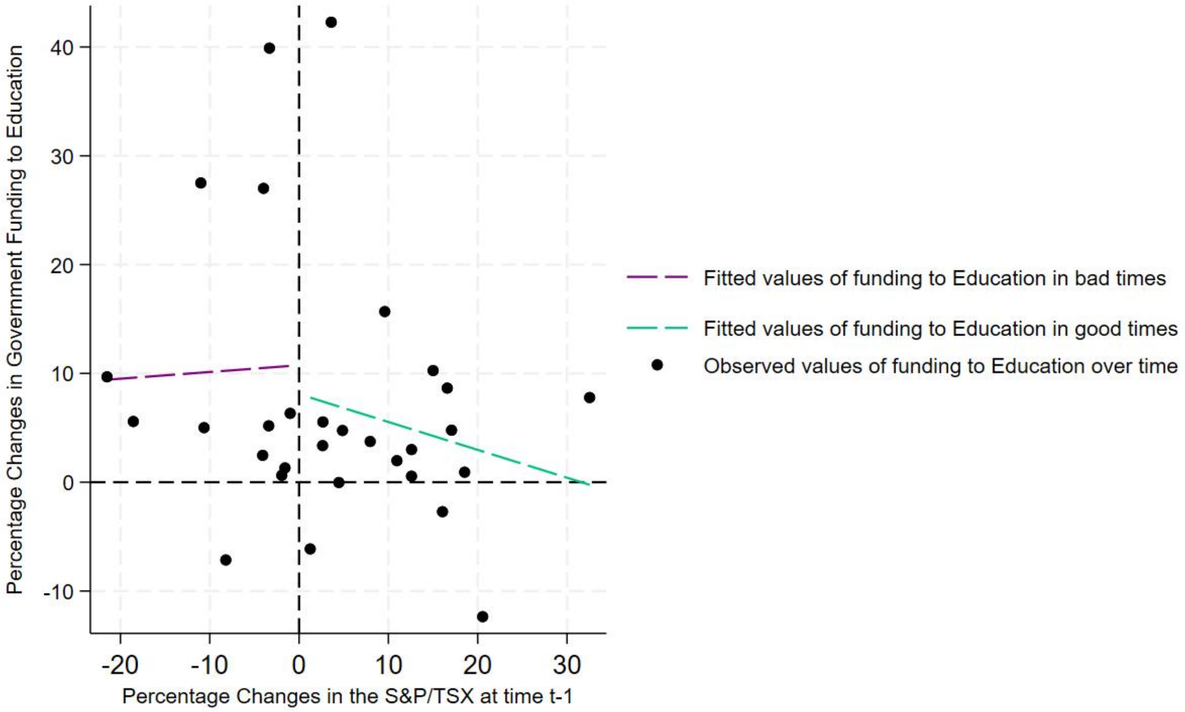
Figure 2.8 Changes in the S&P/TSX and Aggregate Government Funding to Relief of Povertyfrom 1992 to 2021 with Trendlines (CA)



Source: author's calculations from the T3010 data base and stock market data (see table 2.1 for source).

Note: Differences from figure 2.7 are that when lagged sptsx < 0, the slope of the fitted line is −0.25, with a 95% percentile bootstrap confidence interval of [−2.15, 0.32]. When lagged sptsx > 0, the slope is −0.26, with a bootstrap confidence interval of [−0.87, 0.03].

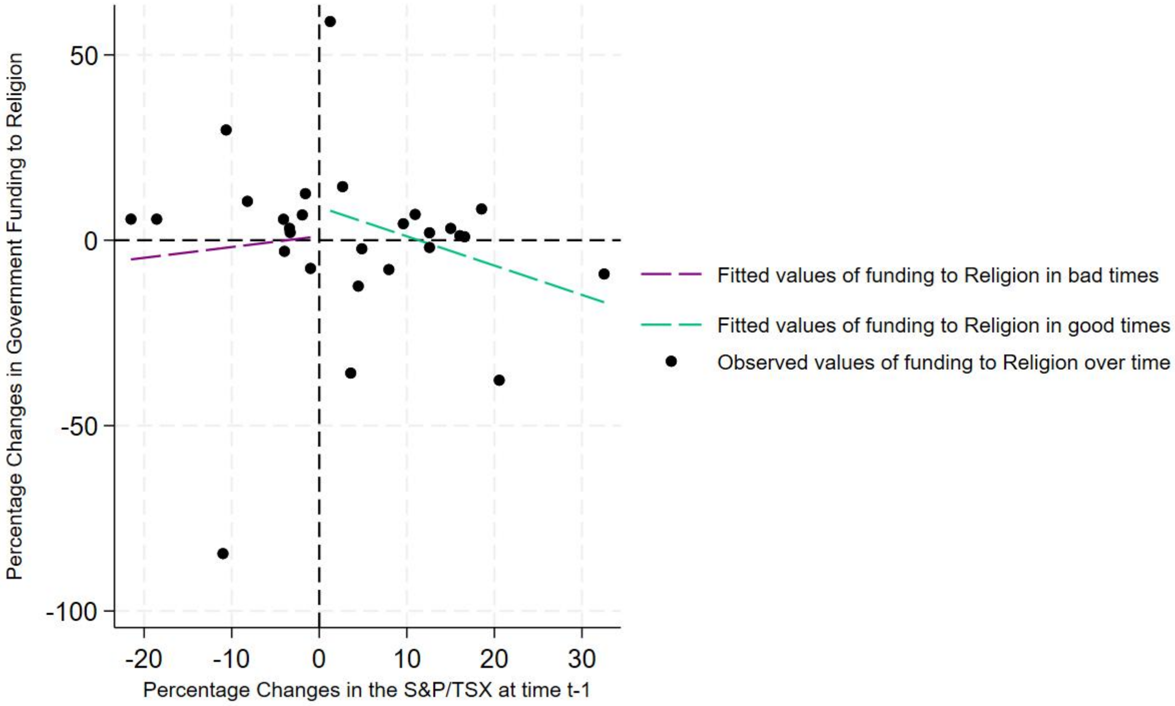
Figure 2.9 Changes in the S&P/TSX and Aggregate Government Funding to Educationfrom 1992 to 2021 with Trendlines (CA)



Source: author's calculations from the T3010 data base and stock market data (see table 2.1 for source).

Note: Differences from figure 2.7 are that when lagged sptsx < 0, the slope of the fitted line is 0.06, with a 95% percentile bootstrap confidence interval of [−1.16, 1.08]. When lagged sptsx > 0, the slope is −0.26, with a bootstrap confidence interval of [−1.34, 0.27].

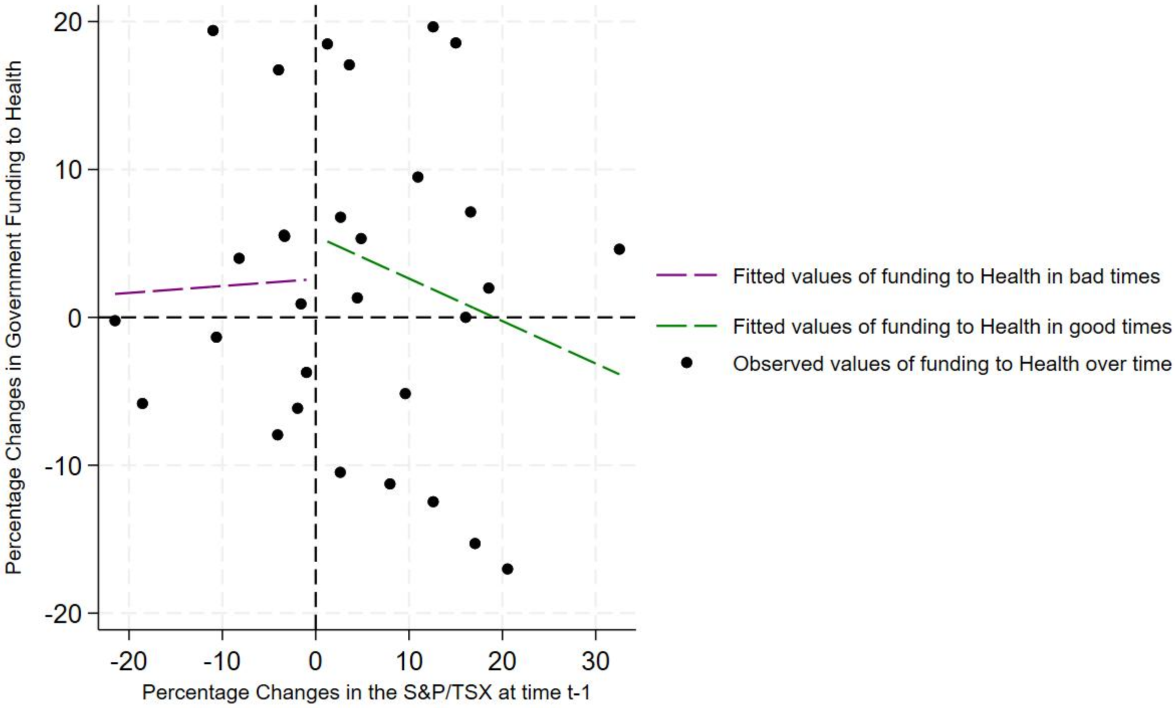
Figure 2.10 Percentage Changes in the S&P/TSX and Aggregate Government Funding to Religion from 1992 to 2021 with Trendlines (CA)



Source: author's calculations from the T3010 data base and stock market data (see table 2.1 for source).

Note: Differences from figure 2.7 are that when lagged sptsx < 0, the slope of the fitted line is 0.29, with a 95% percentile bootstrap confidence interval of [−1.66, 5.77]. When lagged sptsx > 0, the slope is −0.79 with a bootstrap confidence interval of [−2.71, 0.90].

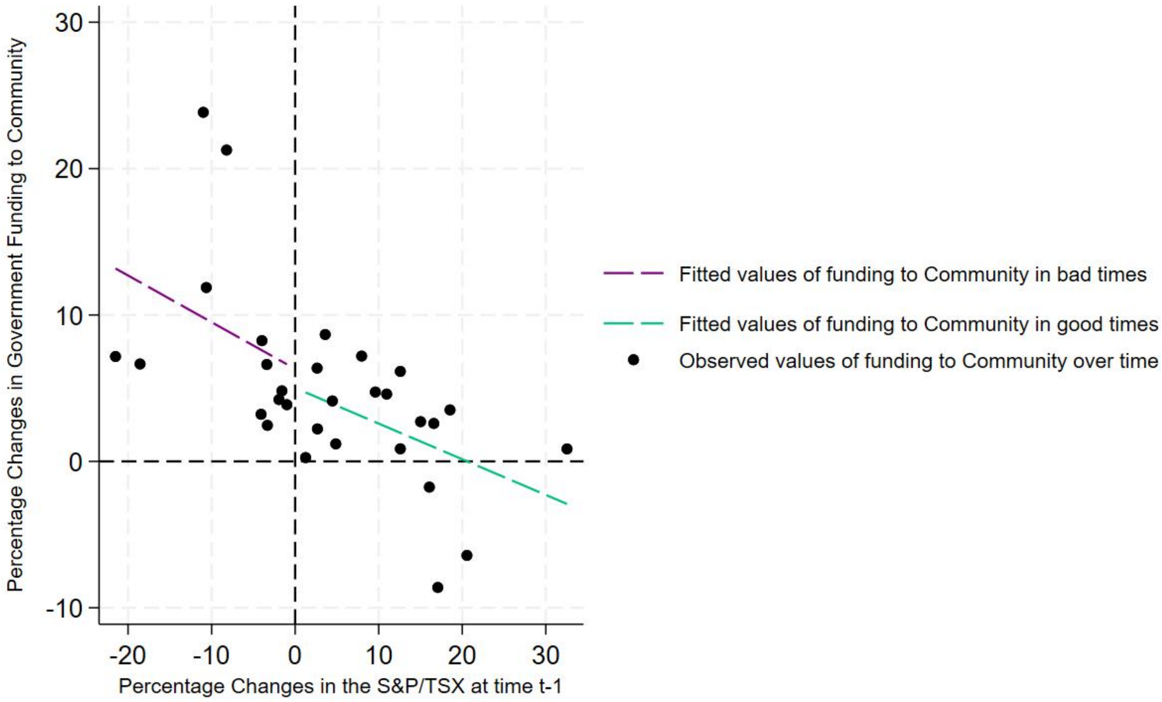
Figure 2.11 Percentage Changes in the S&P/TSX and Aggregate Government Funding to Health from 1992 to 2021 with Trendlines (CA)



Source: author's calculations from the T3010 data base and GDP data (see table 2.1 for source).

Note: Differences from figure 2.7 are that when lagged sptsx < 0, the slope of the fitted line is 0.04, with a 95% percentile bootstrap confidence interval of [−1.62, 0.60]. When lagged sptsx > 0, the slope is −0.28, with a bootstrap confidence interval of [−1.16, 0.30].

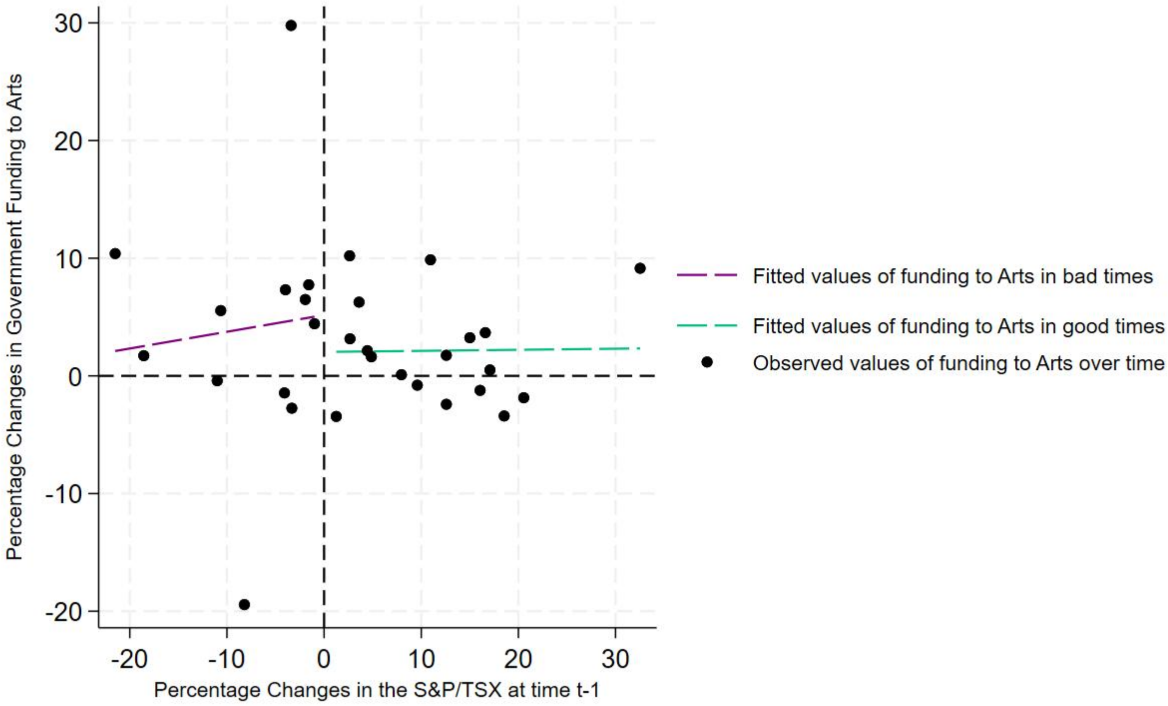
Figure 2.12 Percentage Changes in the S&P/TSX and Aggregate Government Funding to Community from 1992 to 2021 with Trendlines (CA)



Source: author's calculations from the T3010 data base and GDP data (see table 2.1 for source).

Note: Differences from figure 2.7 are that when lagged sptsx < 0, the slope of the fitted line is −0.31, with a 95% percentile bootstrap confidence interval of [−2.15, 0.01]. When lagged sptsx > 0, the slope is −0.24, with a bootstrap confidence interval of [−0.63, -0.05].

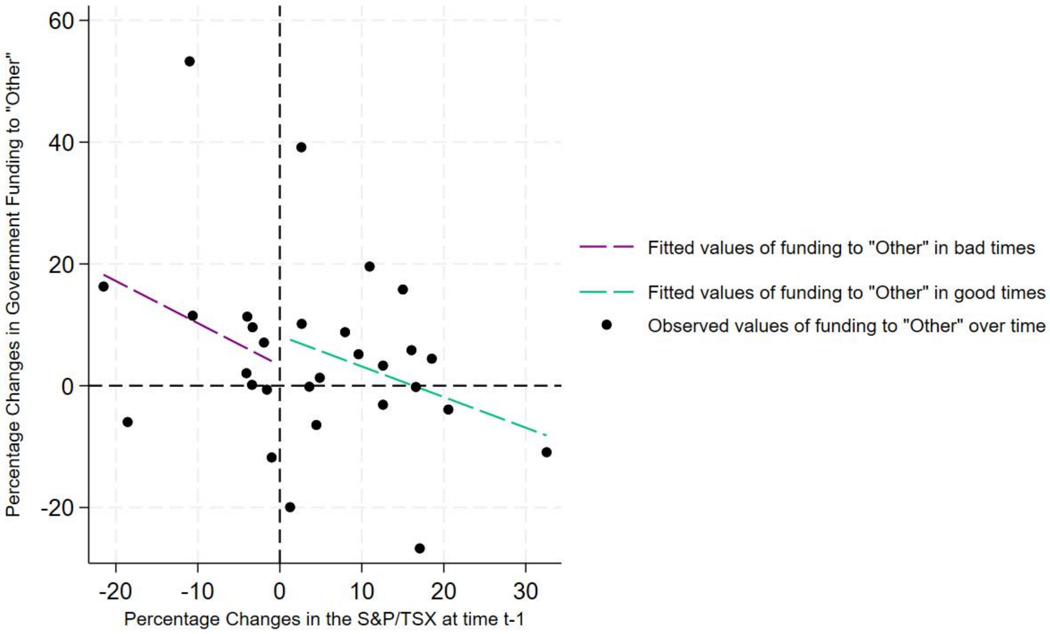
Figure 2.13 Percentage Changes in the S&P/TSX and Aggregate Government Funding to Artsfrom 1992 to 2021 with Trendlines (CA)



Source: author's calculations from the T3010 data base and GDP data (see table 2.1 for source).

Note: Differences from figure 2.7 are that when lagged sptsx < 0, the slope of the fitted line is 0.14, with a 95% percentile bootstrap confidence interval of [−0.41, 1.90]. When lagged sptsx > 0, the slope is 0.01, with a bootstrap confidence interval of [−0.45, 0.25].

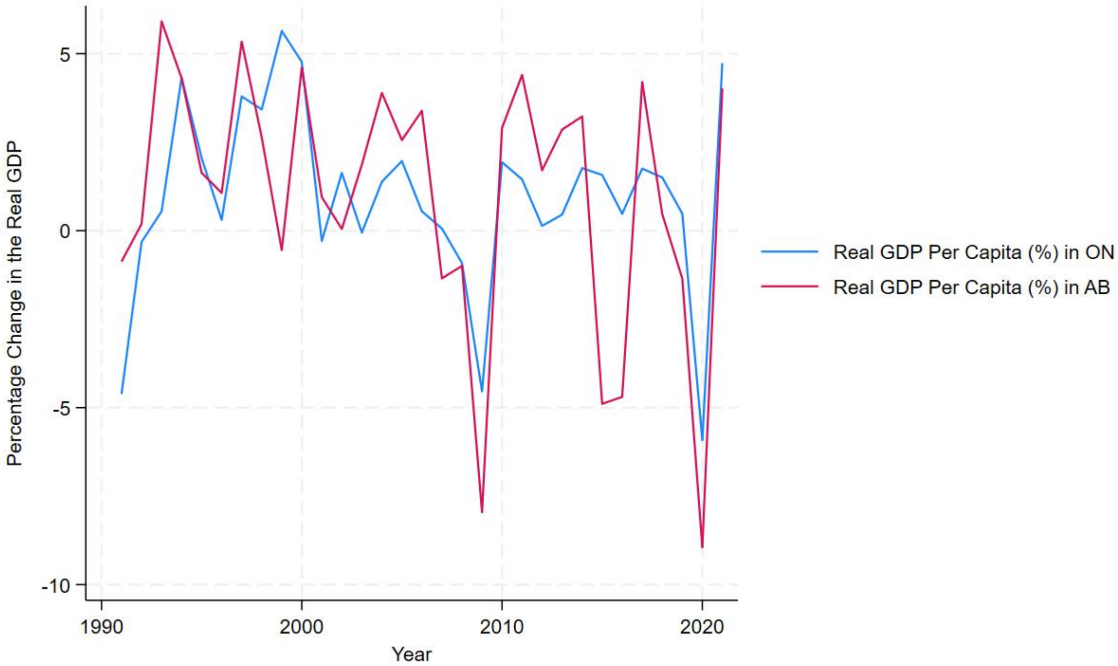
Figure 2.14 Changes in the S&P/TSX and Aggregate Government Funding to "Other" Charities from 1992 to 2021 with Trendlines (CA)



Source: author's calculations from the T3010 data base and GDP data (see table 2.1 for source).

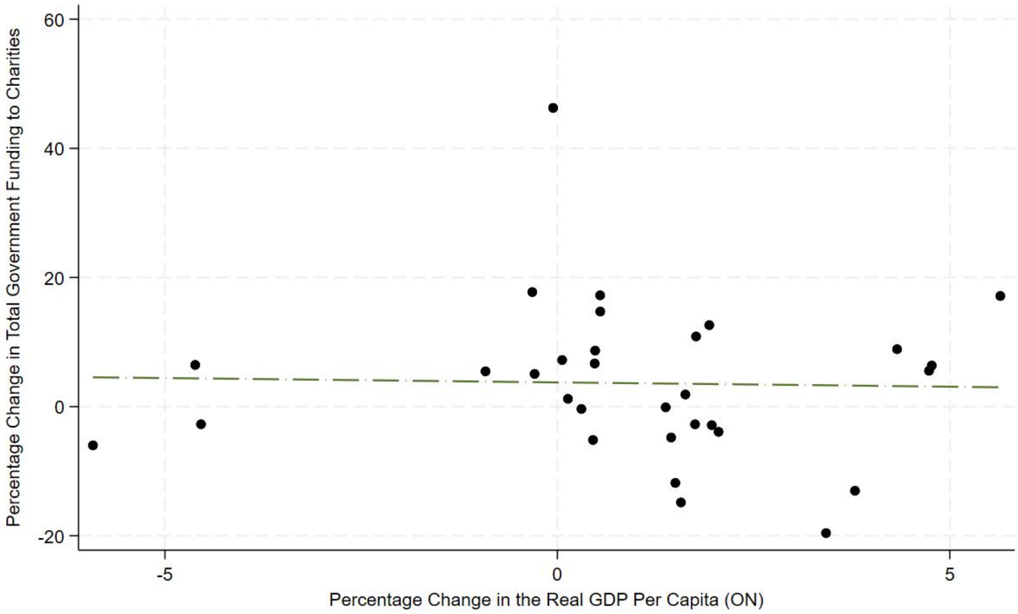
Note: Differences from figure 2.7 are that when lagged sptsx < 0, the slope of the fitted line is −0.69, with a 95% percentile bootstrap confidence interval of [−4.99, 0.43]. When lagged sptsx > 0, the slope is −0.50, with a bootstrap confidence interval of [−1.48, 0.52].

Figure 2.15 Percentage Changes in Real GDP in Ontario and Alberta from 1991 to 2021



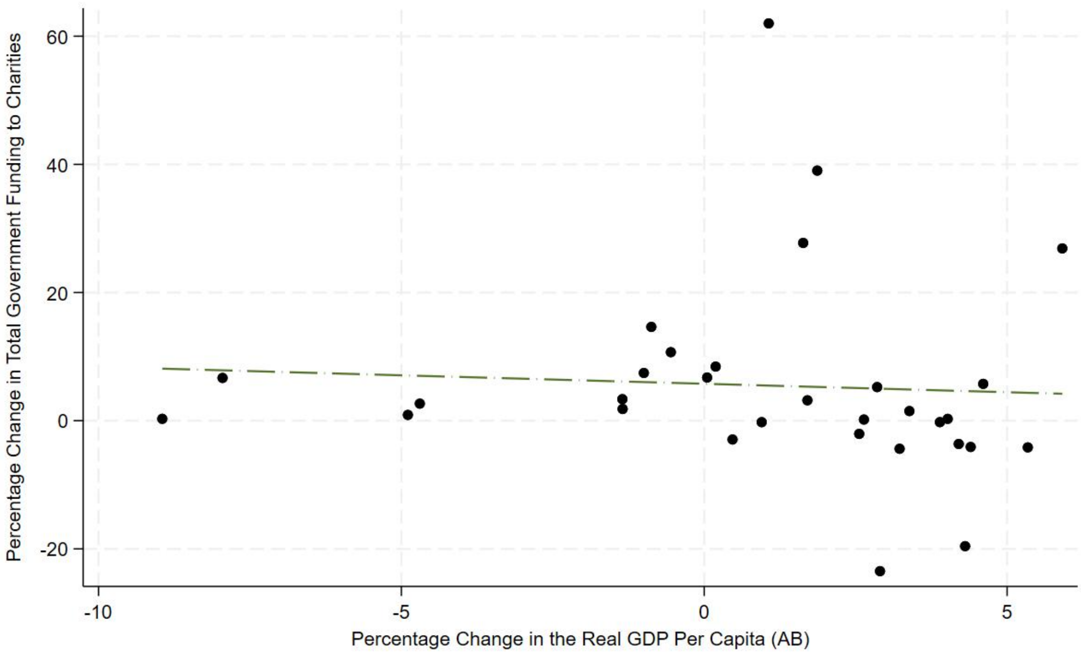
Source: author's calculations from the T3010 data base and GDP data (see table 2.1 for source).

Figure 2.16 Percentage Changes in Real GDP per capita and Real Aggregate Government Funding to Charities per capita from 1991 to 2021 with Trendline (ON)



Source: author's calculations from the T3010 data base and GDP data (see table 2.1 for source).

Figure 2.17 Percentage Changes in Real GDP per capita and Real Aggregate Government Funding to Charities per capita from 1991 to 2021 with Trendline (AB)



Source: author's calculations from the T3010 data base and GDP data (see table 2.1 for source)

Appendix 2.A: T3010 Data Problems and Solutions

2.1A Data Section

The sample period for this study covers the years 1990 to 2021. Appendix A.1 of Chapter One outlines the challenges encountered, including issues with variable consistency, the classification of subordinate charities, and missing values in tax-receipted gifts (line 4500), along with the corresponding solutions. In the following section, I address additional challenges and their resolutions regarding data cleaning, focusing on insights into total government funding and its distribution across different levels to charities.

Problem and Solution: Outliers in Data with Missing Value in Original Line 4500, and in Original Line 4570

Most of the missing values for the receipted gifts are for small charities. Based on Penner (2017) who uses one million and five million Canadian dollars of total revenue as cutoffs for small, medium and large charities. I find that 87.4% of the missing values in line 4500 are from 'small' charities (under $1m in total revenues), 8.25% from medium charities ($1m-5m), and 4.35% from large charities.

When my recalculated receipted gift estimate is three times larger than the historically largest non-missing gift, I consider these to be outliers. I have 0.16% observations as outliers for the recalculated gift. Outliers may exist in the line 4570, in this case, I drop observations higher than 99 percentile of line 4570 by province, by year and by category of charities.

Problem and Solution: Incomplete Information in Components of Line 4570

Between 1997 and 2008, all charities are required to report details of their funding sources, for instance, line 4540 represents federal funding; line 4550 is provincial funding; line 4560 denotes municipal funding; line 4570 means total government funding. Thus line 4570 should be the sum of line 4540 - line 4560. Since 2009, charities that satisfy some conditions are required to fill in schedule 6 (see appendix A.2 for details) to provide specifics of their grants, otherwise, they only report aggregate funding from governments. During 1997-2008, 5.7% of observations in the reported line 4570 do not match with recalculated line 4570. After 2009, for charities that fill in schedule 6, 51% of reported values in line 4570 do not match with recalculated values in aggregate government funding. I replace the original value of line 4570 with recalculated values when at least one of the funding components are non-zero while original values are inconsistent with recalculated values (14.31% of observations have been changed). In the end, around 92% of the observations in the original line 4570 match with recalculated values in line 4570. For those unmatched, I keep original line 4570 as it is, as the inconsistency might comes from years of 1990-1996, or years after 2009 when charities did not fill in schedule 6.

2.2A Schedule 6 Charities

From 2009 onwards, charities are required to fill in schedule 6 when one of following conditions applies:

(1) The charity's revenue exceeds $100,000;

(2) The amount of all property (for example, investments, rental properties) not used in charitable activities is more than $25,000;

(3) The charity has permission to accumulate funds during this fiscal period;

(4) The charity has spent or transferred enduring property during this fiscal period

This classification would affect my analysis for the components of total government funding to charities, from federal, provincial, and municipal governments. I replace original line 4570 with recalculated line 4570 when at least one of the components of government funding is non-zero and charities fill in schedule 6 after 2009. On average, 54.21% of charities fill in schedule 6 after 2009.

Appendix 2.B: Tables

Table 2.1B Selection Critiria to Optimal lags in the Aggregate Data

Variables	AIC	HQIC	SBIC
△ln(RGDPC)	Lag = 0	Lag = 0	Lag = 0
△ln(RGDPC_neg)	Lag = 0	Lag = 0	Lag = 0
△ln(RGDPC_pos)	Lag = 0	Lag = 0	Lag = 0
△ln(Total)	Lag = 0	Lag = 0	Lag = 0
△ln(Poverty)	Lag = 0	Lag = 0	Lag = 0
△ln(Edu)	Lag = 0	Lag = 0	Lag = 0
△ln(Religion)	Lag = 0	Lag = 0	Lag = 0
△ln(Health)	Lag = 0	Lag = 0	Lag = 0
△ln(Comm)	Lag = 0	Lag = 0	Lag = 0
△ln(Art)	Lag = 2	Lag = 0	Lag = 0
△ln(Other)	Lag = 0	Lag = 0	Lag = 0

Note: The optimal lags (up to 4) based on selection criteria such as Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQIC) and Schwarz Bayesian Information Criterion (SBIC) are reported in the table.

Table 2.2B ARDL Model Diagnostic Tests, in the Form of First Difference

Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Other)
Normality (Shapiro-Francia test)	2.54***[0.01]	3.22***[0.00]	1.91**[0.03]	5.20***[0.00]	0.86[0.19]	2.26***[0.01]	3.08***[0.00]	3.74***[0.00]
Autocorrelation (Breusch-Godfrey LM test)	0.00[0.99]	0.60[0.44]	1.34[0.26]	0.01[0.94]	0.22[0.63]	0.33[0.57]	1.54[0.22]	0.63[0.43]
Heteroscedasticity (Breusch-Pagan-Godfrey test)	4.57**[0.03]	0.09[0.76]	9.58***[0.00]	1.62[0.20]	3.90**[0.05]	0.94[0.33]	6.90***[0.01]	0.22[0.63]
RESET (Ramsey test)	1.11[0.36]	1.15[0.35]	0.46[0.72]	1.75[0.18]	1.03[0.39]	0.18[0.91]	0.96[0.42]	0.31[0.82]

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. Shapiro-Francia test for normality should be applied when observations are between 5 and 5000. P-values are reported in the Normality test. F-statistics are reported in BG LM test and Ramsey test. Chi-square test is reported in the BPG test with p-values included in square brackets. The null hypothesis for Shapiro-Francia test: the residual is normally distributed.. The null hypothesis for LM test: no serial correlation. The null hypothesis for BPG test: the residual is homoscedastic. The null hypothesis for Ramsey test: no omitted variable.

Table 2.3B NARDL Model Diagnostic Tests, in the Form of First Difference

Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Other)
Normality (Shapiro-Francia test)	2.48***[0.01]	3.33***[0.00]	1.89**[0.03]	4.62***[0.00]	0.72[0.23]	2.37***[0.00]	3.09***[0.00]	3.72***[0.00]
Autocorrelation (Breusch-Godfrey LM test)	0.00[0.97]	0.52[0.47]	1.37[0.25]	0.04[0.84]	0.18[0.66]	0.36[0.55]	0.03[0.84]	0.65[0.42]
Heteroscedasticity (Breusch-Pagan-Godfrey test)	3.72**[0.05]	0.01[0.91]	10.14***[0.00]	0.35[0.55]	2.45[0.11]	0.96[0.32]	0.53[0.46]	0.29[0.58]
RESET (Ramsey test)	1.50[0.24]	1.14[0.35]	0.30[0.82]	0.51[0.67]	0.03[0.99]	0.54[0.65]	2.59*[0.08]	0.35[0.79]

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. Shapiro-Francia test for normality should be applied when observations are between 5 and 5000. P-values are reported in the Normality test. F-statistics are reported in BG LM test and Ramsey test. Chi-square test is reported in the BPG test with p-values included in square brackets. The null hypothesis for Shapiro-Francia test: the residual is normally distributed.. The null hypothesis for LM test: no serial correlation. The null hypothesis for BPG test: the residual is homoscedastic. The null hypothesis for Ramsey test: no omitted variable.

Table 2.4B Lag One in the Dependent Variables, Aggregate Government Funding, Bootstrapped ARDL and NARDL

Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Other)
ARDL								
△ln(RGDPC)$_t$	-0.114	-0.522	-0.178	-5.932	0.235	-0.421	0.494	-1.941**
	(0.481)	(0.480)	(0.708)	(5.923)	(0.784)	(0.347)	(0.721)	(0.853)
NARDL								
△ln(RGDPC_neg)$_t$	0.0294	-0.785*	-0.473	-21.66***	1.096	-0.482	-0.977	-1.901
	(0.482)	(0.449)	(0.552)	(7.250)	(0.795)	(0.588)	(0.645)	(1.765)
△ln(RGDPC_pos)$_t$	-0.243	-0.283	0.0876	8.665	-0.545	-0.366	1.739	-1.976
	(1.244)	(1.166)	(1.660)	(9.500)	(1.740)	(0.674)	(1.228)	(1.943)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. I summarise the results of ARDL and NARDL in one table and report the estimated coefficients of real GDP per capita.

Table 2.5B Lag One in the Key Variable of Interests, Aggregate Government Funding, Bootstrapped ARDL and NARDL

Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Other)
ARDL								
△ln(RGDPC)$_t$	-0.134	-0.602	-0.266	-5.913	0.328	-0.451	0.462	-2.032**
	(0.356)	(0.372)	(0.612)	(6.199)	(0.589)	(0.288)	(0.505)	(0.748)
△ln(RGDPC)$_{t-1}$	-0.627	-0.578	-0.972*	-3.954	-0.479	-0.494***	-0.449	0.309
	(0.449)	(0.431)	(0.500)	(3.482)	(0.663)	(0.145)	(0.798)	(0.817)
NARDL								
△ln(RGDPC_neg)$_t$	-0.032	-1.051**	-0.459	-18.90**	1.121	-0.371	-1.645**	-1.820
	(0.431)	(0.493)	(0.658)	(7.966)	(0.694)	(0.600)	(0.598)	(2.154)
△ln(RGDPC_pos)$_t$	-0.574	-1.157	-0.321	12.50	-0.745	-0.481	0.786	-1.443
	(1.379)	(1.108)	(1.790)	(11.77)	(1.942)	(0.890)	(0.698)	(2.308)
△ln(RGDPC_neg)$_{t-1}$	-1.215	-2.156***	-1.343*	8.055	-1.126	-0.428	-2.803**	1.599
	(0.849)	(0.771)	(0.762)	(8.728)	(1.417)	(0.623)	(1.172)	(2.520)
△ln(RGDPC_pos)$_{t-1}$	0.020	1.254	-0.529	-15.76	0.145	-0.579	1.035	-1.162
	(0.934)	(0.900)	(1.283)	(15.04)	(1.513)	(0.855)	(0.940)	(3.498)

Note: I summarise the results of ARDL and NARDL in one table and report the estimated coefficients of lagged real GDP per capita.

Table 2.6B Significant Bootstrapped ARDL Estimation to Aggregate Funding to Charities vs. Funding by Province, 1990-2021

CA								
Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Other)
△ln(RGDPC)$_t$	-1.682**							
	(0.713)							
△ln(rgdpc)$_t$		-0.850*	-0.834***	-1.987**	-17.48***	-5.789**	-10.86***	-4.005***
		(0.425)	(0.249)	(0.793)	(6.104)	(2.235)	(3.025)	(1.436)
AB								
	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(other)
△ln(rgdpc)$_t$	-0.850*	-0.834***						
	(0.425)	(0.249)						
MB								
△ln(rgdpc)$_t$		-1.987**						
		(0.793)						
NB								
△ln(rgdpc)$_t$				-17.48***				
				(6.104)				
NL								
△ln(rgdpc)$_t$				-5.789**				
				(2.235)				
NS								
△ln(rgdpc)$_t$								-10.86***
								(3.025)
ON								
△ln(rgdpc)$_t$								-4.005***
								(1.436)
PE								
△ln(rgdpc)$_t$				-13.91***				

	(3.011)
QC	
$\triangle\ln(rgdpc)_t$	-8.053**
	(3.817)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. All variables are in real values. In the aggregate data, the key independent variable is real GDP per capita. Outcome variables are government funding to charities in total and by fields. In the provincial data, real GDP per capita by province is the key explanatory variable. Funding to charities per capita by province are the explained variables. Since trend is significant in some fields of funding, I assume that trend is non-linear over time so that it is not cancelled out through first difference. The lag used in the aggregate data is based on Akaike Information Criterion (AIC), which is 0, 0, 0, 0, 0, 0, 0, 2, 0 for ln(RGDPC), ln(Total), ln(Poverty), ln(Edu), ln(Religion), ln(Health), ln(Comm), ln(Art), and ln(Other), respectively. The lag used in the provincial data is 1 and 0 for provincial GDP per capita and funding variables, respectively.

Table 2.7B Significant Bootstrapped NARDL Estimation to Aggregate Funding to Charities vs. Funding by Province, 1990-2021

CA								
Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Other)
△ln(RGDPC_neg)$_t$	-	-1.097**	-	-19.11***	1.081*	-	-1.695***	-
		(0.586)		(6.955)	(0.627)		(0.600)	
△ln(RGDPC_pos)$_t$	-	-0.526	-	9.222	-0.457	-	1.566	-
		(1.239)		(10.29)	(1.592)		(1.345)	
	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(other)
AB								
△ln(rgdpc_neg)$_t$	-	-	-1.058*	-14.59**	-	-	-1.483*	-
			(0.549)	(7.033)			(0.783)	
△ln(rgdpc_pos)$_t$	-	-	1.395	15.85	-	-	0.798	-
			(1.332)	(10.57)			(1.073)	
BC								
△ln(rgdpc_neg)$_t$	-3.028***	-1.953*	-2.679**	-	-	-3.249***	-4.749***	-
	(0.964)	(1.102)	(1.174)			(0.719)	(1.005)	
△ln(rgdpc_pos)$_t$	1.934	0.594	4.425**	-	-	0.690	4.318***	-
	(1.329)	(0.799)	(1.860)			(0.778)	(1.265)	
MB								
△ln(rgdpc_neg)$_t$	-3.132**	-	-	-31.37***	-	-	-	-
	(1.421)			(10.40)				
△ln(rgdpc_pos)$_t$	1.505	-	-	25.45	-	-	-	-
	(1.688)			(19.85)				
NB								
△ln(rgdpc_neg)$_t$	-4.765**	-	-	-22.27***	-	-	-9.945**	-
	(2.246)			(7.071)			(4.173)	
△ln(rgdpc_pos)$_t$	4.930	-	-	-15.62*	-	-	4.998	-

	(3.106)			(8.773)			(3.320)	
NL								
$\triangle\ln(rgdpc\_neg)_t$	-	-	-	-	-	-3.451***	-	-
						(1.143)		
$\triangle\ln(rgdpc\_pos)_t$	-	-	-	-	-	2.051	-	-
						(1.385)		
NS								
$\triangle\ln(rgdpc\_neg)_t$	-	-	-	-26.70***	-	-	-	-14.28***
				(5.394)				(4.235)
$\triangle\ln(rgdpc\_pos)_t$	-	-	-	6.965	-	-	-	-8.689*
				(12.44)				(4.390)
ON								
$\triangle\ln(rgdpc\_neg)_t$	1.344*	-	-	-26.15**	2.044*	-	-	-3.244*
	(0.723)			(9.422)	(1.074)			(1.661)
$\triangle\ln(rgdpc\_pos)_t$	-1.867	-	-	11.61	-3.888*	-	-	-4.584
	(1.652)			(12.05)	(2.075)			(3.519)
PE								
$\triangle\ln(rgdpc\_neg)_t$	-4.388**	-5.759***	-	-18.29***	-14.12**	-1.749	-8.342***	-
	(2.116)	(1.862)		(4.619)	(5.195)	(1.538)	(2.898)	
$\triangle\ln(rgdpc\_pos)_t$	7.185*	2.808	-	-11.82**	20.77	2.103*	-0.813	-
	(3.781)	(1.831)		(4.700)	(13.22)	(1.217)	(6.937)	
QC								
$\triangle\ln(rgdpc\_neg)_t$	-	-2.481***	-1.916***	-22.85***	-	-	-1.728**	-
		(0.808)	(0.617)	(2.195)			(0.802)	
$\triangle\ln(rgdpc\_pos)_t$	-	2.138*	1.621	0.571	-	-	3.594***	-
		(1.177)	(1.181)	(3.755)			(1.226)	

Note: The lag used in the aggregate data is based on Akaike Information Criterion (AIC), which is 0, 0 for ln(RGDPC_neg) and ln(RGDPC_pos), respectively. The lag used in the provincial data is also 0, 0 for asymmetric macroeconomic indicators, respectively. The hyphen denotes nonsignificant estimations.

Table 2.8B PARDL Model Diagnostic Tests, in the Form of First Difference

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(other)
groupwise heteroske dasticity (chi2)	485.51***	25.47***	368.02***	41.52***	365.10***	224.83***	625.89***	329.84***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
contemporaneous correlations	73.86***	346.41***	103.57***	596.22***	59.52	125.65***	259.93***	132.81***
	[0.01]	[0.00]	[0.00]	[0.00]	[0.07]	[0.00]	[0.00]	[0.00]
autocorrelation	0.08	0.03	0.00	0.06	0.00	0.76	10.22***	4.71**
	[0.78]	[0.86]	[0.97]	[0.81]	[0.95]	[0.38]	[0.00]	[0.03]

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. The diagnostic tests are conducted after the command of xtreg, fe. Null hypothesis of the groupwise heteroskedasticity: homoskedasticity; Null hypothesis of contemporaneous correlations: no contemporaneous correlations; Null hypothesis of autocorrelation: no serial correlation. The corresponding stata command for above tests is: xttest3, xttest2, xtqptest, lags(1) .

Table 2.9B PNARDL Model Diagnostic Tests, in the Form of First Difference

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(other)
groupwise heteroskedasticity (chi2)	382.59***	25.75***	379.27***	60.35***	271.10***	189.55***	695.96***	333.58***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
contemporaneous correlations	71.48***	346.50***	94.92***	526.81***	57.81*	118.12***	212.96***	132.76***
	[0.01]	[0.00]	[0.00]	[0.00]	[0.10]	[0.00]	[0.00]	[0.00]
autocorrelation	0.18	0.01	0.00	0.44	0.01	0.46	4.72**	3.82**
	[0.67]	[0.91]	[0.98]	[0.51]	[0.92]	[0.50]	[0.03]	[0.05]

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. The diagnostic tests are conducted after the command of xtreg, fe. Null hypothesis of the groupwise heteroskedasticity: homoskedasticity; Null hypothesis of contemporaneous correlations: no contemporaneous correlations; Null hypothesis of autocorrelation: no serial correlation. The corresponding stata command for above tests is: xttest3, xttest2, xtqptest, lags(1) .

Table 2.10B Lag One in the Key Variable of Interest, Aggregate Government Funding by Province, Panel ARDL and Panel NARDL

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(other)
Panel ARDL								
△ln(rgdpc)$_t$	0.544	-0.056	3.296***	-0.245	0.120	0.289*	-1.154*	-1.884
	(1.109)	(0.369)	(0.837)	(0.684)	(2.905)	(0.145)	(0.546)	(1.188)
△ln(rgdpc)$_{t-1}$	-0.224	-0.500	1.888	-0.320	-2.138	-0.621	1.229*	-2.177
	(0.476)	(0.344)	(1.352)	(0.908)	(2.091)	(0.390)	(0.585)	(1.860)
Panel NARDL								
△ln(rgdpc_neg)$_t$	-2.593	0.378	0.0435	0.486	-5.512*	-1.185	-1.709**	-2.955
	(1.835)	(0.498)	(1.561)	(1.943)	(2.731)	(0.659)	(0.578)	(3.962)
△ln(rgdpc_pos)$_t$	2.021	-0.266	5.471**	-0.732	2.815	0.971**	-0.800	-1.176
	(1.137)	(0.701)	(1.817)	(1.187)	(3.600)	(0.419)	(0.792)	(1.598)
△ln(rgdpc_neg)$_{t-1}$	-0.147	-0.569	8.569	-1.864	-1.589	-0.722	2.223	-0.031
	(1.630)	(0.467)	(5.189)	(1.421)	(4.832)	(0.406)	(1.426)	(2.545)
△ln(rgdpc_pos)$_{t-1}$	-0.227	-0.465	-2.002	0.562	-2.385	-0.544	0.663	-3.402
	(1.083)	(0.598)	(1.233)	(1.624)	(3.395)	(0.437)	(0.523)	(2.164)

Note: I summarise the results of Panel ARDL and Panel NARDL in one table and report the estimated coefficients of (lagged) real GDP per capita.

Table 2.11B Individual VIF Values for Donations in Total and by Field, and GDP

Variables	VIF
$\triangle \ln(\text{total})_{d,t}$	1.69
$\triangle \ln(\text{rgdpc})_{tot,t}$	2.37
$\triangle \ln(\text{poverty})_{d,t}$	1.21
$\triangle \ln(\text{rgdpc})_{pov,t}$	2.32
$\triangle \ln(\text{edu})_{d,t}$	1.03
$\triangle \ln(\text{rgdpc})_{edu,t}$	1.09
$\triangle \ln(\text{religion})_{d,t}$	1.35
$\triangle \ln(\text{rgdpc})_{rel,t}$	1.18
$\triangle \ln(\text{health})_{d,t}$	1.01
$\triangle \ln(\text{rgdpc})_{heal,t}$	1.09
$\triangle \ln(\text{comm})_{d,t}$	1.02
$\triangle \ln(\text{rgdpc})_{com,t}$	1.09
$\triangle \ln(\text{art})_{d,t}$	1.03
$\triangle \ln(\text{rgdpc})_{art,t}$	1.09
$\triangle \ln(\text{other})_{d,t}$	1.10
$\triangle \ln(\text{rgdpc})_{oth,t}$	1.09

Note: The VIF for GDP tells how much the variance of the GDP coefficient is inflated due to its correlation with other variables, including donations. Similarly, the VIF for donations shows how much its variance is inflated due to correlations with other variables, including GDP. If either of these VIF values is significantly high (usually above 10, though some use a threshold of 5), it suggests that GDP and donations may have a multicollinearity issue. The variable indexed by d,t represents donations to all charities, as well as donations by specific fields - Relief of Poverty, Education, Religion, Health, Community, Arts, and "Other" - listed from the top column downward. The variable $\triangle \ln(\text{rgdpc})_{tot,t}$ denotes the first difference of the natural logarithm of real GDP per capita, included as an independent variable in regressions analysing donations to total charities at time t. Similarly, when the index changes, it indicates regressions where donations by field (e.g., Relief of Poverty, Education, Religion, Health, Community, Arts, and "Other"), at time t, are included as independent variables.

Table 2.12B Bootstrapped NARDL Estimation to Aggregate Government Funding to Charities, Measured by Output Gap, 1990-2021

Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Other)
Trend	-0.003**	-0.002	-0.005**	0.004	-0.004**	0.001	0.003	0.006*
	(0.002)	(0.001)	(0.002)	(0.013)	(0.002)	(0.001)	(0.002)	(0.003)
$(\text{Outgap\_neg})_t$	-0.001	-0.015*	-0.002	-0.167	0.009	-0.010	0.004	-0.023
	(0.007)	(0.008)	(0.008)	(0.103)	(0.012)	(0.007)	(0.008)	(0.019)
$(\text{Outgap\_pos})_t$	0.004	-0.001	-0.015	-0.058	0.015	-0.000	0.006	0.014
	(0.01)	(0.010)	(0.026)	(0.080)	(0.016)	(0.006)	(0.012)	(0.029)
Constant	0.084**	0.066*	0.137***	-0.027	0.081*	0.019	-0.038	-0.062
	(0.038)	(0.039)	(0.049)	(0.350)	(0.044)	(0.027)	(0.027)	(0.068)
Observations	31	31	31	31	31	31	29	31
Wald	0.09[0.77]	0.69[0.41]	0.24[0.63]	0.53[0.47]	0.06[0.81]	0.87[0.36]	0.02[0.90]	0.89[0.35]
Model	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (2,0,0)	NARDL (0,0,0)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. All funding variables are real values. Trend is significant in the regression for government funding to total charities, Education, Health and 'Other' charities. The lag used in the analysis is the optimal lag based on Akaike Information Criterion (AIC). The key independent variable of interests is level variable, since the output gap data used in the monetary policy report available in Bank of Canada is in the form of percentage which captures volatility in productions. The rest of funding variables are described by the first difference of natural logarithm.

Table 2.13B Bootstrapped NARDL Estimation to Aggregate Government Funding to Charities, Without Recalculation of Aggregate Funding to Charities, 1990-2021

Variables	△ln(Total)	△ln(Poverty)	△ln(Edu)	△ln(Religion)	△ln(Health)	△ln(Comm)	△ln(Art)	△ln(Other)
Trend	-0.002	-0.008	-0.002	0.007	-0.000	-0.001	0.012	0.005
	(0.018)	(0.014)	(0.021)	(0.015)	(0.023)	(0.012)	(0.011)	(0.011)
$\triangle\ln(RGDPC\_neg)_t$	45.77	40.01	54.33	5.906	62.55	29.75	29.54	28.95
	(48.25)	(39.59)	(56.20)	(41.07)	(62.04)	(30.95)	(35.42)	(32.27)
$\triangle\ln(RGDPC\_pos)_t$	1.283	-1.817	1.184	14.25	-0.634	0.848	6.398*	-2.205
	(5.754)	(3.950)	(6.751)	(9.046)	(6.838)	(3.715)	(3.272)	(3.999)
Constant	0.038	0.154	0.0759	-0.360	0.0545	0.00472	-0.368	-0.00951
	(0.449)	(0.343)	(0.528)	(0.423)	(0.556)	(0.288)	(0.272)	(0.276)
Observations	31	31	31	31	31	31	29	31
Model	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (0,0,0)	NARDL (2,0,0)	NARDL (0,0,0)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. All funding variables are real values. Trend term is nonsignificant in the regression for government funding to charities, suggesting a potential linear relationship between funding variables and time. The lag used in the analysis is the optimal lag based on Akaike Information Criterion (AIC). Variables are described by the first difference of natural logarithm. Before recalculation by adding components of federal/provincial/municipal funding together, 14.31% of observations have unmatched original values of total government funding and recalculated funding amount.

Table 2.14B Panel NARDL Estimation to Funding to Charities by Province, Measured by Unemployment rate, 1990-2021

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(other)
△ln(total)$_{t-1}$	-0.345***							
	(0.044)							
(Unemp_neg)$_t$	0.498	-2.695**	3.778	-7.156	1.586	-1.332	-1.507	6.877
	(7.386)	(0.960)	(9.247)	(4.673)	(11.00)	(1.986)	(1.034)	(8.660)
(Unemp_pos)$_t$	-4.090	-0.162	-4.601**	2.628	-12.88	-0.475	2.188	3.103
	(4.973)	(1.277)	(1.505)	(3.548)	(18.85)	(1.649)	(1.764)	(5.198)
△ln(poverty)$_{t-1}$		-0.131**						
		(0.056)						
△ln(edu)$_{t-1}$			-0.287***					
			(0.021)					
△ln(religion)$_{t-1}$				-0.168**				
				(0.057)				
△ln(health)$_{t-1}$					-0.201*			
					(0.096)			
△ln(comm)$_{t-1}$						-0.097		
						(0.078)		
△ln(art)$_{t-1}$							-0.159*	
							(0.072)	
△ln(other)$_{t-1}$								-0.309***
								(0.038)
Constant	0.127	0.0845*	0.185**	0.0667	0.190	0.0343	0.174	-0.200
	(0.0703)	(0.0444)	(0.0634)	(0.0757)	(0.211)	(0.0374)	(0.137)	(0.184)
Wald	1.30[0.28]	2.38[0.15]	0.41[0.52]	4.74**[0.05]	1.00[0.34]	0.02[0.89]	5.13**[0.04]	0.26[0.62]
Observations	300	300	300	300	300	300	300	300

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. All funding variables are real values per capita.The macroeconomic indicator used is the difference of unemployment rate. The lag used in the analysis is the most common and optimal lag for each of province, based on Akaike Information Criterion (AIC).

Table 2.15B Panel ARDL Estimation to Funding to Charities by Province, with GDP-Province Interaction Terms, 1990-2021

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(other)
△ln(rgdpc)$_t$	0.281	1.011**	3.023**	-2.368**	-0.874	0.736*	0.445	-7.047**
	(1.795)	(0.341)	(1.231)	(0.834)	(5.460)	(0.378)	(0.521)	(2.960)
△ln(rgdpc)$_t$_AB	-0.044	-1.317***	-0.197	2.111***	-0.892	-0.540**	-0.920	5.744***
	(0.870)	(0.142)	(1.039)	(0.396)	(2.354)	(0.227)	(0.601)	(1.302)
△ln(rgdpc)$_t$_BC	0.241	-0.876***	0.620	5.650***	-0.078	-0.706*	-0.193	0.887
	(0.582)	(0.247)	(0.872)	(0.836)	(1.013)	(0.315)	(0.508)	(0.707)
△ln(rgdpc)$_t$_NB	0.143	-1.493***	-3.387**	4.440***	-0.271	-0.209	-0.819**	3.246
	(0.901)	(0.297)	(1.493)	(1.116)	(2.599)	(0.199)	(0.331)	(2.212)
△ln(rgdpc)$_t$_NL	-0.119	-1.427***	0.543	1.509*	0.814	-0.532	-2.480***	4.617*
	(1.430)	(0.220)	(1.003)	(0.703)	(4.688)	(0.324)	(0.227)	(2.294)
△ln(rgdpc)$_t$_NS	-0.012	-0.424**	-3.019***	2.337***	0.747	-0.084	0.111	2.676
	(0.499)	(0.144)	(0.759)	(0.431)	(1.294)	(0.355)	(0.385)	(3.313)
△ln(rgdpc)$_t$_MB	1.793**	-1.602***	2.967***	1.827**	3.722	-0.393	-0.981	6.281**
	(0.656)	(0.210)	(0.433)	(0.621)	(2.130)	(0.480)	(0.659)	(2.195)
△ln(rgdpc)$_t$_PE	1.570*	-0.025	3.156***	-1.174*	4.576**	-0.403**	-3.315***	15.282***
	(0.712)	(0.160)	(0.630)	(0.615)	(1.975)	(0.136)	(0.461)	(1.550)
△ln(rgdpc)$_t$_QC	0.864	0.483***	-1.414**	3.219***	1.698	0.316**	1.114***	5.092***
	(0.705)	(0.096)	(0.529)	(0.469)	(1.755)	(0.107)	(0.198)	(0.555)
△ln(rgdpc)$_t$_SK	1.187	-0.725***	0.869	4.672***	2.535	-0.596**	-0.300	3.855***
	(0.995)	(0.190)	(1.392)	(0.617)	(2.452)	(0.226)	(0.566)	(1.163)
Constant	0.095*	0.090*	0.168**	0.101	0.078	0.031	0.191	-0.200
	(0.045)	(0.046)	(0.060)	(0.058)	(0.083)	(0.039)	(0.138)	(0.173)
Observations	300	300	300	300	300	300	300	300

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. All funding variables are real values per capita.Year fixed effect is considered but not reported in this table.

Table 2.16B Panel NARDL Estimation to Aggregate Government Funding to Charities by Province, Local Sample, 1990-2021

Variables	△ln(total)	△ln(poverty)	△ln(edu)	△ln(religion)	△ln(health)	△ln(comm)	△ln(art)	△ln(other)
△ln(total)$_{t-1}$	-0.213**							
	(0.080)							
△ln(rgdpc_neg)$_t$	-2.889	0.044	0.998	0.876	-18.632	-1.335	-0.925	-2.236
	(3.349)	(0.306)	(2.489)	(1.876)	(13.631)	(0.733)	(1.726)	(3.864)
△ln(rgdpc_pos)$_t$	1.511	0.253	6.086*	-1.003	1.841	0.669*	-1.389	-0.677
	(1.620)	(0.410)	(3.141)	(1.558)	(4.876)	(0.319)	(0.978)	(1.906)
△ln(poverty)$_{t-1}$		-0.204***						
		(0.063)						
△ln(education)$_{t-1}$			-0.348***					
			(0.038)					
△ln(religion)$_{t-1}$				-0.180***				
				(0.052)				
△ln(health)$_{t-1}$					-0.201***			
					(0.057)			
△ln(community)$_{t-1}$						-0.162		
						(0.134)		
△ln(art)$_{t-1}$							-0.236***	
							(0.036)	
△ln(other)$_{t-1}$								-0.310***
								(0.039)
Constant	0.039	0.084	0.084	0.067	-0.083	0.004	0.173	-0.054
	(0.057)	(0.056)	(0.109)	(0.081)	(0.182)	(0.043)	(0.202)	(0.154)
Wald	2.08[0.18]	0.67[0.43]	0.68[0.42]	2.56[0.14]	2.80[0.12]	4.26*[0.07]	0.01[0.91]	0.06[0.82]
Observations	300	300	300	300	300	300	300	300

Note: △ln(rgdpc_neg) and △ln(rgdpc_pos) denote the first difference of the log of negative change in real GDP per capita at time t, the first difference of the log of positive change in real GDP per capita at time t, respectively. See appendix 1.2A for local sample definition.

Table 2.17B Principal Component Analysis to Funding to Charities by Province, Measured by Donations and GDP, 1990-2021

Variables	$\triangle\ln(total)_g$	$\triangle\ln(poverty)_g$	$\triangle\ln(edu)_g$	$\triangle\ln(religion)_g$	$\triangle\ln(health)_g$	$\triangle\ln(comm)_g$	$\triangle\ln(art)_g$	$\triangle\ln(other)_g$
PCA_{tot}	0.004							
PCA_{rp}		-0.002						
PCA_{edu}			0.063*					
PCA_{rel}				-0.124***				
PCA_{heal}					-0.008			
PCA_{com}						0.002		
PCA_{art}							0.065**	
PCA_{oth}								0.056*

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. All funding and donation variables are real values per capita.

Chapter Three: The Location Decision of Charities: Insights from Canada

3.1 Introduction

Between 1991 and 2021, Statistics Canada recorded 7,270 unique Census Subdivisions (CSDs). Of these, only 1,030 CSDs ever hosted a registered charity during the study period, highlighting the highly uneven spatial distribution of charitable activity. As of 2021, Canada had over 60,000 registered charities operating across 969 CSDs. Over the thirty-year span, the average number of new charity entries per CSD was 1.41 per year, while the average number of exits was 0.94. These figures indicate a modest but consistent net expansion of the charitable sector over the period. This organisational growth and turnover could reflect how the charitable landscape evolves in response to shifting local needs, economic conditions, and institutional support. Yet, despite charities' role in social provision, the geographic and time-based drivers of charity entry and exit remain poorly understood – particularly in the Canadian context, where the interplay between poverty, public funding, and spatial disparities has received limited empirical attention.

This chapter examines the spatial and temporal patterns of charity formation and dissolution across Canada over three decades. Drawing on detailed panel data at the CSD-year level and using a Poisson Pseudo Maximum Likelihood estimator with high-dimensional fixed effects (PPMLHDFE), I identify the local demographic and institutional determinants of entry and exit. I find that poverty – measured by the proportion of residents living below the Low-Income Cut-Off (LICO) – is positively associated with charity entry, particularly for organisations focused on Relief of Poverty and Education. However, LICO shows no consistent relationship with exit, suggesting that need drives formation but not necessarily dissolution.

Government funding is an important factor. Charity entry is positively related to the proportion of existing charities receiving government support in the current year and the year ahead, suggesting that charitable organisations form in response to favourable and anticipated funding environments. In contrast, exit decisions are most sensitive to funding deprivation in the previous year, particularly for Relief of Poverty and Community charities, highlighting that dissolution tends to reflect lagged financial strain rather than contemporaneous or expected conditions.

The analysis also reveals mixed patterns of competition and complementarity across charity types in their entry and exit decisions. With respect to entry, some types – such as Relief of Poverty – respond positively to the presence of organisations in other sectors (e.g., Education), whereas others, such as Health, display substitution dynamics. Charities serving remote areas, defined as those located more than 100 kilometres from a Census Metropolitan Area (CMA), are particularly likely to enter the poverty-relief and community development sectors, reflecting spatial responsiveness to underserved regions. In terms of exit, charities in Relief of Poverty, Religion, Health, and Arts are more likely to dissolve when the density of peer organisations is higher, consistent with intra-type competition. By contrast, religious charities consistently exhibit inter-type complementarity.

This study extends the literature in three key ways. First, it provides the first nationwide analysis of charity entry and exit in Canada using longitudinal data at the CSD level, explicitly linking regional poverty, rent costs, and demographic conditions to organisational dynamics (patterns of charity formation and closure). Second, it offers new empirical evidence on the role of government funding for the charitable sector, distinguishing between past, contemporaneous, and anticipated funding exposure and showing how timing shapes both formation and dissolution. Third, it examines whether new charities complement or substitute existing charities by type, revealing nuanced spatial and strategic behaviour that varies across sectors and regions. In doing so, this chapter advances understanding of how charities respond to local need, institutional support, and competitive pressures – insights that have direct implications for nonprofit policy and funding design.

The remainder of the chapter is organised as follows. Section 3.2 reviews the existing literature on the determinants of charity entry and exit, with attention to the influence of socioeconomic conditions, public funding, and inter-charity dynamics. Section 3.3 presents the data. Section 3.4 outlines the empirical framework, details variable construction and estimation strategy, and reports the main results. Section 3.5 addresses identification concerns and provides robustness checks. Section 3.6 concludes with a summary of findings and their implications for policy and future research.

3.2 Location Decisions of Charities: Literature Review

The geographic distribution of charitable organisations seems to reflect socioeconomic conditions, government funding policies, and the strategic behaviour of other charities. A small literature has emphasised the importance of understanding where and why charities choose to locate, as these decisions affect service coverage, accessibility, and sustainability in the nonprofit sector. This section integrates key findings from the literature on the determinants of charity entry and exit, the role of public funding, and the competitive and cooperative dynamics among charities, highlighting both established findings and underexplored areas relevant to the Canadian context.

3.2.1 Socioeconomic Determinants of Charity Entry and Exit

Charities often emerge in response to observable needs, and local socioeconomic conditions are a strong predictor of their formation. Twombly (2003) emphasises that charities tend to enter in areas with high levels of economic vulnerability, such as poverty and welfare dependency. Subsequent studies have confirmed these patterns across various contexts. Peck (2008) finds that poverty and unemployment consistently correlate with higher nonprofit formation. Building on this, Yan et al. (2014) find that rental occupancy also plays a role in the establishment of antipoverty organisations, suggesting that such nonprofits emerge in areas where their services are most needed. Most of this research focuses on urban centres in the United States, and little is known about how similar mechanisms operate within the Canadian context.

While socioeconomic hardship may drive charity formation, it also influences organisational stability and survival. Twombly (2003) shows that the entry and exit of human service nonprofits in US metropolitan areas are shaped by organisational size, age, and broader policy changes such as welfare reform. Using tax data, Harrison and Laincz (2008) find that smaller and younger nonprofits face higher rates of exit, while larger and more established organisations are more likely to survive. Hager (1999), drawing on a longitudinal study, highlights how resource competition, limited legitimacy, and organisational size contribute to closures. From a financial management perspective, Lu et al. (2020) demonstrate that overhead costs, revenue mix, and limited diversification are key predictors of nonprofit dissolution, with risks following a U-shaped pattern. Collectively, these studies underscore that nonprofit exits are often linked to internal factors – such as size, age, and financial structure – as well as external pressures from competition and policy shifts. However, most of these findings are drawn from US data, studies examining exit dynamics in Canada remain limited.

3.2.2 Government Funding and Charity Dynamics

The structure and allocation of government funding can significantly shape where and when charities enter or exit. In Canada, government funding represents a larger share of nonprofit revenues than in many other countries (Elson, 2011). Minaker and Payne (2017) find that government grants increase charity revenues by about 16 percent, though over-reliance on such support can undermine longer-term stability. Lecy and Van Slyke (2013) show that government funding contributes more strongly to nonprofit density than private donations, pointing to the role of the state in sustaining sector growth. Clément (2019), using a comprehensive database of provincial grants in British Columbia from 1960 to 2014, demonstrates how shifts in public funding priorities have structured the development of the nonprofit sector over time. Devlin and Planatscher (2023) zero in on government funding to charities that serve Indigenous peoples. A higher proportion of Indigenous-serving charities receive government funding compared with their non-Indigenous counterparts (56% vs 35%), with off-reserve entrants more likely to obtain support than those located on reserve. Modest evidence suggests that government funding may encourage charities to serve Indigenous peoples. Altogether, the literature supports the idea that government support is a mechanism shaping charity formation and density, even if evidence for Canadian communities remains limited.

Government support is equally important for charity survival, as it provides a buffer against organisational exit. Harrison and Laincz (2008) and Harrison and Oxley (2025) show that grants help sustain nonprofits by reducing the likelihood of exit, even in competitive environments. Devlin and Planatscher (2023) similarly find that a higher share of exiting Indigenous-serving charities had government funding compared with their non-Indigenous counterparts, with off-reserve organisations again more likely to receive such support. At the same time, Lu et al. (2020) caution that reliance on narrow revenue bases and short-term contracts makes nonprofits vulnerable to policy shifts and dissolution. Stick and Ramos (2021), in their analysis of Halifax between 1996 and 2016, highlight the risks that arise when municipal funding declines despite persistent social needs, leaving high-need organisations exposed. Overall, these studies indicate that government funding can support the survival of charities by lowering exit risks, though its protective effect depends on funding type, duration, and policy context.

The broader literature also debates whether government funding displaces private donations – a phenomenon known as the “crowding out” effect. Andreoni and Payne (2011, 2013) provide evidence from Canada that charities reduce fundraising when awarded grants, leading to partial crowding out of contributions from foundations and other charities. Grasse et al. (2022) show that these dynamics vary across levels of government and charity types, with some cases of crowding in where public funding complements private support. Further Canadian evidence on the link between government funding and private donations is provided by Devlin and Planatscher (2025), who show that private donations react differently to funding to Indigenous-serving charities versus non-Indigenous-serving ones. In sum, the direction of the crowding effect appears to be context-dependent and may vary by organisational type, policy environment, and regional donor culture.

These studies collectively point to the role of the state in enabling charity formation and dissolution. More research is needed to understand how these mechanisms function in Canada, particularly across different regions and policy regimes.

3.2.3 Complementarity and Competition Among Charities

Charities rarely operate in isolation. Their location decisions are often shaped by the presence of other organisations – either as potential collaborators or as competitors. This dynamic is central to understanding how nonprofits evolve over time.

Gill et al. (2008), in their study of New Brunswick, show that cooperation is particularly important in rural areas, where limited resources and small populations encourage charities to adopt collaborative models for service delivery. Yet, while complementarity can foster the coexistence of charities, resource competition remains a significant force in exit decisions. Hager (1999) finds that the absence of strong inter-charity connections contributes to organisational demise, pointing to substitution pressures where resource competition dominates.

Funding patterns may encourage charities serving certain groups over others, thereby indirectly shaping opportunities for inter-type collaboration or competition. While these studies do not directly examine complementarity or substitution, they provide important context on how resources are distributed. Corrigall-Brown and Ho (2017) show that federal funding for Indigenous, women's, and environmental nonprofits in Canada between 1972 and 2014 was widely "sprinkled," with allocations reflecting shifting political and economic contexts. Similarly, Kay and Ramos (2017) analyse provincial funding in Nova Scotia between 1960 and 2014 and find that subnational governments increased support for women's organisations during critical events.

Together, these studies suggest that the charitable sector is shaped by scarce resources and competition for limited funding. The uneven allocation across subgroups further complicates the sector.

3.2.4 International Comparisons and Lessons for Canada

It is useful to consider international comparisons to Canada's charitable sector. The US nonprofit landscape is more fragmented and market-oriented, with greater reliance on private giving and corporate sponsorships (Andreoni & Payne, 2011, 2013).

By contrast, the European model, particularly in countries like Germany and the Netherlands, reflects closer integration between charities and the public sector. Meinhard et al. (2015) describe how European governments collaborate with nonprofits as core service delivery partners, closer to the Canadian approach. However, in Canada, centralised funding structures often favour established organisations, potentially reducing flexibility and responsiveness to emerging social needs (Clément, 2019). As such, while Canada's system offers greater stability, it may do so by hindering quick responses to changing needs.

3.2.5 Research Gaps

Among the most relevant works for this chapter are Twombly (2003), Harrison and Laincz (2008), and Harrison and Oxley (2025). Twombly (2003) focuses on entry and exit among US human service nonprofits, identifying the influence of organisational traits and policy reforms, but offers limited generalisability outside metropolitan settings. Harrison and Laincz (2008) provide evidence of lower exit rates among nonprofits compared to for-profits, but do not account for the role of government funding or local socioeconomic context. Harrison and Oxley (2025) highlight the growth of the US nonprofit sector, attributing it largely to low exit rates.

This chapter seeks to address these limitations by examining the entry and exit of registered charities in Canada over three decades. It focuses on the role of local poverty, rent payment, and public funding in shaping organisational dynamics, and explores whether new entrants act as complements or substitutes to existing charities. In doing so, it contributes to a deeper understanding of how institutional context, spatial characteristics, and funding regimes influence the evolution of the charitable sector in Canada.

3.3 Data

This study combines publicly available and confidential microdata to examine the entry and exit behaviour of registered charities in Canada between 1990 and 2021. The data span financial, operational, demographic, and geographic information, enabling a detailed analysis of charity dynamics across space and time. Data sources are available in table 3.1.

3.3.1 Publicly Available Data

I use the Canada Revenue Agency (CRA)'s T3010 Registered Charity Information Return dataset from 1990 to 2021. The dataset includes annual filings from all registered charities, reporting detailed information on revenues, expenditures, and organisational activities. These data allow us to identify the timing of charity entry and exit, as well as to characterise organisational scope.

To capture geographic context, I use shapefiles for CSDs and CMAs from census years 1991, 1996, 2001, 2006, 2011, 2016, and 2021, accessed via the University of Ottawa Library's Scholars Portal. I calculate the distance between the centroid of each charity's CSD and the urban core of the nearest CMA to proxy spatial access to urban resources and population centres. Using the Postal Code Conversion File Plus (PCCF+), which links six-digit postal codes to geographic units and provides coordinates and identifiers for CSDs and CMAs, I assign each charity to a CSD, identify the corresponding centroids, and compute the distance to the nearest CMA core. Further details on the procedure are provided in appendix 3.2B. While precise charity locations are available, I rely on CSD centroids because the analysis is conducted at the CSD level, not at the individual charity level.

3.3.2 Confidential Data

I access confidential microdata through Statistics Canada's Research Data Centre network. These include the Census of Population for 1991 to 2021 and the National Household Survey for 2011, which together provide detailed demographic and socioeconomic information at the CSD level. I focus on variables commonly associated with charitable activity, such as income levels, poverty rates, education, rent payment, labour force participation, immigration, and visible minority.

To align charity locations with demographic context, I use the geographic identifiers derived from the previously described PCCF+ geocoding. This enables consistent spatial matching between charities and their surrounding demographic environments and allows me to aggregate neighbourhood characteristics to the CSD level.

3.4 Empirical Strategy

I examine the determinants of charity entry and exit using a panel data framework at the CSD level, observed at five-year intervals from 1991 to 2021. The dependent variable is a count of charity entries (or exits) within each CSD in each census year. Using counts of organisations to measure entry and exit is standard practice in the nonprofit and organisational dynamics literature (Bielefeld, 1994; Harrison and Oxley, 2025). Net growth is not used because it combines entry and exit into a single measure and therefore discards useful information. Using net growth would reduce the effective sample size and weaken statistical power. Modeling entry and exit separately preserves more variation and allows the analysis to capture potentially different responses of entry and exit to local socio-economic conditions.

The choice of CSD as the unit of analysis is driven by both empirical objectives and data constraints. First, CSDs provide a finer geographic unit than CMAs. The research question concerns how local socioeconomic conditions shape charity entry and exit. Using CSDs allows the analysis to capture within-CMA heterogeneity and local variation that would be obscured at the metropolitan level. In contrast, CMAs aggregate across multiple municipalities and neighbourhoods, which can mask differences in poverty, rents, and funding environments that are relevant for charitable location decisions. Second, CSDs offer a consistent unit for integrating multiple data sources. Charity records report postal codes, which are converted into geographic identifiers using the PCCF+. The PCCF+ allows postal codes to be mapped to several geographic levels, including latitude and longitude, provinces, CMAs, dissemination areas, and CSDs. Among these options, CSDs provide a stable bridge between the charity data and Census-based population and socioeconomic variables, which are consistently available at the CSD level across census years. Third, CSDs align with how local policy environments and service contexts operate. Many factors relevant to charity entry and exit—such as local need, housing conditions, and access to municipal services—are organised at the CSD level. Using CSDs therefore offers a closer approximation to the local environments in which charities register, operate, and make organisational decisions.

A related interpretive concern is that some charities are created for specific, time-limited purposes and exit once those objectives are achieved, such as disaster relief, issue-specific advocacy, or temporary programme delivery. However, existing research also shows that a substantial share of nonprofit exit is associated with financial pressure, funding volatility, and changes in local economic conditions rather than purely planned dissolution. For example, Carroll and Stater (2009) link nonprofit exit to revenue instability and local economic environments, while Harrison and Oxley (2025) show that exit responds to changes in public funding and fiscal conditions. In this context, observed exits reflect a mix of mechanisms. The analysis does not interpret every exit as financial distress but instead studies systematic correlations between local socio-economic conditions and charity dynamics at the aggregate level.

A separate measurement concern is that a charity's registered location may not coincide with the precise location of service delivery, particularly for organisations headquartered in large urban centres but operating across wider geographic areas. Information on service locations at the CSD level is not available, which prevents direct verification of this alignment. Nevertheless, even when services are delivered elsewhere, socio-economic conditions at the registered location can shape operating costs, fundraising capacity, and administrative feasibility. These factors influence whether a charity enters, remains active, or exits, making local conditions at the place of registration informative for entry and exit decisions.

To evaluate whether misalignment between registered location and service area affects the results, Chapter Two conducts a robustness analysis focusing on charities that report provincial-level service provision and relates their outcomes to provincial economic conditions. The results remain consistent with the baseline estimates, suggesting that the main conclusions are not driven by the spatial assignment of charities to local units.

Beyond measurement and interpretation issues, the analysis faces three core empirical challenges: (i) A large share of the CSD-year observations record no new entry or exit of charities. Specifically, 66.02% of observations have zero entry, while 72.70% have zero exit. In 58.02% of cases, both entry and exit are zero in the same year; (ii) unobserved time-invariant heterogeneity across CSDs; and (iii) common shocks across years that may affect all regions simultaneously.

To address these challenges, I estimate a PPMLHDFE model. This estimator is well-suited for count data with many zeros and is robust to model misspecification, including heteroskedasticity and violations of distributional assumptions that commonly affect traditional Poisson models (Silva and Tenreyro, 2006). In contrast to linear models, PPML does not require the assumption that the variance of the outcome equals its mean, making it a flexible and consistent estimator under weaker distributional assumptions.

The Poisson pseudo-maximum likelihood approach allows for the inclusion of both CSD and year fixed effects. CSD fixed effects absorb time-invariant characteristics of a given geographic unit over the period in which it exists, including historical settlement patterns, long-run income composition, urban versus rural status, and persistent institutional or social features. Year fixed effects capture nationwide shocks common to all CSDs, such as changes in monetary policy, federal fiscal policy, aggregate business cycles, and country-wide policy reforms. When a CSD splits into multiple units, the original CSD and the resulting units are treated as distinct observational entities in the periods in which they exist. A limitation of this approach is that I cannot observe the internal evolution of CSD boundaries over time following splits, mergers, or redefinitions. In principle, such boundary changes could generate mechanical changes in measured charity entry and exit. In practice, however, boundary changes are relatively infrequent over the sample period and affect a small share of observations. In each census, approximately 1 – 5 percent of CSDs appear and 2 – 7 percent disappear, indicating that boundary changes are unlikely to affect the results. This structure isolates within-CSD variation over time, allowing for more credible inference on the effect of local demographic, economic, and policy variables – such as poverty rates, population size, or government funding – on charity dynamics. Moreover, all regressions are clustered at the CSD level to allow for arbitrary serial correlation within regions over time.

According to Silva and Tenreyro (2006), through the Poisson pseudo-maximum likelihood approach, the estimated coefficient on a covariate represents the log change in the expected count of the dependent variable for a one-unit increase in that covariate, holding other variables constant. To express the result in percentage terms, one can exponentiate the coefficient and subtract one. For instance, if the coefficient on the explanatory variable is β, this implies that a one-unit increase in the explanatory variable is associated with an approximately $(e^{\beta} - 1) \times 100\%$ increase in the expected number of charity entries.

The baseline models are specified as follows:

$$EN_{c,t+i} = exp(\alpha + \beta_{1,i}^{en} LICO_{c,t} + \beta_{2,i}^{en} Control_{c,t} + CSDFE_c + TIMEFE_t) + error_{c,t} \quad (3.1)$$

$$EX_{c,t+i} = exp(\alpha + \beta_{1,i}^{ex} LICO_{c,t} + \beta_{2,i}^{ex} Control_{c,t} + CSDFE_c + TIMEFE_t) + error_{c,t} \quad (3.2)$$

In equation (3.1), I examine the count of charity entrants in each CSD at time $t+i$, where i = 0, 1, ..., 4. For example, if the census year is 1991, I use the 1991 census covariates to explain charity entry in 1991, 1992, 1993, 1994, and 1995. This means I run five separate regressions – one for each year of entry following the census – rather than summing entrants across years. Importantly, when I refer to entry in 1992, I mean the number of new charities that appeared in 1992 alone; it does not include those that entered in 1991.

The key independent variable is the poverty rate, measured as the proportion of individuals aged 15 and older living below the LICO in CSD *c* at census year *t*. Control variables include the proportion of the population with at least a high school diploma, the unemployment rate, average monthly rent, the share of immigrants, and the share of visible minorities. I also include a binary indicator for geographic remoteness, coded as 1 if the distance between the centroid of a CSD and the centroid of the nearest CMA exceeds 100 kilometers. This measure provides a practical but imperfect proxy for remoteness. A key limitation is that both the CSD and the CMA urban core are represented by single points, which abstracts from within area heterogeneity and does not capture actual travel distance. For geographically large CSDs or polycentric metropolitan areas, the centroid of the urban core may therefore not fully reflect the location of economic activity. Despite these limitations, centroid based distance measures are commonly used in the spatial economics and applied literature as transparent and consistent proxies when precise address level data are unavailable (Bliss et al., 2012). Their main advantage is that they enable systematic comparison across regions using a uniform and replicable rule. Figure 3.1 maps CSDs, CMAs, CMA centroids, and charities in Canada in 2021. CSD and year fixed effects control for time-invariant local characteristics and year-specific shocks, respectively. Equation (3.2) adopts the same structure but models the count of charity exits instead of entries.

Table 3.2 reports summary statistics of charities and socio-demographic characteristics by CSD. The dataset contains 5,760 CSD-year observations. On average, 1.410 charities entered and 0.941 charities exited per CSD-year. The share of people with at least a high school diploma is 57.2%, the average unemployment rate is 10.2%, the average income is $27,735, and 8.4% of people fall below the low-income cutoff.

Table 3.3 reports the results from estimating the effect of local poverty on charity entry. Column (1) shows that a one percentage point increase in the proportion of individuals below the LICO is associated with a 1.74 percent increase in the number of new charity entries at time *t*.[38] As discussed earlier, in the PPMLHDFE model, coefficients can be interpreted as semi-elasticities: the exponentiated coefficient approximates the percentage change in the outcome for a unit change in the independent variable.

Several control variables also exhibit statistically significant associations with charity entry.[39] Higher unemployment rates, a larger share of visible minorities, and being located more than 100 kilometers from the nearest CMA (as indicated by a binary distance indicator) are all positively associated with the number of entries at time *t*. These findings suggest that charities may be more likely to enter areas with greater socioeconomic needs or weaker access to urban infrastructure.

Column (2) shows that the poverty rate remains positively associated with charity entry one year after the census year (at time *t+1*), with a slightly larger effect. This likely reflects

[38] Technically, the effect corresponds to a 1.75 percent change. For example, the interpretation of the coefficient should be $(e^{0.01*1.739}-1)\times 100\%$. The factor 0.01 appears because LICO is measured as a proportion ranging from 0 to 1, rather than as a percentage from 0 to 100. Since the change is small, I approximate this expression by $\beta\%$.

[39] I calculate VIFs for all control variables: proportion of visible minorities, proportion of immigrants, educational attainment (high school or above), average rent, proportion below LICO, unemployment rate, and distance dummy. All VIFs are below 5, indicating that multicollinearity should not be a concern.

the time required to establish a new organisation: even if poverty at time *t* triggers the decision to form a charity, the process of registration, securing premises, and mobilising staff and volunteers often delays actual entry until the following year. After *t+1*, the effect diminishes. One possible explanation is that larger charities, which take longer to move from planning to registration, constitute only a small share of overall entrants, whereas smaller grassroots organisations, more flexible and quicker to establish, account for most new entries. As a result, the influence of poverty fades after the initial lagged response.

The proportion of individuals with education above the high school level and the share of immigrants show no consistent relationship with charity entry across all time horizons. In contrast, the proportion of visible minorities remains a robust positive predictor. The signs of the coefficients on average rent and the distance indicator vary across columns, e.g., between columns (1) and (2). This pattern may reflect the correlation between distance from the CMA and local rental costs, as rents tend to be lower in CSDs farther from urban centres. To assess multicollinearity, I examined the VIFs for the distance dummy and average rent. Both are below 5, well under the conventional threshold, indicating that multicollinearity is unlikely to be a concern. In applied work, a VIF threshold of five is often used as a conservative rule of thumb, with values below five generally indicating limited inflation of standard errors and values above ten viewed as more problematic (O'Brien, 2007).

Table 3.4 presents the estimated coefficient of the determinants of charity exit. In contrast to the entry results, local poverty does not appear to significantly predict charity exits. Instead, average rent is negatively associated with exits at time *t+1*, *t+3*, and *t+4*, though the estimated effects are modest. For example, a one dollar increase in average monthly rent is associated with a 0.1 percent decrease in the number of exits at *t+1*. One possible explanation is the structure of Canada's commercial leasing environment. Under the *Ontario Commercial Tenancies Act* (1990), for example, commercial rents are not subject to rent control, unlike residential rents, which face provincially regulated annual caps. Charities typically operate under multi-year leases that include pre-specified or inflation-linked rent escalations. Because breaking such leases can be costly, and relocating often entails higher market rents and additional expenses, organisations may be more likely to remain in their current premises even as average rents rise. In this setting, observed increases in rent may coincide with lower exit rates, reflecting the high costs and risks of relocation.

Lastly, the proportion of immigrants is positively associated with charity exit in several specifications, while the share of visible minorities is not a significant predictor in the exit model. This contrasts with the entry results. The positive association between visible minority share and charity entry suggests that demographic diversity can stimulate the creation of new organisations, as minority communities mobilise to address unmet needs or to provide culturally specific services. By contrast, the positive link between immigrant share and charity exit should be interpreted with caution: although statistically significant in several specifications, the magnitude is very small (around a 0.01% increase in exits) and thus economically modest. A possible explanation is that immigrant-serving charities face greater challenges in sustaining operations, such as dependence on unstable funding or limited volunteer capacity, making them slightly more vulnerable to exit.

To further explore heterogeneity in charity formation and closure, I decompose the aggregate counts of charity entry and exit by type of charitable activity at time *t*. Specifically, I estimate separate models for each charity type k = 1, 2, ..., 8, where the eight categories correspond to the primary purposes defined by the CRA: Relief of Poverty, Education, Religion, Health, Community, Arts, Foundations, and "Other" charitable activities. This disaggregated approach allows me to examine whether the relationship between local socioeconomic conditions and charity dynamics varies across sectors with distinct missions and operational models. For each charity type *k,* I estimate separate models for entry and exit, as specified in equations (3.3) and (3.4).

$$EN_{k,c,t} = exp(\alpha + \beta^{en}_{1,k} LICO_{c,t} + \beta^{en}_{2,k} Control_{c,t} + CSDFE_c + TIMEFE_t) + error_{k,c,t} \quad (3.3)$$

$$EX_{k,c,t} = exp(\alpha + \beta^{ex}_{1,k} LICO_{c,t} + \beta^{ex}_{2,k} Control_{c,t} + CSDFE_c + TIMEFE_t) + error_{k,c,t} \quad (3.4)$$

Table 3.5 presents the results from estimating charity entry models separately by charitable purpose. Among the eight categories, only the entry of charities focused on Relief of Poverty shows a statistically significant positive association with the local poverty rate (LICO). This finding suggests that the aggregate positive effect identified in table 3.3, column (1), is primarily driven by charities targeting poverty alleviation.

In addition, the positive coefficient on average rent observed in table 3.3 appears to be mainly driven by Relief of Poverty and Foundations charities. This result implies that these types of organisations are more likely to enter even in areas with higher rental costs – possibly because their sources of finance (e.g., public grants, endowments, or external donations) make them less sensitive to local operating expenses, or because they target high-need urban areas where costs are generally higher.

The distance from a CMA also plays a role for poverty-related charities: those located more than 100 kilometers from a CMA core are more likely to see new entries in this category. This may reflect an effort to reach underserved or remote communities where poverty is more acute and fewer service providers exist.

For charity types such as Health, Arts, and "Other," the distance variable is dropped from the regression due to perfect collinearity, likely reflecting limited variation in their geographic distribution or overlap with other location-related controls. Since the omission arises from lack of variation rather than endogeneity, it does not bias the estimation but limits inference regarding geographic effects for these categories.

Table 3.6 presents the results of the exit regressions by charity type. For education-related charities, the number of exits at time *t* increases significantly with higher poverty rates. According to the CRA's classification, this group includes teaching institutions, organisations supporting schools and education, education in the arts, research institutes, and foundations advancing education. The positive association may reflect the challenges these organisations face in economically disadvantaged areas, where limited community resources and greater service demands make it harder to sustain schools, arts programmes, or research initiatives over time.

Other covariates – including the proportion of individuals with education above the high school level, average rent, the share of visible minorities, and the distance from a CMA – do not show statistically significant associations with charity exit across any of the specified types at time *t*. These null effects suggest that, once poverty is accounted for, these socioeconomic and demographic characteristics are not strong predictors of short-term exit behaviour within the sector.

To examine the role of government funding in shaping charity dynamics, I construct a variable indicating the proportion of existing charities in each CSD that received government funding at time $t+j$, where j = -1, 0, 1. This variable captures the local funding environment faced by potential entrants and is used in the entry model specified in equation (3.5).

$$EN_{k,c,t} = exp(\alpha + \beta^{en}_{1,k,j} Prop\_Existing\_WithFund_{k,c,t+j} + \beta^{en}_{2,k,j} LICO_{c,t} + \beta^{en}_{3,k,j} Control_{c,t} + CSDFE_c + TIMEFE_t) + error_{k,c,t} \quad (3.5)$$

$$EX_{k,c,t} = exp(\alpha + \beta^{ex}_{1,k,j} Prop\_Existing\_WithoutFund_{k,c,t+j} + \beta^{ex}_{2,k,j} LICO_{c,t} + \beta^{ex}_{3,k,j} Control_{c,t} + CSDFE_c + TIMEFE_t) + error_{k,c,t} \quad (3.6)$$

I choose this specification for two reasons. First, because the analysis is conducted at the CSD level, I cannot use a binary indicator for whether an individual charity receives funding. Second, using the average amount of government funding per charity in a CSD may lead to biased estimates due to extreme values – some charities may receive disproportionately large grants, while others receive none, which would distort the average. By contrast, using the proportion of charities receiving any funding provides a more stable and interpretable measure of the overall accessibility of public support within a given locality, while avoiding concerns related to skewness and outliers.

I also investigate the relationship between government funding and charity exit by using the proportion of existing charities not receiving government funding at time *t-1*, *t*, and *t+1* as the main explanatory variable. This formulation, presented in equation (3.6), tests whether lack of public support is associated with higher exit rates over time.

Table 3.7 reports the relationship between local government funding and charity entry. The results indicate that the proportion of charities receiving funding at time *t* and *t+1*, is positively associated with the number of new charity entries. Specifically, a one percentage point increase in the share of charities receiving funding at time *t* is associated with a 1.61 percent increase in the number of charity entries at time *t* based on the exponentiated coefficient from the PPMLHDFE model. The estimated effect is smaller for the funding variable measured at time *t+1*, suggesting that anticipated funding opportunities, rather than historical patterns, are more influential in shaping entry decisions.

A potential concern is whether funding increases because new charities enter an area, or whether charities enter an area because they anticipate a favourable local funding environment. To address this, the measure of "expected funding" is constructed using funding received by charities that are already operating in the Census Subdivision, rather than by new entrants. This construction is intended to capture the local funding environment and government funding practices that are observable in advance, rather than funding that is mechanically triggered by entry. Because the expected funding variable is based on funding to incumbent organisations, it is less likely to reflect funding allocated in response to the entry decisions being analysed. The results are therefore interpreted as associations consistent with forward-looking entry behaviour rather than as causal effects.

Moreover, after controlling for the funding environment, the coefficient on the low-income rate remains significant in table 3.7 and similar in magnitude to that reported in table 3.3, column (1). This result indicates that the positive association between local poverty and charity entry is not driven by the availability of government support. Rather, it suggests that in communities with higher poverty, new charitable organisations are more likely to emerge to address local needs, regardless of whether public funding is present.

Table 3.8 presents the results for charity exit as a function of the proportion of organisations not receiving government funding at times *t-1*, *t*, and *t+1*. The findings suggest that a lack of funding in the recent past is a significant predictor of exit. Specifically, a one percentage point increase in the share of charities not receiving government funding at time *t-1* is associated with a 0.98 percent increase in the number of exits. By contrast, the proportion of unfunded charities at times *t* and *t+1* shows no significant association with exit, indicating that exit decisions are more responsive to past funding conditions than to contemporaneous or anticipated funding availability.

The local poverty rate, the proportion of visible minorities, and the distance from the nearest CMA remain statistically insignificant across all specifications, suggesting these factors do not strongly link to exit patterns. Notably, in column (3), after including the proportion of unfunded charities at *t+1*, average rent becomes a significant predictor of exit. This may reflect cost pressures becoming more pronounced once funding expectations are accounted for, implying that fixed operational costs could become decisive when financial support is uncertain.

To further explore heterogeneity in the relationship between government funding and organisational dynamics, I examine charity entry and exit by type, incorporating the models with funding patterns specific to each category. Specifically, I analyse the number of entries by charity type as a function of the proportion of existing charities within the same type that received government funding at times *t-1*, *t*, and *t+1*. This approach captures how type-specific funding environments may be associated with entry decisions differently across sectors. A similar strategy is applied to model charity exits by type, using the proportion of existing charities within each type that did not receive government funding at times *t-1*, *t*, and *t+1*. This allows me to assess whether the absence of public financial support differentially corresponds to organisational sustainability across types of charitable activity.

Table 3.9 presents the results of charity entry regressions by type, using as the main explanatory variable the proportion of existing charities within the same type that received government funding at times *t*.[40] This disaggregated approach allows for a closer examination of how type-specific funding environments influence entry behaviour across sectors.

Table 3.9 indicates that funding at time *t* is positively associated with charity entry across nearly all types, with the exception of religious organisations. The largest estimated effect is for Community charities (coefficient: 2.589), followed by Health and Relief of

[40] I also examine the effect of government funding in periods *t-1* and *t+1*. The results indicate that funding relates to charity entry at *t+1*, but not at *t-1*. Entry is not immediate: even if funding signals emerge in *t–1*, the process of registration, staffing, and fundraising takes time.

Poverty charities. These findings suggest that current funding availability may serve as a strong signal of institutional support or policy prioritisation, encouraging new organisational formation. Education and Relief of Poverty charities respond positively to LICO, reinforcing the link between community need and new charitable activity in these sectors.

In line with earlier findings (e.g., table 3.5), average rent remains positively associated with the entry of poverty-relief and foundation-type charities, possibly reflecting their greater tolerance for operational costs due to external funding or their preference for locating in high-demand urban centres. Moreover, distance from the nearest CMA is positively associated with the entry of Relief of Poverty and Community charities, indicating that these organisations are more likely to enter remote or underserved areas. These results underscore the importance of current public support in shaping the geography of charitable activity, especially for organisations addressing poverty, community development, and health.

Finally, I examine the relationship between government funding and charity exit by type, where the key independent variable is the proportion of existing charities within the same type that did not receive government funding at times *t-1*, *t*, and *t+1*.

Table 3.10 shows that the proportion of unfunded charities at time *t-1* is positively associated with exit for most charity types, with the exceptions of Arts and Foundations, where the relationship is not statistically significant.[41] Community and Relief of Poverty charities are sensitive to lagged funding conditions. The same categories appear in the entry models, but the timing differs: exit responds at *t-1*, while entry responds at *t* and *t+1*.. This suggests that past funding scarcity is a key predictor of organisational closure, especially in sectors dependent on external support. Notably, LICO remains unrelated to exit across most types, with the exception of Education charities, for which higher poverty is associated with increased exit when lagged funding is accounted for.

In the end, I examine whether the entry and exit of charities in each category at time *t* are associated with the presence of charities within the same category (intra-type effects) or in other categories (inter-type effects) at time *t+j*, where *j* = -1, 0, 1. This analysis allows me to assess potential patterns of competition or complementarity across different types of charitable organisations within local areas.

$$EN_{k,c,t} = exp(\alpha + \lambda^{en}_{1,k,j} Number\_Existing_{k,c,t+j} + \lambda^{en}_{2,k,j} LICO_{c,t} + \lambda^{en}_{3,k,j} Control_{c,t} + CSDFE_c + TIMEFE_t) + error_{k,c,t} \quad (3.7)$$

[41] I examine the association between government funding and charity exits at *t* and *t+1*, and find no clear relationship in either period.

$$EX_{k,c,t} = exp(\alpha + \lambda_{1,k,j}^{ex} Number\_Existing_{k,c,t+j} + \lambda_{2,k,j}^{ex} LICO_{c,t} + \lambda_{3,k,j}^{ex} Control_{c,t} + CSDFE_c + TIMEFE_t) + error_{k,c,t} \quad (3.8)$$

Table 3.11 focuses on the relationship between charity entry at time *t* and the number of existing charities at time *t-1*.[42] After controlling for demographic and socioeconomic covariates, the results suggest that health-related charities exhibit intra-type substitution: a larger number of Health charities at *t-1* is associated with fewer new Health entries at *t*, possibly reflecting saturation or competitive crowding within that sector. In contrast, for other charity types, there is no strong evidence that the number of past organisations of the same type significantly deters or encourages new entry.

In terms of inter-type effects, the entry of one type of charity often reflects a complex mix of substitution and complementarity with other types. For instance, the entry of Relief of Poverty charities at time *t* is positively associated with the number of existing Education charities, suggesting complementarity in service provision or target populations. At the same time, it is negatively associated with the number of Community charities, indicating potential competition over similar resources or beneficiaries.

Similarly, the entry of Education charities is positively related to the prior presence of Health charities but negatively related to the number of existing Relief of Poverty and Community charities, again highlighting mixed substitution-complementarity dynamics across sectors. Religious charities appear unaffected by the presence of other charity types at *t-1*, suggesting that their entry decisions are independent of other fields or driven by separate mechanisms.

The patterns are similarly mixed for Community and Foundations charities. Notably, the entry of Arts and Foundations charities is consistently positively associated with the number of existing Community charities, indicating a complementary relationship – possibly because these types often co-locate or collaborate in shared cultural or civic spaces.

An interesting asymmetry emerges in the relationship between the entry of Education and Relief of Poverty charities. The entry of Relief of Poverty charities is positively associated with the number of existing Education charities, suggesting complementarity between the two sectors. Education organisations often provide skills training, literacy programmes, or schooling that heighten awareness of social needs and expose gaps that poverty-relief organisations can address. By contrast, the entry of Education charities is

[42] I study the relationship between charity entry at time *t* and the number of existing charities by type at *t* and *t+1*. Similar to the findings in table 3.11, entry patterns for Relief of Poverty, Health, and Community charities reflect a mix of substitution and complementarity with existing charities, even after controlling for demographic and socioeconomic characteristics.

negatively associated with the number of existing poverty-relief organisations, which may reflect competition for scarce resources. In communities where poverty-relief providers are already numerous, donors and volunteers may prioritise immediate assistance over longer-term educational initiatives, thereby constraining the scope for new Education charities.

One question that arises is how to reconcile the finding that Education charities do not respond directly to poverty levels (LICO), while their entry is negatively associated with the presence of Relief of Poverty charities. A possible explanation is that LICO measures economic deprivation in a narrow sense, whereas Education charities often pursue broader aims such as literacy, skills training, arts, or research.

Turning to charity exit decisions, table 3.12 presents results using the number of existing charities at time *t-1*.[43] The findings suggest that exits increase with higher past levels of existing charities for Relief of Poverty, Religion, Health, and Arts, implying that greater past saturation in these categories may elevate the likelihood of exits. In contrast, religious charities consistently exhibit inter-type complementarity, with exits negatively associated with the presence of other charity types at *t-1*. This pattern suggests a form of crowd-in from unrelated sectors.

Overall, I examine how different types of charities respond to local socioeconomic conditions by estimating regressions on entries and exits at time *t*, including specifications that incorporate funding and the number of existing charities by type. The results reveal both consistent patterns across types and important differences in how they adjust to local conditions. First, charities focused on the Relief of Poverty display a statistically significant positive association between entry and the local poverty rate (LICO). After accounting for funding, I find that receiving government support at time *t* is positively associated with entry across nearly all types, with poverty-relief charities showing a particularly strong response to both LICO and funding. Second, for education-related charities, exits at time *t* increase significantly with higher poverty rates. Once funding is considered, the proportion of unfunded charities at time *t-1* is positively associated with exits across most types. Third, the entry of health-related charities exhibit intra-type substitution, while other charity types show no clear evidence of intra-type substitution. More generally, inter-type comparisons reveal a mix of substitution and complementarity across charity types. Finally, exits rise with higher past levels of existing charities in several categories, including Relief of Poverty, Religion,

[43] Results are robust to using the number of existing charities at *t* and *t+1*. .In particular, religious charities continue to show complementarities across types, as their exits decline when other charities are present.

Health, and Arts. Religious charities in particular show consistent inter-type complementarity.

In Chapters One and Two, I examined how macroeconomic conditions influence private donations and government funding to the charitable sector. In this chapter, I extend the analysis by investigating how macroeconomic conditions relate to the entry and exit dynamics of charities.

$$EN_{c,t+i} = exp(\alpha + \lambda_{1,i}^{en} Macro_{p,t} + \lambda_{2,i}^{en} Control_{c,t} + \ CSDFE_c + TIMEFE_t) + error_{c,t} \tag{3.9}$$

$$EX_{c,t+i} = exp(\alpha + \lambda_{1,i}^{ex} Macro_{p,t} + \lambda_{2,i}^{ex} Control_{c,t} + \ CSDFE_c + TIMEFE_t) + error_{c,t} \tag{3.10}$$

where $Macro_{p,t}$ includes real GDP per capita and the unemployment rate measured at the provincial level at time *t,* and *p* denotes the province in which CSD *c* is located. The unemployment rate differs from previous specifications, which used the CSD-level measure, by instead focusing on the provincial rate.

Table 3.13 presents the relationship between the count of charity entries and the provincial unemployment rate. The results show a positive association between unemployment and charity entry at time *t* and *t+1*. Specifically, a one percentage point increase in the provincial unemployment rate is associated with a 0.047 percent increase in the number of new charity entries at time *t*, with an even larger coefficient at time *t+1*. This may reflect the fact that economic downturns initially increase community needs, prompting charitable responses through new organisational formation. However, at longer horizons – *t+3* and *t+4* – the sign of the coefficient turns negative. This reversal may suggest that the initial wave of responsive entry slows down as prolonged economic stress reduces the resources needed to sustain operations., or that early entries crowd the space, making further entry less viable.

After controlling for macroeconomic factors, the coefficient on LICO remains similar in magnitude and significance to the estimates in table 3.3, columns (1) and (2). This pattern suggests that macroeconomic shocks and local poverty conditions may operate through overlapping but distinct channels in influencing charity entry.

Table 3.14 explores the relationship between the count of charity exits and the provincial unemployment rate. The results indicate that the unemployment rate is negatively associated with exit only at time *t+3*, implying that higher unemployment may delay closures, perhaps due to increased demand for services or policy responses that provide temporary stability. The LICO variable remains insignificant across nearly all time horizons. In addition, average rent continues to show a negative association with exit at times *t+1*, *t+3*, and *t+4*, consistent with earlier findings that charities may be less likely to exit from high-cost areas once established.

3.5 Robustness

To assess the robustness of the main findings, I conduct a series of complementary analyses. First, I test whether local service providers are more responsive to neighbourhood needs than the full sample of charities. Second, I address potential data discontinuities by excluding early years in which reporting gaps may confound entry and exit measurement. Third, I examine sensitivity to the poverty measure by replacing LICO with average income. Fourth, I estimate dynamic specifications using GMM to account for the possibility that lagged entries and exits influence current outcomes. Fifth, I address endogeneity concerns by lagging the poverty measure. Finally, I explore whether poverty interacts with government funding in shaping entry and exit. Taken together, these exercises suggest that the results are not driven by sample definition, measurement error, or model specification, but instead reflect consistent underlying patterns.

A natural robustness test is to consider whether the observed relationships between socioeconomic conditions and charity dynamics are driven by organisations that are explicitly local in scope. It is reasonable to expect that charities delivering direct services – such as food banks, soup kitchens, and shelters – be more sensitive to neighbourhood-level needs and economic stress than charities with broader mandates. To explore this, I construct a count of charities classified as food banks, soup kitchens, or shelters for each CSD and year. These organisations are explicitly service-oriented and geographically anchored and thus are taken as a proxy for "local" charities.[44]

I find that over 90 percent of observations record zero entries or exits between 1991 and 2021. Only about 10 percent of observations involve a single entry, compared with roughly 2 percent that involve a single exit of locally oriented charities. This low frequency and restricted range suggest that the sample is not suitable for regression-based analysis. Given the sparsity of local entries and exits, I conclude that separate estimation for this subgroup would offer limited additional insight and may not yield statistically meaningful results. This descriptive exercise therefore reflects the behaviour of a wider range of charities that respond to local socioeconomic and demographic conditions, rather than only local service providers.

[44] In appendix 1.A of Chapter One (Section 1.2A), I classify charities as local, national, or international. There, I define a charity as local if its activities are carried out within a single rural, urban, or metropolitan area, or confined to a province or territory. In this chapter, however, the term local has a narrower meaning: it refers only to charities identified as food banks, soup kitchens, or shelters. Thus, local in the present context should be understood as a subset of the broader local category introduced in Chapter One.

As discussed in appendix 3.1A, approximately 17.4 percent of charities exhibit gaps of two or more years in their fiscal reporting, and only 1.34 percent experience gaps longer than three years. To minimise the potential for misclassifying re-entries or exits due to data discontinuities, I restrict the main analysis to charities observed from 1993 onward. This ensures that, for any charity observed in 1993, I can verify its reporting status in the preceding years (1990-1992), reducing the risk of false entry classification. Tables 3.1C and 3.2C present subsample regression results for entries and exits from 1993 onward.

The findings are consistent with those in tables 3.7 and 3.8 in both the significance and magnitude of the estimated coefficients for government funding at time t and $t+1$ and for the proportion of LICO. These results suggest that any misclassification of re-entries or exits due to data discontinuities is likely minimal.

In the main analysis, the LICO is used as the key explanatory variable to capture neighbourhood-level poverty in each CSD. As a robustness check, I replace LICO with average income, an alternative measure of local economic status. This allows me to assess whether the results are sensitive to the specific poverty metric used. Tables 3.3C and 3.4C report estimates using average income as the key explanatory variable. The results align with those in tables 3.7 and 3.8. In table 3.3C, average income is positively and significantly associated with the number of entries at time t. In addition, the proportion of charities receiving funding at $t-1$ and $t+1$ is positively related to entries. Table 3.4C shows that government funding at $t-1$ is significantly associated with exits, whereas average income has no statistically significant effect on exit counts.

In table 3.3, I find that LICO is positively associated with charity entry both at time t and $t+1$. A natural question is whether there exists a dynamic link in which poverty at t influences entry at t, which in turn affects entry at $t+1$. To explore this possibility, I include entry at t as a covariate in the regression for entry at $t+1$. This introduces a dynamic specification that may give rise to endogeneity, as past entry could be correlated with unobserved determinants of current entry. To address this issue, I estimate the model using the GMM, which is well-suited for panel settings involving potentially endogenous lagged dependent variables as indicated in Chapters One and Two. Tables 3.5C and 3.6C present dynamic estimates, where entry or exit at $t+1$ is modeled as a function of entry or exit at t using GMM. After controlling for lagged entry and exit, LICO remains relevant for entry but not for exits, consistent with the main results.

To address concerns about reverse causality – namely, that charity entry at time t might influence poverty measured in the same year – I re-estimate the model using lagged poverty

$LICO_{t-1}$ in place of $LICO_t$. This adjustment helps mitigate simultaneity bias by ensuring that the explanatory variable reflects economic conditions prior to the observed charity behaviour. While lagging LICO does not fully resolve endogeneity concerns (e.g., due to omitted variables), it serves as a useful robustness check to test the stability of the estimated relationship between poverty and charity entry. Tables 3.7C and 3.8C present the results of entry and exits using LICO at *t-1* as the key variable of interest. Table 3.7C shows that LICO at *t-1* is not associated with entries at *t*, whereas funding at *t+1* remains positively related to entries. Table 3.8C indicates that, after accounting for lagged LICO, exits are linked to this variable, although no such relationship is found for LICO at *t*. This pattern suggests that local low-income conditions may affect charity exits with a lag, while current conditions have a weaker association.

Finally, I include an interaction term between LICO at *t* and the proportion of charities receiving funding at *t-1*, *t*, and *t+1* to examine its association with charity entries (table 3.9C). For exits, I interact LICO at *t* with the proportion of charities not receiving funding at the corresponding *t-1*, *t*, and *t+1* (table 3.10C). The results indicate that the interaction term is not related to either charity entries or exits. For entries, LICO remains an important indicator, and funding at *t* and *t+1* continues to matter, consistent with table 3.7. For exits, LICO shows no association, while only funding at *t-1* is linked to exit counts, consistent with table 3.8.

3.6 Conclusion

This chapter analyses the determinants of charity entry and exit across Canadian CSDs from 1991 to 2021, with a focus on socioeconomic conditions, government funding patterns, geographic proximity to urban centres, and inter-organisational relationships. The empirical strategy uses a PPMLHDFE model, and the findings provide several insights into how charitable location decisions respond to local conditions and government support..

The results show that poverty – measured by the share of individuals below the Low-Income Cut-Off (LICO) – is positively associated with charity formation in the census year and the year immediately after. This finding suggests that charitable activity responds quickly to perceived need in the local community, consistent with prior evidence that nonprofit entry is more likely in areas of greater socioeconomic vulnerability (Twombly, 2003; Peck, 2008; Yan et al., 2014). The association is particularly strong for charities focused on Relief of Poverty and Education. In contrast, poverty does not show a robust relationship with charity exit, indicating that while economic need may prompt new organisations to form, it does not directly increase the likelihood of their dissolution. This pattern aligns with studies emphasising that exit is more closely linked to organisational resources and financial structure than to contemporaneous measures of need (Hager, 1999; Harrison and Laincz, 2008).

Government funding plays an important and time-sensitive role in shaping both entry and exit patterns. Charity entry is positively related to the share of existing organisations receiving public funding in the same year and in the year following. This pattern suggests that organisations are forward-looking and respond to a favourable funding environment when deciding whether to enter, corroborating previous evidence that public funding contributes to nonprofit density and sector growth (Lecy and Van Slyke, 2013). Entry is most sensitive to funding availability for charities in the community development, health-related, and poverty-relief sectors. By contrast, past government funding – measured in the year prior to entry – does not significantly relate to formation, indicating that resources may take time to translate into actual formation.

For charity exit, the absence of funding in the year prior to observed exit is most strongly associated with charity closure. In sectors such as poverty-relief and community services, a higher share of unfunded charities one year earlier is linked to more exits, pointing to a delayed impact of funding scarcity. In contrast, contemporaneous and expected future funding are not significantly related to exit, highlighting that charity dissolution tends to reflect financial strain accumulated in the past rather than immediate conditions. This asymmetry between entry and exit mirrors findings in the nonprofit literature showing that formation is forward-looking, while exit reflects past revenue instability and funding shocks (Carroll and Stater, 2009).

The presence of other charities also influences both formation and dissolution. The entry of new charities is shaped by the existing density of both similar and different types of organisations. Some sectors exhibit complementary behaviour – such as Relief of Poverty charities being more likely to enter where Education charities already operate – while others suggest substitution, with Education charities less likely to enter areas where Relief of Poverty or Community charities are already prevalent. Health-related charities further demonstrate intra-type substitution. These patterns reflect a mix of coordination and competition across sectors (e.g., Hager, 1999; Gill et al., 2008). Exit dynamics reveal that charities in Relief of Poverty, Religion, Health, and Arts are more likely to dissolve when the number of peer organisations is higher, suggesting possible intra-type competition. By contrast, religious charities consistently exhibit inter-type complementarity, as their presence is associated with fewer exits among other charity types.

Geographic location further shapes these dynamics. Charities focused on Relief of Poverty and Community are more likely to enter remote CSDs located farther from urban cores, indicating a role in filling spatial service gaps. Exit, however, appears largely unrelated to remoteness, pointing to different mechanisms driving formation and closure across geographic space.

Robustness checks lend further credibility to the main findings. Replacing LICO with average income yields comparable results, supporting the interpretation that economic need – however measured – is a key driver of charity formation. Using lagged poverty measures helps address concerns about reverse causality, and dynamic specifications that control for entry and exit momentum show that LICO remains an important factor for entry. Additional exercises – including restricting the sample to explicitly local service providers, excluding early years with potential reporting gaps, and testing interactions with government funding – produce results that are broadly consistent with the baseline estimates.

From a policy perspective, these findings have several implications for nonprofit regulation and public funding design. First, the responsiveness of charity entry to both local need and expected funding conditions suggests that public funding plays an important signalling role, shaping where and when new organisations form. At the same time, the association between charity exit and past funding shortfalls indicates that instability or gaps in public support can have lasting effects on organisational survival. Together, these patterns imply that short-term or volatile funding regimes may both encourage entry and simultaneously increase the risk of subsequent exit. Policies that prioritise predictability and continuity in funding, particularly in high-need sectors such as poverty relief and community services, may improve sector stability and reduce welfare losses associated with instability in organisational presence. More broadly, the results suggest that nonprofit regulation and funding frameworks should account for differences in local socioeconomic conditions, geographic remoteness, and the local density and interactions among charities, rather than relying on uniform or centrally designed allocation rules. Of course, in dynamic sectors, one expects entry and exit. My work cannot say anything about how desirable the current rate of entry and exits is, highlighting a gap in our knowledge of the ‘optimal’ provision of charitable services.

In sum, this chapter demonstrates that charity entry and exit in Canada are shaped by both local socioeconomic conditions and government support. Charities are more likely to enter in high-need areas with favourable funding conditions and more likely to exit in the aftermath of sustained financial strain. These findings underscore the importance of targeted, stable public funding to ensure the responsiveness and sustainability of the charitable sector across regions. They also highlight how inter-organisational and spatial dynamics shape the evolving landscape of charitable activities in Canada. Overall, these findings are broadly consistent with existing evidence on nonprofit dynamics, while extending the literature to the Canadian context and offering policy-relevant insights into how funding design and regulatory frameworks shape the structure and performance of the charitable sector.

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Table 3.1 Data Sources

Variables	Tables	Data Sources
Real GDP by province (at 2017 constant prices), 1990-2021	36-10-0222-01	Statistics Canada
Unemployment rate in Canada and by province, both sex, 15 to 64 years, 1990-2021	14-10-0327-01	Statistics Canada
Estimates of population by province	17-10-0060-01	Statistics Canada
Geographical Information Data: Census Subdivision (CSD) and Census Metropolitan Area (CMA) shapefiles		Scholars GeoPortal
The proportion people whose highest degree is high school or above, average monthly rent by case, the proportion of immigrants, unemployment rate, average income, proportion of people below low income cutoff (for those who aged 15 or older), proportion of visible minority, and total populations		Census of Population, 1991-2021, in five-year intervals, Research Data Center
Number of charity entry and exit		T3010

Table 3.2 Descriptive Statistics of Socio-demographic information by CSD and Macroeconomic Indicators by Province, 1991-2021

Variable	Mean	SD	N
No. Entry	1.410	6.831	5760
No. Exit	0.941	5.140	5760
Proportion of highest school or above	0.572	0.125	5760
Average monthly rent by cash	112.393	102.835	5760
Proportion of immigrants	0.080	0.085	5760
Unemployment rate	0.102	0.073	5760
Average income	27735.060	11609.520	5760
Proportion of people below LICO	0.084	0.071	5760
Proportion of visible minority	0.042	0.082	5760
Total population	28072.590	116835.900	5760

Note: All statistics are based on weighted values from the Census of Population. In the 1991 census, the weight variable is compw4; for 1996 to 2021, it is compw2. The variables in the first column are calculated at the CSD level: number of charity entry, the number of charity exit, the proportion people whose highest degree is high school or above, average monthly rent by case, the proportion of immigrants, unemployment rate, average income, proportion of people below low income cutoff (for those who aged 15 or older), proportion of visible minority, and total populations.

Table 3.3 Regression Results on the Number of Charity Entries by CSD, 1991-2021

Variables	en_t	en_t1	en_t2	en_t3	en_t4
LICO (%)	1.739***	2.462***	1.331	0.641	1.249
	(0.560)	(0.868)	(0.913)	(0.988)	(1.009)
High School or Above (%)	0.670	0.105	-1.266	-0.988	-2.309**
	(0.940)	(1.055)	(1.163)	(1.132)	(1.062)
Average rent	0.001*	-0.001*	-0.000	-0.002***	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Immigrants (%)	-0.004	-0.002	0.000	0.003	-0.001
	(0.004)	(0.003)	(0.004)	(0.007)	(0.005)
Unemployment Rate	1.987**	2.237*	1.870	-0.962	-1.107
	(0.988)	(1.188)	(1.281)	(1.236)	(1.236)
Visible Minority (%)	1.893***	0.988*	1.497***	1.591***	1.549***
	(0.450)	(0.510)	(0.533)	(0.547)	(0.458)
Population	0.000***	0.000***	0.000***	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distant	0.840**	-0.899**	0.255	0.675	0.280
	(0.349)	(0.457)	(0.253)	(0.488)	(0.661)
Constant	0.489	0.896	1.657**	2.251***	2.797***
	(0.618)	(0.743)	(0.807)	(0.810)	(0.737)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. The independent variables in the first column are measure at CSD level: the proportion of individuals aged 15 or older below the low-income cut-off; the proportion with at least a high school diploma; average monthly rent; the proportion of immigrants; unemployment rate; the proportion of visible minorities; total population; and a dummy indicating whether the CSD core is more than 100 km from the nearest metropolitan area. The dependent variables in the first row represent the number of charity entries at time t, t +1, t+2, t +3, and t+ 4. Standard errors are clustered at CSD level.

Table 3.4 Regression Results on the Number of Charity Exits by CSD, 1991-2021

Variables	ex_t	ex_t1	ex_t2	ex_t3	ex_t4
LICO (%)	1.167	-0.255	1.465	1.014	1.445
	(0.736)	(1.035)	(1.311)	(1.537)	(1.039)
High School or Above (%)	1.937*	0.261	1.621	-4.281***	2.080
	(1.095)	(1.354)	(1.327)	(1.348)	(1.377)
Average rent	-0.001	-0.001*	-0.000	-0.003***	-0.002**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Immigrants (%)	0.014***	0.014	0.020**	0.013**	0.008
	(0.005)	(0.009)	(0.008)	(0.006)	(0.007)
Unemployment Rate	2.092**	-0.945	0.321	-2.707*	-0.776
	(0.940)	(1.572)	(1.539)	(1.387)	(1.354)
Visible Minority (%)	0.225	0.730	0.261	-0.578	0.528
	(0.466)	(0.624)	(0.671)	(0.738)	(0.449)
Population	0.000**	0.000	0.000	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distant	0.093	0.330	0.805	0.473	0.799
	(0.364)	(0.474)	(0.591)	(0.369)	(0.861)
Constant	0.120	1.602*	0.510	5.132***	0.336
	(0.805)	(0.952)	(0.933)	(1.029)	(0.985)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. The independent variables in the first column are measure at CSD level: the proportion of individuals aged 15 or older below the low-income cut-off; the proportion with at least a high school diploma; average monthly rent; the proportion of immigrants; unemployment rate; the proportion of visible minorities; total population; and a dummy indicating whether the CSD core is more than 100 km from the nearest metropolitan area. The dependent variables in the first row represent the number of charity exits at time t, t +1, t+2, t +3, and t+ 4. Standard errors are clustered at CSD level.

Table 3.5 Regression Results on the Number of Entries at Time t, by Type and by CSD, 1991-2021

Variables	$EN\_Poverty_t$	EN_Edu_t	$EN\_Religion_t$	EN_Health_t	EN_Comm_t	EN_Art_t	EN_Found_t	EN_Other_t
LICO (%)	6.292***	0.574	-0.393	3.350	-1.064	1.524	-0.509	-3.643
	(1.700)	(1.781)	(1.031)	(2.250)	(1.918)	(3.814)	(1.704)	(5.084)
High School or Above (%)	-0.771	-0.293	0.498	2.216	-0.417	-2.863	0.271	-8.408
	(2.319)	(2.614)	(1.744)	(3.284)	(2.281)	(3.304)	(3.416)	(8.204)
Average rent	0.003***	0.001	-0.000	0.002	0.001	0.000	0.003***	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Immigrants (%)	-0.002	-0.005	-0.010*	-0.028**	-0.005	-0.017	-0.009	-0.018
	(0.007)	(0.009)	(0.006)	(0.013)	(0.008)	(0.011)	(0.009)	(0.033)
Unemployment Rate	1.846	-4.030	4.645***	-4.329	3.104	8.647*	1.299	5.889
	(2.141)	(3.026)	(1.735)	(3.575)	(2.062)	(4.826)	(2.949)	(5.569)
Visible Minority (%)	0.746	3.002**	2.374***	0.929	2.577	-0.819	2.153	1.381
	(1.013)	(1.190)	(0.607)	(1.524)	(1.609)	(2.020)	(1.542)	(3.726)
Population	0.000***	0.000**	0.000	0.000	0.000	0.000	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distant	2.183**	0.215	-0.598	-	0.927	-	0.690	-
	(0.859)	(0.853)	(0.649)	-	(0.751)	-	(0.739)	-
Constant	-1.766	-0.247	0.349	-2.297	-0.654	1.291	-2.000	3.134
	(1.439)	(1.824)	(1.223)	(2.263)	(1.475)	(2.688)	(2.385)	(6.148)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. The independent variables are the same as in table 3.3. The dependent variables in the first row represent the number of charity entries at time t, decomposed by charity type: Relief of Poverty; Education; Religion; Health; Community; Arts; Foundations; and "Other". Distance dummy is omitted from the Health, Arts, and "Other" columns due to collinearity. Standard errors are clustered at CSD level.

Table 3.6 Regression Results on the Number of Exits at Time t, by Type and by CSD, 1991-2021

Variables	$EX\_Poverty_t$	EX_Edu_t	$EX\_Religion_t$	EX_Health_t	EX_Comm_t	EX_Art_t	EX_Found_t	EX_Other_t
LICO (%)	1.448	4.545**	-0.177	1.654	1.773	-3.861	-1.419	7.931
	(1.862)	(2.235)	(1.144)	(3.102)	(2.021)	(4.113)	(2.620)	(8.335)
High School or Above (%)	3.292	0.081	2.926	2.697	0.734	-3.735	-5.866	15.652
	(2.553)	(2.903)	(2.136)	(3.707)	(2.946)	(4.272)	(3.863)	(13.559)
Average rent	-0.001	-0.001	-0.001	0.001	-0.001	-0.002	0.001	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
Immigrants (%)	-0.002	0.027**	0.026**	-0.028	0.009	-0.027	0.006	-0.085
	(0.015)	(0.014)	(0.012)	(0.028)	(0.027)	(0.024)	(0.019)	(0.068)
Unemployment Rate	1.110	-2.035	2.478	4.189	0.670	14.455***	6.622**	12.942
	(2.607)	(2.558)	(1.663)	(4.003)	(2.279)	(5.141)	(3.263)	(8.043)
Visible Minority (%)	-0.712	0.563	0.699	0.125	-0.953	2.054	-1.013	-1.210
	(1.200)	(1.245)	(0.701)	(1.867)	(1.452)	(1.956)	(1.402)	(3.954)
Population	0.000**	0.000**	0.000	-0.000	0.000	-0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distant	-0.723	-	-0.728	-	0.173	-	-0.086	-
	(0.899)	-	(0.712)	-	(0.983)	-	(0.562)	-
Constant	-2.509	-1.180	-1.470	-1.851	-0.739	4.601	3.794	-13.553
	(1.842)	(2.319)	(1.532)	(2.775)	(2.179)	(3.253)	(2.810)	(10.862)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. The independent variables are the same as in table 3.3. The dependent variables in the first row represent the number of charity exits at time t, decomposed by charity type: Relief of Poverty; Education; Religion; Health; Community; Arts; Foundations; and "Other". Distance dummy is omitted from the Education, Health, Arts, and "Other" columns due to collinearity. Standard errors are clustered at CSD level.

Table 3.7 Regression Results on Charity Entry at Time t, with Proportion Funded at t – 1, t, and t + 1, 1991-2021

Variables	en_t	en_t	en_t
Fund_t-1	-0.048		
	(0.240)		
Fund_t		1.609***	
		(0.265)	
Fund_t+1			1.460***
			(0.249)
LICO (%)	1.895***	1.847***	1.803***
	(0.569)	(0.576)	(0.559)
High School or Above (%)	0.867	-0.131	-0.115
	(0.949)	(0.976)	(0.959)
Average rent	0.001*	0.001	0.001
	(0.000)	(0.000)	(0.000)
Immigrants (%)	-0.003	-0.006	-0.006
	(0.004)	(0.004)	(0.004)
Unemployment Rate	1.781*	1.659*	1.683*
	(1.000)	(1.007)	(0.991)
Visible Minority (%)	1.872***	1.786***	1.792***
	(0.450)	(0.449)	(0.448)
Population	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Distant	0.809**	0.838**	0.841**
	(0.351)	(0.351)	(0.350)
Constant	0.381	0.405	0.455
	(0.630)	(0.638)	(0.629)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. In addition to the independent variables in table 3.3, three additional variables are included in the first column: the proportion of charities receiving government funding at time t − 1, t, and t + 1. The dependent variables in the first row represent the number of charity entries at time t. Standard errors are clustered at CSD level.

Table 3.8 Regression Results on Charity Exit at Time t, with Proportion Not Funded at t – 1, t, and t + 1, 1991-2021

Variables	ex_t	ex_t	ex_t
NoFund_t-1	0.984***		
	(0.243)		
NoFund_t		0.270	
		(0.230)	
NoFund_t+1			0.292
			(0.227)
LICO (%)	1.173	1.120	1.109
	(0.753)	(0.739)	(0.746)
High School or Above (%)	2.103*	1.927*	1.774
	(1.081)	(1.095)	(1.097)
Average rent	-0.001	-0.001	-0.001*
	(0.000)	(0.000)	(0.000)
Immigrants (%)	0.016***	0.014***	0.015***
	(0.005)	(0.005)	(0.005)
Unemployment Rate	2.388**	2.254**	2.139**
	(0.955)	(0.947)	(0.952)
Visible Minority (%)	0.174	0.185	0.182
	(0.450)	(0.459)	(0.461)
Population	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)
Distant	-0.001	-0.016	0.029
	(0.376)	(0.368)	(0.359)
Constant	-0.019	-0.567	0.091
	(0.818)	(0.810)	(0.821)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. In addition to the independent variables in table 3.3, three additional variables are included in the first column: the proportion of charities not receiving government funding at time t − 1, t, and t + 1. The dependent variables in the first row represent the number of charity exits at time t. Standard errors are clustered at CSD level.

Table 3.9 Regression Results on Entry by Type, with Proportion of Charities Receiving Fund at t, 1991-2021

Variables	$EN\_Poverty_t$	EN_Edu_t	$EN\_Religion_t$	EN_Health_t	EN_Comm_t	EN_Art_t	EN_Found_t	EN_Other_t
Fund_t	2.202***	1.318***	0.423	2.463***	2.589***	1.805***	1.097***	0.742*
	(0.240)	(0.223)	(0.399)	(0.332)	(0.265)	(0.309)	(0.243)	(0.422)
LICO (%)	5.735***	0.854	-0.353	5.666**	-0.629	2.274	0.624	-0.648
	(2.054)	(1.822)	(1.051)	(2.536)	(2.906)	(4.032)	(2.214)	(6.656)
High School or Above (%)	-0.610	-0.791	0.170	4.215	-1.042	-1.229	0.508	5.212
	(2.575)	(2.812)	(1.808)	(3.747)	(2.970)	(3.606)	(3.663)	(10.054)
Average rent	0.002**	0.000	-0.000	0.002**	0.000	-0.001	0.003***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Immigrants (%)	0.009	-0.002	-0.008	-0.017	-0.014	-0.019	-0.004	-0.046
	(0.008)	(0.010)	(0.006)	(0.014)	(0.009)	(0.012)	(0.009)	(0.044)
Unemployment Rate	3.662	-4.776	4.458**	-8.655**	3.322	3.455	0.342	10.415*
	(2.347)	(3.298)	(1.818)	(3.693)	(2.494)	(5.385)	(3.156)	(6.300)
Visible Minority (%)	0.242	2.519**	2.374***	1.331	0.929	-1.451	0.967	-0.420
	(1.130)	(1.184)	(0.607)	(1.620)	(1.773)	(2.045)	(1.591)	(3.254)
Population	0.000***	0.000**	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distant	1.922**	-0.051	-0.950	-	2.589***	-	0.333	-
	(0.815)	(1.210)	(0.592)	-	(0.689)	-	(0.811)	-
Constant	-3.373**	-0.195	0.496	-5.421**	-1.545	-0.463	-1.929	-5.622
	(1.618)	(1.962)	(1.265)	(2.678)	(1.958)	(2.941)	(2.668)	(7.738)

Note: In addition to the independent variables in table 3.3, the proportion of charities receiving fund at time t is added. The dependent variables in the first row represent the number of different types of charity entry at time t. Distance dummy is omitted from the Health, Arts, and “Other” columns due to collinearity. Standard errors are clustered at CSD level.

Table 3.10 Regression Results on Exit by Type, with Proportion of Charities Not Receiving Fund at t–1, 1991-2021

Variables	EX_Poverty$_t$	EX_Edu$_t$	EX_Religion$_t$	EX_Health$_t$	EX_Comm$_t$	EX_Art$_t$	EX_Found$_t$	EX_Other$_t$
NoFund_t-1	1.215***	0.748***	0.852**	1.085***	1.323***	0.323	0.405	1.988***
	(0.352)	(0.267)	(0.336)	(0.400)	(0.316)	(0.354)	(0.260)	(0.661)
LICO (%)	1.207	4.288*	0.060	1.793	2.302	-4.043	-0.317	10.158
	(1.866)	(2.233)	(1.226)	(3.368)	(2.171)	(4.093)	(2.528)	(7.832)
High School or Above (%)	2.851	0.693	3.069	3.509	1.992	-3.799	-6.709*	18.093
	(2.588)	(2.988)	(2.076)	(4.120)	(3.047)	(4.617)	(3.955)	(18.544)
Average rent	-0.001	-0.001	-0.000	0.002	-0.001	-0.002	0.001	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
Immigrants (%)	0.001	0.034**	0.028**	-0.018	0.040**	-0.023	0.014	-0.025
	(0.014)	(0.014)	(0.012)	(0.028)	(0.019)	(0.022)	(0.018)	(0.072)
Unemployment Rate	0.392	-2.284	3.027*	3.381	-0.202	12.983**	5.157	12.525
	(2.649)	(2.489)	(1.677)	(4.166)	(2.725)	(5.121)	(3.349)	(9.644)
Visible Minority (%)	-1.039	0.318	0.602	-0.144	-0.547	2.334	-1.837	-4.208
	(1.138)	(1.258)	(0.674)	(1.877)	(1.479)	(1.971)	(1.369)	(4.299)
Population	0.000**	0.000**	0.000	-0.000	0.000	-0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distant	-0.567	-	-0.819	-	0.242	-	0.072	-
	(0.855)	-	(0.658)	-	(1.020)	-	(0.536)	-
Constant	-2.434	-1.971	-2.297	-2.838	-2.121	4.594	4.219	-14.896
	(1.890)	(2.373)	(1.509)	(3.169)	(2.277)	(3.520)	(2.920)	(14.759)

Note: In addition to the independent variables in table 3.3, the proportion of charities not receiving fund at time t-1 is added. The dependent variables in the first row represent the number of different types of charity exits at time t. Distance dummy is omitted from the Education, Health, Arts, and “Other” columns due to collinearity. Standard errors are clustered at CSD level.

Table 3.11 Regression Results on Entry at t by Type, with the Number of Existing Charities by Type at t–1, 1991-2021

Variables	$EN\_Poverty_t$	EN_Edu_t	$EN\_Religion_t$	EN_Health_t	EN_Comm_t	EN_Art_t	EN_Found_t	EN_Other_t
Existing_Poverty_t-1	-0.003	-0.007*	-0.002	0.003	0.010***	-0.005	0.001	0.005
	(0.003)	(0.004)	(0.001)	(0.004)	(0.003)	(0.003)	(0.005)	(0.018)
Existing_Edu_t-1	0.009***	0.000	-0.002	0.004	-0.012*	-0.005	0.001	-0.002
	(0.003)	(0.003)	(0.003)	(0.005)	(0.007)	(0.005)	(0.004)	(0.009)
Existing_Religion_t-1	0.001	0.001	-0.001	-0.001	0.002	0.006**	0.001	0.004
	(0.002)	(0.003)	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)	(0.009)
Existing_Health_t-1	0.018	0.050***	-0.017	-0.040**	0.018	-0.019	0.009	0.047
	(0.015)	(0.016)	(0.011)	(0.019)	(0.019)	(0.024)	(0.016)	(0.040)
Existing_Comm_t-1	-0.019***	-0.019***	0.007	0.006	0.016	0.023**	0.013*	0.002
	(0.007)	(0.006)	(0.008)	(0.011)	(0.011)	(0.012)	(0.007)	(0.021)
Existing_Art_t-1	0.005	0.002	-0.001	-0.006	-0.010***	0.002	-0.001	-0.019
	(0.003)	(0.004)	(0.002)	(0.005)	(0.002)	(0.004)	(0.003)	(0.013)
Existing_Found_t-1	-0.007	-0.009*	0.002	0.010**	0.001	-0.000	-0.000	-0.001
	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)	(0.006)	(0.003)	(0.013)
Existing_Other_t-1	0.009	-0.036	-0.002	-0.025	-0.000	-0.054*	-0.059**	-0.101
	(0.032)	(0.024)	(0.020)	(0.039)	(0.029)	(0.030)	(0.025)	(0.096)
LICO (%)	4.281	3.851	-1.593	-2.981	0.403	9.195	0.371	-2.912
	(3.878)	(3.455)	(2.627)	(5.429)	(4.684)	(6.814)	(3.593)	(9.632)
High School or Above (%)	5.794*	0.266	4.731	-0.179	0.552	4.295	-2.820	-12.119
	(3.256)	(4.995)	(3.856)	(6.963)	(6.669)	(8.171)	(5.114)	(11.882)
Average rent	0.003**	0.001	-0.001	-0.001	0.002	0.002	0.005***	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)
Immigrants (%)	-0.013	-0.031*	-0.010	-0.025	-0.017	-0.014	0.003	-0.005
	(0.012)	(0.017)	(0.009)	(0.022)	(0.011)	(0.015)	(0.015)	(0.041)
Unemployment Rate	3.234	-5.481	4.903*	-6.911	6.008	5.066	5.551	4.123
	(3.691)	(5.168)	(2.502)	(6.041)	(4.314)	(6.918)	(4.568)	(8.024)
Visible Minority (%)	0.161	-0.526	2.306*	1.187	3.600*	-5.425	1.175	3.697

	(1.754)	(2.404)	(1.336)	(3.308)	(1.880)	(3.339)	(2.268)	(5.716)
Population	0.000	0.000	0.000**	-0.000	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distant	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
Constant	-5.303**	0.434	-1.607	2.632	-2.431	-6.937	-2.198	7.333
	(2.537)	(3.906)	(2.974)	(5.906)	(4.985)	(7.022)	(4.472)	(8.516)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. In addition to the independent variables in table 3.3, this specification includes the proportion of existing charities by type at time t-1. Charity types are: Relief of Poverty, Education, Religion, Health, Community, Arts, Foundations, and Other. The dependent variables in the first row are the number of new entries in each corresponding category. Distance dummy is omitted from estimations because of collinearity. Standard errors are clustered at CSD level.

Table 3.12 Regression Results on Exit at t by Type, with the Number of Existing Charities by Type at t–1, 1991-2021

Variables	$EX\_Poverty_t$	EX_Edu_t	$EX\_Religion_t$	EX_Health_t	EX_Comm_t	EX_Art_t	EX_Found_t	EX_Other_t
Existing_Poverty_t-1	0.009**	0.001	0.004	0.004	-0.012*	-0.012***	-	0.030
	(0.004)	(0.004)	(0.003)	(0.010)	(0.007)	(0.004)	-	(0.031)
Existing_Edu_t-1	0.007	0.003	-0.013**	-0.013	-0.007	0.009	-	-0.006
	(0.005)	(0.006)	(0.005)	(0.009)	(0.006)	(0.007)	-	(0.016)
Existing_Religion_t-1	-0.004	0.002	0.005**	-0.008**	0.013***	0.006*	-	0.018
	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)	-	(0.013)
Existing_Health_t-1	-0.003	-0.035***	-0.001	0.063**	-0.012	-0.028	-	-0.096**
	(0.015)	(0.012)	(0.011)	(0.025)	(0.023)	(0.023)	-	(0.046)
Existing_Comm_t-1	0.001	0.016*	0.005	-0.011	0.012	0.007	-	0.130***
	(0.009)	(0.008)	(0.006)	(0.018)	(0.013)	(0.013)	-	(0.044)
Existing_Art_t-1	-0.003	0.001	-0.012**	-0.002	0.000	0.014***	-	0.007
	(0.003)	(0.004)	(0.005)	(0.007)	(0.005)	(0.005)	-	(0.018)
Existing_Found_t-1	0.000	0.008*	-0.006**	0.002	-0.003	-0.004	-	0.004
	(0.003)	(0.004)	(0.002)	(0.008)	(0.007)	(0.006)	-	(0.014)
Existing_Other_t-1	0.011	-0.009	-0.003	-0.007	-0.053	-0.023	-	0.211*
	(0.019)	(0.021)	(0.018)	(0.042)	(0.056)	(0.033)	-	(0.126)
LICO (%)	1.415	3.460	-0.714	8.471	7.019	-4.279	-	10.798
	(4.945)	(3.474)	(2.585)	(5.661)	(4.355)	(6.739)	-	(17.599)
High School or Above (%)	3.240	-3.103	-0.661	7.563	-8.288	-6.481	-	8.711
	(5.365)	(4.582)	(3.644)	(7.491)	(5.959)	(8.502)	-	(21.665)
Average rent	-0.001	-0.002	0.001	0.007***	-0.000	-0.001	-	-0.007
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	-	(0.007)
Immigrants (%)	0.011	0.041**	-0.023	0.018	0.052***	-0.008	-	0.096
	(0.026)	(0.019)	(0.020)	(0.038)	(0.018)	(0.027)	-	(0.075)
Unemployment Rate	2.531	-0.300	1.290	-3.641	-4.081	11.091*	-	11.517
	(4.250)	(3.283)	(2.608)	(5.761)	(4.506)	(6.656)	-	(9.831)
Visible Minority (%)	-1.290	2.581	-4.096***	-0.899	-2.244	3.311	-	3.644

	(2.543)	(2.014)	(1.573)	(3.382)	(2.366)	(3.221)	-	(5.309)
Population	0.000	-0.000	0.000**	0.000	-0.000	-0.000**	-	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	-	(0.000)
Distant	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
Constant	-2.498	0.996	1.103	-6.473	4.229	5.289	-	-18.760
	(4.191)	(3.447)	(2.852)	(5.572)	(4.370)	(6.942)	-	(16.496)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. In addition to the independent variables in table 3.3, this specification includes the proportion of existing charities by type at time t-1. Charity types are: Relief of Poverty, Education, Religion, Health, Community, Arts, Foundations, and Other. The dependent variables in the first row are the number of charity exits in each corresponding category. Due to the residual disclosure vetting rule in the RDC, the results for the Foundations category are not available. Distance dummy is omitted from estimations because of collinearity. Standard errors are clustered at CSD level.

Table 3.13 Regression Results on Entry Counts and the Provincial Unemployment Rate, 1991-2021

Variables	en_t	en_t1	en_t2	en_t3	en_t4
Provincial Unemployment Rate	0.047**	0.056***	-0.003	-0.064***	-0.043**
	(0.020)	(0.018)	(0.021)	(0.024)	(0.019)
LICO (%)	1.750***	2.556***	1.682*	0.837	1.292
	(0.574)	(0.859)	(0.916)	(0.863)	(0.964)
High School or Above (%)	0.228	-0.364	-1.532	-0.681	-2.101**
	(0.932)	(1.029)	(1.182)	(1.095)	(1.061)
Average rent	0.001*	-0.001**	-0.000	-0.001**	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Immigrants (%)	-0.004	-0.003	0.001	0.005	-0.000
	(0.004)	(0.003)	(0.004)	(0.007)	(0.005)
Visible Minority (%)	2.011***	1.072**	1.607***	1.632***	1.581***
	(0.439)	(0.533)	(0.554)	(0.508)	(0.464)
Population	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distant	0.826**	-0.947**	0.241	0.658	0.285
	(0.351)	(0.457)	(0.264)	(0.483)	(0.655)
Constant	0.639	1.071	1.887**	2.219***	2.801***
	(0.605)	(0.738)	(0.812)	(0.764)	(0.718)

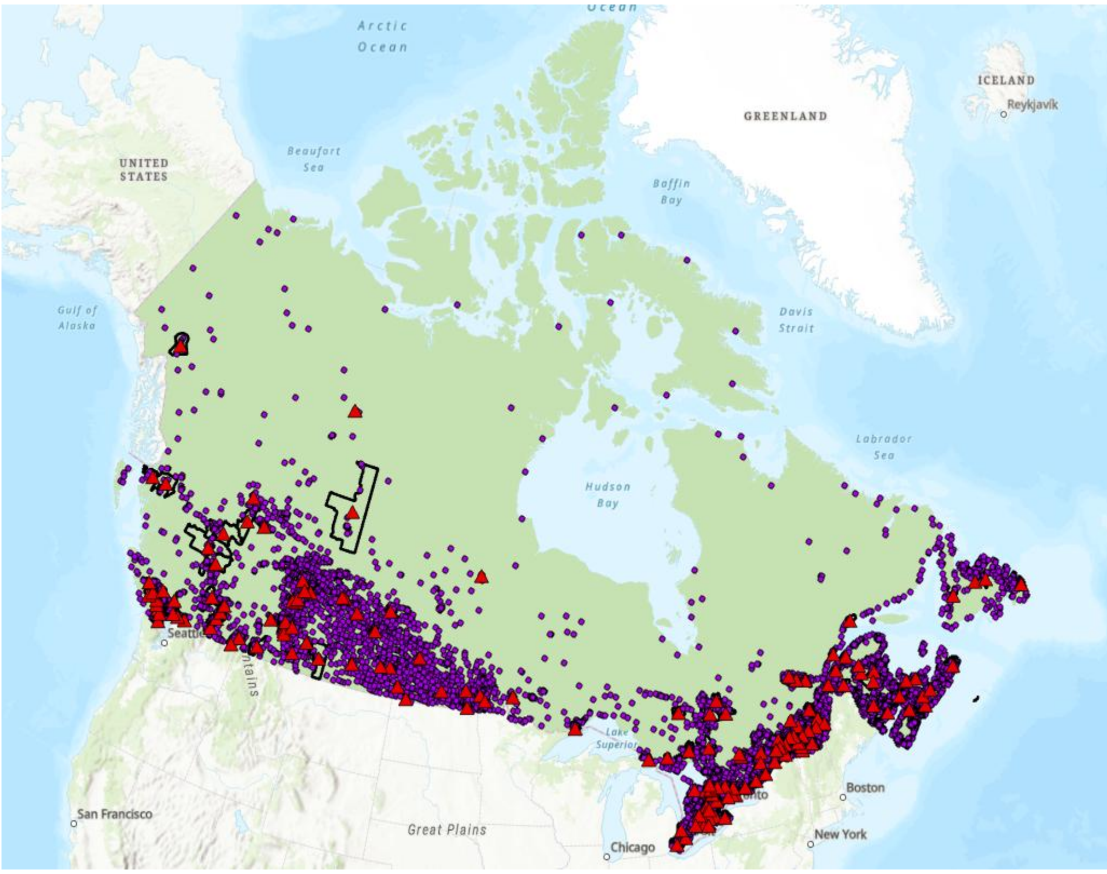
Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. In addition to the independent variables in table 3.3, this specification includes provincial unemployment rate. The dependent variables in the first row represent the number of charity entries at time t, t + 1, t + 2, t + 3, and t + 4. Standard errors are clustered at CSD level.

Table 3.14 Regression Results on Exit Counts and the Provincial Unemployment Rate, 1991-2021

Variables	ex_t	ex_t1	ex_t2	ex_t3	ex_t4
Provincial Unemployment Rate	0.012	0.014	0.016	-0.066**	-0.012
	(0.015)	(0.025)	(0.024)	(0.028)	(0.020)
LICO (%)	1.432*	-0.557	1.433	0.911	1.323
	(0.771)	(1.003)	(1.245)	(1.449)	(0.992)
High School or Above (%)	1.833	0.196	1.497	-3.667***	2.188
	(1.121)	(1.361)	(1.321)	(1.264)	(1.363)
Average rent	-0.001	-0.002*	-0.000	-0.003***	-0.001**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Immigrants (%)	0.016***	0.013	0.019**	0.014**	0.008
	(0.005)	(0.009)	(0.008)	(0.006)	(0.007)
Unemployment Rate	0.405	0.672	0.258	-0.549	0.583
	(0.472)	(0.636)	(0.681)	(0.716)	(0.470)
Visible Minority (%)	0.000***	0.000	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population	0.114	0.336	0.803	0.464	0.805
	(0.363)	(0.466)	(0.593)	(0.368)	(0.865)
Distant	0.130	1.600*	0.553	4.862***	0.302
	(0.826)	(0.943)	(0.934)	(0.978)	(0.977)
Constant	0.012	0.014	0.016	-0.066**	-0.012
	(0.015)	(0.025)	(0.024)	(0.028)	(0.020)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. In addition to the independent variables in table 3.3, this specification includes provincial unemployment rate. The dependent variables in the first row represent the number of charity exits at time t, t + 1, t + 2, t + 3, and t + 4. Standard errors are clustered at CSD level

Figure 3.1 Map of CSDs, CMAs, Charities, and CMA Centroids, 2021



Note: Green areas represent CSDs; black circles represent CMAs; red triangles mark CMA centroids; purple dots indicate charities in Canada in 2021.

Appendix 3.A: Data Problems and Solutions

3.1A Problem 1. Reporting Gaps and the Classification of Entry and Exit

A central challenge in constructing consistent measures of charity entry and exit lies in the treatment of reporting gaps – periods during which a charity ceases to file returns but later resumes activity under the same business number (BN). In the full dataset of 122,316 unique charities, approximately 20.5 percent report with at least one gap during the observation period. Among these, 17.4 percent have gaps of two or more years, which could plausibly reflect either temporary inactivity or closure and re-registration. Gaps of exactly two years account for 15.2 percent, while gaps of three years and more than three years make up 1.42 percent and 1.34 percent, respectively.

To explore whether these gaps vary by organisational scale, I classify charities by size based on total annual revenues: small (≤ \$249,999), medium (\$250,000-\$999,999), and large (≥ \$1 million). Among charities with gaps of at least two years (17.4 percent), 14.76 percent are small, 1.31 percent are medium, and 0.83 percent are large. The remaining 0.5 percent cannot be categorised due to missing financial data. These patterns suggest that smaller organisations are more prone to irregular reporting, potentially due to limited administrative capacity or unstable funding.

The key question is how to treat a charity that disappears from the data for multiple years and then reappears under the same BN. While continuity in identifier might suggest that it is the same organisation, long gaps in reporting raise concerns about whether these cases represent a continuation or a new organisational form.

Solution 1: Identifying Re-entries Using Closure Records

To address this ambiguity, I draw on the closed charities dataset, which records a single registration and closure date for each business number. This dataset provides a definitive source for identifying formal organisational shutdowns. By comparing the reported closure year of each BN with its reporting timeline in the main dataset, I identify cases where a charity reappears in the data after its registered closure date.

In such instances, I treat the post-closure reappearance as a new entry, regardless of whether the BN remains the same. This decision is based on the assumption that a charity which has formally ceased operations and then resumes filing is more accurately interpreted as a re-registered entity than a continuous one. This assumption is consistent with the regulatory framework of the Canada Revenue Agency, which requires re-registration following formal dissolution.

This procedure enhances the accuracy of entry and exit classification, particularly for the 17.4 percent of charities that exhibit multi-year gaps in reporting. By distinguishing between true organisational continuity and re-registration, it mitigates potential biases in estimating patterns of charity formation and dissolution – specifically, it helps avoid undercounting entries and misclassifying reactivations as continuous operations. The results of this matching process indicate that only 0.43% (based on CRA closure records and data from 1991-2021) of business numbers resume reporting after their official closure dates, suggesting that the issue is limited in scope. This finding supports the conclusion that, for most cases, reclassification of reappearing entities as new entrants is not necessary, though the adjustment remains important for ensuring robustness in a small subset of observations.

3.2A Problem 2: Assigning Charities to Census Subdivisions (CSDs) over Time

A core methodological challenge involves assigning each charity to the appropriate Census Subdivision (CSD) in a way that is consistent across time. This assignment is essential for aggregating charity entry and exit counts at the CSD level and linking them to local demographic and geographic characteristics. However, the choice of method affects both the precision and consistency of spatial classification, especially given boundary changes over time.

I considered two approaches. In the first, I use the Postal Code Conversion File (PCCF) to assign each charity to a CSD based on the most recent census year. This method yields 1,030 unique CSDs with charitable activity – identical to the number observed when aggregating entry and exit counts. By contrast, the full set of CSDs reported by Statistics Canada across all census years from 1991 to 2021 includes 7,270 unique CSDs. Thus, my dataset covers only a subset of spatial units, concentrated in areas with active charitable presence.

The first method, which I refer to as the Static CSD Allocation approach, converts postal codes into CSDs using the most recent PCCF and assumes that CSD boundaries are constant over time. This method allows for continuous tracking of charity entries from 1991 to 2021, facilitates a straightforward merge with census-year-based geographic data (e.g., CSD-CMA distances), and avoids complications arising from shifting administrative boundaries. However, it implicitly assumes that a charity's geographic classification remains unchanged, even as census boundaries evolve. This introduces potential misclassification, particularly in cases where CSDs are merged, split, or redefined across censuses.

As a more accurate but computationally intensive alternative, I also considered a Dynamic CSD Allocation method using ArcGIS. This approach geocodes each charity based on its postal code and assigns it to the appropriate CSD using historical boundary shapefiles for each census year. It ensures that the spatial classification of charities reflects boundary changes, allowing entry counts to be precisely aligned with the corresponding geographic definitions used in demographic and distance calculations. However, this method limits the analysis to census years only (1991, 1996, 2001, etc.), and it requires significant geospatial processing, including repeated geocoding across time.

Solution 2: Relying on Static CSD Assignment with Validation from Dynamic Matching

To balance spatial accuracy with temporal coverage, I adopt the Static CSD Allocation (Method 1) as the primary approach for constructing a continuous panel of charity entry and exit from 1991 to 2021. This choice ensures a consistent geographic frame for longitudinal analysis and allows integration with yearly data on macroeconomic conditions and local characteristics.

To validate this approach, I implement the Dynamic CSD Allocation (Method 2) for census years and compare the resulting charity entry counts by CSD. The comparison reveals no significant differences in entry numbers between the two methods for the census years (1991, 1996, 2001, 2006, 2011, 2016, and 2021). This suggests that potential misclassification arising from boundary changes is minimal in practice, and that the static assignment procedure provides a reasonable approximation of charities' geographic locations over time.

Appendix 3.B: Calculations

3.1B Identifying Charity Entry and Exit at the CSD Level

To measure the dynamics of charitable activity over time, I construct indicators for charity entry and charity exit at the CSD-year level. The unit of observation is a CSD in a given year, and the outcome variables are counts of new entries and exits of registered charities.

The construction begins at the charity level. I define entry as the first year in which a charity appears in the dataset, conditional on having no observed activity in the previous year and starting after 1990. Similarly, exit is defined as the last year a charity appears before it permanently disappears from the dataset, with no subsequent filings, and prior to 2021. These definitions ensure that observed entry and exit reflect genuine organisational changes rather than gaps in reporting for the first or last years of the sample window.

Once entry and exit are defined for each charity, I aggregate this information to the CSD-year level by summing the number of entries and exits occurring in each CSD in each year. This aggregation allows me to construct a panel dataset of entry and exit counts across Canadian CSDs from 1991 to 2021.

To generate aligned measures of yearly entry and exit, I further organise the panel by sorting CSDs chronologically and assigning observed entry and exit values to the appropriate years. For each year between 1991 and 2021, the entry count reflects the number of charities that newly appear in that CSD, while the exit count reflects the number of charities that were active in the previous year but do not appear in the current year. This structure enables consistent comparison across years and supports the construction of lead and lag variables used in the empirical analysis.

3.2B Measuring Distance Between CSDs and CMAs

To investigate how geographic location influences charity entry and exit, I construct a measure of each CSD's proximity to the nearest Census Metropolitan Area (CMA). Because my empirical framework focuses on socioeconomic conditions measured at the CSD level – such as poverty rates, educational attainment, and demographic composition – it is appropriate to work at the level of CSDs rather than individual charities. Consequently, I adopt a centroid-based approach to measure spatial distance.

The procedure consists of three stages. First, I assign each charity to a CSD using spatial matching based on geographic boundaries. This matching is implemented using the "intersect" method, which links a charity's location (identified by coordinates) to the CSD whose boundary contains or touches that point. In cases where a location lies at the intersection of multiple CSDs, the charity is assigned to the CSD with the greatest area of overlap. This method ensures robust geographic assignment, including for charities located at administrative boundaries. A review of the data confirms that no charity entries occur exactly on CSD borders without being assigned, validating the use of the intersect approach.

Second, I compute centroids for both CSDs and CMAs using shapefiles from Statistics Canada. The centroid of each CSD represents its geographic centre and serves as the anchor point for distance calculations. Similarly, CMA centroids are derived based on the polygonal outlines of urban cores.

Third, I calculate the great-circle distance between the centroid of each CSD and the centroid of the closest CMA. This continuous measure of spatial proximity captures the relative remoteness of each CSD from major urban centres. The resulting variable is used in the main regressions as a proxy for geographic isolation or urban access, helping to test whether distance from economic and population hubs influences charitable presence and sustainability.

This centroid-based distance is a tractable and theoretically consistent proxy for spatial frictions, particularly in models where the unit of analysis is the CSD and all socioeconomic variables are defined at the same level.

Appendix 3.C: Tables

Table 3.1C Regression Results on Entry at t with the Proportion of Charities Receiving Funds at t – 1, t, and t + 1, 1993-2021 (Subsample)

Variables	en_t	en_t
Fund_t	1.600***	
	(0.359)	
Fund_t+1		1.503***
		(0.345)
LICO (%)	1.121*	1.152*
	(0.618)	(0.616)
High School or Above (%)	-0.163	-0.148
	(1.087)	(1.083)
Average rent	0.001***	0.001***
	(0.000)	(0.000)
Immigrants (%)	-0.777	-0.732
	(1.030)	(1.029)
Unemployment Rate	1.847*	1.842*
	(1.088)	(1.076)
Visible Minority (%)	2.921***	2.895***
	(0.820)	(0.820)
Population	0.000	0.000
	(0.000)	(0.000)
Distant	0.753**	0.763**
	(0.353)	(0.352)
Constant	0.553	0.562
	(0.810)	(0.806)

Note: The results for funding at t-1 are not reported because, under RDC disclosure rules, the number of observations in this column differs from other columns by fewer than five, and thus cannot be released. Standard errors are clustered at CSD level.

Table 3.2C Regression Results on Exit at t with the Proportion of Charities Not Receiving Funds at t – 1, t, and t + 1, 1993-2021 (Subsample)

Variables	ex_t	ex_t	ex_t
NoFund_t-1	1.035***		
	(0.252)		
NoFund_t		0.313	
		(0.247)	
NoFund_t+1			0.364
			(0.245)
LICO (%)	0.833	0.782	0.764
	(0.822)	(0.796)	(0.808)
High School or Above (%)	1.326	1.151	1.008
	(1.079)	(1.092)	(1.095)
Average rent	-0.001*	-0.001**	-0.001**
	(0.000)	(0.000)	(0.001)
Immigrants (%)	-2.555**	-2.607**	-2.718**
	(1.137)	(1.144)	(1.145)
Unemployment Rate	2.024**	1.854*	1.739*
	(1.004)	(0.992)	(0.998)
Visible Minority (%)	1.628**	1.658**	1.721**
	(0.769)	(0.762)	(0.764)
Population	0.000	0.000*	0.000*
	(0.000)	(0.000)	(0.000)
Distant	0.107	0.079	0.126
	(0.364)	(0.362)	(0.352)
Constant	0.489	1.048	1.158
	(0.849)	(0.863)	(0.870)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. A minor difference from table 3.7 is that the observation period begins in 1993 rather than 1990. Standard errors are clustered at CSD level.

Table 3.3C Regression Results on Entry at t and the Proportion of Charities Receiving Funds at t – 1, t, and t + 1, with Average Income as a Key Independent Variable, 1991-2021

Variables	en_t	en_t	en_t
Fund_t-1	0.068		
	(0.242)		
Fund_t		1.617***	
		(0.263)	
Fund_t+1			1.436***
			(0.252)
Average Income	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
High School or Above (%)	1.053	0.008	0.090
	(1.052)	(1.071)	(1.061)
Average rent	-0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.001)
Immigrants (%)	-2.349**	-2.696**	-2.551**
	(1.050)	(1.063)	(1.095)
Unemployment Rate	2.022**	1.782*	1.789*
	(0.969)	(0.990)	(0.983)
Visible Minority (%)	4.170***	4.436***	4.331***
	(0.730)	(0.755)	(0.777)
Population	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Distant	0.833**	0.826**	0.834**
	(0.384)	(0.383)	(0.381)
Constant	0.341	0.387	0.398
	(0.758)	(0.742)	(0.738)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. A minor difference from table 3.7 is that the key independent variable is average income at CSD rather than the proportion of people below LICO at time t. Standard errors are clustered at CSD level.

Table 3.4C Regression Results on Exit at t and the Proportion of Charities Not Receiving Funds at t – 1, t, and t + 1, with Average Income as a Key Independent Variable, 1991-2021

Variables	ex_t	ex_t	ex_t
NoFund_t-1	1.028***		
	(0.254)		
NoFund_t		0.279	
		(0.239)	
NoFund_t+1			0.331
			(0.227)
Average Income	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
High School or Above (%)	1.746	1.494	1.356
	(1.126)	(1.148)	(1.145)
Average rent	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Immigrants (%)	-2.606**	-2.743**	-2.818**
	(1.159)	(1.172)	(1.170)
Unemployment Rate	2.625**	2.390**	2.323**
	(1.042)	(1.029)	(1.039)
Visible Minority (%)	1.654**	1.778**	1.807**
	(0.833)	(0.837)	(0.835)
Population	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Distant	-0.055	-0.046	0.007
	(0.403)	(0.403)	(0.392)
Constant	0.325	0.915	1.016
	(0.865)	(0.885)	(0.882)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. A minor difference from table 3.8 is that the key independent variable is average income at CSD rather than the proportion of people below LICO at time t. Standard errors are clustered at CSD level.

Table 3.5C Regression Results of Entry at t on Entry at t + 1, Using GMM, 1991-2021

Variables	en_t1
en_t	0.358***
	(0.132)
LICO (%)	3.904***
	(1.104)
Constant	0.485***
	(0.172)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. The dependent variable is the number of charity entries at t + 1, and the key independent variable is the number of entries at t, with the proportion of people below the LICO included as a control. Other variables are excluded from this specification, as their inclusion leads to multicollinearity in the GMM estimation.

Table 3.6C Regression Results of Exit at t on Exit at t+1, using GMM, 1991-2021

Variables	ex_t1
ex_t	-45.335
	(1,290.710)
LICO (%)	-143.645
	(4,033.944)
Constant	48.408
	(1,352.230)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. The dependent variable is the number of charity exits at t + 1, and the key independent variable is the number of exits at t, with the proportion of people below the LICO included as a control. Other variables are excluded from this specification, as their inclusion leads to multicollinearity in the GMM estimation.

Table 3.7C Regression Results on Entry at t and the Proportion of Charities Receiving Funds at t – 1, t, and t + 1, with LICO at t – 1 as a Key Independent Variable, 1991-2021

Variables	en_t	en_t	en_t
Fund_t-1	0.390		
	(0.270)		
Fund_t		1.503***	
		(0.409)	
Fund_t+1			1.386***
			(0.393)
LICO_t-1 (%)	0.687	0.570	0.659
	(0.998)	(0.995)	(0.997)
High School or Above (%)	0.406	-0.122	-0.035
	(1.155)	(1.143)	(1.148)
Average rent	0.001***	0.001**	0.001**
	(0.000)	(0.000)	(0.000)
Immigrants (%)	-0.035	-0.282	-0.208
	(1.278)	(1.265)	(1.267)
Unemployment Rate	2.026*	1.917*	1.789
	(1.084)	(1.105)	(1.102)
Visible Minority (%)	2.615***	2.770***	2.727***
	(0.843)	(0.855)	(0.853)
Population	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Distant	0.687*	0.675*	0.687*
	(0.352)	(0.358)	(0.356)
Constant	0.602	0.605	0.569
	(0.906)	(0.887)	(0.889)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. A minor difference from table 3.7 is that the key independent variable is the proportion of people below LICO at time t-1 rather than at time t. Standard errors are clustered at CSD level.

Table 3.8C Regression Results on Exit at t and the Proportion of Charities Not Receiving Funds at t – 1, t, and t + 1, with LICO at t – 1 as a Key Independent Variable, 1991-2021

Variables	ex_t	ex_t	ex_t
NoFund_t-1	0.985***		
	(0.264)		
NoFund_t		0.319	
		(0.262)	
NoFund_t+1			0.364
			(0.256)
LICO_t-1 (%)	1.750*	1.687*	1.673*
	(1.024)	(1.010)	(1.011)
High School or Above (%)	1.256	1.190	1.036
	(1.141)	(1.164)	(1.164)
Average rent	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)
Immigrants (%)	-2.123	-2.211	-2.338*
	(1.393)	(1.371)	(1.374)
Unemployment Rate	2.106*	1.946*	1.773
	(1.098)	(1.088)	(1.095)
Visible Minority (%)	1.087	1.164	1.237
	(0.917)	(0.899)	(0.900)
Population	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)
Distant	0.109	0.071	0.130
	(0.379)	(0.390)	(0.376)
Constant	0.316	0.779	0.903
	(0.898)	(0.920)	(0.925)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. A minor difference from table 3.8 is that the key independent variable is the proportion of people below LICO at time t-1 rather than at time t. Standard errors are clustered at CSD level.

Table 3.9C Regression Results on Entry Counts at t and the Interaction between Fund and LICO, 1991-2021

Variables	en_t	en_t	en_t
Fund_t-1	0.232		
	(0.320)		
Fund_t		1.572***	
		(0.343)	
Fund_t+1			1.427***
			(0.322)
LICO (%)	2.925***	1.867*	1.860**
	(0.993)	(0.993)	(0.945)
Fund_t-1 and LICO (%)	-2.683		
	(1.842)		
Fund_t and LICO (%)		0.156	
		(1.697)	
Fund_t+1 and LICO (%)			0.083
			(1.606)
High School or Above (%)	0.809	-0.371	-0.337
	(0.979)	(0.992)	(0.975)
Average rent	0.001	0.001	0.001
	(0.000)	(0.001)	(0.001)
Immigrants (%)	-1.618	-1.755*	-1.652
	(1.047)	(1.066)	(1.083)
Unemployment Rate	1.665*	1.282	1.323
	(0.973)	(0.993)	(0.977)
Visible Minority (%)	2.900***	2.995***	2.949***
	(0.646)	(0.663)	(0.679)
Population	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Distant	0.824**	0.845**	0.849**
	(0.354)	(0.359)	(0.357)
Constant	0.512	0.796	0.809
	(0.754)	(0.740)	(0.730)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. A minor difference from table 3.7 is the inclusion of interaction terms between funding at t-1, t, and t +1 and LICO at t. Standard errors are clustered at CSD level.

Table 3.10C Regression Results on Exit Counts at t and the Interaction between Fund and LICO, 1991-2021

Variables	en_t	en_t	en_t
NoFund_t-1	0.957***		
	(0.287)		
NoFund_t		0.210	
		(0.278)	
NoFund_t+1			0.271
			(0.287)
LICO (%)	1.198	0.937	1.231
	(1.418)	(1.393)	(1.496)
NoFund_t-1 and LICO (%)	-0.418		
	(2.118)		
NoFund_t and LICO (%)		-0.016	
		(2.036)	
NoFund_t+1 and LICO (%)			-0.577
			(2.183)
High School or Above (%)	1.813*	1.650	1.431
	(1.052)	(1.064)	(1.062)
Average rent	-0.001**	-0.001**	-0.001***
	(0.000)	(0.000)	(0.000)
Immigrants (%)	-2.485**	-2.609**	-2.674**
	(1.139)	(1.152)	(1.155)
Unemployment Rate	2.378**	2.219**	2.091**
	(0.940)	(0.929)	(0.937)
Visible Minority (%)	1.391*	1.489*	1.517*
	(0.785)	(0.786)	(0.790)
Population	0.000	0.000**	0.000**
	(0.000)	(0.000)	(0.000)
Distant	0.022	0.008	0.056
	(0.390)	(0.381)	(0.371)
Constant	0.243	0.801	0.971
	(0.820)	(0.831)	(0.832)

Note: ***, ** and * denote a significance level of 1%, 5% and 10%, respectively. A minor difference from table 3.8 is the inclusion of interaction terms between funding at t − 1, t, and t + 1 and LICO at t. Standard errors are clustered at CSD level.