THREE ESSAYS ON PUBLIC ECONOMICS

A Dissertation

by

SUNYOUNG LEE

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Chair of Committee,	Yu Yvette Zhang
Committee Members,	Yonghong An
	David J. Leatham
	Ximing Wu
Head of Department,	Mark Waller

May 2021

Major Subject: Agricultural Economics

ABSTRACT

The research involves three studies. The first study examined state-level marijuana legalization and its impacts on crime rates. The second study explored the nudging technique—deliberate and impulsive type information—to promote charitable giving to food banks amidst the COVID-19 pandemic. The final study analyzed the transformation of donation decisions under the impact of the COVID-19 pandemic for food banks and other nonprofit organizations. The major findings are as follows: 1) While the results from difference-in-differences and the synthetic control methods showed mostly insignificant relationships between recreational marijuana legalization and crime rates as extant literature, significant increases in crime rates were found when used synthetic control inference with staggered adoption. 2) The second research confirmed that deliberate nudging information is more efficient to increase donation rate for food banks during the COVID-19 pandemic and that how to frame donation timing affects giving decisions as well. Also, the deliberate nudging information was particularly more efficient in increasing the giving rate of those with low empathy. 3) The final study provided a detailed decomposition of changes in actual giving decisions and found the probabilities of changes in giving decisions for food banks and other nonprofit organizations before and after the COVID-19 outbreak by individuals' characteristics. The results from using the conditional inference tree suggest that the experience as a food assistance recipient and marital status are the prominent factors to explain the changes in donation status under the impact of the COVID-19.

DEDICATION

To God alone,

who taught me the fear of the LORD is the beginning of wisdom

ACKNOWLEDGMENTS

I would like to express my special thanks of gratitude to my committee chair, Dr. Zhang, and Dr. An, Dr. Leatham, Dr. Nayga, and Dr. Wu, for their guidance and support throughout this research. I would also thank Pulkit Marwah for his kind help and cooperation.

Thanks also go to my friends and colleagues including Jennifer Kee, Chrystol Thomas, and Lizzy (Lizhihan) Yu making my time at Texas A&M University a great experience.

Finally, thanks to Maya Zhan and Raley Kirk for their assistance in preparing the questionnaire and manuscript.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supervised by a dissertation committee consisting of Professors Yu Yvette Zhang, David J. Leatham, and Ximing Wu of the Department of Agricultural Economics, Professor Yonghong An of the Department of Economics. This work was supervised also by Professor Rodolfo M. Nayga, Jr. of the Department of Agricultural Economics and Agribusiness of the University of Arkansas.

The research ideas, and survey and experimental designs for Chapters 2 and 3 were provided by Professor Yu Yvette Zhang. The literature review for Chapters 2 and 3 was provided in part by Professors Yu Yvette Zhang and Rodolfo M. Nayga, Jr. The survey and experiment for Chapters 2 and 3 were conducted in part by Pulkit Marwah of the Department of Agricultural Economics.

All other work conducted for the dissertation was completed by the student independently under the advisement of Professor Yu Yvette Zhang of the Department of Agricultural Economics.

Funding sources

There are no outside funding contributions to acknowledge related to the research and compilation of the first chapter of this work. The second and third chapters of this study were made possible in part under Texas A&M University President's Excellence Fund -T3 Research Grant for Yu Yvette Zhang and Tyson Endowment Fund in Food Policy Economics for Rodolfo M. Nayga, Jr.

TABLE OF CONTENTS

LIST OF FIGURES

Page

LIST OF TABLES

Page

CHAPTER I

INTRODUCTION

The research involves three studies. The first study in chapter 2 examined state-level recreational marijuana legalization and its impacts on crime rates. The second study in chapter 3 explored the nudging technique—deliberate and impulsive type information—to promote charitable giving to food banks amidst the COVID-19 pandemic. The final study in chapter 4 analyzed the transformation of donation decisions under the impact of the COVID-19 pandemic for food banks and other nonprofit organizations. Finally, chapter 5 concludes this work.

Recreational marijuana legalization and crime rates

Marijuana legalization has been one of the top issues in the United States in the last decade. Since Colorado and Washington legalized it at the state level for the first time in the United States, the trend of its legalization has been accelerated. According to the Drug Policy Alliance report, 21% of the U.S. population lives in a state with legal medical and recreational marijuana and 41% with medical marijuana only (Drug Policy Alliance 2017). Accordingly, there are also rising concerns about its social impacts in diverse fields, such as public health, safety, youth, economy, and more. As Colorado (Amendment 64) and Washington (Initiative 502) legalized recreational marijuana and commercialized it in the same years, the current study used this data and evaluated the impacts of recreational marijuana legalization (RML) on crime rates.

History of the U.S. cannabis legality

The first prohibition of marijuana began in Massachusetts in 1911, and it required a prescription for sale. The prohibition trend expanded, and 29 states criminalized cannabis by 1933. In 1937, cannabis was prohibited at the federal level by the Marijuana Tax Act. Although medical use was still permitted, new fees and regulatory requirements significantly curtailed its use. Forty years later, the trend began to reverse. In 1973, Texas declared possession of four ounces or less to be a misdemeanor. In 1996, medical marijuana legalization (MML) started in California, followed by Nevada and Colorado in 2000. In 2012, and Colorado and Washington became the first two states to introduce recreational marijuana laws. Colorado Amendment 64 allowed the personal use and

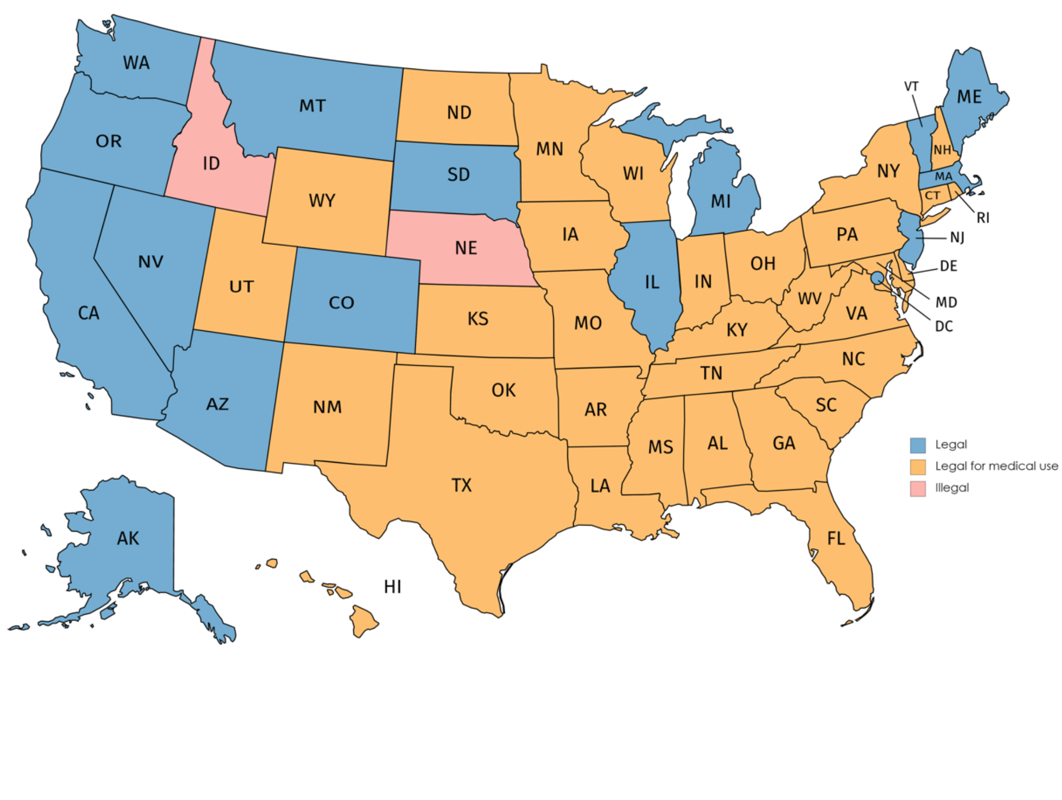


Figure 1.1. Legality of Cannabis in the United States in 2020

Note: Created with mapchart.net based on the data collected from Wikipedia (https://en.wikipedia.org/wiki/Legality_of_cannabis) regulation of marijuana for adults of 21 and over, commercial cultivation, manufacture, and sale regulating marijuana in a similar manner to alcohol. Washington Initiative 502 allowed possession of up to 1 ounce (28g) of marijuana by adults. In January 2014, commercial sales began in Colorado, and 6 months later, the first marijuana store opened in Washington as well. In 2016, California, Nevada, Maine, and Massachusetts joined the legalization of recreational cannabis. The legalization trend swept the U.S. as the House of Representatives passed the historic Marijuana Opportunity Reinvestment and Expungement Act (MORE Act) in 2019 to deschedule marijuana at the federal level.

The social impacts of the legalization have been very controversial, and its impact on the crime rate was not an exception. According to the Colorado Bureau of Investigation, the violent crime rate increased in five straight years after the law change. Violent crime rate increased by 5.99% in 2015, 8.23% in 2016, 7.57% in 2017, and 7.95% in 2018. The murder rate skyrocketed by 9.25% in 2016, and 14.81% in 2017. The number of hate crimes was 185 in 2018, up from 96 in 2017 (Colorado Crime Statistics 2018). Such reports caused serious concerns to the public and related officials. John Hickenlooper, the long-time governor of Colorado, even mentioned the possibility of banning marijuana again for this reason (McLean and Weisfeldt 2018).

However, the opposite trend in crime rate appeared in Washington after RML. Although the overall U.S. crime rate showed a decreasing trend, the decrease in Washington State's crime rate was particularly eye-catching, as it recorded double-digit decreases since 2011. Some argued that legal marijuana has had an impact on Washington State's decreasing crime rate because trading marijuana is legally protected and safer after the law change. However, this decreasing trend in Washington State started even years before marijuana legalization became effective. It would be worth studying to see if RML should take credit for it. Therefore, this research aims to provide a precise analysis of the relationship between crime rate changes and recreational marijuana legalization.

Donation to food banks amidst the COVID-19 pandemic

The second topic examines how to promote charitable giving to food banks amidst the COVID-19 pandemic using information nudge techniques. The economic fallout from the COVID-19 pandemic drove up the rate of food insecurity across America. Philanthropy played a critical role in society to fill the gap that is beyond the reach of a government or a market (Osili 2020) during the COVID-19 as it has been in other previous crises, and so did food banks. Feeding America, the largest network of U.S. food banks, reported in November 2020 that they experienced an overall 50% increase in demand since the COVID-19 outbreak and estimated that 54 million people in the U.S. could face food insecurity. After the COVID-19 outbreak, from March to October 2020, food banks served an estimated 4.2 billion meals nationwide in the U.S. (Feeding America 2020)

The charitable giving market in the U.S. has been growing through good and bad times. Historically, the growth rate of the donation was one-third of the stock market, and its market size matches 2.1% of GDP in 2018 (Giving USA 2020). According to a Charities Aid Foundation report in 2019, 62% of Americans have donated in the last 12 months. Giving to the poor has been the second most popular cause in the U.S. charitable giving market (Charities Aid Foundation 2019). The biggest source of the contributions is from individuals. In 2019, the estimated sum of the contributions from individual giving was about 69% of total giving (Giving USA 2020). Therefore, it is critical to understand how individuals make giving decisions. For this purpose, the current research examined the types of information given by charities that would efficiently promote individuals' giving to food banks.

Transformation in donation behavior under the impact of the COVID-19 pandemic

The third topic explores who charitable behavior has been changed under the impact of the COVID-19 pandemic. In times of major crises, many aspects of people's lives are affected, and altruism toward the impacted is a prominent reaction that people have. COVID-19 has greatly transformed people's lives, and donation behavior would not be an exception. Philanthropy plays a critical role in society to fill the gap that is beyond the reach of a government or a market in times of crisis, (Osili 2020), and it needs to play an important role more than ever during the unprecedented COVID-19 pandemic. For example, after the COVID-19 outbreak, from March to October 2020, food banks served an estimated 4.2 billion meals nationwide in the United States, and the number of meals served in October was 50% higher than the same time last year (Feeding America 2020). For a nonprofit organization (NPO) such as a food bank, charitable giving is essential, therefore understanding how donation patterns changed under the impact of the COVID-19 would be critical.

While gifts from celebrities or some corporations often get the limelight, the biggest contribution has been from individuals (Giving USA 2020). In the United States, about 90% of individuals give to at least one charitable cause per year (Dellavigna et al. 2012), and especially when humanitarian crises hit, many people would like to make monetary contributions out of their generosity. Rooney (2017) found that after Katrina, around half of Americans donated money, and almost 75% gave after 911. He said that the typical amount was $50 per household, and few households donated over $100 for both crises. In 2019, the gifts from individuals were $309.66 billion or 69% of total giving, which was the largest source of giving (NPT 2020). Therefore, studying the patterns of, or changes to, individual giving would be critical for philanthropy to play its role in society. Center for Disaster Philanthropy (CDP) also found that going through 2017 and 2018 which were the first and fourth most costly years in the United States with the occurrence of 30 major natural disasters, about 31% and 29% of the United States' households made disaster-related contributions in 2017 and 2018 respectively. Considering the size of contributions from individuals and the role of philanthropy during disasters, the purpose of this study is to explore the transformation in the charitable giving behaviors during the unprecedented crisis of the COVID-19 pandemic.

CHAPTER II

RECREATIONAL MARIJUANA LEGALIZATION AND CRIME RATES

Introduction and literature review

This chapter aims to provide a precise analysis of the relationship between crime rate changes and recreational marijuana legalization. Few pieces of literature studied the relationship between state-level recreational marijuana legalization and crime rates. Among them, there are two main approaches to address the topic. One approach used geospatial data of marijuana dispensaries and studied its impact on crime rates in the local and neighboring regions, and the other used comparative methodology using state-year panel data with RML as a treatment in the treated states. Fisher et al. (2017) studied the relationship between marijuana outlets and crime rates in the transition period from medical marijuana law to recreational marijuana law. They argued that areas adjacent to marijuana outlets experienced an increase in property crime rate, but the density of marijuana outlets did not affect the crime rates in local areas of Denver, Colorado. However, Hughes et al. (2020) studied a similar topic and suggested very different results. They examined crime rates in the relation to the locations of medical and recreational marijuana dispensaries in Colorado and found that most of the crime rates increased except for murder and motor vehicle crime rates using Bayesian spatiotemporal Poisson regression. However, Colorado and Washington experienced very different crime trends. It remains uncertain if the significant increases in Colorado would be limited to Colorado only or could be generalized to other regions. Dragone et al. (2019) examined the crime rate and RML in Washington and Oregon using

Difference-in-Spatial-Discontinuity design and found reductions in rape and property crime rates in the Washington-Oregon border area.

Lu et al. (2019) studied the impact of cannabis legalization on the crime rate in Colorado and Washington during 1999-2016 using time series analysis. Their results suggested that recreational marijuana law had a minimal effect on crime rates in Colorado and Washington states. Wu et al. (2020) explored how RML affected crime rates in CO and WA, and the neighboring states using difference-in-differences (DID). They argued that Colorado experienced significant drops in property crime rates, but the effect of RML in neighboring regions may vary depending on the types of crimes and states. Maier et al. (2017) examined the impacts of changing marijuana law on crime rates in the states that decriminalized or legalized cannabis and found that there existed no significant relationship with crime rates between 2010 and 2014.

Most of the extant literature that used DID approaches argued that RML had insignificant or negative impacts on crime rates. The DID model is built based on parallel trend assumption, which is violated in this research setting. This is where the synthetic control method (SCM) could be a useful alternative to construct a good counterfactual with a data-driven procedure. Using SCM, Chu et al. (2019) studied the effect of MML on crime rates and found on strong effect in individual states except for California where both violent and property crime rates and decreased by 20%. Moreover, Wu et al. (2021) found some evidence demonstrating a crime-exacerbating effect of RML including property and violent crime overall, as well as other crimes such as burglary, motor vehicle theft, larceny, and aggravated assault in Oregon. However, Cao and Lu (2019) argued that SCM also has its limitation as well since it cannot use the data of late-adoption states, which may lead to losing the closer fit to the treated states.

Data

The crime data used in this study was collected from the publicly available website of the Federal Bureau of Investigation (FBI), which collects U.S. crime data through the Uniform Crime Reporting Program (UCR). Every month, law enforcement agencies voluntarily report the number of crimes happening in their jurisdictions, and the FBI annually reports the crime statistics. FBI UCR classifies crimes into two broad categories—violent and property crimes. Violent crimes include aggravated assault, forcible rape, murder, and robbery; property crimes include arson, burglary, larceny-theft, and motor vehicle theft. However, the definition of rape was revised in 2013, and the number of rapes was counted differently according to the change in its definition. Unfortunately, neither old nor new definitions of rape have long enough panel data to be used. Moreover, the degree of reporting arson varies by agency. Thus, rape and arson were excluded from this study. Population data and number of law enforcement data were also obtained from FBI UCR.

The panel data consists of 51 units including 50 states and the District of Columbia for 19 years (2001-2019), but the numbers of years and states used to run regressions varied across the model types in this study. This is because the SCM requires a long pre-treatment panel than DID (Cao and Lu 2019). The years of recreational and medical marijuana legalization by states are described in Table A.1 in Appendix A. The states with MML only were used as a control group for DID methods in this study. The states with MML represent the states that maintained medical marijuana law during 2007-2018 and did not adopt RML, and there were 4 MML states—HI, MT, NM, RI—that meet the condition. I restricted the period to be 2007-2018 since there is a trade-off between the number of states in the control group and the longer panel period. Colorado and Washington State are the treatment group.

‘Drinking’ represents the percentage of the adult population who reported binge drinking. Centers for Disease Control and Prevention (CDC) defines binge drinking as 4 or more drinks for a woman or 5 or more drinks for a man on an occasion in the last 30 days. ‘police’ is the number of law enforcement officers per 1,000 people. Some may argue that the ‘police’ variable could be endogenous to explain the changes in crime rates. However, in reality, in a relatively short period of 10 years, the number of law enforcement officers can be considered as predetermined or affected by other state-specific conditions such as budget.

Summary statistics

Table 2.1 shows the summary statistics for crime rate and other control variables for the United States, the four states with MML, Colorado, and Washington separately from 2007 to 2019. According to the summary statistics, the overall violent crime rates of Colorado and Washington were lower than the average of the United States, but the property crime rates were higher in these two states. Especially, Washington State had a much higher property crime rate of about 3,506 per 100,000 people, while the U.S. average was 2,700.

Figure 2.2 illustrates the trends of each type of crime for the U.S., Colorado, and Washington State. The left column represents the rates for the total violent crime and its sub-categories, the right column represents the rates for the total property crimes and its sub-categories.

The overall violent crime rate trends of the U.S. and Washington evolved in similar patterns although the average U.S. violent crime rate has been much higher. However, the violent crime rate trend of CO was in a very different shape from the trends of the U.S. and WA, experiencing a rise since 2014. This is also the case for assault rate trends. The large increases in murder and assault rates of Colorado are also prominent.

The trends of overall property crime rates of the U.S. and Washington State were decreasing while the property crime rate of Colorado did not change much at the level of around 2,600-2,800. The burglary rate trends of CO, WA, and U.S. were downward, but the decreasing rate of CO was slower than the trends of the other two.

As shown in the graphs in Figure 2.2, the crime rate trend changes were in very different shapes across the different regional units. We can tell, even at first glance, that the parallel trend assumption is violated. In particular, the motor vehicle theft rate trends were very different in their patterns. Washington State experienced huge fluctuations in motor vehicle theft rate, and its rate in Colorado soared since 2014, while the U.S. average did not change much. Therefore, the DID method may not produce reliable estimates in such a condition

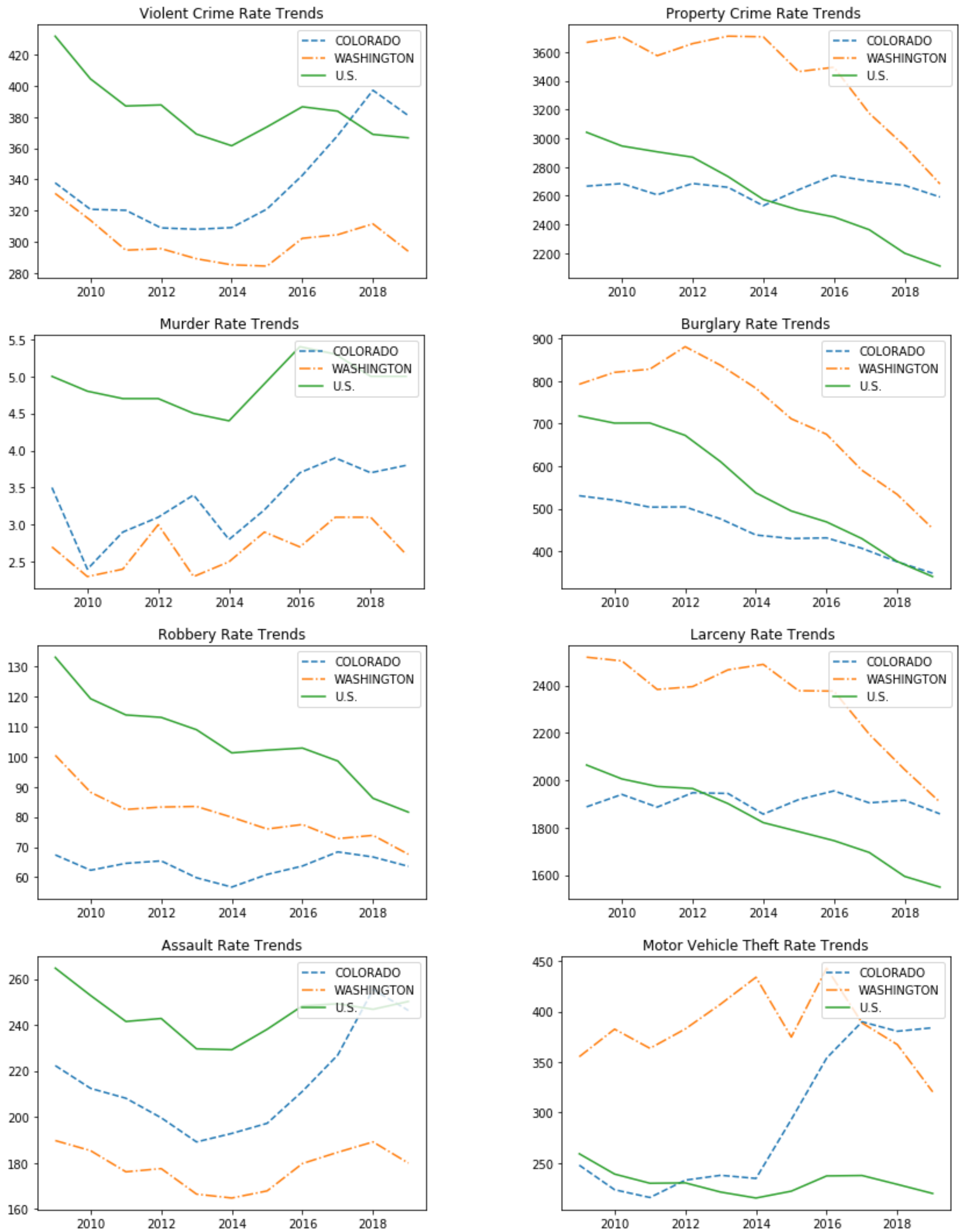


Figure 2.1. Crime rate trends

Note: crime rates are per 100,000 people.
Source: FBI Crime Data Explorer (https://crime-data-explorer.fr.cloud.gov/)

Table 2.1. Summary statistics

	U.S.			States with MML		
Variables	Obs.	Mean	Std.Dev.	Obs.	Mean	Std.Dev.
violent	663	386.567	190.222	52	372.596	183.247
murder	663	4.807	3.343	52	3.569	2.17
robbery	663	95.584	85.621	52	67.367	36.012
assault	663	247.785	119.197	52	258.531	148.228
property	663	2700.214	735.23	52	2924.012	652.429
burglary	663	559.186	233.319	52	572.358	250.155
larceny	663	1909.869	482.583	52	2065.427	381.02
vehicle	663	231.161	129.185	52	286.237	115.178
police	663	3.057	.958	52	2.663	.578
unemployment	663	5.875	2.247	52	5.787	2.225
population	663	15.136	1.034	52	14.094	.287
drink	663	16.57	3.251	52	17.438	2.526

	Colorado			Washington		
Variables	Obs.	Mean	Std.Dev.	Obs.	Mean	Std.Dev.
violent	13	338.892	28.688	13	305.392	17.48
murder	13	3.285	.438	13	2.708	.281
robbery	13	64.508	3.944	13	82.785	9.797
assault	13	217.154	20.503	13	180.631	9.993
property	13	2694.708	120.541	13	3505.531	367.417
burglary	13	471.354	73.866	13	732.331	131.839
larceny	13	1929.977	58.52	13	2370.592	205.759
vehicle	13	293.377	67.682	13	402.631	63.958
police	13	3.278	.189	13	2.127	.084
unemployment	13	5.285	2.243	13	6.477	2.031
population	13	15.481	.056	13	15.762	.053
drink	13	18.092	1.39	13	16.008	.93

Note: Crime rates are per 100,000 people.
Source: FBI Crime Data Explorer (https://crime-data-explorer.fr.cloud.gov/)

Model specifications

Difference-in-differences

DID with fixed effects model is one of the most frequently used models for a comparative study of policy intervention (Fredriksson and Oliveira 2019) assuming that controlled and treated states follow parallel trends. The current research aims to find out the impact of recreational marijuana legalization on crime rates for the states that previously had had medical marijuana laws. The treatment is the law change from medical marijuana law to recreational marijuana law. The treatment group includes Colorado and Washington State that experienced the law changes, and the control group includes the states that maintained medical marijuana laws during 2007-2018. The state fixed effects were also included to control for time-constant factors for each state; and the time fixed effects, for common factors of all states, for in each given year.

$$\log (CrimeRate_{st}) \\ = \alpha_s + \lambda_t + \beta\, RML_{st} + \gamma\, Z_{st} + \varepsilon_{st}$$

where s indicates state, t represents year, α_s are state fixed effects, λ_t are time fixed effects, RML is a binary indicator for recreational marijuana legalization, which equals to 1 if the intervention happened, Z_{st} is a vector for observed characteristics, and ε_{st} is an error term. The identifying assumption for the model above is that the controlled state provides a good counterfactual for the treated states in the absence of recreational marijuana legalization.

Table 2.2 presents that recreational marijuana legalization may not have significant effects on crime rates. Also, such results are consistent with a previous study that analyzed the impacts of marijuana legalization on certain aspects of society. However, because the assumption on parallel crime rate trends was violated, using the DID model would not be recommended in this context.

Synthetic control method

The SCM can be a desirable alternative to DID to find the impact of RML on crime rates (Abadie et al. 2010). The SCM aims to construct the counterfactual for treated states, Colorado and Washington, in the absence of RML by allowing for the controlled states in the donor pool to have different weights. The SCM is a particularly helpful tool when a treatment group has only a few units with a long panel. Here I adopt the methodology of Abadie et al. (2010). Although negative weights or weights greater than one are possible, this study restricted a synthetic control to be a convex combination of controlled states,

$$\|X_1 - X_0W\|v = \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)}$$

where W is an (S ×1) vector of non-negative weights that sum to one and $W = (w_2, \dots, w_s, w_{S+1})'$. Subscript s represents each state with 1 being the treated state, and s belongs to [2, S+1] which are the untreated state in donor pool. S is the total number of untreated states. X_1 is a (k × 1) vector of preintervention characteristics including observed covariates (Z_{st}) and X_0 is for the states in the donor pool. V is (k × k) symmetric and positive semidefinite matrix. W^* is (S × 1) vector of specific weight chosen to minimize $\|X_1 - X_0W\|$ so that synthetic states reproduce the crime rates that would have been observed in the absence of RML. Then, the estimated treatment effect is as following:

$$\hat{\tau}_{1t} = Y_{1t} - \sum_{s=2}^{S+1} w_s^* Y_{st}$$

where Y_{st} is the outcome variable that represents crime rates.

Synthetic control inference for staggered adoption

Synthetic control inference for staggered adoption (SCISA) provides the dynamic average treatment effects on the treated (ATT) units using a treatment introduced to multiple units in different time frames (Cao and Lu 2019). This method overcomes the limitation of the DID model by avoiding the assumptions on homogeneity across treatment effects and on parallel trends. Also, it can employ more closely matched units for synthetic controls than the SCM. The SCM uses only untreated units dropping the units of late treatment which can be possibly the closest matches to the treated units, but SCISA uses all of the possible candidates by adopting event-time average treatment effects on the treated. The current research applied this methodology as it allows for examining the dynamic effects of RML on crime rates for all of the treated states. Following Cao and Lu (2019), the individual treatment effects of RML on crime rates are defined as

$$\tau_{i,t} = y_{i,t}(1) - y_{i,t}(0)$$

where $y_{i,t}(1)$ is the potential crime rate if state *i* adopted RML at year *t,* otherwise $y_{i,t}(0)$. Even time is defined as

$$e_{i,t} = \sum_{r \leq t} \mathbb{1}\{d_{i,r} = 1\}$$

where r is the year that a state legalized recreational marijuana.

$$ATT_s^e = \frac{\sum_{i,t} \tau_{i,t} \mathbb{1}\{e_{i,t} = s\}}{\sum_{i,t} \mathbb{1}\{e_{i,r} = s\}} = l'_s \hat{\tau}$$

For $l'_s = (\mathbb{1}\{e_{i,t} = s\} / \sum_{i,t} \mathbb{1}\{e_{i,t} = s\})_{(i,t) \in D.}$

Results

Difference-in-differences

Table 2.2 presents the results of the DID model. First, I combined the two RML states—Colorado and Washington—as a single treated group and ran a DID model with fixed effects (FE). The post-treatment period is 2012-2017, but the controlled group consists of four other states that maintained MML until 2018 to prevent a possible systematic difference between the states that adopted RML in 2018 and the rest of the MML states. Second, I ran the same models for Colorado and Washington separately. This is because the crime rates have been following very different trends across these two states as shown in Figure 2.2 and RML may have heterogeneous effects on the crime rates in the two treated states.

Whether the treated states were combined or individually regressed, the change in crime rates turned out to be mostly insignificant. Although there were some significant results on violent, assault, and larceny rates, the significant level was only at 10% level. Where Colorado and Washington States were combined into a single treatment group, the decrease in assault rate appeared to be significant ($p < 0.1$) controlling for fixed effect. When Colorado and Washington were separately regressed, the decreases in assault rates were also statistically significant ($p < 0.1$) for both states. Besides, we observe that the overall violent crime rate was decreased ($p < 0.1$) in Washington in comparison to the controlled states. However, the estimates for the effects on assault and overall violent crime rates were insignificant when covariates were included in the DID regressions. Therefore, the results from the DID model seemed to support the findings from previous literature that recreational cannabis legality may not have significant impacts or have only minimal effects on crime rates.

When running a regression with Colorado as a sole treated unit, we observe the increase in larceny rate ($p < 0.1$) and the insignificant effect on property crime rate that contradicts the findings of some extant literature. Brinkman and Mok-Lamme (2019) found a decrease in property crime rates using short-term local panels. Dragone et al. (2019) also showed a decreasing effect on property crime rates in Colorado. However, the results obtained from DID should be interpreted with care since parallel trend assumptions are violated.

Synthetic control method

To overcome the parallel trend assumption, the SCM method was applied. For a synthetic control unit, 39 states that never experienced recreational marijuana legalization until 2018 were selected into the donor pool. However, the current study did not rule out the states that had adopted legal medical marijuana law or decriminalization. Since the SCM seeks for the weighted average of a controlled state that would have shown similar changes in crime rates with the ones of Colorado and Washington based on the pretreatment period data, the smaller gap between treated and controlled states in the pre-RML period, the more accurate the estimated treatment effect.

Tables 2.3 and 2.4 show the outcomes for each crime type from using the SCM. The results of the estimates of violent crime rates in Colorado and Washington are illustrated in Figures 2.3 and 2.4 respectively. Figures 2.5 and 2.6 show the results for property crime rates. Since the SCM allows only one unit in a treatment group, the crime rates of Colorado and Washington were separately analyzed. In Figures 2.3-2.6, the left column shows the crime rate trends of treated and synthetic states; and the right column describes the effect of RML on crime rates, which is the gap of crime rates between treated and synthetic states. The vertical lines in 2012 represent the timing of the law intervention. As shown in these two figures, most of the crime rates in treated and synthetic control units evolved in a very similar pattern in the pretreatment period. The gap generated between 2011 and 2012 should not be interpreted as a gap before RML because the data is yearly.

The results from the SCM were mostly insignificant. Therefore, interpreting the values of the estimates would not be meaningful. However, in this section, I try to draw some insights from the changing patterns of the crime rates and treatment effects that evolved. Overall, the treatment effect estimates (the right columns of Figures 2.3 - 2.6), we observe mostly upward slopes for Colorado and fluctuations for Washington. As some previous studies concluded that RML brought reductions in crime rates in the affected states, some results were below zero in the first few years after RML. For example, the effect of RML on overall violent crime in Colorado was negative until 2017 (Figure 2.3). However, it increased and became positive in later periods. A similar pattern appeared for robbery and assault rates in Colorado. This may imply that the impact of RML on crime rates should be scrutinized in the long run.

As shown in the right column of Figure 2.5, all types of property crime rates in Colorado exhibited upward trends, and the trends were very similar in their shapes—decreased until 1-3 years before RML and rose again. However, since the upward slopes started 1-3 years before adopting RML, it is doubtful that if this was caused by RML. One possible explanation is that Colorado experienced some other event before RML that caused the increasing effect on crime rates. The other possible explanation is that people's anticipation of cannabis legality may cause the effect of RML earlier than the intervention year of 2012.

The graphs in the left column of Figure 2.5 presents the property crime rate changes for Colorado and synthetic Colorado. What commonly appeared is that the gap in property crime rates between Colorado and synthetic control became greater starting from 2014. This is the year that marijuana retail sales began in Colorado. Although it may require further studies, the commercialization of recreational marijuana could be a possible explanation for the increase in the gap.

The effects of RML on violent crime rates in Washington were very different in shape across crime types. For the overall violent crime rate and assault rate, the RML effect remained negative throughout, while the effect on the robbery rate was positive and mostly increasing in its magnitude. The overall property crime rate of WA had been higher than synthetic WA until 2018. The treatment effects of RML on the overall property crime and its sub-categories in WA experienced fluctuations and decreasing tendencies in later periods.

Placebo tests for the synthetic control method

Tables 2.3 and 2.4, and Figures 2.7 and 2.8 show the results of placebo tests. There is no standard method yet for inference of the SCM, but placebo tests are commonly used for inference of synthetic control methods (Abadie et al. 2010; Li 2020). If the effects in placebo states turned out to be as large as the effects of actually treated states, the treatment effects might have happened by mere chance. In the figures illustrating the results of placebo tests, the thin lines represent the thirty-nine untreated states receiving sham placebo treatments, and the thick line represents the treatment effects of real-treatment states.

In Tables 2.3 and 2.4, a standardized p-value is a p-value divided by its RMSPE in the pre-treatment period. As previously mentioned, the p-values here were large and most of the results were insignificant. This may be due to a small number of observations for each period and each treated state not having enough power to reject the null hypothesis. Therefore, it is not clear if

RML had a critical influence on the crime rates or if the data was not enough to investigate the true effect.

Synthetic control inference for staggered adoption

Previously, I used the SCM to show the dynamics of the RML effect on crime rates in Colorado and Washington. Although the SCM does not require a parallel trend assumption, the SCM uses untreated states only for synthetic control. This may not produce the best fit for synthetic control as the early treated states may have more common with the late-treated states than untreated states. Besides, the SCM focuses on the single treated state and cannot show the overall average treatment effect for all the treated states.

To overcome such limitations, the SCISA method (Cao and Lu 2019) was applied. This method would be a desirable alternative to study the dynamic effects of RML on crime rates for the following reasons. First, it shows how treatment effects evolve allowing for including late-treatment states using the SCM. Second, it does not require a large number of observations as the DID methodology does. Third, it allows the freedom to use all the states that adopted RML in later years. Forth, it estimates the averaged effects of ATT estimates for all the treated states, which is more efficient than exploring the treated effect separately for each state.

Table 2.5 shows the results obtained from using SCISA, and Figure 2.9 illustrates the long-run ATT effects over event time. The red dots represent the ATT estimates at each event time, blue lines represent the changes in the ATT estimates over years, and the error bars show the 95% confidence intervals of the estimates.

Figures 2.10 and 2.11 show treatment effects for each treated state with calendar time (graphs at the top) and event time (graphs at the bottom). Each color represents the treated states. In the calendar time graph, the dotted vertical line represents the last year (2011) before the first law intervention in CO and WA. Since this method uses all the treated states, the different treated times are normalized to be 1 in the event time graphs. The ATT estimates in Figure 2.9 represent the averaged value of the effects of all the treated states at each event time.

First, in the left column of Figure 2.9, we observe the clear positive results of RML on violent crime rates. For overall violent crime, the ATT estimate was much higher in the 7th event time, than the previous periods. In the 7th, the overall violent crime rate increased by 19.6% ($exp(0.1791) \risingdotseq 1.196,\ p < 0.05$). Please note that the dependent crime rate is logged crime rate per 100,000 people. The effect on the murder rate was negative in the 2nd and 3rd periods but became positive in the long run. At the 7th event time, the murder rate was higher than the synthetic control by 12.7% ($exp(0.1194) \risingdotseq 1.1268,\ p < 0.05$). The increase in the ATT effect on the robbery rate rose very sharply. Although RML seemed to have the effect of decreasing the robbery rate in the first few years, the robbery rate was up by 22.6% in the 7th period ($exp(0.1194) \risingdotseq 1.2256,\ p < 0.05$). The ATT estimate of assault rate showed fluctuations but remained positive since the 4th period. Therefore, the current results suggest that RML may have increased the violent crime rates in the affected states.

The graphs in the right column of Figure 2.9 show the ATT estimates for the property crimes. The ATT estimate of overall property crime was increasing but plunged in the 6th period. The ATT estimates of burglary and larceny dropped in the same period. The ATT on motor vehicle theft rate was negative in the first two periods, and it became positive and the estimate was 6.7% in the 7th period ($exp(0.0653) \risingdotseq 1.067,\ p < 0.05$). Overall, the ATT estimates for property crimes were positive as well in the long run.

Although the current research benefitted from using SCISA as it allows to observe the dynamic ATT estimates easily for all treated states, it has a limitation with the given limited data set. It would be ideal if long enough post-treatment panel data is available for all the treated states. However, RML is ongoing in the United States, and some states recently adopted the policy. While the length of the event time of Colorado and Washington states is 7, other late adoption states have shorter event times than that. Therefore, the number of treated states is different across event times. This could be problematic in the case that the early adoption states and the late adoption states were systematically different. In the 6th and 7th periods, the treated states are only two. Therefore, the sudden drops of ATT estimates of property crime rates in the 6th event time could be generated by the changes in treated states and not by the decreased effects.

Table 2.2. DID results

	Crimes	DID (1)	DID with Covariates (2)
Colorado &Washington	Violent	-0.100*	-0.131
		(0.053)	(0.085)
	Murder	-0.007	-0.099
		(0.117)	(0.122)
	Robbery	-0.109	-0.099
		(0.118)	(0.108)
	Assault	-0.103*	-0.134
		(0.041)	(0.076)
	Property	0.037	0.078
		(0.062)	(0.057)
	Burglary	0.037	0.128
		(0.104)	(0.124)
	Larceny	0.025	0.064
		(0.055)	(0.042)
	Motor vehicle theft	0.073	0.059
		(0.157)	(0.176)
Colorado	Violent	-0.068	-0.112
		(0.048)	(0.095)
	Murder	0.019	-0.074
		(0.118)	(0.139)
	Robbery	-0.063	-0.075
		(0.115)	(0.106)
	Assault	-0.106*	-0.144
		(0.041)	(0.086)
	Property	0.049	0.080
		(0.062)	(0.057)
	Burglary	-0.014	0.067
		(0.098)	(0.126)
	Larceny	0.042	0.076*
		(0.054)	(0.035)
	Motor vehicle theft	0.136	0.090
		(0.153)	(0.190)
Washington	Violent	-0.132*	-0.132
		(0.048)	(0.094)
	Murder	-0.032	-0.128
		(0.118)	(0.130)
	Robbery	-0.155	-0.137
		(0.115)	(0.117)
	Assault	-0.099*	-0.130
		(0.041)	(0.087)
	Property	0.026	0.076
		(0.062)	(0.062)
	Burglary	0.088	0.187
		(0.098)	(0.118)
	Larceny	0.007	0.051
		(0.054)	(0.044)
	Motor vehicle theft	0.009	0.030
		(0.153)	(0.188)

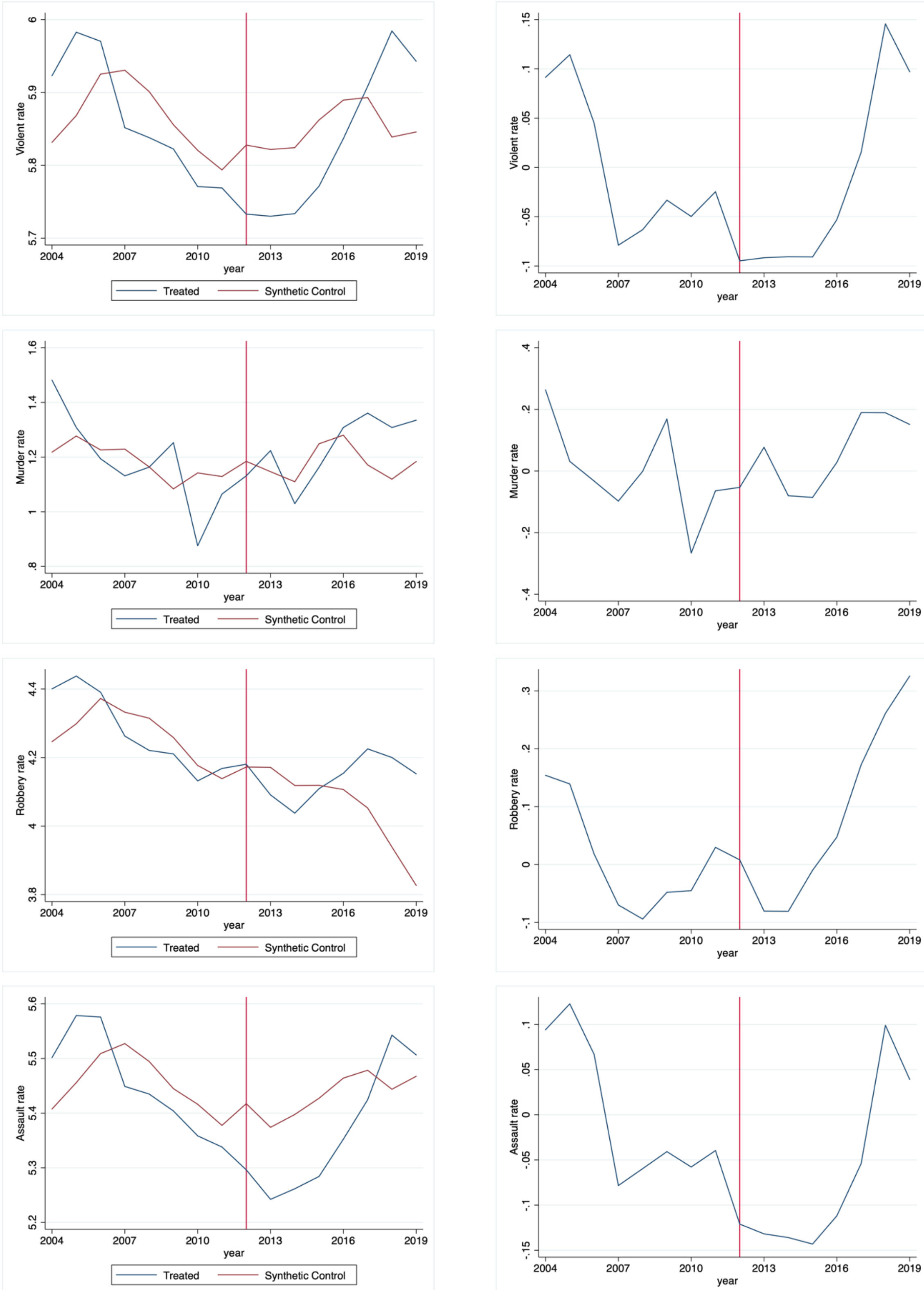


Figure 2.2. **Results for violent crime rates in CO**

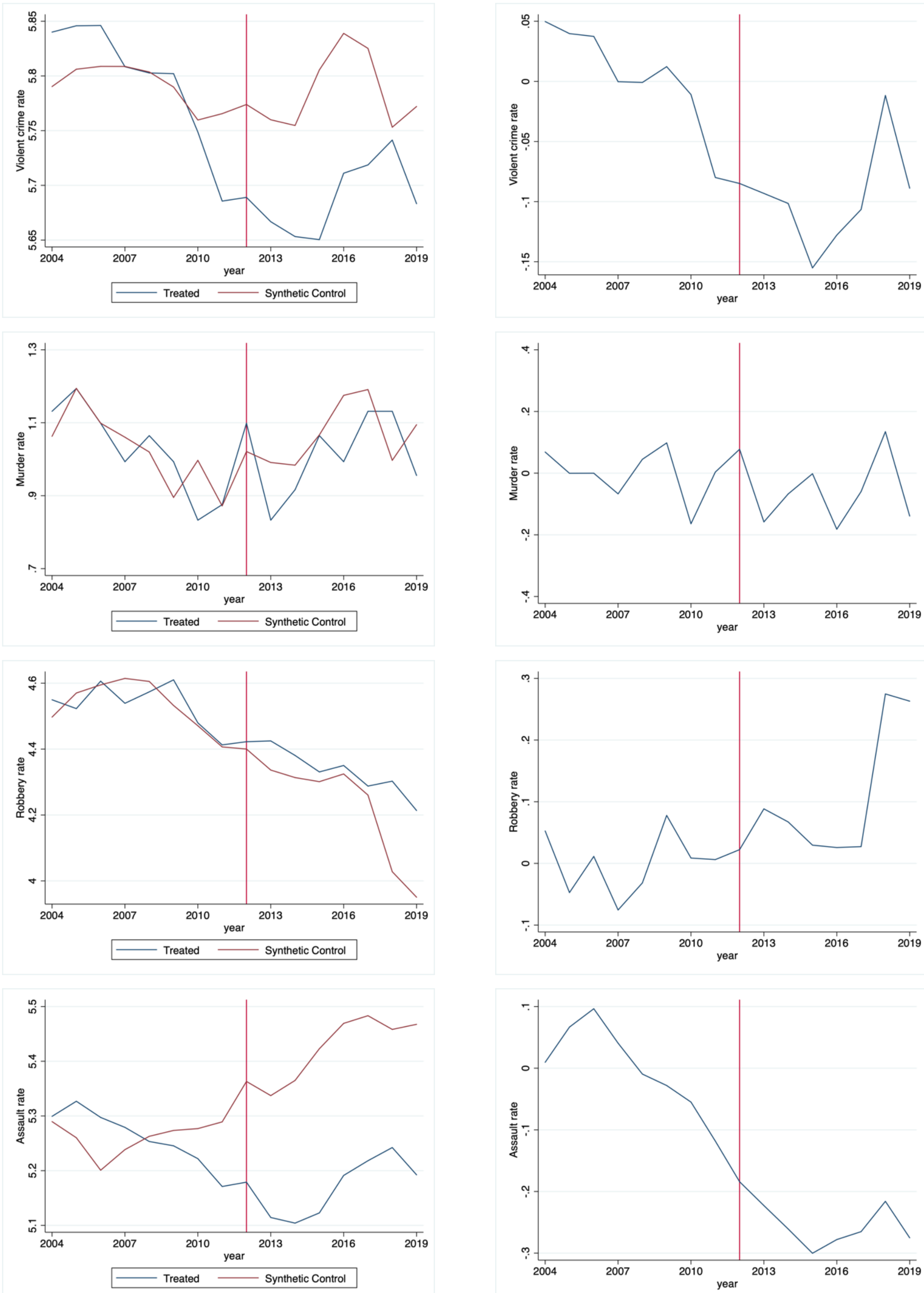


Figure 2.3. Results for violent crime rates in WA

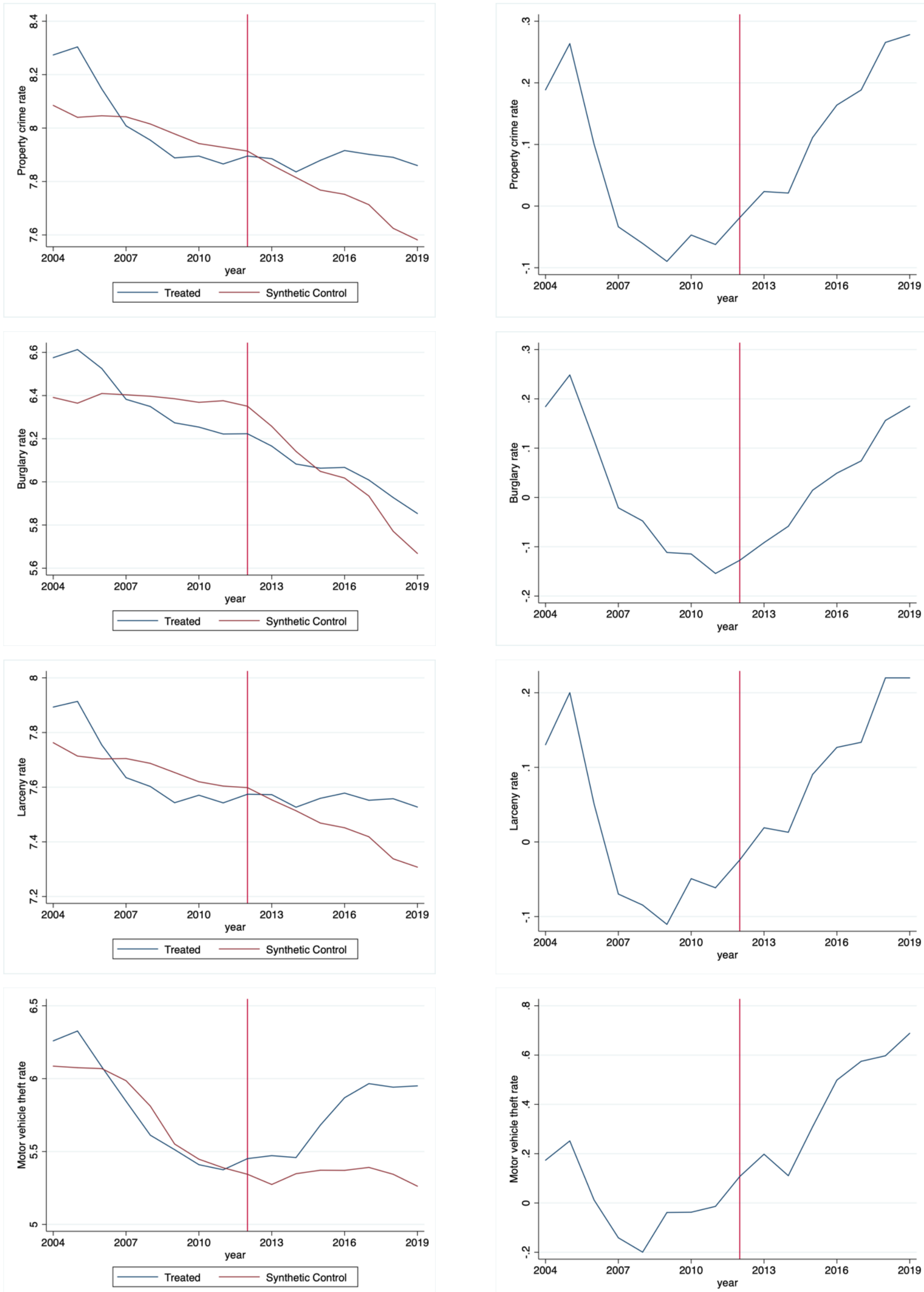


Figure 2.4. Results for property crime rates in CO

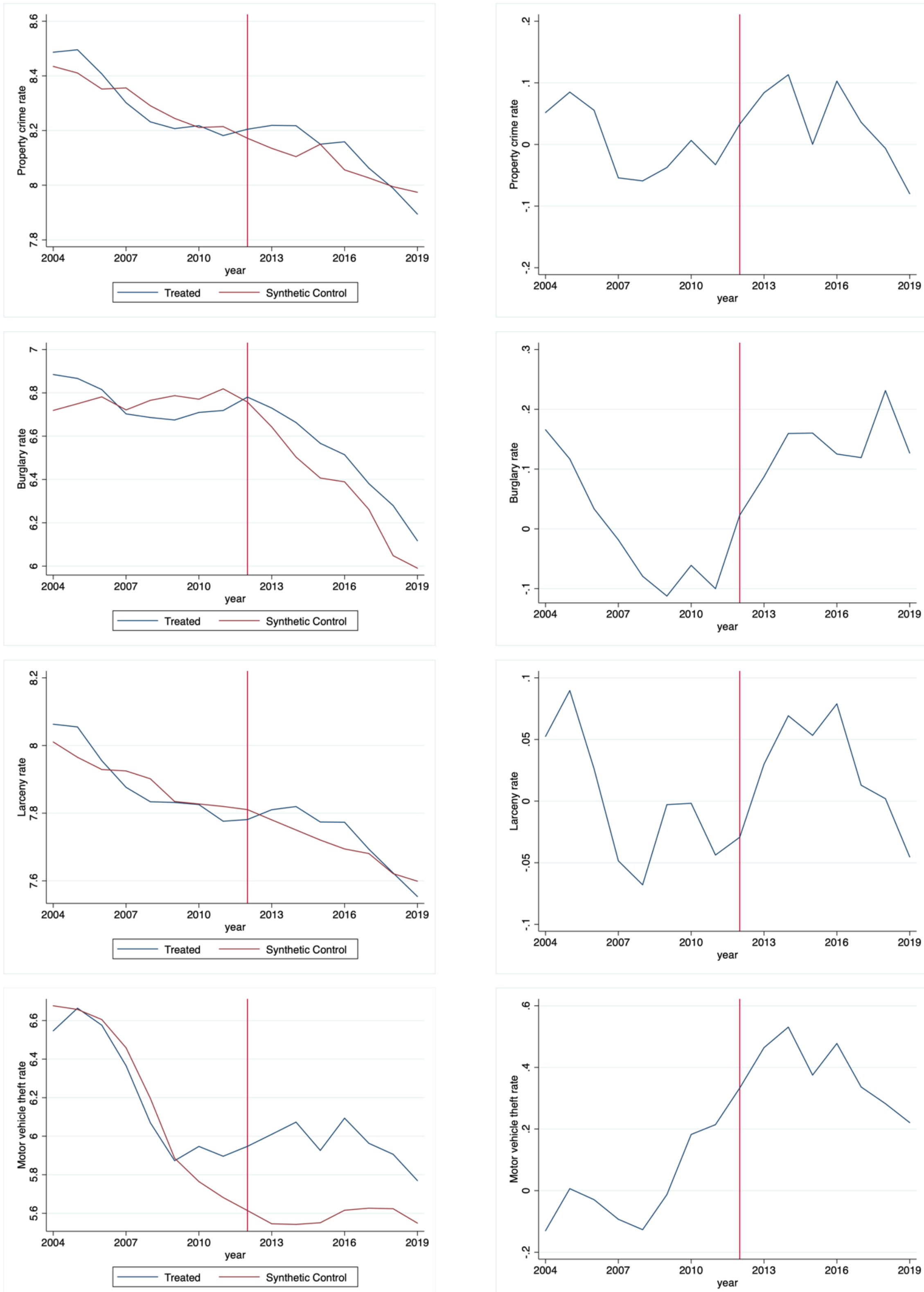


Figure 2.5. Results for property crime rates in WA

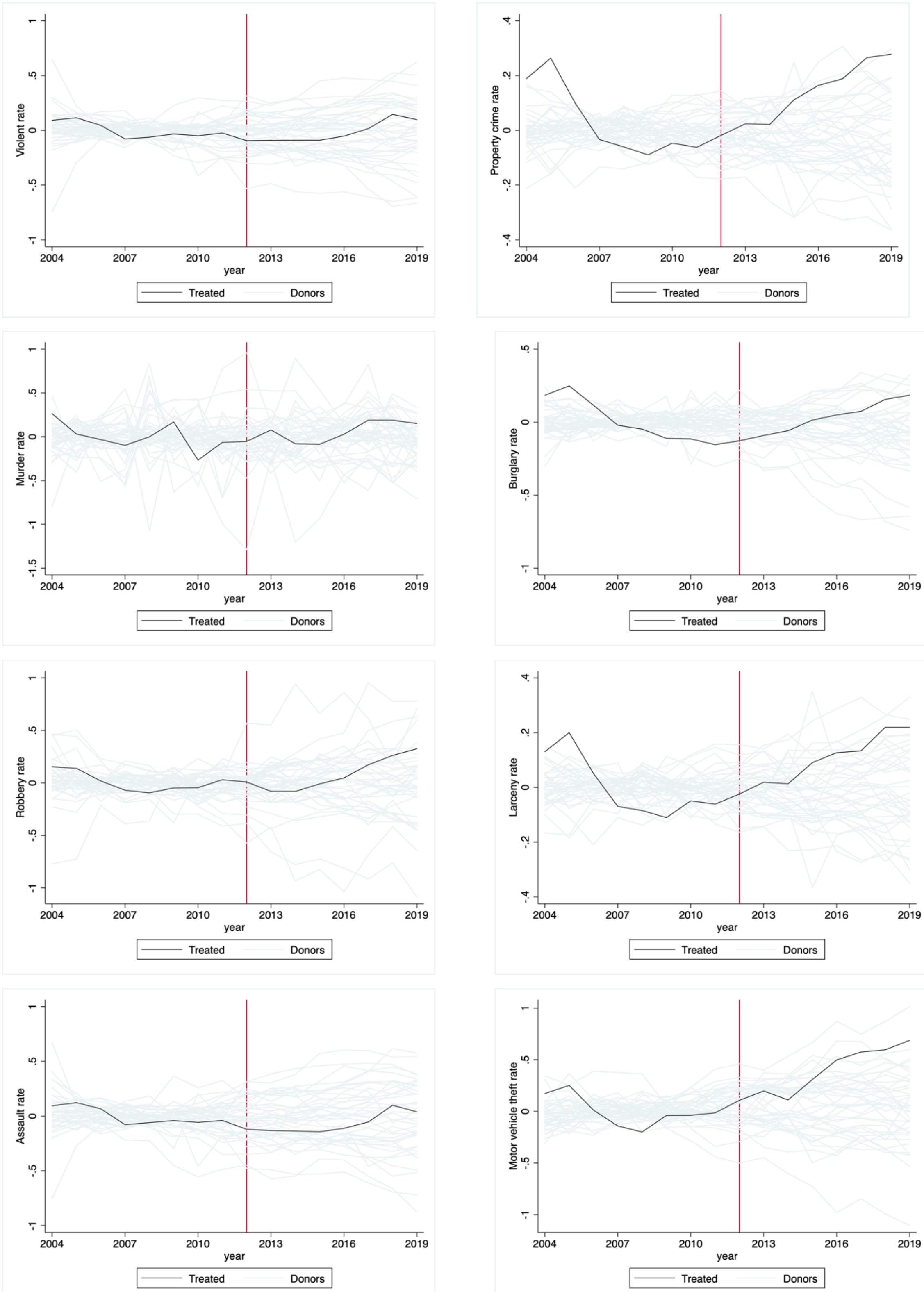


Figure 2.6. Placebo test results for CO

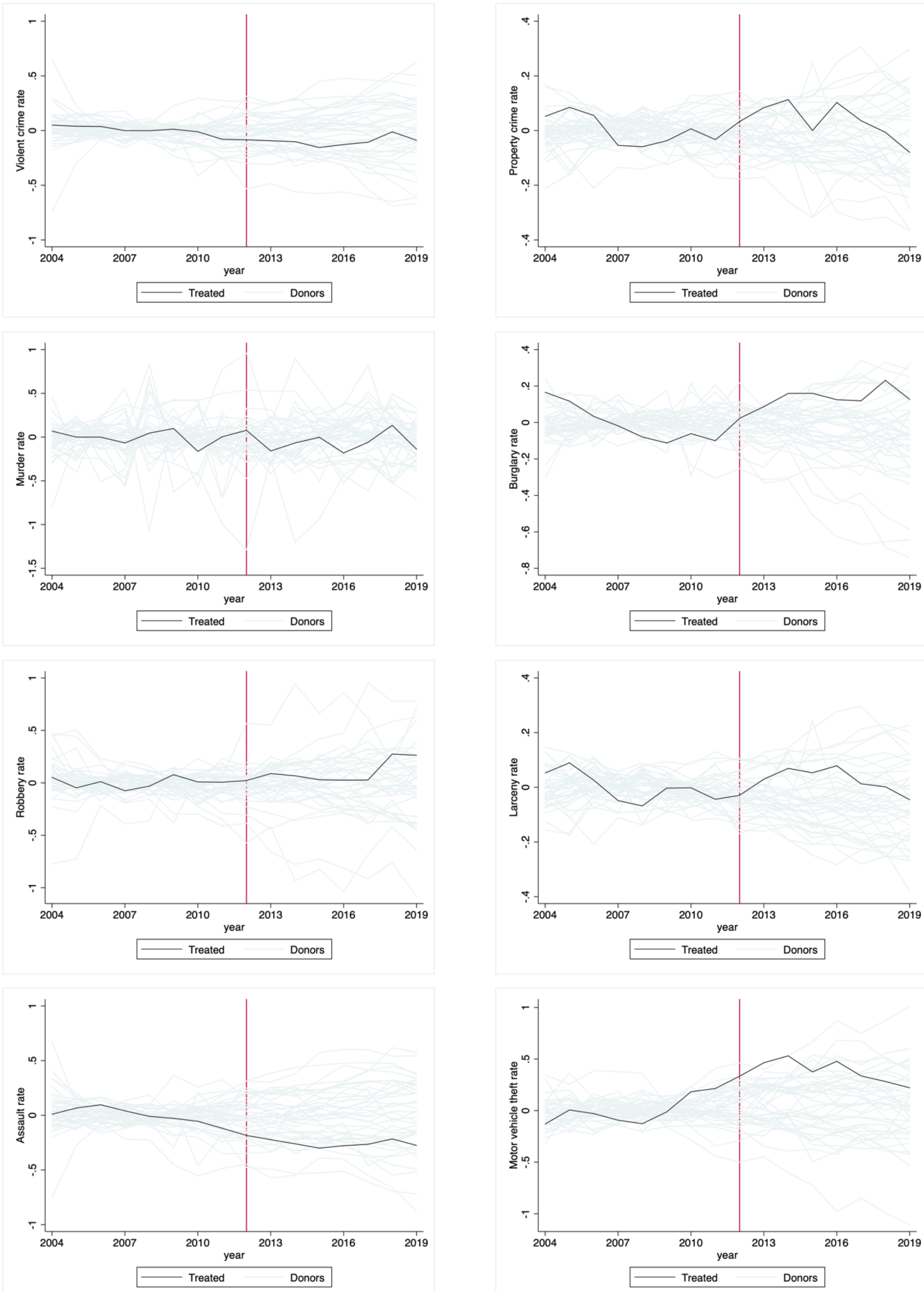


Figure 2.7. Placebo test results for WA

Table 2.3. SCM and placebo test results for violent crime rates

		Colorado			Washington		
	Event time	Coef.	P	Std P.	Coef.	P	Std P.
Violent crime	1	-0.095	0.538	0.487	-0.085	0.538	0.282
	2	-0.092	0.538	0.513	-0.093	0.538	0.205
	3	-0.091	0.641	0.667	-0.102	0.590	0.231
	4	-0.091	0.692	0.641	-0.155	0.462	0.154
	5	-0.053	0.846	0.821	-0.128	0.641	0.333
	6	0.015	0.974	0.974	-0.107	0.718	0.513
	7	0.146	0.641	0.641	-0.012	1.000	1.000
	8	0.097	0.769	0.769	-0.089	0.795	0.641
Murder	1	-0.053	0.821	0.795	0.078	0.641	0.410
	2	0.077	0.615	0.615	-0.158	0.410	0.077
	3	-0.080	0.692	0.769	-0.067	0.692	0.590
	4	-0.086	0.615	0.615	-0.002	1.000	1.000
	5	0.028	0.897	0.974	-0.182	0.410	0.154
	6	0.190	0.487	0.462	-0.060	0.692	0.538
	7	0.189	0.487	0.462	0.134	0.564	0.308
	8	0.151	0.410	0.385	-0.139	0.410	0.205
Robbery	1	0.008	0.949	0.974	0.022	0.846	0.718
	2	-0.080	0.641	0.692	0.088	0.615	0.359
	3	-0.081	0.538	0.538	0.067	0.564	0.462
	4	-0.010	0.949	0.974	0.030	0.897	0.795
	5	0.047	0.821	0.923	0.026	1.000	0.923
	6	0.172	0.564	0.487	0.027	0.846	0.846
	7	0.261	0.385	0.282	0.275	0.385	0.077
	8	0.326	0.359	0.282	0.263	0.436	0.077
Assault	1	-0.121	0.590	0.487	-0.184	0.385	0.128
	2	-0.132	0.590	0.436	-0.223	0.308	0.154
	3	-0.136	0.615	0.538	-0.261	0.179	0.077
	4	-0.143	0.641	0.487	-0.300	0.154	0.077
	5	-0.112	0.692	0.667	-0.278	0.256	0.179
	6	-0.054	0.872	0.897	-0.265	0.385	0.333
	7	0.099	0.821	0.821	-0.216	0.564	0.436
	8	0.039	0.949	0.923	-0.275	0.462	0.205

Table 2.4. SCM and placebo test results for property crime rates

		Colorado			Washington		
	Event time	Coef.	P	Std P.	Coef.	P	Std P.
Property	1	-0.019	0.769	0.949	0.033	0.615	0.769
	2	0.024	0.821	1.000	0.084	0.333	0.385
	3	0.021	0.795	0.949	0.113	0.128	0.308
	4	0.111	0.333	0.744	0.000	1.000	1.000
	5	0.164	0.128	0.641	0.103	0.410	0.385
	6	0.188	0.103	0.641	0.036	0.795	0.795
	7	0.266	0.026	0.615	-0.006	1.000	1.000
	8	0.278	0.103	0.718	-0.080	0.692	0.795
Burglary	1	-0.128	0.154	0.487	0.023	0.821	0.897
	2	-0.092	0.256	0.718	0.087	0.256	0.538
	3	-0.059	0.487	0.821	0.160	0.077	0.282
	4	0.015	0.821	0.923	0.160	0.256	0.487
	5	0.049	0.795	0.923	0.125	0.385	0.641
	6	0.074	0.564	0.872	0.119	0.436	0.564
	7	0.156	0.385	0.667	0.231	0.231	0.462
	8	0.185	0.385	0.718	0.127	0.538	0.718
Larceny	1	-0.024	0.718	0.897	-0.029	0.718	0.718
	2	0.019	0.769	0.872	0.030	0.692	0.769
	3	0.013	0.897	0.923	0.069	0.615	0.615
	4	0.090	0.436	0.718	0.053	0.744	0.744
	5	0.127	0.231	0.692	0.079	0.590	0.641
	6	0.134	0.282	0.692	0.013	0.923	0.923
	7	0.220	0.154	0.615	0.002	1.000	1.000
	8	0.220	0.154	0.615	-0.045	0.769	0.795
Motor vehicle theft	1	0.107	0.641	0.795	0.333	0.051	0.077
	2	0.198	0.487	0.667	0.464	0.000	0.128
	3	0.111	0.744	0.821	0.531	0.051	0.154
	4	0.309	0.308	0.487	0.375	0.205	0.333
	5	0.498	0.103	0.282	0.478	0.128	0.282
	6	0.575	0.077	0.231	0.336	0.256	0.436
	7	0.597	0.051	0.231	0.282	0.359	0.564
	8	0.688	0.051	0.128	0.221	0.538	0.692

Table 2.5. SCISA results

Event time	Crime	ATT est.	95% CI lower	95% CI upper	Crime	ATT est.	95% CI lower	95% CI upper
1	Violent	0.0281	0.0217	0.0334	Property	-0.034	-0.0395	-0.0288
2		-0.0288	-0.0368	-0.0242		-0.0038	-0.0065	0.0057
3		-0.0162	-0.0246	0.0002		0.0214	0.0168	0.0462
4		0.0197	0.017	0.0368		0.1249	0.1113	0.1489
5		0.075	0.0732	0.0951		0.1816	0.1706	0.2009
6		0.0435	0.0342	0.0626		0.004	-0.0229	0.0403
7		0.1791	0.17	0.1881		0.0216	-0.0047	0.0337
1	murder	-0.03	-0.0624	0.0203	Burglary	-0.0749	-0.0956	-0.0677
2		0.0351	0.0351	0.072		-0.0236	-0.0443	-0.013
3		-0.0801	-0.0811	-0.046		-0.0069	-0.0227	0.014
4		0.0077	-0.001	0.0233		-0.0213	-0.0368	-0.0037
5		0.0489	0.0269	0.092		0.0014	-0.0058	0.0368
6		0.0393	0.0452	0.113		-0.039	-0.0394	0.0014
7		0.1194	0.1353	0.2118		0.0563	0.0525	0.0698
1	Robbery	-0.1484	-0.1601	-0.1281	Larceny	0.008	-0.0006	0.021
2		-0.1018	-0.1095	-0.0862		0.0379	0.0273	0.0485
3		-0.0789	-0.0766	-0.0622		0.0679	0.0576	0.0844
4		0.0589	0.0523	0.0629		0.1364	0.1169	0.1614
5		-0.0238	-0.0319	-0.0196		0.1897	0.1663	0.2193
6		0.0996	0.0888	0.1192		0	-0.0108	0.0387
7		0.2275	0.2157	0.2474		0.0608	0.0494	0.0775
1	Assault	0.0599	0.0418	0.0772	Motor	-0.0737	-0.0929	-0.0645
2		-0.015	-0.0415	-0.0071		-0.0132	-0.0348	-0.0007
3		-0.0056	-0.0328	0.0177		0.0068	-0.0169	0.0181
4		0.0777	0.0699	0.1061		0.0608	0.0446	0.086
5		0.0968	0.0897	0.1255		0.0385	0.0223	0.0582
6		0.0164	0.0086	0.0339		0.0322	-0.0024	0.0942
7		0.096	0.0876	0.1043		0.0653	0.0291	0.0961

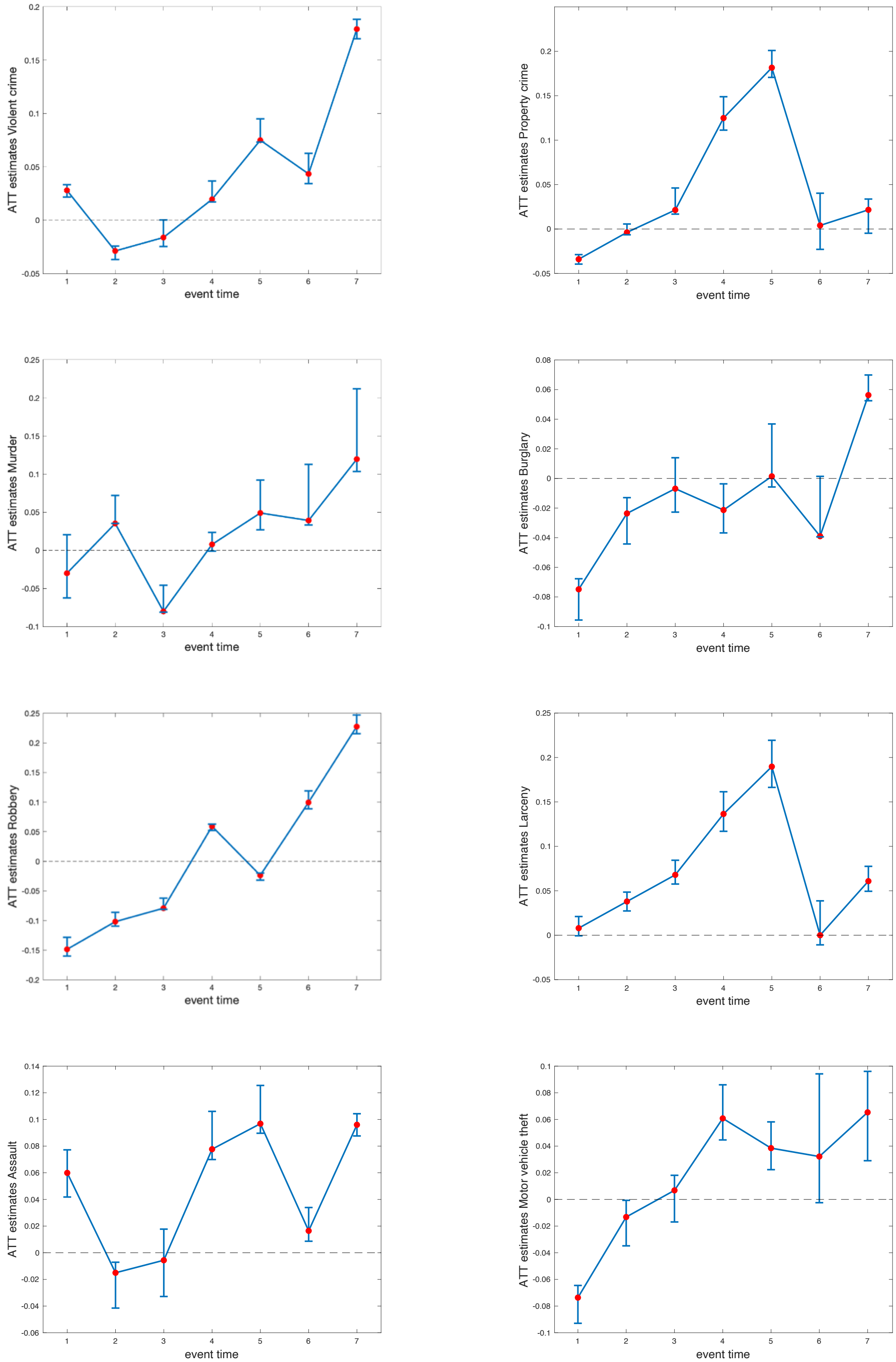


Figure 2.8. ATT estimates using SCISA

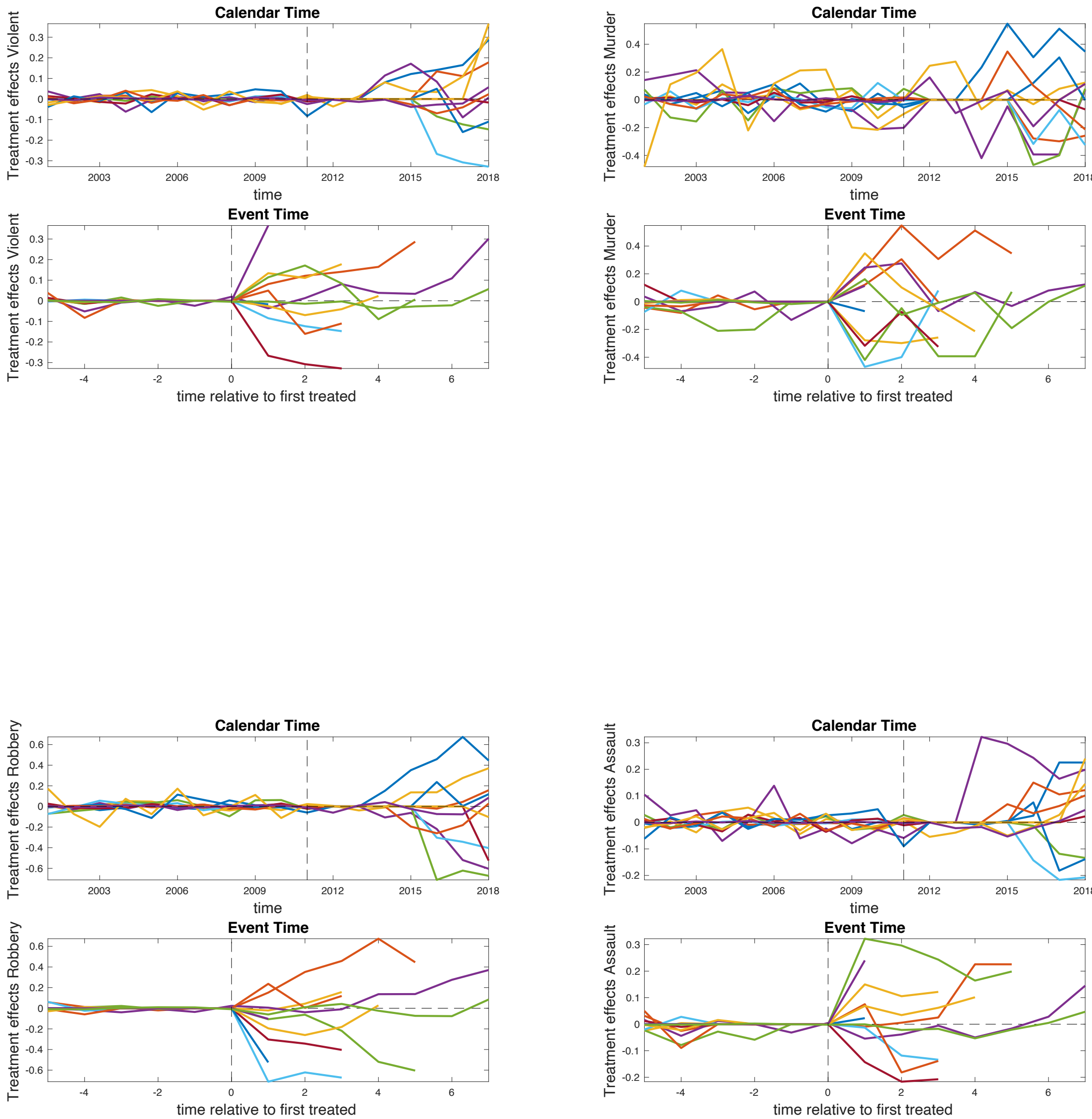


Figure 2.9. Treatment effects using SCISA for violent crime rates

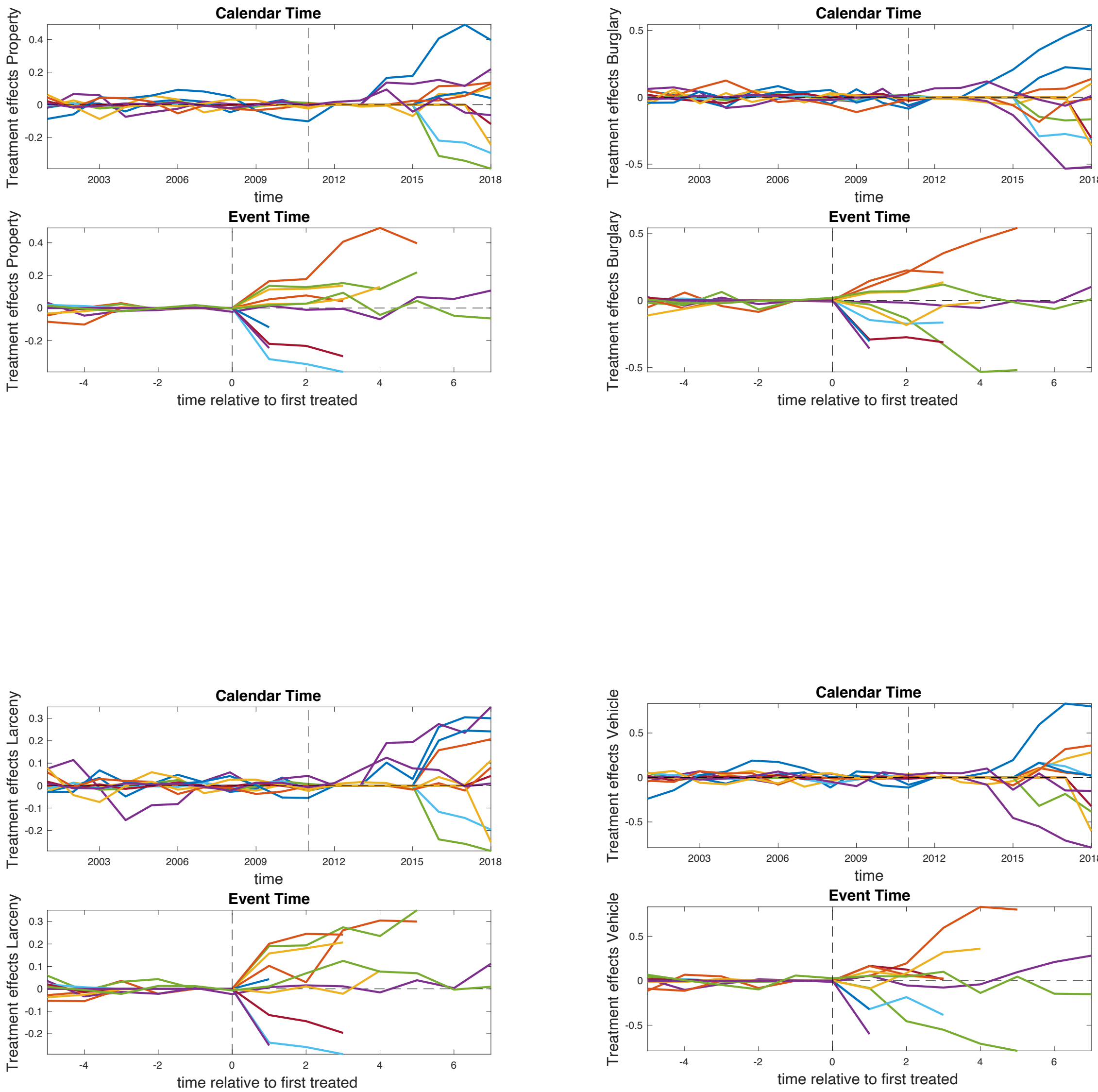


Figure 2.10. Treatment effects using SCISA for property crime rates

References

Abadie, A., Diamond, A., & Hainmueller, J., 2010. Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American statistical Association*, *105*(490), 493-505.

Abadie, A., Diamond, A., & Hainmueller, J., 2015. Comparative politics and the synthetic control method. *American Journal of Political Science*, *59*(2), 495-510.

Aydelotte, J. D., Brown, L. H., Luftman, K. M., Mardock, A. L., Teixeira, P. G., Coopwood, B., & Brown, C. V., 2017. Crash fatality rates after recreational marijuana legalization in Washington and Colorado. *American journal of public health*, *107*(8), 1329-1331.

Brinkman, J., & Mok-Lamme, D., 2019. Not in my backyard? Not so fast. The effect of marijuana legalization on neighborhood crime. *Regional Science and Urban Economics*, *78*, 103460.

Cerdá, M., Wall, M., Feng, T., Keyes, K. M., Sarvet, A., Schulenberg, J., ... & Hasin, D. S., 2017. Association of state recreational marijuana laws with adolescent marijuana use. *JAMA pediatrics*, *171*(2), 142-149.

Cerdá, M., Mauro, C., Hamilton, A., Levy, N. S., Santaella-Tenorio, J., Hasin, D., ... & Martins, S. S., 2020. Association between recreational marijuana legalization in the United States and changes in marijuana use and cannabis use disorder from 2008 to 2016. *JAMA psychiatry*, *77*(2), 165-171.

Chu, Y.W.L. and Townsend, W., 2019. Joint culpability: The effects of medical marijuana laws on crime. *Journal of Economic Behavior & Organization*, *159*, pp.502-525.

Crost, B., & Rees, D. I., 2013. The minimum legal drinking age and marijuana use: New estimates from the NLSY97. *Journal of health economics*, *32*(2), 474-476.

Dragone, D., Prarolo, G., Vanin, P., & Zanella, G., 2019. Crime and the legalization of recreational marijuana. *Journal of economic behavior & organization*, *159*, 488-501.

Drug Policy Alliance., 2017. Marijuana Facts. *Drug Policy Alliance*. report. Retrieved from https://www.drugpolicy.org/sites/default/files/dpa_marijuana_booklet_january2018_0.pdf

Fredriksson, A. and de Oliveira, G.M., 2019. Impact evaluation using Difference-in-Differences. *RAUSP Management Journal*.

Freisthler, B., Gaidus, A., Tam, C., Ponicki, W. R., & Gruenewald, P. J., 2017. From medical to recreational marijuana sales: marijuana outlets and crime in an era of changing marijuana legislation. *The journal of primary prevention*, *38*(3), 249-263.

Hughes, L. A., Schaible, L. M., & Jimmerson, K., 2020. Marijuana dispensaries and neighborhood crime and disorder in Denver, Colorado. *Justice Quarterly*, *37*(3), 461-485.

Hansen, B., Miller, K., & Weber, C., 2020. Early evidence on recreational marijuana legalization and traffic fatalities. *Economic inquiry*, *58*(2), 547-568.

Kepple, N. J., & Freisthler, B., 2012. Exploring the ecological association between crime and medical marijuana dispensaries. *Journal of studies on alcohol and drugs*, *73*(4), 523-530.

Li, K.T., 2020. Statistical inference for average treatment effects estimated by synthetic control methods. *Journal of the American Statistical Association*, *115*(532), pp.2068-208

Lu, R., Willits, D., Stohr, M. K., Makin, D., Snyder, J., Lovrich, N., ... & Hemmens, C., 2019. The cannabis effect on crime: Time-series analysis of crime in Colorado and Washington State. *Justice Quarterly*, 1-31.

Maier, S. L., Mannes, S., & Koppenhofer, E. L., 2017. The implications of marijuana decriminalization and legalization on crime in the United States. *Contemporary Drug Problems*, *44*(2), 125-146.

Makin, D.A., Willits, D.W., Wu, G., DuBois, K.O., Lu, R., Stohr, M.K., Koslicki, W., Stanton, D., Hemmens, C., Snyder, J. and Lovrich, N.P., 2019. Marijuana legalization and crime clearance rates: Testing proponent assertions in Colorado and Washington State. *Police quarterly*, *22*(1), pp.31-55.

Mark Anderson, D., Hansen, B., & Rees, D. I., 2013. Medical marijuana laws, traffic fatalities, and alcohol consumption. *The Journal of Law and Economics*, *56*(2), 333-369.

Mark Anderson, D., Hansen, B., & Rees, D. I., 2015. Medical marijuana laws and teen marijuana use. *American Law and Economics Review*, *17*(2), 495-528.

Miller, A. M., Rosenman, R., & Cowan, B. W., 2017. Recreational marijuana legalization and college student use: Early evidence. *SSM-Population Health*, *3*, 649-657.

Plunk, A. D., Peglow, S. L., Harrell, P. T., & Grucza, R. A., 2019. Youth and adult arrests for cannabis possession after decriminalization and legalization of cannabis. *JAMA pediatrics*, *173*(8), 763-769.

Scott McLean, Sara Weisfeldt (2018). Colorado governor won't rule out banning marijuana again. Here's why. article. *CNN*, Retrieved from https://edition.cnn.com/2018/04/20/us/colorado-marijuana-and-crime/index.html

Wang, G. S., Davies, S. D., Halmo, L. S., Sass, A., & Mistry, R. D., 2018. Impact of marijuana legalization in Colorado on adolescent emergency and urgent care visits. *Journal of Adolescent Health*, *63*(2), 239-241.

Wu, G., Boateng, F. D., & Lang, X., 2020. The Spillover Effect of Recreational Marijuana Legalization on Crime: Evidence From Neighboring States of Colorado and Washington State. *Journal of Drug Issues*, 0022042620921359.

Wu, G., Wen, M. and Wilson, F.A., 2021. Impact of recreational marijuana legalization on crime: Evidence from Oregon. *Journal of criminal justice*, *72*, p.101742.

CHAPTER III

DONATION TO FOOD BANKS AMIDST THE COVID-19 PANDEMIC: EXPERIMENT ON IMPULSIVE VS DELIBERATE NUDGES

Introduction and literature review

This chapter examined the types of information given by charities that would efficiently promote individuals' giving to food banks during the COVID-19 pandemic.

Deliberate and impulsive nudging

The present study applied the nudging techniques introduced in the works by Bennet (2009) and Karlan et al. (2019) to design the treatment information.

According to Karlan et al. (2019), deliberate giving refers to thoughtful contributions that resist the temptation of fast and feel-good donor experiences and more deeply account for the recipient of the aid and its results. Using their definition of deliberate giving, the 'deliberate' nudging information in this study was framed to be analytic with the specific value of the impact that a potential donor can make.

Karlan et al. (2019) argued that impulsive giving involves little analysis. Bennet (2009) examined impulsive donation decisions to a hospice chain using the data obtained from the two actual donations websites. One website was imagery and emotive oriented, and the other was information oriented. On the donation page of the websites, the donors were asked what prompted them to donate. He concluded that the imagery and emotive website was associated with a higher volume of impulsive donations than an informative website by 31%. He ran a logistic regression with a binary dependent variable (whether impulsive or planned donation) on individual traits such as 'personal impulsiveness.' Personal impulsiveness increased impulsive donations for both types of websites, but the magnitude was greater in the imagery/emotive website. Employing the findings of the extant literature, this study set the imagery and less analytic nudging information as 'impulsive' treatment.

The present research aims to examine which type of information is more efficient to facilitate donations to food banks using deliberate and impulsive nudging techniques with intertemporal giving choices (Andreoni and Serra-Carcia 2019) amidst the COVID-19 pandemic.

Deliberate and impulsive charitable giving

One way to classify individuals' giving decisions is to divide them into deliberate and impulsive ones. Likewise, the information that charities provide to potential donors can also be classified into deliberate and impulsive categories. The deliberate type employs analytical facts and numbers that summarize the needs for contributions and the impacts that potential donors can make (Karlan et al. 2019), and the impulsive type involves imagery and emotive information (Bennet 2009).

A large body of literature has examined the effects of being impulsive on individuals' donation decisions. In extant literature regarding charitable giving or consumer behavior, the definition of impulsivity includes some common factors such as unplanned and emotional urges (Stern 1962; Rook and Fisher 1995; Rook 1987; Barley and Nancarrow 1998).

The extant literature showed mixed conclusions on the influence of being impulsive on charitable giving. Taute and McQuitty (2004) studied conceptual relations of impulsivity and social and personal norms to charitable giving and suggested that impulsive characteristics have a positive influence on giving. On the other hand, Andreoni et al. (2018) found a negative relationship between impulsivity and giving rates. They conducted a lab experiment that elicited real donations to a charity and measured individuals' impulsive traits using Intertemporal Reactivity Index (IRI; Davis 1983) and suggested impulsive traits were related to lower donation rates when financial means to donate were scarce. However, to the best of our knowledge, there is no previous literature that specifically compared the effects of impulsive and deliberate nudging information in different giving timings.

Other factors that affect donation decisions

Other than deliberate and impulsive traits, empathy is one of the most widely studied in extant philanthropy literature. Empathy is defined as how compassionate an individual feels towards others (Lee et al. 2014; Li et al. 2019), and the extant literature repeatedly suggested that empathy has a positive influence on charitable giving. Liu et al. (2018) conducted an empirical study for the synthesis of diverse perspective on motivations of giving and found that empathy and perceived credibility were the key factors for crowdfunding. Gerber et al. (2012) and Rick et al. (2008) also found that individuals were motivated to give for specific crowdfunding projects out of empathetic feelings. Li et al. (2019) studied if empathy played a moderating role between social interaction and donation and argued that empathy was a critical factor that promotes donations. Andreoni et al. (2018) found through a lab experiment that a one standard deviation increase in empathetic concern score corresponded with an eight percentage point increase in the likelihood of giving. Kim and Kou (2014) broke down the components of empathy in detail and showed the heterogeneous effects on charitable giving by different components of empathy.

In addition to empathy, additional determinants include perceived credibility of a charitable project (Liu et al. 2018) and self-interest such as rewards and reputational benefits (Small and

Cryder 2016). Communal relationship with a victim led to sympathetic feelings towards others in the same type of afflictions (Small and Simonsohn 2007).

Although there exists a previous study that explored how personal impulsive traits affect donation decisions independently (Andreoni 2018; Li et al. 2019), to the best of our knowledge, there has been little attention to how impulsive and deliberate types of information affect individuals' charitable giving decisions. To fill this gap, this study examined individuals' giving decisions affected by the different types of information while controlling for the determinants that were repeatedly confirmed to be prominent for charitable giving decisions in extant literature.

Research methodology

The data in the present study was collected from a total of 537 participants nationwide through a survey conducted through Amazon MTurk between Oct 5 - Oct 15, 2020. The sample size was reduced to 527 after excluding the observations that failed the attention checks, which were very simple calculation questions. The participants earned \$2 for completing the survey and were given an extra \$1 or \$2 of which they chose either to donate to food banks or keep for themselves. The

Deliberate treatment group	**Impulsive treatment group**
Your impact: \$1 = 10 meals Every dollar you give can provide at least 10 meals to families in need through the Feeding America network of food banks	Below is a photo showing a sea of cars lined up for food assistance from the San Antonio Food Bank in Texas during the COVID-19 outbreak. (by Adrees Latif/Reuters) The photo was here in the survey.

Figure 3.1. Nudging information by treatment group

Note: The participants saw either of the information on their screens according to the random treatment. The photo in 'Impulsive treatment group' is removed in this work for copyright concern.

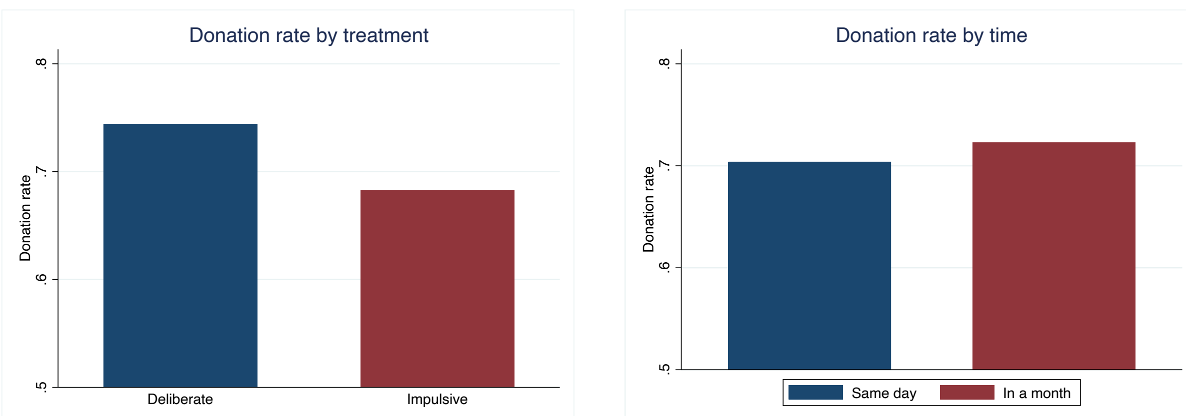
participants were randomly assigned to either a deliberate treatment group with analytic information with the specific value of contribution (impact of \$1 = 10 meals) or an impulsive treatment group with imagery nudging information (a photo of cars lined up at a food bank parking lot) as shown in Figure 3.1.

In addition to the between-subject design using the nudging information, a within-subject design was also applied to study the intertemporal donation decision (Andreoni and Serra-Carcia 2019). Each participant was asked about his/her willingness to donate in a month AND willingness to donate the same day. At the end of the survey, one of these two answers was randomly chosen as the binding payment for the participant. To convince participants the donations would be completed as described, we announced that we will post the donation receipts on our websites so that participants can check their donation with the survey completion time of each participant.

Questions on personal traits were followed. Time discount factor and risk preference were measured following Andersen, Steffen, et al. (2008) and Eckel and Grossman (2008) respectively, and the specific values used in the questionnaire were adjusted according to the context of this study. Empathy was measured by participants' answers on the degree of sharing the feelings of others in specific situations using the extant literature (Schlegelmilch et al. 1997; Lee and Chang 2008) adjusted in the current research setting. Standard demographic questions were also asked. Trust in food banks was measured as the level of the belief that the money donated to food banks will be used efficiently to fight hunger. The details on how we measured time discount rate, risk preference, food assistance recipient experience, and empathy are described in Appendix B.

Summary statistics

Table 3.1 presents summary statistics of the data collected for this study. The donation rates were 74.42% and 68.3% for the deliberate and impulsive group respectively, and 70.8% and 72.8% for donation same day and in a month respectively. The donation rate of the deliberate group was 6.1% higher than those of the impulsive group ($p = 0.01$), and the giving rate was 1.9% higher if the donation will be made in a month than on the same day ($p = 0.07$). This indicates that people were also responsive to the time discounting factor in donation behavior, which aligns with economic theory. Also, our results suggest that deliberate type information would promote donations more efficiently than impulsive type information during the pandemic.



(a) By treatment **(b) By time**

Figure 3.2. Donation rate by treatment group and donation time

65.65% of the participants were classified as the high empathy group and 34.35% as the low empathy group. 54.46% of the participants reported that they had the food assistance program beneficiary experience. Also, more than 70% of the participants answered positively (including somewhat agree and strongly agree) to the question on their beliefs in donation impacts on reducing social or economic inequality. Those who gave positive answers (including somewhat agree and strongly agree) to the question on trust in food banks were over 73%.

The demographics of our sample were somewhat unevenly distributed for some variables including gender and race. In our sample, 62.94% were male, and 37.06% were female; about 19% of the participants were African American; 73% participants, white; the rest, a mere 7.82%. The mean age was approximately 37, and about 71% of participants were married. 42.13% of the participants reported that they were receiving Supplemental Nutrition Assistance Program (SNAP) benefits, 49.52% of the participants reported that they received food from food banks previously or during COVID-19. At the time of the survey (October 2020), the unemployment rate of the survey participants was about 7.02%, which is close to the unemployment rate of 6.8% estimated by the U.S. Bureau of Labor Statistics. Lastly, more than one-fifth of survey participants answered that they were infected with the coronavirus.

Model specification

The main model used in the present study is Random Effect Probit (REP) model. As the Hausman test failed to reject the null hypothesis on no correlation between regressors and unobserved effects, we used random effect for efficiency. In addition, the random effect model would be preferred because the treatment was randomly assigned to the participants so that the errors were uncorrelated with the treatment and because we expect there exist correlation within individual choices across different time frames (same day and in a month).

$$P(Y_{it} = 1|X_i,\ c_i) = \ P(Y_{it} = 1|X_{it},\ c_i)$$
$$= \Phi(X_{it}\beta + c_i)$$

$$f(y_1, \dots, y_t|x_i;\theta)$$
$$= \int_{-\infty}^{\infty} \prod_{t=1}^{T} [f(y_t|x_{it}, c; \beta)](1/\sigma_c)\phi(c/\sigma_c)dc$$

where $Y_{it} = 1$ if individual i chose to donate at time t, and otherwise 0. $t = 1$ represents same day, $t = 2$, in a month. c_i is the unobserved effect of individual i, and X_i contains X_{it} for all t and $c_i|x_i \sim Normal\ (0, \sigma_c^2)$. The conditional log-likelihood for each i is produced by taking the log of equation (2) (Wooldridge 2002).

In addition, we used the Seemingly Unrelated Probit (SUP) models. By treating 'donatesameday' and 'donatemonth' as two separate dependent variables, we constructed a system of two Probit regressions with identical control variables. Since each participant answered the two questions (donate on the same day and donate in a month), the error terms were likely to be correlated across equations within individual choices, and we assumed that the error terms were uncorrelated across individuals. Therefore, SUP would be a proper choice as well to examine the donation decisions in the current intertemporal setup.

$$\begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} = \begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

$$\beta^{SUP} = [X'\Omega^{-1}X][X'\Omega^{-1}Y]$$

where $j = 1,2$ represents two equations with 'donate same day' and 'donate in a month' decisions respectively, and X_j is a vector of explanatory variables. Here, u_{ij} is assumed to have zero mean, homoskedastic, and independent across individual choices. And, for a given individual, the covariance of the error term across equations is: $E\left[u_{ij}u_{ij'}\middle|X\right] = \sigma_{jj'} * I_N \neq 0\ where\ j \neq j'$. Ω^{-1} is a weighting matrix based on the covariance of the error terms.

Results and discussion

Tables 3.2 and 3.3 present the REP regression results and the marginal effects, respectively. Table 3.4 shows the separate results for 'donate same day' and 'donate in a month' using SUP models, and Table 3.5 presents its marginal effects.

Deliberate vs impulsive nudging

In addition to the summary statistics, the regression results further confirm that deliberate nudging is a better strategy for charitable giving to food banks in the time of the pandemic. From the REP regression controlling other factors, the participants in the deliberate group showed 5.7% higher donation rates ($p < 0.1$) than the impulsive group as shown in Table 3.3.

The SUP model also confirmed the positive association between deliberate nudging and the giving rate as suggested by the REP model. As shown in Table 3.5, the marginal effects of deliberate nudging on donation rate from the SUP model were 6.1% ($p < 0.05$) and 4.6% ($p < 0.1$) (column (1) and (2), respectively). The magnitude of the marginal effect in the SUP model was very close to the results from the REP models.

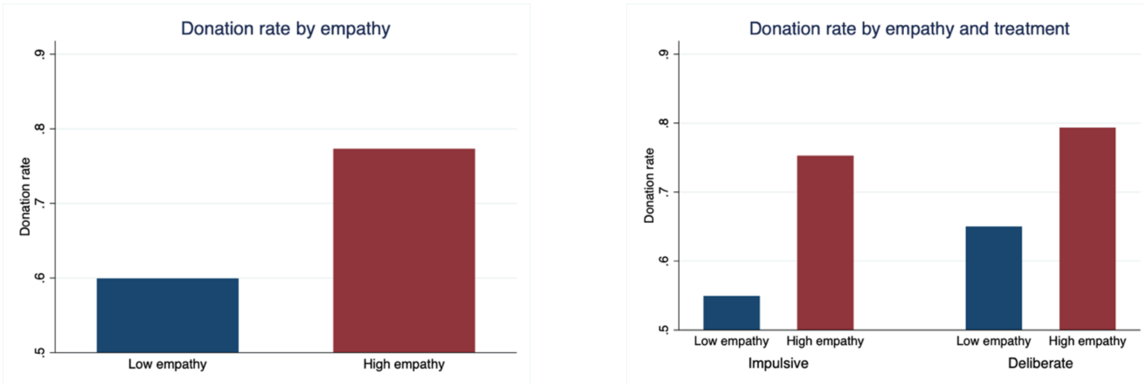
Empathy

Our research confirmed that those with higher empathy showed a higher donation rate. From Tables 3.3 and 3.5, we observe the positive and statistically significant association between empathy and the donation rate, and the magnitude was greater for the impulsive group. The REP regressions suggest that 'high empathy' was associated with 8.8% ($p < 0.01$) higher giving rate if received 'deliberate' treatment, and 14.2% ($p < 0.01$) higher giving rate if received 'impulsive' treatment. The SUP regressions provided similar results that 'high empathy' was associated with

10.1% ($p < 0.01$) higher giving rate if received 'deliberate' treatment and 14.9% ($p < 0.01$) higher giving rate if received 'impulsive' treatment. In addition, we observe in Figure 3.3 that although the overall donation rate for those with high empathy and those in the deliberate treatment group was higher, the increase in the donation rate when received deliberate treatment was greater for the low-empathy group.

Experience in receiving food assistance

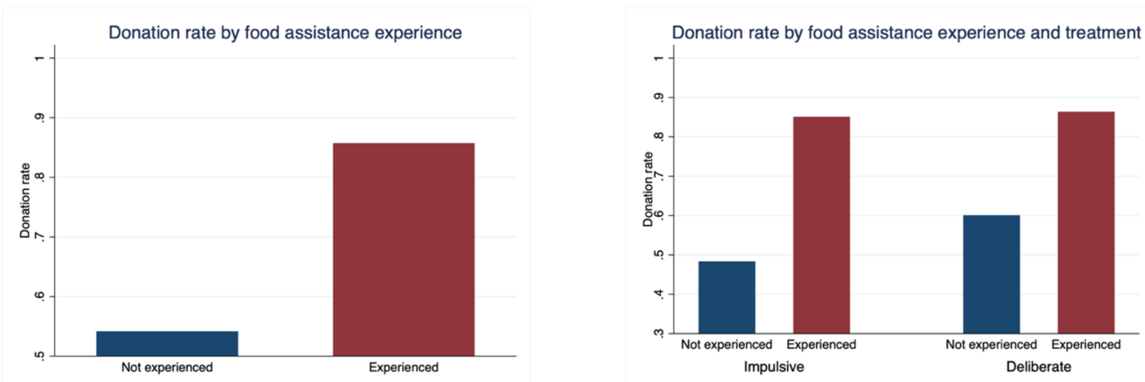
It is also noteworthy that experience with receiving food assistance had a significant positive association with the donation rate for all regressions. In Table 3.3 column (1) and (2), we observe that those with experience with food assistance were 24.2% ($p < 0.01$) or 14.8% ($p < 0.01$) more likely to donate to food banks. Figure 3.4 illustrates that the donation rate of those with such experience remained at around 85% for both treatment groups while the donation rate for those with no such experience was higher in the deliberate group than the impulsive group. Therefore, the results suggested that experience in food assistance programs was strongly associated with the donation rate to food banks, and the deliberate nudging was more efficient to promote the giving rate for those with no such experience.



(a) Empathy

(b) Empathy and treatment

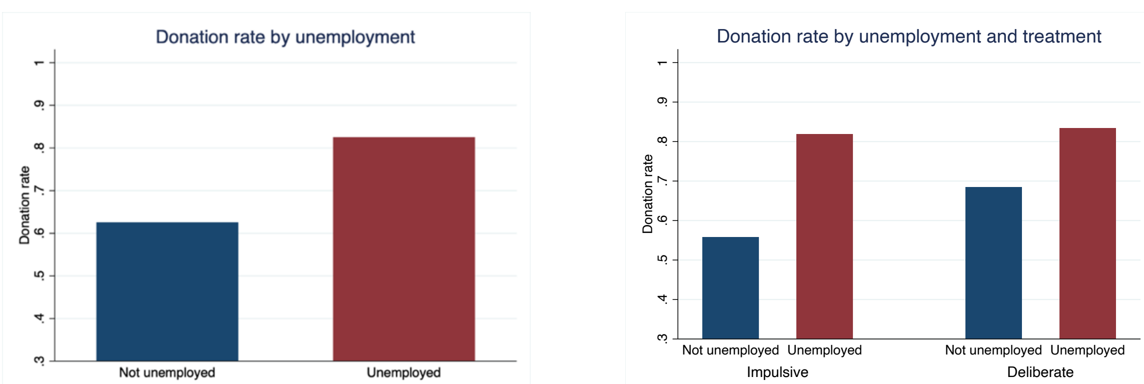
Figure 3.3. Donation rate by empathy and treatment



(a) Food assistance experience

(b) Food assistant experience and treatment

Figure 3.4. Donation rate by food assistance experience and treatment



(a) Unemployment

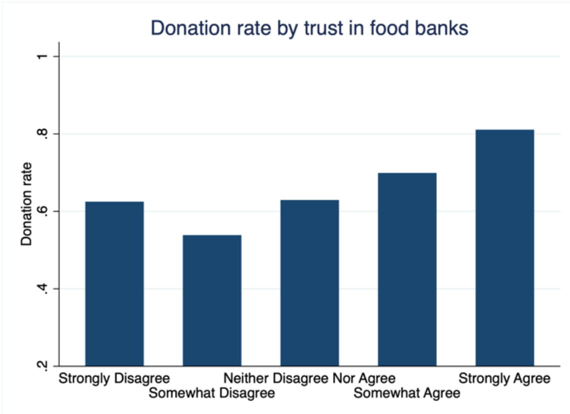
(b) Unemployment and treatment

Figure 3.5. Donation rate by unemployment due to the COVID-19 and treatment

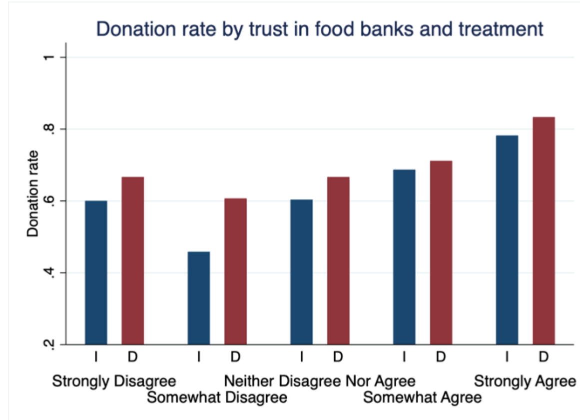
Such results suggest that many of the recipients were not only beneficiaries but also givers to society. It would require further study to see why this was the case, however, the results of the present study repeatedly confirmed that those who experienced some difficulties showed higher donation rates. For example, when compared the donation rates between those who experienced unemployment due to COVID-19 and those who did not, those who experienced unemployment due to the COVID-19 showed a much higher donation rate, which is described in Figure 3.5. Specifically, the donation rate for those who lost a job due to the COVID-19 was 82.54% while for those who did not, 62.54%. We can see that those who lost their jobs due to COVID-19 showed high giving rates around 82% no matter what treatment they received.

Trust in food banks

Moreover, trust in food banks turned out to have a strong association with giving decisions. As shown in Figure 3.6, the high level of belief was associated with a higher giving rate, and the deliberate group showed the higher donation rates across all levels of trust in food banks. The REP regression results suggest that stronger trust in food banks was related to 4.3% ($p < 0.01$) higher giving rate for both groups and with 4.8% ($p < 0.05$) higher giving rate for the deliberate group. However, there was no statistically significant association for those who were treated with impulsive nudging. The SUP model results also indicate that stronger trust in food banks was associated with a 4.4% ($p < 0.01$) higher giving rate for both groups and with a 5.3% ($p < 0.01$) higher giving rate for the deliberate group. The SUP results also show a positive and significant result for those in the impulsive group, and the level of trust in food banks was related with a 3.4% ($p < 0.05$) higher giving rate. This implies that trust in food banks was positively associated with the donation rate, and its impact was greater for the deliberate group.

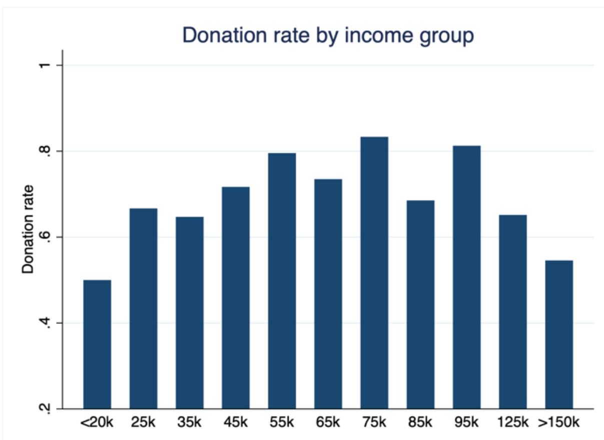


(a) Trust in food banks

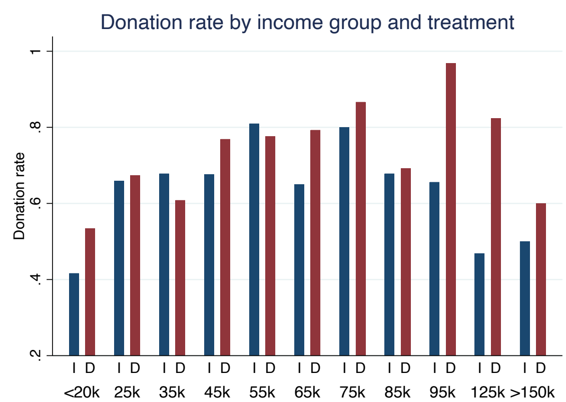


(b) Trust in food banks and treatment

Figure 3.6. Donation rate by trust in food banks and treatment



(a) Income



(b) Income and treatment

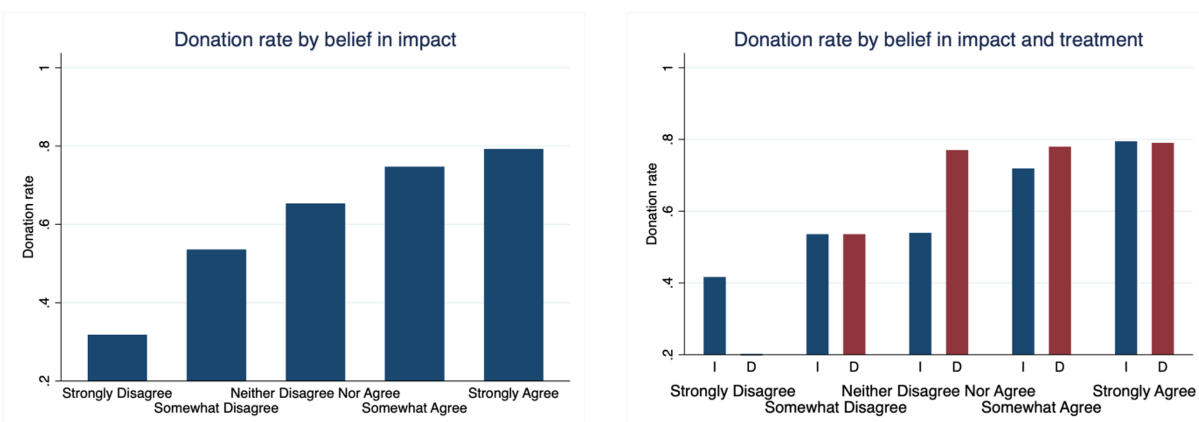
Figure 3.7. Donation rate by income group and treatment

Income

One might expect that higher income would lead to higher donation rates. However, the results suggest that a higher income level does not necessarily lead to a higher giving rate. The giving rates were higher in the middle and the giving rates were lower for the lowest (<20k) and highest (>150K) income brackets. Figure 3.7 shows that the association between the donation rate and income is in a flipped U-shaped curve rather than a linear correlation. The extant literature also suggested that giving money and income are not necessarily positively correlated. List (2011) showed that the gift as a percentage of income was higher for lower and higher income groups and lower in the middle-income groups. Although there is a discrepancy in that his work is about gift share as a percentage of income and that the current study is about donation rate, both studies showed some aspect of that income is not a prominent predictor to explain donation decisions.

From Figure 3.7, we see that the deliberate group had higher donation rates for most of the income groups. The difference in giving rates between deliberate and impulsive groups was greater for lower and higher income groups compared to middle-income groups. Besides, our results obtained from using the REP and SUP regressions suggest that income did not correlate with the donation rate. The marginal effects of income on the donation rates were in the range between -0.001 and 0.001.

Belief in impact



(a) Belief in impact

(b) Belief in impact and treatment

Figure 3.8. Donation rate by belief in impact and treatment

The results also show that those with a stronger belief in the impact of donation in reducing inequality were more likely to donate. Both results from the REP and SUP regressions suggested similar, but the p-values of the estimates of the SUP model were smaller. The results of the SUP model suggested that one level increase in 'belief in impact' led to 6.3% ($p < 0.01$) or 3.4% ($p < 0.05$) higher donation rates.

Other factors

Most of the other demographic variables did not have a statistically significant effect on donation behavior. However, the impact of marital status on the donation rate was notable. The REP results tell us that the probability of giving from those who were married was 15.9% ($p < 0.01$) higher than those who were not. Moreover, conservative political standing showed positive relationships with the giving rates, but it was not significant for the deliberate group. 'white,' the race variable, showed a positive and significant relationship with the donation rate for the deliberate group only. In addition, the results from the REP and SUP models indicate that both COVID-19 infection and the frequency of attendance to religious service had positive associations with the donation rates.

Using the SUP model, we confirmed that the time discounting factor had a negative influence on the donation decisions, which is consistent with economic theory. The magnitude of the negative relation between time discount factor and donation rates was greater for donation on the same day than a donation in a month. Even if the donation amount was only $1 in this study, the participants were still more likely to donate when asked to give in a month as compared to the same day. This implies that how to frame giving timings would affect giving decisions.

Table 3.1. Summary statistics

Variable	Description	Value
deliberate	0=Impulsive group, 1=Deliberate group	0 = 266, 1=271
dollar amount	1=Extra $1 given, 2=Extra $2 given	1 = 471, 2=66
donatesameday	1=If chose to donate same day, 0=otherwise	0=29.60%, 1=70.40%
donatemonth	1=If chose to donate in a month, 0=otherwise	0=27.70%, 1=72.30%
high_empathy	Empathy level measured as Appendix B: 0=Low empathy, 1=High empathy	0=34.35%, 1=65.65%
exper_foodassist	1= Experienced in receiving food assistance from SNAP, food stamps, or food banks, 0=otherwise	0=45.54%, 1==54.46%
belief in impact	Belief in the impact of donation in reducing inequality: 0=strongly disagree, 1=somewhat disagree, 2=Neither agree nor disagree, 3=somewhat agree, 4=strongly agree	0=2.09%, 1=10.63%, 2=14.23%, 3=48.39%, 4=24.67%
timedis	Time discount factor: 0=inconsistent, 1=lowest time discount rate, …, 4=highest time discount rate	0=24.67%, 1=6.26%, 2=10.25%, 3=19.73, 4=39.09
trust_fb	Belief that the money donated to food banks will be efficiently to fight hunger: 0=Strongly disagree, 1=Somewhat disagree, 2=Neither disagree nor agree, 3=Somewhat agree, 4=Strongly agree	0 = 4.47% , 1= 5.03%, 2 = 16.95%, 3=40.41%, 4 = 33.15%
female	Gender: 0=Male, 1=Female	0= 62.94%, 1=37.06%
married	0=Not married, 1=Married	Mean=.711, SD=.454
age	Age	Mean=37.393, SD=1.85
income	Household annual income in 2019 tax year	Mean= $75055.03, SD=$45145.46
employed	0=Not employed, 1=employed, self-employed	0=7.08%, 1=92.92%
hhsize	The total number of people in household	Mean=3.428, SD=1.406
covidself	0=Not infected, 1=Infected	0=77.87%, 1=22.16%
Black	Race: 1=Black, 0=Otherwise	1=19.37%, 0=80.63%
White	Race: 1=White, 0=Otherwise	1=72.81%, 0=92.18%
Others	Race: 1=Non-White & non-Black, 0=Otherwise	1=7.82%, 0=27.19%
children	Number of children in household	Mean=2.19, SD=1.15
religion	0=Seldom, never, no answer, 1= A few times a year, 2=once or twice/month, 3=Once/week, 4= More than once/week	0=26.83%, 1=9.87%, 2=20.11%, 3=35.20%, 4=8.19%
conservative	1=Extremely liberal, 2=Liberal, 3=Slightly liberal, =Moderate/decline to answer, 5=Slightly conservative, 6=Conservative, 7=Extremely conservative	1=10.43%, 2=14.90%, 3=6.15%, 4=13.22%, 5=8.75%, 6=26.07%, 7=20.48%

Table 3.2. REP model: Donation rate

	REP: Both groups		REP: Deliberate		REP: Impulsive	
	(1)	(2)	(3)	(4)	(5)	(6)
deliberate	0.753*	0.577				
	(0.447)	(0.388)				
inamonth	0.246	0.246	0.186	0.190	0.317	0.310
	(0.168)	(0.167)	(0.228)	(0.231)	(0.249)	(0.244)
high_empathy	1.446***	1.423***	1.067*	1.090**	1.951*	1.964***
	(0.496)	(0.408)	(0.552)	(0.508)	(1.013)	(0.678)
belief in impact	0.769***	0.393*	0.704**	0.405	0.828	0.388
	(0.277)	(0.225)	(0.324)	(0.303)	(0.520)	(0.334)
exper_foodassist	3.200***	1.912***	2.540***	1.845***	4.118	1.708***
	(0.589)	(0.436)	(0.588)	(0.610)	(3.067)	(0.662)
timedis	-0.259**	0.009	-0.279*	-0.191	-0.259	0.158
	(0.126)	(0.121)	(0.167)	(0.173)	(0.225)	(0.182)
risk	0.071	-0.110	-0.316	-0.505	0.643	0.387
	(0.327)	(0.290)	(0.388)	(0.393)	(0.631)	(0.457)
dollar amount		0.018		0.498		-0.720
		(0.513)		(0.657)		(0.817)
trustfb		0.551**		0.600**		0.452
		(0.216)		(0.293)		(0.320)
female		0.265		-0.058		0.497
		(0.382)		(0.502)		(0.640)
age		-0.010		-0.014		-0.014
		(0.020)		(0.022)		(0.037)
married		2.058***		2.156***		2.242**
		(0.634)		(0.822)		(0.994)
children		-0.004		-0.130		0.192
		(0.225)		(0.264)		(0.385)
employed		-0.067		-0.439		0.817
		(0.972)		(1.192)		(1.394)
income		0.001		0.013		-0.011
		(0.007)		(0.009)		(0.011)
conservative		0.197*		0.104		0.273*
		(0.101)		(0.122)		(0.163)
white		0.350		1.120*		-0.699
		(0.440)		(0.634)		(0.816)
covidself		1.519***		1.068		1.460*
		(0.574)		(0.779)		(0.847)
religion		0.431**		0.321		0.547*
		(0.182)		(0.227)		(0.308)
Constant	-2.171**	-6.141***	-0.679	-5.224**	-3.300	-6.095**
	(0.883)	(1.714)	(1.067)	(2.163)	(2.222)	(2.776)
N	1054	1054	524	524	530	530

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3. REP margins: Donation rate

	margins: Both groups		margins: Deliberate		margins: Impulsive	
	(1)	(2)	(3)	(4)	(5)	(6)
deliberate	0.057*	0.045				
	(0.032)	(0.029)				
inamonth	0.019	0.019	0.015	0.015	0.022	0.022
	(0.013)	(0.013)	(0.019)	(0.019)	(0.019)	(0.018)
high_empathy	0.109***	0.110***	0.088**	0.088**	0.134	0.142***
	(0.037)	(0.028)	(0.044)	(0.040)	(0.101)	(0.038)
impact	0.058***	0.030*	0.058**	0.033	0.057	0.028
	(0.020)	(0.017)	(0.027)	(0.024)	(0.044)	(0.024)
exper_foodassist	0.242***	0.148***	0.210***	0.149***	0.283***	0.123***
	(0.044)	(0.031)	(0.049)	(0.044)	(0.103)	(0.042)
timedis	-0.020**	0.001	-0.023*	-0.015	-0.018	0.011
	(0.009)	(0.009)	(0.013)	(0.014)	(0.017)	(0.013)
risk	0.005	-0.008	-0.026	-0.041	0.044	0.028
	(0.025)	(0.022)	(0.032)	(0.031)	(0.040)	(0.033)
dollar amount		0.001		0.040		-0.052
		(0.040)		(0.053)		(0.060)
trustfb		0.043***		0.048**		0.033
		(0.015)		(0.021)		(0.021)
female		0.020		-0.005		0.036
		(0.029)		(0.040)		(0.046)
age		-0.001		-0.001		-0.001
		(0.002)		(0.002)		(0.003)
married		0.159***		0.174***		0.162***
		(0.039)		(0.053)		(0.056)
children		-0.000		-0.010		0.014
		(0.017)		(0.021)		(0.028)
employed		-0.005		-0.035		0.059
		(0.075)		(0.095)		(0.099)
income		0.000		0.001		-0.001
		(0.001)		(0.001)		(0.001)
conservative		0.015**		0.008		0.020*
		(0.008)		(0.010)		(0.011)
white		0.027		0.090**		-0.050
		(0.033)		(0.045)		(0.057)
covidself		0.117***		0.086		0.105*
		(0.041)		(0.060)		(0.058)
religion		0.033***		0.026		0.039*
		(0.013)		(0.016)		(0.020)
N	1054	1054	524	524	530	530

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4. **SUP: Donation rate**

	SUP: Both groups		SUP: Deliberate		SUP: Impulsive	
Donate Same day	(1)	(2)	(3)	(4)	(5)	(6)
deliberate	0.214**	0.174*				
	(0.087)	(0.092)				
high_empathy	0.406***	0.448***	0.332**	0.416***	0.503***	0.565***
	(0.093)	(0.097)	(0.137)	(0.142)	(0.129)	(0.136)
belief_in_impact	0.199***	0.131**	0.165**	0.101	0.227***	0.159**
	(0.047)	(0.052)	(0.068)	(0.074)	(0.065)	(0.074)
exper_foodassist	0.839***	0.583***	0.746***	0.657***	0.893***	0.474***
	(0.094)	(0.103)	(0.135)	(0.148)	(0.129)	(0.148)
timedis	-0.089***	-0.020	-0.095**	-0.071	-0.090**	0.026
	(0.029)	(0.031)	(0.042)	(0.045)	(0.040)	(0.044)
risk	0.028	-0.025	-0.047	-0.148	0.118	0.069
	(0.070)	(0.072)	(0.098)	(0.105)	(0.100)	(0.100)
dollar_amount		0.069		0.219		-0.207
		(0.131)		(0.174)		(0.198)
trust_fb		0.120**		0.115		0.123*
		(0.048)		(0.072)		(0.069)
female		0.089		0.078		0.057
		(0.096)		(0.132)		(0.144)
age		-0.004		-0.004		-0.004
		(0.005)		(0.006)		(0.007)
married		0.541***		0.593***		0.631***
		(0.120)		(0.182)		(0.163)
children		-0.014		-0.112		0.084
		(0.055)		(0.077)		(0.078)
employed		0.007		-0.081		0.151
		(0.189)		(0.266)		(0.279)
income		0.001		0.007***		-0.003
		(0.002)		(0.002)		(0.002)
conservative		0.068***		0.075**		0.060*
		(0.024)		(0.033)		(0.036)
white		0.130		0.363**		-0.226
		(0.111)		(0.162)		(0.159)
covidself		0.317**		0.213		0.289
		(0.138)		(0.200)		(0.182)
religion		0.151***		0.114**		0.202***
		(0.041)		(0.056)		(0.060)
constant	-0.565***	-1.859***	-0.113	-1.734***	-0.772***	-1.706***
	(0.161)	(0.353)	(0.240)	(0.509)	(0.209)	(0.511)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4. SUP: Donation rate (Continued)

	SUP: Both groups		SUP: Deliberate		SUP: Impulsive	
Donate in a month	(1)	(2)	(3)	(4)	(5)	(6)
deliberate	0.176**	0.151				
	(0.089)	(0.094)				
high_empathy	0.370***	0.397***	0.306**	0.311**	0.445***	0.558***
	(0.094)	(0.100)	(0.134)	(0.143)	(0.133)	(0.139)
belief_in_impact	0.215***	0.108**	0.262***	0.160**	0.172***	0.074
	(0.048)	(0.052)	(0.070)	(0.077)	(0.064)	(0.071)
exper_foodassist	0.866***	0.576***	0.794***	0.529***	0.917***	0.534***
	(0.096)	(0.105)	(0.133)	(0.149)	(0.134)	(0.149)
timedis	-0.062**	0.031	-0.076	-0.048	-0.054	0.076*
	(0.031)	(0.032)	(0.048)	(0.048)	(0.039)	(0.043)
risk	0.010	-0.024	-0.135	-0.187*	0.183*	0.160
	(0.068)	(0.070)	(0.090)	(0.098)	(0.106)	(0.109)
dollar_amount		-0.081		0.093		-0.243
		(0.138)		(0.188)		(0.198)
trust_fb		0.208***		0.293***		0.140**
		(0.048)		(0.075)		(0.066)
female		0.072		-0.094		0.233*
		(0.093)		(0.134)		(0.134)
age		-0.003		-0.006		-0.004
		(0.005)		(0.006)		(0.007)
married		0.620***		0.825***		0.572***
		(0.124)		(0.181)		(0.164)
children		0.023		0.023		0.024
		(0.057)		(0.074)		(0.080)
employed		-0.054		-0.220		0.295
		(0.188)		(0.266)		(0.265)
income		-0.001		0.001		-0.003
		(0.002)		(0.002)		(0.002)
conservative		0.048*		-0.025		0.094***
		(0.025)		(0.035)		(0.035)
white		0.024		0.296*		-0.183
		(0.114)		(0.157)		(0.162)
covidself		0.677***		0.649***		0.610***
		(0.152)		(0.210)		(0.199)
religion		0.094**		0.109*		0.107*
		(0.042)		(0.058)		(0.059)
constant	-0.575***	-1.618***	-0.335	-1.502***	-0.645***	-1.667***
	(0.161)	(0.354)	(0.239)	(0.512)	(0.214)	(0.488)
N	1054	1054	524	524	530	530

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5. SUP margins: Donation rate

	margins: Both groups		margins: Deliberate		margins: Impulsive	
	(1)	(2)	(3)	(4)	(5)	(6)
deliberate	0.061**	0.046*				
	(0.025)	(0.024)				
high_empathy	0.120***	0.119***	0.098***	0.101***	0.147***	0.149***
	(0.026)	(0.025)	(0.038)	(0.036)	(0.036)	(0.033)
belief_in_impact	0.063***	0.034**	0.064***	0.035*	0.063***	0.034*
	(0.013)	(0.014)	(0.020)	(0.020)	(0.018)	(0.018)
exper_foodassist	0.262***	0.161***	0.235***	0.164***	0.276***	0.131***
	(0.024)	(0.026)	(0.036)	(0.037)	(0.032)	(0.036)
timedis	-0.024***	0.000	-0.026**	-0.017	-0.023**	0.012
	(0.008)	(0.008)	(0.013)	(0.012)	(0.011)	(0.011)
risk	0.006	-0.007	-0.026	-0.045*	0.044	0.027
	(0.020)	(0.019)	(0.027)	(0.026)	(0.029)	(0.026)
dollar_amount		0.002		0.044		-0.058
		(0.035)		(0.046)		(0.051)
trust_fb		0.044***		0.053***		0.034**
		(0.013)		(0.018)		(0.017)
female		0.023		0.000		0.033
		(0.025)		(0.035)		(0.035)
age		-0.001		-0.001		-0.001
		(0.001)		(0.002)		(0.002)
married		0.160***		0.190***		0.161***
		(0.031)		(0.044)		(0.041)
children		0.000		-0.014		0.016
		(0.015)		(0.019)		(0.020)
employed		-0.005		-0.039		0.054
		(0.051)		(0.071)		(0.072)
income		0.000		0.001*		-0.001
		(0.000)		(0.001)		(0.001)
conservative		0.017***		0.008		0.019**
		(0.006)		(0.009)		(0.009)
white		0.024		0.091**		-0.055
		(0.029)		(0.041)		(0.040)
covidself		0.131***		0.111**		0.108**
		(0.036)		(0.052)		(0.046)
religion		0.035***		0.031**		0.044***
		(0.011)		(0.015)		(0.014)
N	1054	1054	524	524	530	530

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

References

Andersen, S., Harrison, G.W., Lau, M.I. and Rutström, E.E., 2008. Eliciting risk and time preferences. *Econometrica*, *76*(3), pp.583-618.

Andreoni, J., Koessler, A.K. and Serra-Garcia, M., 2018. Who gives? The roles of empathy and impulsiveness. In *The Economics of Philanthropy: Donations and Fundraising* (pp. 49-62). the MIT Press.

Bekkers, R. and Wiepking, P., 2011. A literature review of empirical studies of philanthropy: Eight mechanisms that drive charitable giving. *Nonprofit and voluntary sector quarterly*, *40*(5), pp.924-973.

Bennett, R., 2009. Impulsive donation decisions during online browsing of charity websites. *Journal of Consumer Behaviour: An International Research Review*, *8*(2-3), pp.116-134.

Champ, P.A. and Bishop, R.C., 2001. Donation payment mechanisms and contingent valuation: an empirical study of hypothetical bias. *Environmental and resource economics*, *19*(4), pp.383-402.

Champ, P.A., Bishop, R.C., Brown, T.C. and McCollum, D.W., 1997. Using donation mechanisms to value nonuse benefits from public goods. *Journal of environmental economics and management*, *33*(2), pp.151-162.

Dave, C., Eckel, C.C., Johnson, C.A. and Rojas, C., 2010. Eliciting risk preferences: When is simple better?. *Journal of Risk and Uncertainty*, *41*(3), pp.219-243.

Dean Karlan, Piyush Tantia, Sarah Welch., 2019. "Behavioral Economics and Donor Nudges: Impulse or Deliberation?" Stanford Social Innovation Review, Retrieved from https://ssir.org/articles/entry/behavioral_economics_and_donor_nudges_impulse_or_deliberation#

Eckel, C.C. and Grossman, P.J., 2008. Forecasting risk attitudes: An experimental study using actual and forecast gamble choices. *Journal of Economic Behavior & Organization*, *68*(1), pp.1-17.

Feeding America., 2020. "FA_Supply_Deamnd_One-paper_Final."

Giving USA., 2020. "Giving USA 2020: The Annual Report on Philanthropy for the Year 2019."

Gerber, E.M. and Hui, J., 2013. Crowdfunding: Motivations and deterrents for participation. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *20*(6), pp.1-32.

Taute, H. and McQuitty, S., 2004. Feeling good! Doing good! An exploratory look at the impulsive purchase of the social good. *Journal of Marketing Theory and Practice*, *12*(2), pp.16-27.

Kim, S.J. and Kou, X., 2014. Not all empathy is equal: How dispositional empathy affects charitable giving. *Journal of Nonprofit & Public Sector Marketing*, *26*(4), pp.312-334.

Lee, Y.K. and Chang, C.T., 2008. Intrinsic or extrinsic? Determinants affecting donation behaviors. *International Journal of Educational Advancement*, *8*(1), pp.13-24.

Li, B., Hou, F., Guan, Z. and Chong, A.Y.L., 2019. How Social Experience Encourages Donation Intention to Charitable Crowdfunding Projects on Social Media: Empathy and Personal Impulsiveness. In *PACIS* (p. 195).

Liu, L., Suh, A. and Wagner, C., 2018. Empathy or perceived credibility? An empirical study on individual donation behavior in charitable crowdfunding. *Internet Research*.

List, J.A., 2011. The market for charitable giving. *Journal of Economic Perspectives*, *25*(2), pp.157-80.

Pew Research Center, September 2020, "Economic Fallout From COVID-19 Continues To Hit Lower-Income Americans the Hardest"

Piff, P.K., Kraus, M.W., Côté, S., Cheng, B.H. and Keltner, D., 2010. Having less, giving more: the influence of social class on prosocial behavior. *Journal of personality and social psychology*, *99*(5), p.771.

Rick, S.I., Cryder, C.E. and Loewenstein, G., 2008. Tightwads and spendthrifts. *Journal of consumer research*, *34*(6), pp.767-782.

Schlegelmilch, B.B., Love, A. and Diamantopoulos, A., 1997. Responses to different charity appeals: the impact of donor characteristics on the amount of donations. *European Journal of Marketing*.

Small, D.A. and Cryder, C., 2016. Prosocial consumer behavior. *Current Opinion in Psychology*, *10*, pp.107-111.

Small, D.A. and Simonsohn, U., 2008. Friends of victims: Personal experience and prosocial behavior. *Journal of Consumer Research*, *35*(3), pp.532-542.

University of Illinois College of Agricultural, Consumer and Environmental Sciences., 2020. "Some U.S. states hit harder by COVID-19 food insecurity." ScienceDaily. ScienceDaily, 12 November 2020.

Verhaert, G.A. and Van den Poel, D., 2011. Empathy as added value in predicting donation behavior. *Journal of Business Research*, *64*(12), pp.1288-1295.

CHAPTER IV

TRANSFORMATION IN DONATION BEHAVIOR UNDER THE IMPACT OF THE COVID-19 PANDEMIC

Introduction and literature review

The third topic explores the changes in charitable giving decisions under the impact of the COVID-19 pandemic. For non-profit organizations (NPOs) such as a food bank, charitable giving is essential, therefore the information on how donation patterns have been changed under the impact of the COVID-19 would be critical for an NPO to secure necessary resources during the pandemic.

Charitable giving in the time of crisis

CDP also reported that the scale of a disaster and the number of people affected by it were the most prominent factors for contributing to disaster relief funds in those years. Also, the personal connection to the location of a disaster and to the impact of the disaster, media coverage, and being able to evaluate the effectiveness and impact of their donation had strong influences as well (CDP 2019).

There exists little literature studying the motivation for the transformation in charitable giving in a time of crisis. In the extant literature, the effect of media coverage of disaster was confirmed to be an important factor in previous literature. Minty (2008) suggested media coverage was a prominent determinant for disaster relief giving. Lobb et al. (2012) studied the link between donation and the media coverage of the earthquake in Haiti in 2010. They found a strong positive relationship with both traditional (ABC news) and new types of media (Twitter and Facebook) coverage: every 10% increase in messages on Twitter was related to an increase of $236,540 in giving and each additional coverage of ABC news with a $963,800 increase.

Some literature studied the impacts of an experience as a victim or close connections to victims. Brown et al. (2012) investigated the effect of contributions to the victims of the Indian Ocean tsunami in 2005 on contributions to other charitable causes and found that there was no crowding-out effect on planned gifts due to the unplanned giving to the tsunami victims. Small and Simonsohn (2007) argued that a communal relationship with a victim was an important factor for sympathetic feelings towards others in the same type of afflictions.

Gao (2011) found that institutional pressure had a positive influence on disaster relief giving. Torrey et al. (2011) showed how people respond to disaster relief in online communities. Brown and Manesi et al. (2019) argued that prosocial traits (social value orientation and social mindfulness), educational attainment, and political ideology were the most important predictors based on their survey results.

However, the COVID-19 outbreak is very different in the magnitude and scope of its impact from other humanitarian or natural disasters. Unlike other crises, the COVID-19 pandemic is happening at a global level, and it is threatening every economy and life across the globe. Facing such uncertain times during the pandemic, the motivations or behavior patterns of charitable giving could be different from ordinary times and even from the times of other disasters.

In the context of the COVID-19, previous literature has focused on what motivates charitable giving during the pandemic. Castiglioni and Lozza (2020) found that trust in fund management was an important factor for financial contributions to the Italian National Health System during the pandemic. Kobayashi et al. (2021) conducted a survey on the influence of COVID-19 on donors' attitude toward development aid, and they found that if donors thought that aid helps curb the disease in their own country by first alleviating its impact in developing countries then they were more supportive of giving the aid. Sarea and Bin-Nashwan (2020) suggested that a religious belief played a moderating role between external aspects, i.e. charity projects and trust in charities, and donors' attitudes toward fundraising appeal for the fight against COVID-19. Abel and Brown (2020) studied the correlation between prosocial behavior and role models during the COVID-19. Mafei (2020) found that donors' emotional value was the most relevant motivational factor and that, interestingly, the higher income the lower probability of giving during the COVID-19. Also, it was argued that people who usually donated more to medical causes were the most likely to engage in altruistic behavior for COVID-19 related issues.

The previous studies explored the prominent determinants for charitable giving during the pandemic, but little attention was given to how donation behavior has been transformed before and after the outbreak. However, the knowledge on the transformation of the giving patterns would be critical to philanthropy to fundraise so that it can play its role during the pandemic. In this context, the current study aims to answer the questions on how charitable giving to food banks and other NPOs was affected and on what drove the changes during the COVID-19 pandemic.

Triggers of charitable giving

The topic on who contributes how much has been widely studied and the primary focus has been on the characteristics and certain circumstances under which people are more likely to give. The most common predictors to explain charitable giving include intrinsic characteristics such as empathy, trust, and impulsivity, and external treatments such as solicitation, advertisement, and social norm. Dellavigna et al. (2012) conducted a field experiment and found altruism and social pressure were the important factors. Andereoni et al. (2017) argued that verbal asking was powerful in increasing the donation rate. Kim and Kou (2014) suggested that empathy was an important motive for charitable giving and that the different components of dispositional empathy had different associations with giving patterns. Also, Bekkers and Wiepking (2011) conducted a literature review on the mechanism of philanthropy, and they classified it into eight categories: awareness of need, solicitation, costs and benefits, altruism, reputation, psychological benefits, values, and efficacy. Manesi et al. (2019) found that social value orientation, social mindfulness, educational attainment, and political ideology were the most prominent predictors of donation decisions and that donation amount was related to social value orientation, social mindfulness, educational attainment, and religiosity. The present study included the most frequently appeared determinants such as empathy and trust in the organization as controlling factors.

The rest of this paper is organized as follows: the next section explains how the data was collected, followed by a description of overall statistics on donation. Decomposition describes in detail how giving patterns were changed amidst COVID-19 from various aspects. Results include the major findings from analysis of the data to illuminate the most prominent determinants explaining the changes in giving behaviors during the pandemic. The present paper concludes with its contributions and suggestions for further study.

Data

Data was collected nationwide through Amazon MTurk between Oct 5 - Oct 15, 2020. Participants were rewarded with $2 for successfully completing the survey. The total number of participants was 537, but the sample size used in the analysis was 527 after excluding 10 observations that failed the attention checks, which were simple calculation questions. The participants answered questions regarding their actual donation status to food banks and other NPOs before and after the COVID-19 outbreak. They also answered questions regarding their actual annual average donation amount to food banks and other NPOs before the outbreak and the donation amounts during the pandemic. It was followed by questions measuring empathy, trust, other characteristics such as time discount rate and risk preference, that were attributed to affecting donation decisions in previous literature.

Time discount rate was measured by the answers to the choice questions asking when the participant would receive money (today or in one year) with a different amount (Andersen et al. 2008). Risk preference was measured with preferred gamble choices (Eckel and Grossman 2008). Empathy was measured by the participants' answers on the degree of sharing the feelings of others in specific situations using the extant literature (Schlegelmilch et al. 1997; Lee and Chang 2008) adjusted according to the current research setting. Finally, the participants answered general demographic questions. The details on how we measured time discount factor, risk preference, and empathy are described in Appendix B.

Summary statistics

Table 4.1 presents the summary statistics regarding the changes in the donation for food banks and other NPOs amidst the COVID-19. The donation rates to food banks before and after the COVID-19 outbreak were .689 and .613 respectively. The donation rates to other NPOs before and after the COVID-19 outbreak were .858 and .704 respectively. The changes in donation rates are also illustrated in Figure 4.1. The donation rates dropped for both food banks and other NPOs during the pandemic, and the magnitude of decrease was greater for other NPOs. Among the participants, about 20.12% of previous non-donors of food banks made monetary contributions to food banks after the COVID-19 outbreak, while the previous donors to food banks before COVID-19 answered that they did not donate during the pandemic. Also, 32% of people who did not give to any other nonprofit organization answered that they donated during the pandemic; 23% of previous donors did not donate after the outbreak.

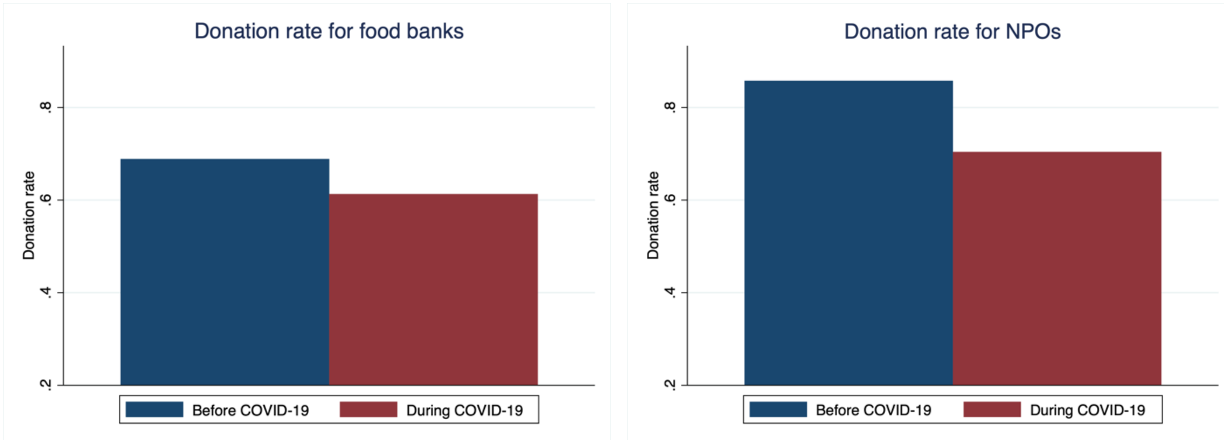
Figure 4.2 illustrates the changes in the annual donation amount before (average annual donation amount before the pandemic) and after the COVID-19 pandemic (until the time of the survey in October 2020). The annual donation amount to food banks remained almost the same around $221 during the year before and after the outbreak, but the amount for other NPOs dropped sharply by about $84 from $363 (The averages were calculated as the sum of contributions divided by the number of participants).

The average donation amount to food banks remained almost the same because the average donation amount from those who gave increased although the number of donors decreased during the pandemic. For food banks, 363 participants reported an average of $321.32 in contributions before the COVID-19, and 323 participants reported an average of $360.54 in contributions after the outbreak. However, for NPOs, we observe decreases in both the donation rate and the average amount. 452 participants reported an average of $423.39 in contributions before the COVID-19, and 371 participants reported an average of $396.29 in contributions after the outbreak.

The survey of the present study asked two questions regarding employment status. 'covidunemp' is a binary indicator if ever lost a job due to the COVID-19 pandemic; and 'employed' is also a binary variable which is 1 if employed or self-employed at the time of survey, otherwise 0.

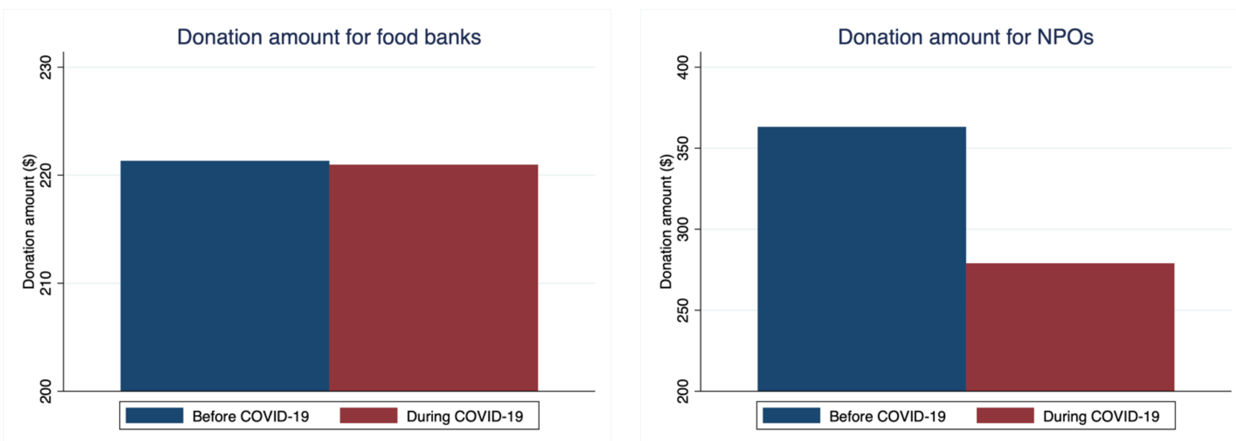
Table 4.1. Summary statistics

Variable	Description	Value
donatedfbbf	1 = if donated to food banks before COVID-19, 0=otherwise	Mean = .689 SD=.463
donatedfbdr	1 = if donated to food banks during COVID-19, 0=otherwise	Mean = .613 SD=.488
donatednpbf	1 = if donated to NPOs before COVID-19, 0=otherwise	Mean = .858 SD=.35
donatednpdr	1 = if donated to NPOs during COVID-19, 0=otherwise	Mean = .704 SD=.457
donatedfbbfamt	Average donation amount to food banks for a year before COVID-19	Mean = $221.328 SD=$611.268
donatedfbdramt	Donation amount to food banks during COVID-19	Mean = $220.977 SD=$456.797
donatednpbfamt	Average donation amount to NPOs for a year before COVID-19	Mean = $363.131 SD=$996.584
donatednpdramt	Donation amount to NPOs during COVID-19	Mean = $278.985 SD=$820.028
high_empathy	Empathy level measured as in Appendix B: 0=Low empathy, 1=High empathy	Mean = 65.65%, SD=.475
belief in impact	Belief in the impact of donation in reducing inequality: 0=strongly disagree, 1=somewhat disagree, 2=Neither agree nor disagree, 3=somewhat agree, 4=strongly agree	0=2.09%, 1=10.63%, 2=14.23%, 3=48.39%, 4=24.67%
exper_foodassist	Food assistance program recipient experience: 0=No, 1=Yes	Mean = 1.269 S.D.= 1.308
high_timedis	Time discount rate measured as in Appendix B: 0= Low time discount rate , 1=High time discount rate	0=41.18%, 1=58.82%
female	Gender: 0=male, 1=female	0= 62.94%, 1=37.06%
age	Age	Mean=37.393, SD=1.85
income	Annual household income in the 2019 tax year	Mean= $75055.03, SD=$45145.46
married	Marital status: 0=not married, 1=married	Mean=.711, SD=.454
employed	0=Not employed, 1=employed, self-employed	0=7.08%, 1=92.92%
COVID-19	COVID-19 infection: 0=not infected, 1=infected before or currently	0=77.87%, 1=22.16%
covidunemp	If ever unemployed due to COVID-19: 0=No, 1=Yes	0=55.98%, 1=44.02%
Black(race)	1=Black, 0=Otherwise	0=80.63%, 1=19.37%
White(race)	1=White, 0=Otherwise	0=22.18%, 1=72.81%
Others(race)	1=Non-White & non-Black, 0=Otherwise	0=27.19%, 1=7.82%
children	Number of children in household	Mean=2.19, SD=1.15
religion	Frequency of attendance to religious service : 0=seldom, never, no answer, 1= A few times a year, 2=Once or twice/month, 3=Once/week, 4= More than once/week	0=26.83%, 1=9.87%, 2=20.11%, 3=35.20%, 4=8.19%
conservative	1=Extremely liberal, 2=Liberal, 3=Slightly liberal, 4=Moderate/Decline to answer, 5=Slightly conservative, 6=Conservative, 7=Extremely Conservative	1=10.43%, 2=14.90%, 3=6.15%, 4=13.22%, 5=8.75%, 6=26.07%, 7=20.48%



(a) Food banks (b) Other NPOs

Figure 4.1. Donation rate changes



(a) Food banks (b) Other NPOs

Figure 4.2. Average donation amount changes

Model specifications

To investigate the changes in donation decisions, we used the ordered Probit, OLS, and conditional inference tree methods.

Ordered Probit model

The ordered Probit models were used to explore the direction of changes in donation status before and after the COVID-19 outbreak. Using the data on donation status (1 if donated, 0 otherwise) before and after the COVID-19, we generated an ordered type of dependent variable, which represents the changes in donation status before and after the COVID-19 outbreak: -1 if donated before the COVID-19 outbreak and did not donate during the pandemic ('Yes-No'), 0 if donation status did not change (either 'Yes-Yes' or 'No-No'), and 1 if did not donate before the COVID-19 outbreak but donated during the pandemic ('No-Yes'). This method is useful to explain the negative or positive changes in donation decisions during the pandemic. We used a standard ordered Probit model as below:

$If\ j = -1,$

$$\mathrm{P}(D_i = -1) = \Phi(\mu_0 - X_i{}'\beta)$$

$If\ j = 0\ or\ 1,$

$$\mathrm{P}(D_i = j) = \Phi\left(\mu_j - X_i{}'\beta\right) - \Phi\left(\mu_{j-1} - X_i{}'\beta\right)$$

where D_i is the ordered variable, which represents the changes in individuals' donation decisions, j = {-1, 0, 1} are the values that D_i takes, $X_i{}'$ is the vector of control variables, and Φ is the CDF.

Conditional inference tree

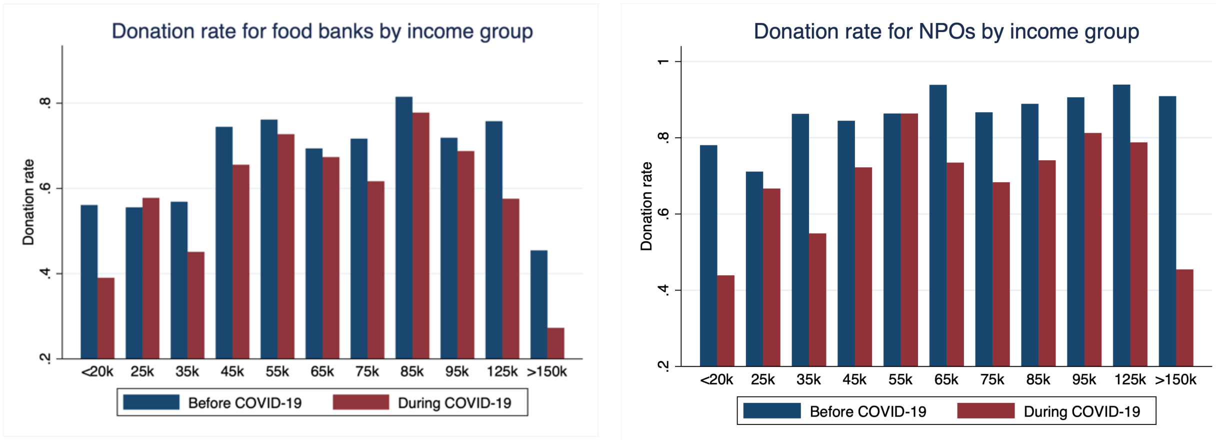
In addition, we also used the decision tree with a conditioning inference framework method (Hothorn et al. 2006) to measure the association between changes in donation decisions and individual characteristics. This method is suitable for exploring the changes in donation decisions as it estimates the chances for each decision choice based on the characteristics of individuals. Although this approach cannot provide marginal effects, it can select the most prominent factor to explain the changes in giving behavior based on the data, and interpreting the final nodes is fairly convenient. Besides, the conditional inference tree method is preferred when we want to avoid overfitting and selection bias towards covariates which often occur in binary partitioning algorithms (Hothorn et al. 2006).

Table 4.2. Decomposition of donation changes for food banks

Variable	Category	Donation rate		Donation amount	
		Before	During	Before	During
Income	<20	0.561	0.390	64.878	40.000
(in $1,000)	25	0.556	0.578	60.111	84.111
	35	0.569	0.451	222.255	261.373
	45	0.744	0.656	130.944	147.500
	55	0.761	0.727	333.977	247.841
	65	0.694	0.673	249.694	348.469
	75	0.717	0.617	466.083	394.083
	85	0.815	0.778	291.667	342.407
	95	0.719	0.688	185.781	211.875
	125	0.758	0.576	123.485	171.970
	>150	0.455	0.273	60.909	17.727
high_empathy					
	No	0.602	0.552	215.497	174.972
	Yes	0.734	0.645	224.379	245.043
exper_foodassist					
	No	0.500	0.338	72.875	51.833
	Yes	0.847	0.843	345.470	362.422
covidunemp					
	No	0.556	0.437	96.831	117.051
	Yes	0.858	0.836	379.634	353.125
covid_self					
	No	0.614	0.520	170.530	160.639
	Yes	0.964	0.955	409.554	444.554
race					
	Black	0.760	0.830	272.500	308.600
	Other	0.684	0.575	217.889	207.720
	White	0.561	0.439	128.902	132.073
married					
	No	0.474	0.279	68.247	62.045
	Yes	0.777	0.751	284.531	286.595
high_timedis					
	No	0.793	0.751	284.424	321.912
	Yes	0.616	0.516	177.161	150.323
risk					
	Averse	0.618	0.477	124.523	133.454
	Neutral	0.758	0.753	307.535	286.837
	Loving	0.760	0.720	357.900	396.400

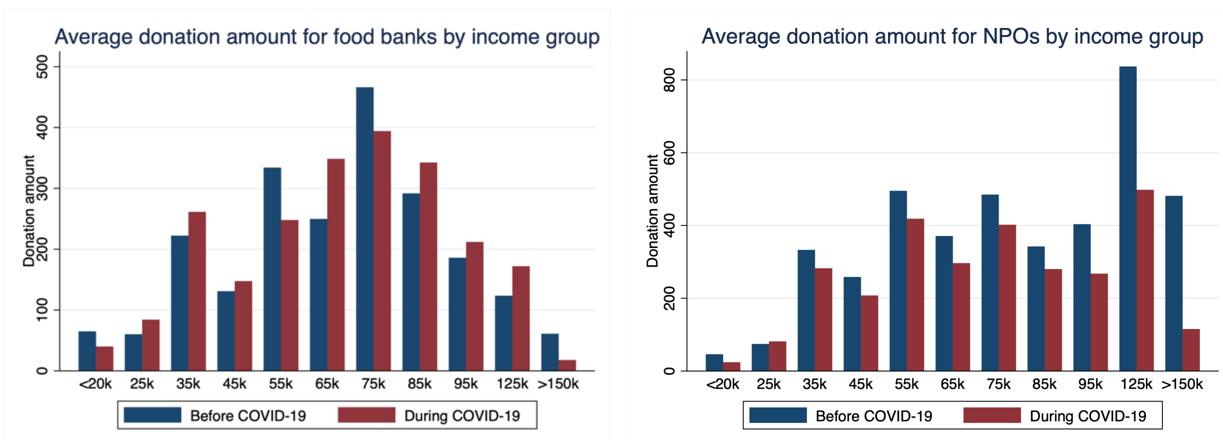
Table 4.3. Decomposition of donation changes for other NPOs

Variable	Category	Donation rate		Donation amount	
		Before	During	Before	During
income	<20	0.780	0.439	46.220	24.146
(in $1,000)	25	0.711	0.667	74.333	81.333
	35	0.863	0.549	332.941	282.353
	45	0.844	0.722	258.389	207.556
	55	0.864	0.864	495.114	418.523
	65	0.939	0.735	370.918	296.531
	75	0.867	0.683	484.750	401.833
	85	0.889	0.741	342.222	280.185
	95	0.906	0.813	403.438	267.500
	125	0.939	0.788	836.970	497.879
	>150	0.909	0.455	481.364	115.455
high_empathy					
	No	0.796	0.635	263.840	245.774
	Yes	0.890	0.740	415.072	296.358
exper_foodassist					
	No	0.779	0.504	290.458	162.042
	Yes	0.923	0.871	423.902	376.777
covidunemp					
	No	0.827	0.573	303.780	193.271
	Yes	0.897	0.871	438.599	387.974
covid_self					
	No	0.824	0.631	291.771	211.578
	Yes	0.982	0.973	627.545	528.750
race					
	Black	0.900	0.840	505.850	401.400
	Other	0.850	0.689	328.990	262.681
	White	0.829	0.512	336.463	133.902
married					
	No	0.766	0.416	214.058	127.662
	Yes	0.895	0.823	424.678	341.461
high_timedis					
	No	0.871	0.806	470.991	378.756
	Yes	0.848	0.632	287.629	209.145
risk					
	Averse	0.855	0.615	279.542	183.626
	Neutral	0.851	0.800	471.512	386.023
	Loving	0.900	0.760	335.100	318.400



(a) Food banks (b) Other NPOs

Figure 4.3. Donation rate changes by income group



(a) Food banks (b) Other NPOs

Figure 4.4. Average donation amount changes by income group

Decompositions

Tables 4.2 and 4.3 provide the decompositions of transformation of giving behaviors under the impact of the COVID-19 for food banks and other NPOs respectively. The tables describe the donation rate and the average donation amount before and during the COVID-19 over multiple determinants related to donation decisions. We acknowledge that there is an issue on the time span before and after the COVID-19 outbreak. It was less than a year after the outbreak until the survey. Therefore, comparing donation rates and annual donation amounts before and after the COVID-19 will have an issue. To address this problem, another survey will be conducted a year after the COVID-19 outbreak in the USA.

Income and giving

Overall, the giving rate decreased for both food banks and other NPOs across most of the income groups, and the income level and giving behavior were not in a positive association. The donation rate changes by income groups for food banks and other NPOs are also shown in Figure 4.3. For food banks, we observe that the overall giving rate fell for all income groups except for the $25k income group after the COVID-19 and the highest giving rate occurred in the $85k income group both before and after the outbreak. For other NPOs, we observe that the differences in giving rates across income groups were greater after the outbreak than the differences before the outbreak. After the COVID-19 outbreak, the giving rate to other NPOs fell for all the income groups and the sharpest decrease occurred for the lowest and highest income groups. The highest giving rates occurred in the $65k income group before the outbreak and in the $55k income group after the outbreak.

Figures 4.4 presents the changes in average giving amount by income groups for food banks and other NPOs. The giving amount to food banks was highest in the $75k income group for both before and after the outbreak. There seemed to be no specific pattern to explain an increase or decrease in the average giving amount in terms of income. The average giving amount decreased for some income groups and increased for some other groups. The giving amount to other NPOs was highest in the $125k income group for both before and after the outbreak. The average amount of monetary contribution for other NPOs decreased for all income groups except for the $25k income group. The biggest decline in the average giving amount occurred in the over $150k income group.

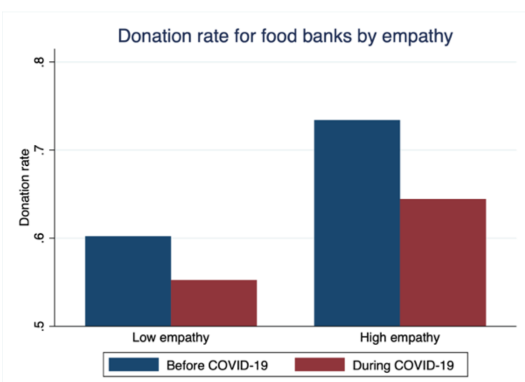
List (2011) argued that income does not have a positive relationship with giving. He analyzed the donation share as a percentage of income and found that households in the lower-income group ($20k - $40k) gave 5% of their income and the share of giving fell as income grew (up to around $70k) but increased back to 3% in the highest income group. Although there is a discrepancy in that he analyzed the gift share as a percentage of income and the present study analyzed the donation rate and amount, our results align with his argument in that giving and income are not necessarily in a positive association. It would be interesting to examine the changes in the donation share as a percentage of annual income, but the annual income data during the COVID-19 was not collected because the survey was conducted before one year passed after the outbreak. Therefore, it could be a possible further study once the data is collected and would provide more detailed knowledge on the association between income and donation decisions.

Empathy and giving

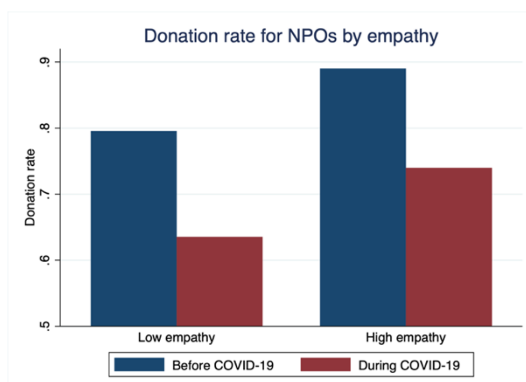
Empathy is one of the most frequently studied characteristics in charitable giving literature. This section aims to decompose the changes in donation behavior by empathy level. Empathy in the current study was measured following Schlegelmilch et al. (1997) and Lee and Chang (2008); it was modified as a binary (high and low) variable.

The donation rate for food banks decreased for both high and low empathy groups: from 0.602 to 0.552 for the low empathy group and from 0.734 to 0.645 for the high empathy group. The average donation amount for food banks decreased for low empathy groups but increased high empathy group: from $215 to $174 for the low empathy group and from $224 to $245 for the high empathy group. We see that the reason why the average donation amount remained almost the same before and after the outbreak was that the giving amount from those with high empathy increased.

The donation rate for other NPOs fell for both high and low empathy groups: from 0.796 to 0.635 for the low empathy group 0.89 to 0.74 for the high empathy group. Unlike the average giving amount to food banks, the giving amount to other NPOs decreased sharply. The average donation amount for other NPOs decreased for both low and high empathy groups: from $264 to $246 for the low empathy group and from $415 to $296 for the high empathy group. The possible explanations are the crowding-out effect from the donors with high empathy considering the different needs during the pandemic and that the economic impact made the donors reduce the giving amount and the donors to other NPOs might have been more responsive to the economic impact than the donors to food banks.

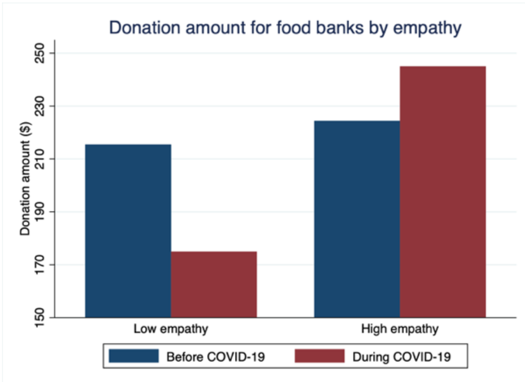


(a) Food banks

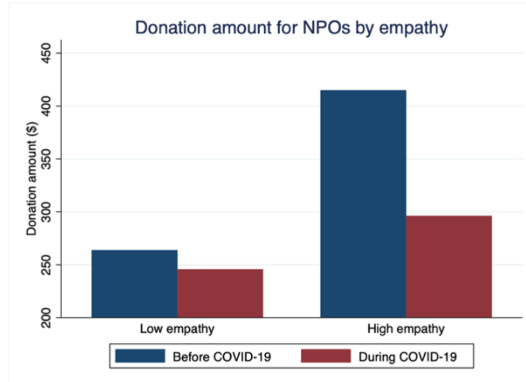


(b) Other NPOs

Figure 4.5. Donation rate changes by empathy level

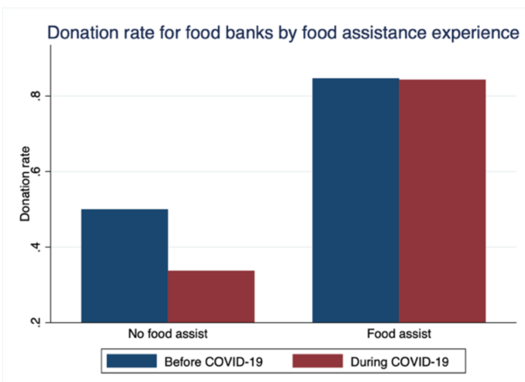


(a) Food banks

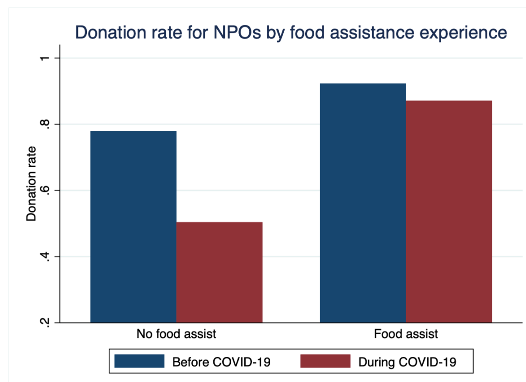


(b) Other NPOs

Figure 4.6. Average donation amount changes by empathy level

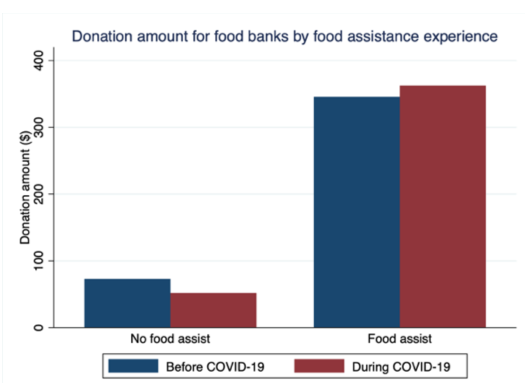


(a) Food banks

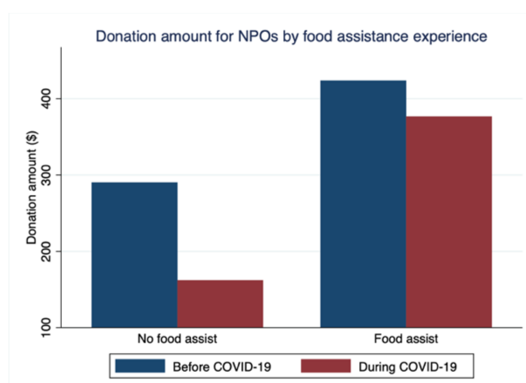


(b) Other NPOs

Figure 4.7. Donation rate changes by food assistance experience



(a) Food banks



(b) Other NPOs

Figure 4.8. Average donation amount changes by food assistance experience

Food assistance beneficiary experience and giving

This section described the results from decomposing the changes in giving patterns based on food assistance beneficiary experience. This experience was measured as a binary variable indicating whether anyone in a household received in the past or was receiving at the time of survey any type of food assistance from food banks, SNAP, or food stamps.

Figure 4.7 presents the changes in the donation rate before and after the outbreak by food assistance beneficiary experience for food banks and other NPOs respectively. The donation rate for the household with food assistance program beneficiary experience was much higher for food banks than the households who never benefitted from a food assistance program. Even after the outbreak, the giving rate of those with food recipient experience did not fall much and was approximately 0.84 both before and after the outbreak. For non-beneficiary groups, however, it was 0.5 before the pandemic and fell to 0.338 after the break. For the giving rates to other NPOs, we observe similar changes as food banks, but the giving rate to other NPOs from non-beneficiaries was higher than the giving rate to food banks.

Figure 4.8 illustrates the changes in the average donation amount before and after the outbreak by food assistance recipient experience for food banks and other NPOs respectively. We observe that the average amount from those with food assist recipient was higher for both food banks and other NPOs. Besides, the average giving amount to food banks from those with food assist recipient experience increased during the pandemic, while the amount to other NPOs from the same group decreased. Therefore, there might have been a crowding-out effect for those with such beneficiary experience to food banks from other NPOs during the COVID-19.

One possible explanation for the high giving rate to food banks from the households with food assistance experience while the overall giving rates fell during the pandemic could be that their previous exposure to food assistance increased their beliefs in such program, empathy, or some other factors that positively influenced their giving decisions. Since they received food assistance before, they could be more willing to, or somehow felt obligated to, give back in a similar way. It also could be that they may better understand the position of households with a similar need, which could trigger them to give more in the time of the pandemic.

Other determinants and giving

We also examined the changes in donation behavior in terms of job security. The decomposition results show that the donation rate to food banks for those who did not lose their job fell from 0.556 to 0.437, while the donation rate for those who experienced unemployment due to COVID-19 fell only by a little from 0.858 to 0.836. However, the average amount increased for those who did not lose their jobs and gave. We also observe that those who were married at the time of the survey showed a much higher giving rate and giving amount than those who were not married. The giving rate of those who were married decreased only by 2% and their giving amount increased by $2. However, the giving amount of those who were not married decreased by around $6.

We also observe that the time discount rate might have affected the changes in the giving rate and the amount. For food banks, those with a high time discount rate were less likely to donate and their giving amount was smaller than those with low time discount rate. The average amount of those with a high time discount rate decreased their giving amount from $177 to $150, on the other hand, the average giving amount of those with low time discount rate increased from $284 to $321. However, the giving amount to other NPOs decreased regardless of the time discount rate.

Results and discussions

Tables 4.4 and 4.5 present the results from ordered Probit models and the marginal effects respectively. The marginal effects in Table 4.5 are from the regressions in columns (2) and (4) of Table 4.4. These regressions illuminate the direction of changes in donation decisions before and after the COVID-19. The dependent variable is the changes in donation status before and after the COVID-19 outbreak: -1 if donated before the COVID-19 outbreak but did not donate during the pandemic ('Yes-No'), 0 if no change, and 1 if did not donate before the COVID-19 outbreak but donated during the pandemic ('No-Yes').

For food banks, those with food assistance recipient experience was 5.9% less likely to stop giving ('Yes-No' category) and 2.9% more likely to start giving ('No-Yes' category). In other words, if an individual had an experience in a food assistance program, then s/he would be more likely to start giving than stop giving. The race variable 'white' turned out to be significant, and the results suggest that if one reported being white, then s/he is 5.6% more likely to be in the 'Yes-No' category which means stopping giving after the COVID-19 outbreak. However, the race variable in our same was somewhat off from even distribution, so the interpretation should be made with care.

For other NPOs, the results suggest that marriage was positively related to the changes in donation status before and after the outbreak. The results imply that if married, then s/he was 8.6% less likely to stop giving ('Yes-No' category) and 1.8% more likely to start giving ('No-Yes' category) to other NPOs. We also observe the same direction of changes in donation decisions in association with the coronavirus infection and with the frequency of attendance to religious services. However, those who received the stimulus check showed the opposite directions: 10.7% more likely to be in the 'Yes-No' category and 3.7% less likely to be in the 'No-Yes' category.

Changes in the donation amount

Table 4.6 describes the results from the OLS model on changes in logged donation amounts before and during the COVID-19 pandemic. Since the donation amount remained approximately the same for food banks, the controlling factors such as personal intrinsic characteristics and demographic variables did not show statistically significant relationships with the changes in giving amount except for 'sti_check,' which is a binary indicator indicating if received the first-round stimulus payment. The results suggest that receiving stimulus check was negatively associated with 0.283 logged dollars for food banks.

For other NPOs, we observed a negative correlation with income. A 1% increase in income was associated with a decrease in 0.303 logged giving amount ($p < 0.05$). The negative relation between income and donation amount change could be because those who had donated more money potentially had more room to decrease their donation. We also observe the significant correlation between donation amount to other NPOs and income before COVID-19 ($p < 0.01$), but the significance disappears during the pandemic. Also, it was constantly confirmed that those who were married increased the giving amount.

However, there is a chance that the results from Table 4.6 lost the systematic difference between those who did not donate before and during the COVID-19 pandemic and those who kept donating the same amount for the same periods since the changes in donation amount became same to be 0. Therefore, it would be desirable to differentiate those who did not donate for both periods from those who donated the same amounts before and during the COVID-19. To this end, we ran regressions on the changes in donation amount separately for previous donors and previous non-donors. This way, we could rule out the possibility that those who did not donate and those who donated the same amounts for both periods have the same value of zero for the dependent variable (changes in donation amount).

Tables 4.7 and 4.8 describe the results on the change in donation amount for previous donors and previous nondonors respectively. The results from Table 4.7 show that the time discounting factor had a significant negative relationship with the changes in donation amount to food banks for previous donors. For other NPOs, we observe that food assistance beneficiary experience had a positive association with the changes in donation amount for previous donors, while income had a negative association. For previous nondonors, changes in donation amount to food banks were positively associated with the food assistance recipient experience and with less risk-averse characteristics. Risk-taking behavior was not a significant factor in terms of the changes in donation status, but it showed a significant association with the changes in giving amount to food banks. For other NPOs, we observe the positive association between the amount changes and the coronavirus infection. It is not clear what was the mechanism between the infection with coronavirus and giving amount, but one possible explanation could be that the experience as a victim of the COVID-19 could have made them more empathetic for those who were also the victim of the COVID-19 and led them to be more generous in giving money during the pandemic. This explanation is consistent with extant literature which argued the previous experience as a victim or as a close connection to victims shows a positive association with empathy and giving (Brown et al. 2012; Small and Simonsohn 2007).

Table 4.4. Ordered Probit model: Donation status changes

	Ordered Probit: Food banks		Ordered Probit: NPOs	
	(1)	(2)	(3)	(4)
high_empathy	-0.182	-0.158	-0.014	0.039
	(0.125)	(0.131)	(0.133)	(0.143)
belief_in_impact	0.054	0.034	-0.003	-0.021
	(0.058)	(0.060)	(0.062)	(0.067)
exper_foodassist	0.414***	0.292*	0.472***	0.259*
	(0.132)	(0.157)	(0.133)	(0.154)
high_timedis	-0.029	0.073	-0.252**	-0.133
	(0.121)	(0.129)	(0.120)	(0.131)
risk	0.155*	0.146	0.173*	0.118
	(0.087)	(0.089)	(0.089)	(0.095)
female		-0.055		-0.062
		(0.122)		(0.125)
age		-0.002		-0.004
		(0.006)		(0.005)
married		0.227		0.332**
		(0.164)		(0.162)
children		-0.015		0.029
		(0.053)		(0.060)
employed		0.240		-0.060
		(0.228)		(0.266)
income		-0.002		-0.001
		(0.002)		(0.002)
conservative		0.020		0.029
		(0.028)		(0.027)
white		-0.306**		0.121
		(0.132)		(0.123)
covid_self		-0.010		0.240*
		(0.129)		(0.125)
religion		0.091*		0.203***
		(0.053)		(0.054)
sti_check		-0.331**		-0.486***
		(0.152)		(0.145)
cut1	-0.794***	-0.936**	-0.701***	-0.587
	(0.193)	(0.420)	(0.193)	(0.403)
cut2	1.916***	1.898***	1.961***	2.333***
	(0.207)	(0.410)	(0.224)	(0.438)
N	527	527	527	527

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The dependent variable is -1 if donated before the COVID-19 outbreak but did not donate after, 0 if not changed, 1 if did not donate before the COVID-19 outbreak but did donate after.

Table 4.5. Ordered Probit margins: Donation status changes

	Margins: Food banks			Margins: NPOs		
	(1) Yes-No	(2) No change	(3) No-Yes	(4) Yes-No	(5) No change	(6) No-Yes
high_empathy	0.030	-0.014	-0.017	-0.010	0.007	0.002
	(0.024)	(0.010)	(0.015)	(0.035)	(0.026)	(0.009)
belief_in_impact	-0.007	0.003	0.003	0.005	-0.004	-0.001
	(0.012)	(0.006)	(0.006)	(0.016)	(0.012)	(0.004)
exper_foodassist	-0.059*	0.030*	0.029*	-0.064	0.048	0.016*
	(0.032)	(0.018)	(0.016)	(0.039)	(0.030)	(0.010)
high_timedis	-0.015	0.007	0.007	0.032	-0.023	-0.009
	(0.026)	(0.013)	(0.013)	(0.031)	(0.022)	(0.009)
risk	-0.029	0.014	0.015	-0.029	0.021	0.007
	(0.018)	(0.009)	(0.009)	(0.023)	(0.017)	(0.006)
female	0.011	-0.005	-0.006	0.015	-0.011	-0.004
	(0.025)	(0.012)	(0.012)	(0.031)	(0.023)	(0.008)
age	0.000	0.000	0.000	0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
married	-0.048	0.026	0.022	-0.086*	0.068*	0.018**
	(0.036)	(0.022)	(0.015)	(0.045)	(0.037)	(0.008)
children	0.003	-0.001	-0.002	-0.007	0.005	0.002
	(0.011)	(0.005)	(0.005)	(0.014)	(0.011)	(0.004)
employed	-0.053	0.033	0.021	0.014	-0.010	-0.004
	(0.057)	(0.040)	(0.017)	(0.061)	(0.043)	(0.018)
income	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
conservative	-0.004	0.002	0.002	-0.007	0.005	0.002
	(0.006)	(0.003)	(0.003)	(0.007)	(0.005)	(0.002)
white	0.056**	-0.021**	-0.035**	-0.030	0.023	0.007
	(0.022)	(0.009)	(0.017)	(0.031)	(0.025)	(0.007)
covid_self	0.002	-0.001	-0.001	-0.054**	0.037**	0.017*
	(0.026)	(0.013)	(.)	(0.027)	(0.018)	(0.010)
religion	-0.018*	0.009	0.009*	-0.049***	0.037***	0.013***
	(0.011)	(0.006)	(0.005)	(0.013)	(0.011)	(0.004)
sti_check	0.061**	-0.023**	-0.038*	0.107***	-0.070***	-0.037**
	(0.025)	(0.010)	(0.020)	(0.029)	(0.018)	(0.015)

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Note: The predicted values are based on column 2 in Table 4.4 for food banks and based on column 4 in Table 4.4 for NPOs.

Table 4.6. Donation amount changes

	OLS: Food banks		OLS: NPOs	
	(1)	(2)	(3)	(4)
high_empathy	63.133	67.071	-120.543*	-69.668
	(59.958)	(61.600)	(64.156)	(54.210)
belief_in_impact	-5.732	-6.199	17.506	27.803
	(24.432)	(25.652)	(43.679)	(44.946)
exper_foodassist	19.880	50.076	96.882	117.563*
	(38.471)	(36.699)	(76.055)	(68.196)
high_timedis	-59.615	-68.447*	43.915	21.018
	(45.515)	(41.028)	(78.532)	(74.537)
risk	-10.238	-4.523	10.693	10.336
	(33.331)	(32.017)	(45.737)	(48.725)
female		17.471		-17.819
		(41.371)		(65.091)
age		1.150		-5.897**
		(1.288)		(2.800)
married		-32.211		42.460
		(38.362)		(85.077)
children		9.418		-27.609
		(17.964)		(35.236)
employed		23.348		398.237
		(30.625)		(256.624)
log(income)		1.502		-163.254***
		(29.715)		(41.855)
conservative		-1.432		6.253
		(13.778)		(20.800)
white		-23.538		77.672
		(43.144)		(99.470)
covid_self		64.671		-31.411
		(73.246)		(105.252)
religion		-30.423		-44.120
		(20.695)		(30.261)
sti_check		-120.821**		-14.716
		(52.633)		(74.027)
constant	4.775	65.541	-139.518	346.145
	(67.249)	(165.325)	(126.934)	(433.794)
N	527	527	527	527

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.7. Donation amount changes for previous donors

	Probit: Food banks		Probit: NPOs	
	(1)	(2)	(3)	(4)
high_empathy	107.372	118.339	-126.231	-78.559
	(97.725)	(99.873)	(79.541)	(71.178)
belief_in_impact	-14.145	-20.491	33.564	41.588
	(39.229)	(42.975)	(54.774)	(56.749)
exper_foodassist	33.586	81.033	140.218	159.741**
	(51.334)	(51.383)	(92.962)	(80.760)
high_timedis	-92.862	-108.399*	64.883	39.163
	(66.152)	(63.050)	(94.203)	(88.693)
risk	-20.659	-9.316	14.295	20.879
	(46.845)	(45.432)	(52.314)	(54.001)
female		7.918		-25.587
		(61.379)		(73.988)
age		1.925		-5.511
		(1.970)		(3.347)
married		-38.749		66.701
		(62.446)		(99.954)
children		7.883		-37.926
		(24.513)		(41.993)
employed		10.276		481.303
		(56.069)		(315.214)
log(income)		15.007		-175.774***
		(47.609)		(47.773)
conservative		-0.182		1.546
		(17.857)		(23.837)
white		-36.358		69.273
		(64.310)		(114.104)
covid_self		99.482		-25.812
		(86.437)		(109.572)
religion		-48.250		-55.487
		(30.755)		(37.845)
sti_check		-163.845**		0.578
		(77.569)		(83.941)
constant	-8.348	57.775	-249.401	249.641
	(103.522)	(224.000)	(163.341)	(550.724)
N	363	363	452	452

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.8. Donation amount changes for previous nondonors

	Probit: Food banks		Probit: NPOs	
	(1)	(2)	(3)	(4)
high_empathy	15.846	10.737	-70.930	-51.024
	(13.228)	(16.598)	(56.459)	(49.440)
belief_in_impact	9.756	7.002	-7.580	-29.197
	(7.582)	(7.548)	(17.574)	(25.047)
exper_foodassist	61.861***	62.391*	46.930	-47.651
	(22.056)	(31.986)	(54.459)	(70.981)
high_timedis	-10.110	-8.685	-26.936	10.601
	(19.052)	(20.102)	(47.722)	(49.967)
risk	24.779*	19.537*	-38.414	-31.134
	(13.753)	(11.723)	(44.348)	(37.013)
female		29.895*		95.104
		(16.329)		(66.906)
age		0.174		-2.288
		(0.788)		(2.008)
married		10.338		69.957
		(15.687)		(86.004)
children		1.905		-4.411
		(9.540)		(18.899)
employed		13.560		-26.975
		(17.483)		(46.631)
log(income)		13.070		-2.386
		(25.476)		(28.314)
conservative		-2.270		-4.359
		(5.462)		(12.634)
white		21.157		40.345
		(16.303)		(37.516)
covid_self		37.613		494.012**
		(85.451)		(222.878)
religion		5.236		25.632
		(5.905)		(15.836)
sti_check		-26.434		-61.215*
		(18.895)		(32.899)
constant	-25.322	-100.446	151.631	211.045
	(19.572)	(103.646)	(92.592)	(167.530)
N	164	164	75	75

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Conditional inference tree

The condition inference tree method was also applied to explore the probabilities in the donation status changes before and after the COVID-19 outbreak. The target variable is the change in donation status before and after the COVID-19 outbreak, which is 1 if did not donate both periods, 2 if donated before but did not donate after, 3 if donated before but did not donate after, and 4 if donated for both periods. This method is particularly useful as it can estimate the probabilities of each category of the target variable based on the data.

The results from the conditional inference tree suggest that the most important predictor to explain the change in donation status was 'experience in food assistance recipient' as shown in Figure 4.9. According to the results, the probability that people with no such experience did not donate for both periods was over 40%, and the probability of giving during the pandemic for those who did not give before was about 20%. For those who experienced in a food assistance program, the probability of giving both periods was more than 80% if their time discount rates were not high. However, if they had a high time discount rate, and belief in the impact of the giving was low, then the rate of giving for both periods dropped almost in half. Rather, the rates of not giving both periods and of stopping donating if they donated before went up to around 20%. Also, less risk-averse individuals were most likely to donate both periods and least likely not to donate both periods.

Figure 4.10 presents the changes in donation status for food banks using demographic variables. Among the demographic variables, the most prominent predictor turned out to be marital status followed by coronavirus infection. For those who were not married and not infected with the COVID-19, the category of 'no donation for both periods' showed the highest probability. However, if infected, there were no participants who did not donate during the pandemic although the sample size was only 10 in this node. Those who were married and ever infected with the coronavirus showed the highest probability of giving to food banks for both periods.

As shown in Figure 4.11, the experience in benefitting from food assistance program turned out to be the most prominent predictor as well followed by ‘belief in impact’ to explain donation status for other NPOs. ‘belief in impact’ was less than or equal to two if the survey participant reported to disagree on that charitable giving has an impact to reduce inequality. For those who had experience in a food assistance program, believed in the impact of charitable giving, and were less risk-averse, the chance to make donations to other NPOs in both periods (category 4) was around 90%. For those with no food assist recipient experience, the chance to stop giving (category 2) during the pandemic was around 30% and the chance not to give in both before and during the pandemic was a little less than 20%.

Figure 4.12 presents the changes in donation status for other NPOs using demographic variables. The result suggests that marital status was the most important predictor followed by the coronavirus infection. The influences of each variable were in the same directions with the changes in donation status to food banks. Those who were married, attended religious service at least once a month, or were ever infected with coronavirus show mostly high probabilities for giving both periods although the number of observations was not large. For those who were neither married nor infected with the COVID-19, the chance of stop giving (category 2) was about 40%, and the chance to start giving to other NPOs during the pandemic was very low.

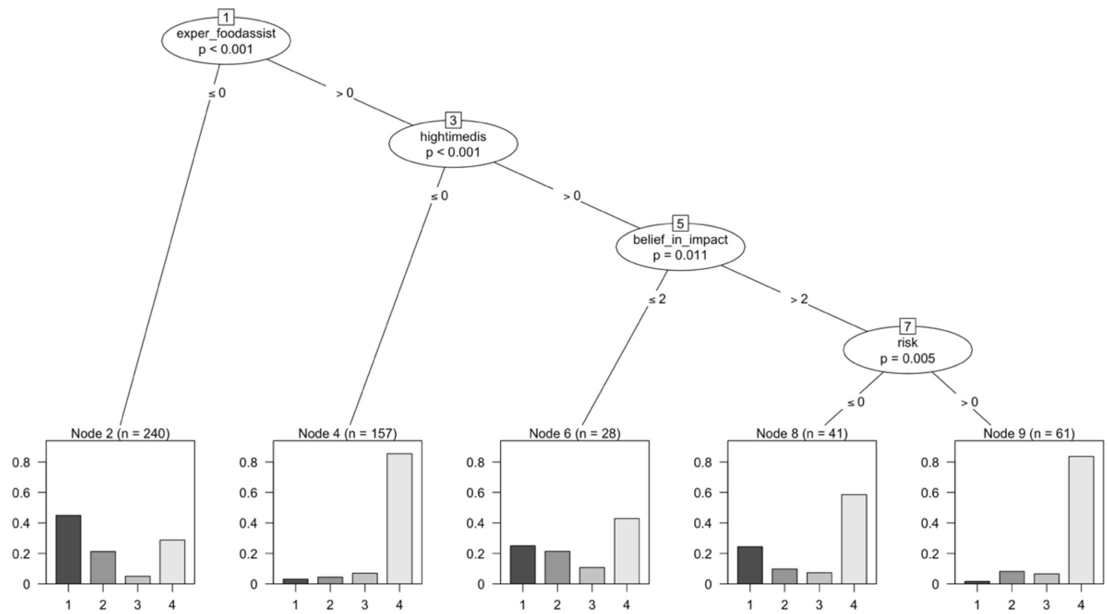


Figure 4.9. Changes in donation status for food banks using personal characteristic variables

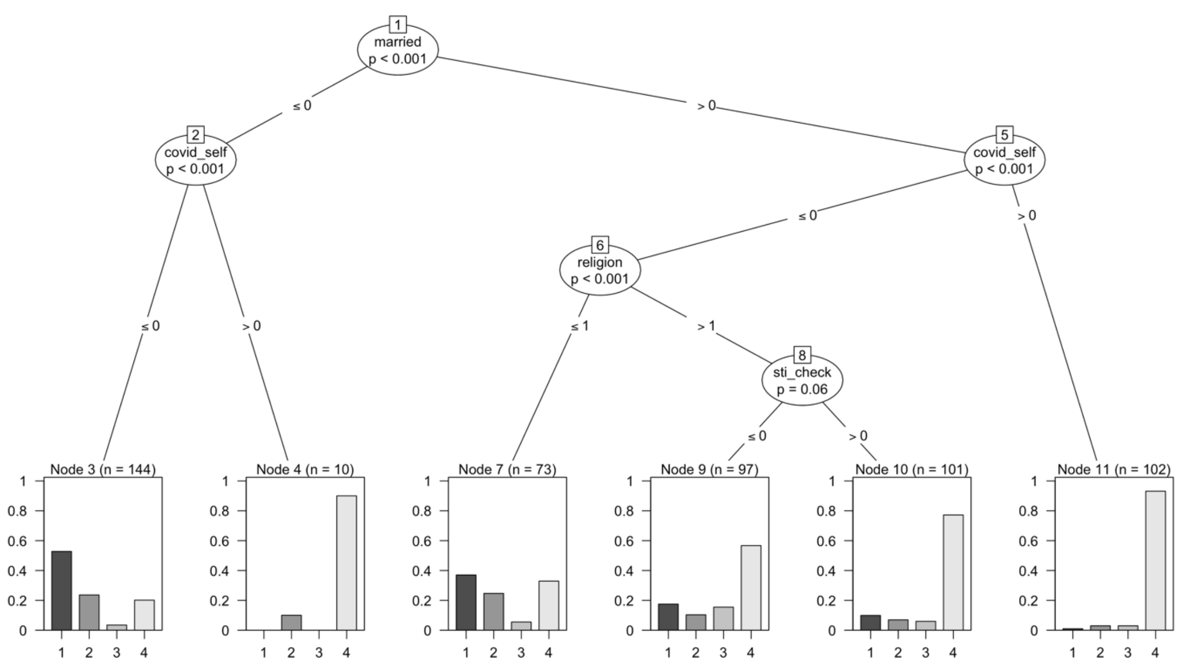


Figure 4.10. Changes in donation status for food banks using demographic variables

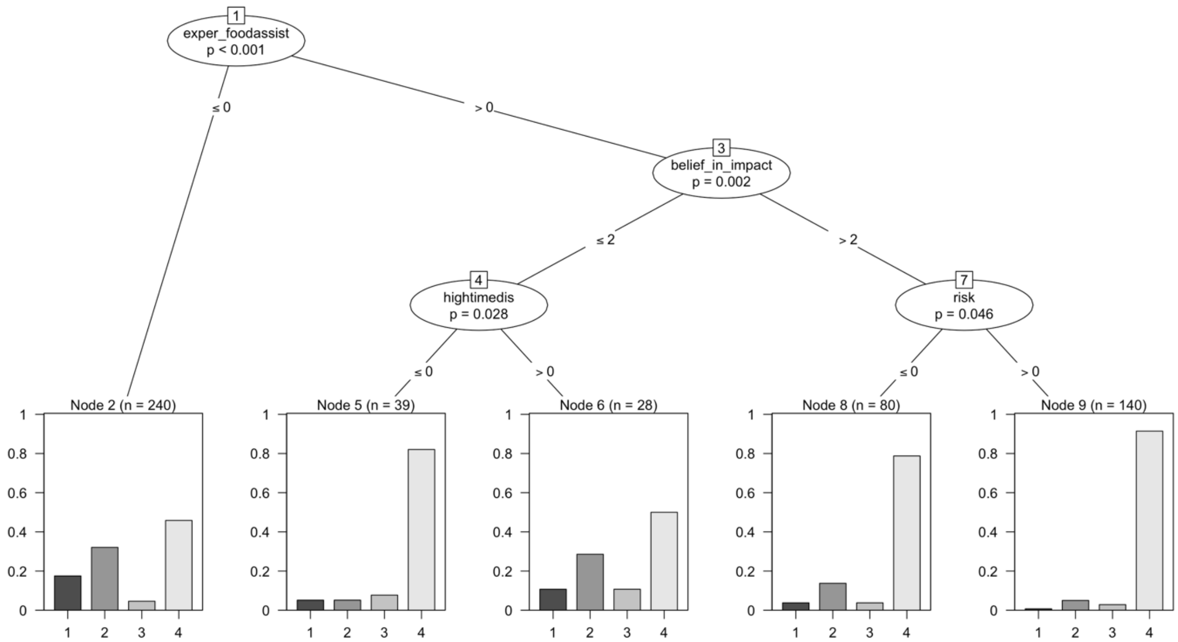


Figure 4.11. Changes in donation status for NPOs using personal characteristic variables

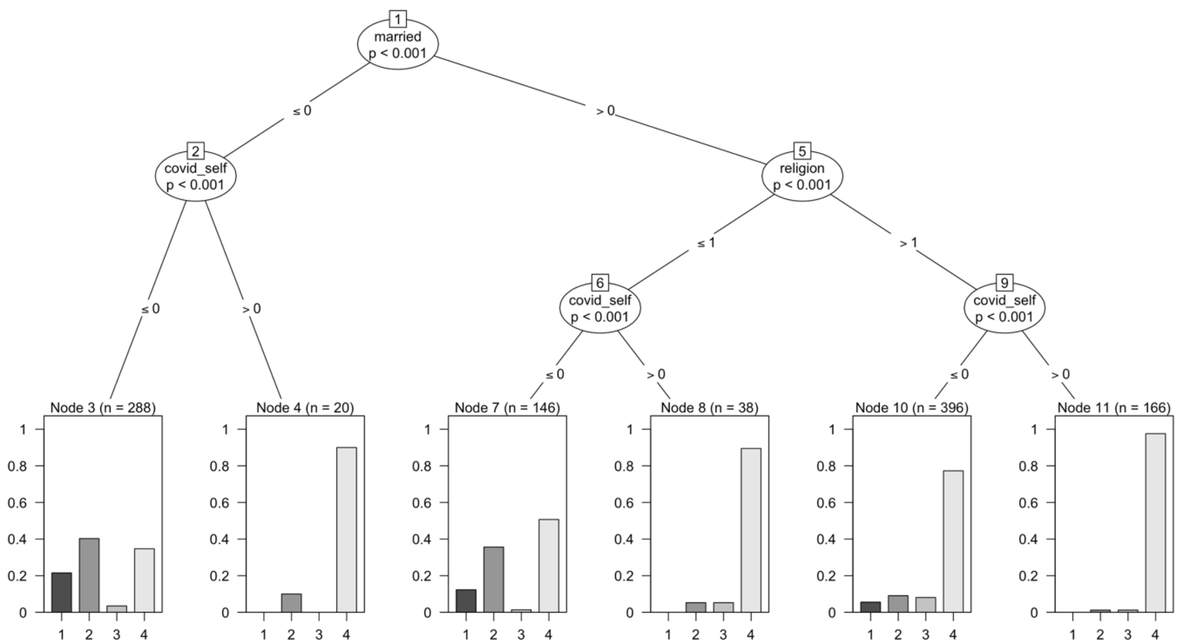


Figure 4.12. Changes in donation status for NPOs using demographic characteristics

Donation status for previous donors and non-donors

It would be also interesting to see what motivated previous donors and non-donors to make contributions during the pandemic separately. Tables C.1 – C.4 in Appendix C provide the Probit regression results and marginal effects from the analysis on donation status during COVID-19 for previous donors and non-donors before the pandemic. From these regression results, we repeatedly confirm that food assistance recipient experience was a prominent factor in giving decisions. Besides, the results imply that for previous non-donors, the belief in the impact of charitable giving increased the giving rate by 6.2% to food banks during the pandemic. In addition, we observe that risk-taking characteristic was correlated with giving to other NPOs ($p = 0.05$). Previous donors infected with coronavirus showed a positive correlation with giving for both food banks and other NPOs: the probability of giving increased by 13.9% ($p = 0.01$) and 22.5% ($p = 0.01$) for food banks and other NPOs respectively. However, there was no significant effect for previous non-donors. Our results also suggest that the frequency of attending religious service was positively associated with giving from both previous donors and non-donors to both food banks and other NPOs.

Donation status changes using multinomial Probit models

Table C.5 describes the results of multinomial Probit models using personal characteristic variables. The dependent variable is donation status before and after the COVID-19 outbreak: 1 is where a participant did not donate for both periods (No-No); 2 is for a participant who donated before the COVID but did not donate during the pandemic (No-Yes); 3 is where a participant did not donate before the COVID-19 but donated during the COVID-19 (Yes-No); 4 is where a participant donated for both periods (Yes-Yes). The base category is 4, which is omitted from the results. Table C.6 presents the marginal effects of the results of multinomial Probit models. Those with high empathy were 7.6% more likely to donate to food banks for both periods ('No-No' category), and 3.7% less likely to start giving ('No-Yes' category).

If the belief in the impact of donation in reducing inequality increased by one level, then they were 26.7% less likely not to donate for both periods ('No-No' category). In addition, we also confirmed that the time discounting factor was negatively related to donation decisions. If the time discount factor increased by one level, then the participants were 4.8% less likely to donate for both periods and 2.6% more likely not to donate to food banks for both periods. We also observed that risk-taking behavior influenced donation decisions. Being more risk-averse by one level was related to a 7.8% higher donation rate for both periods.

For other NPOs, those who were in the 'high empathy' group were 8.6% more likely to donate during both periods to other NPOs ($p < 0.05$). The results also suggest that those with a stronger belief in the impact of charitable giving would be less likely not to donate for both periods ('No-No' category). From this, we confirm that the belief in the impact of charitable giving positively affected the giving decisions. Those who with food assistance recipient experience were 26.6% more likely to donate during both periods, but 12.2% less likely not to donate during both periods. Moreover, they were 13.9% less likely to be in the 'Yes-No' category. Those with a higher time discount factor were associated with a 4.3% lower probability of giving during both periods.

References

Andersen, Steffen, et al. 2008. Eliciting risk and time preferences. *Econometrica* 76.3: 583-618.

Abel, M. and Brown, W., 2020. Prosocial behavior in the time of COVID-19: The effect of private and public role models.

Andreoni, J., Rao, J.M. and Trachtman, H., 2017. Avoiding the ask: A field experiment on altruism, empathy, and charitable giving. *Journal of Political Economy*, *125*(3), pp.625-653.

Bekkers, R. and Wiepking, P., 2011. A literature review of empirical studies of philanthropy: Eight mechanisms that drive charitable giving. *Nonprofit and voluntary sector quarterly*, *40*(5), pp.924-973.

Berrebi, C., Karlinsky, A. and Yonah, H., 2021. Individual and community behavioral responses to natural disasters. *Natural Hazards*, *105*(2), pp.1541-1569.

Bin-Nashwan, S.A. and Al-Daihani, M., 2020. Fundraising campaigns via social media platforms for mitigating the impacts of the COVID-19 epidemic. *Journal of Islamic Marketing*.

Bin, O. and Edwards, B., 2009. Social capital and business giving to charity following a natural disaster: An empirical assessment. *The Journal of Socio-Economics*, *38*(4), pp.601-607.

Brown, P.H. and Minty, J.H., 2008. Media coverage and charitable giving after the 2004 tsunami. *Southern Economic Journal*, pp.9-25.

Brown, S., Harris, M.N. and Taylor, K., 2012. Modelling charitable donations to an unexpected natural disaster: Evidence from the US Panel Study of Income Dynamics. *Journal of Economic Behavior & Organization*, *84*(1), pp.97-110.

Castiglioni, C. and Lozza, E., 2020. Determinants of the Financial Contribution to the NHS: The Case of the COVID-19 Emergency in Italy. *Frontiers in Psychology*, *11*, p.3189.

Center for disaster philanthropy., 2019. "U.S Household Disas- ter Giving in 2017 and 2018." Retrieved from https://www.issuelab.org/resources/34757/34757.pdf

Clotfelter, Charles T., 2007. Federal tax policy and charitable giving. University of Chicago Press,

DellaVigna, S., List, J.A. and Malmendier, U., 2012. Testing for altruism and social pressure in charitable giving. *The quarterly journal of economics*, *127*(1), pp.1-56.

Eckel, C.C. and Grossman, P.J., 2008. Forecasting risk attitudes: An experimental study using actual and forecast gamble choices. *Journal of Economic Behavior & Organization*, *68*(1), pp.1-17.

Feeding America., 2020. “The food bank response to COVID, by the numbers.” Hunger Blog., Retrieved from https://www.feedingamerica.org/hunger-blog/food-bank-response-covid-numbers

Gao, Y., 2011. Philanthropic disaster relief giving as a response to institutional pressure: Evidence from China. *Journal of Business Research*, *64*(12), pp.1377-1382.

Havens, J.J., O’Herlihy, M.A. and Schervish, P.G., 2006. Charitable giving: How much, by whom, to what, and how. *The nonprofit sector: A research handbook*, *2*, pp.542-567.

Hothorn, T., Hornik, K. and Zeileis, A., 2006. Unbiased recursive partitioning: A conditional inference framework. *Journal of Computational and Graphical statistics*, *15*(3), pp.651-674.

Indiana University Lilly Family School of Philanthropy, Center for Disaster Philanthropy. 2019., “U.S. Household Disaster Giving In 2017 and 2018.” Retrieved from http://hdl.handle.net/1805/19403

IRS., 2020. “Special $300 tax deduction helps most people give to charity this year – even if they don’t itemize.” IR-2020-264. November 25, 2020.

Kim, S.J. and Kou, X., 2014. Not all empathy is equal: How dispositional empathy affects charitable giving. *Journal of Nonprofit & Public Sector Marketing*, *26*(4), pp.312-334.

Kobayashi, Y., Heinrich, T. and Bryant, K.A., 2021. Public support for development aid during the COVID-19 pandemic. *World development*, *138*, p.105248.

Lee, Y.K. and Chang, C.T., 2008. Intrinsic or extrinsic? Determinants affecting donation behaviors. *International Journal of Educational Advancement*, *8*(1), pp.13-24.

List, J.A., 2011. The market for charitable giving. *Journal of Economic Perspectives*, *25*(2), pp.157-80.

Lobb, A., Mock, N. and Hutchinson, P.L., 2012. Traditional and social media coverage and charitable giving following the 2010 earthquake in Haiti. *Prehospital and disaster medicine*, *27*(4), p.319.

Maftei, A., 2020. The more you have, the less you give? Prospective donation behavior for COVID-19 causes. *Romanian Journal of Psychology*, *22*(1).

Manesi, Zoi, et al., 2020. ”What are the most powerful predictors of charitable giving to victims of typhoon National Philanthropic Trust. ”Charitable giving statistics.” Retrieved from https://www.nptrust.org/philanthropic- resources/charitable-giving-statistics/

Manesi, Z., Van Lange, P.A., Van Doesum, N.J. and Pollet, T.V., 2019. What are the most powerful predictors of charitable giving to victims of typhoon Haiyan: Prosocial traits, socio-demographic variables, or eye cues?. *Personality and Individual Differences*, *146*, pp.217-225.

Osili, Una., 2020, ”Charitable Giving During the COVID-19 Pandemic.” Joint Economic Committee, US Congress

Rooney, Patrick., 2017. ”American generosity after disasters: 4 questions answered.” The Conversation. Retrieved from https://theconversation.com/american-generosity-after- disasters-4-questions-answered-83277

Sarea, A. and Bin-Nashwan, S.A., 2020. Guide to giving during the COVID-19 pandemic: the moderating role of religious belief on donor attitude. *International Journal of Ethics and Systems*.

Small, D.A. and Simonsohn, U., 2008. Friends of victims: Personal experience and prosocial behavior. *Journal of Consumer Research*, *35*(3), pp.532-542.

Torrey, C., Burke, M., Lee, M., Dey, A., Fussell, S. and Kiesler, S., 2007, January. Connected giving: Ordinary people coordinating disaster relief on the Internet. In *2007 40th Annual Hawaii International Conference on System Sciences (HICSS'07)* (pp. 179a-179a). IEEE.

CHAPTER V

CONCLUSIONS

Recreational marijuana legalization and crime rates

Ever since Colorado and Washington legalized recreational marijuana for the first time in the U.S., this trend has been sweeping the United States and a bill of federal level de-scheduling marijuana was passed in the House of Representatives in 2019. In such context, the current research examined the impacts of state-level legalization of recreational marijuana on crime rates in the affected states using the DID, SCM, and SCISA methods.

By using SCISA, I have shown that the ATT estimate of RML on overall violent crime significantly increased over time unlike the results from the DID and SCM methods. Among all crime types, the increases in the overall violent crime, robbery, and motor vehicle theft rates were prominent. This contradicts most of the previous literature that suggested a decrease or insignificant effect of RML on crime rates.

The current research has its contribution in that it showed the averages effect of state-level RML on crime rates for all the states that adopted the recreational cannabis law no matter when it happened. However, it also has its weakness since the data after the law intervention is not long enough for some states. Therefore, the dynamic effect of the ATT in the later event times could be affected by the changes in the number of the treated states rather than the dynamics of the effect of RML on crime rates.

A further study would be beneficial once long enough panel data is collected. However, since the legalization trend is ongoing, it would be hard in the near future to gather the long panel data from all the treated states. Also, if a further study can use county-level data and marijuana sales data, then we may observe the detailed effect of RML and marijuana retail sales on crime rates. Moreover, it would be also interesting to see the effect of the implementation of RML on crime rates. Since the policy change takes time to be implemented, and legalization itself and the implementation of the law intervention may have different impacts on crime rates. If such a 'two-step' treatment effect can be estimated, this could provide a more detailed understanding of how the RML process influenced the crime rates in the treated states.

Donation to food banks amidst the COVID-19

The experiment on information treatments—deliberate and impulsive types—examines what type of information can effectively influence individuals' charitable giving decisions during the pandemic. Our results from the REP and SUP models showed that, in general, if a food bank has to choose either type of information, a deliberate type of information is preferred. Deliberate nudging can be particularly more efficient for those with low empathy and no experience in a food assistance program. The current study has its important contributions in identifying mechanisms that facilitate people to donate more generously so that it can effectively help food banks support those who are most in need during the health and economic crisis caused by the pandemic.

Also, we have found that trust in food banks and belief in the impact of donation to reduce inequality were positively related to giving rates. Therefore, the messages that can help potential donors trust the organization and that emphasize the impact of the contribution would be helpful to promote donation efficiently.

Our results confirmed that time discount rate influences giving rates as well, and this implies that how to frame the giving timing affects giving patterns. Even if the donation amount was $1 only in this study, people were still more likely to donate when asked to give in a month than give on the same day. Also, the present research confirmed that empathy is a prominent predictor for charitable giving, and it can be less or more effective depending on the types of external nudging information given to them.

Another important finding of the current research is that the previous exposure to beneficiary experience may increase the giving rate. Considering that the previous literature did not give much attention to what potential donors experienced while intrinsic traits such as empathy were frequently studied, potential donors' experiences could be an interesting topic for further study. Our results also showed that the donation rates were higher for those who received food assistance, those who lost jobs due to COVID-19, and those who were ever infected with COVID-19. It remains uncertain how such difficult experiences influenced the giving decisions during the pandemic and what the moderating effect was between such experience and the higher donation rate. One possible mechanism could be that if empathy were an important cause to give others as extant literature argued, such experiences could be an opportunity to relate to others in afflictions, this may have led to a higher donation rate. It would be a valuable further study to examine the mechanism between donors' experience and donation decisions.

Transformation in donation behavior under the impact of the COVID-19 pandemic

The last topic explored the transformation in individuals' donation patterns for food banks and other NPOs from various aspects. Donation rates and donation amounts decreased for both types of organizations, but the magnitude was greater for other NPOs than food banks. From the analysis based on income groups, we found that the biggest drop in the donation rate occurred in the highest income group both for food banks and other NPOs.

We also investigated the effects of various characteristics on the changes of giving patterns. The donation rates dropped in both high and low empathy groups for both food banks and other NPOs, but the donation amount to food banks from those with high empathy increased during the pandemic. This would have been a driver that kept the average donation amount for food banks at a similar level as before during the pandemic. It was also found that the experience in a food assistance program was a prominent factor to explain the changes in donation status. Such experience was also positively related to the changes in donation amount to food banks for previous non-donors but not for previous donors.

We also found that although overall donation rates decreased probably due to the economic impact of the COVID-19, there was a tendency among those who gave to increase their contribution amounts if they were employed. We also found that, during the COVID-19 pandemic, the number of donors to food banks decreased but the average individual giving amount was greater than ordinary times. However, a such tendency did not appear for other NPOs. Our results imply that fundraisers should incorporate risk-taking behaviors and time discounting factors on their fundraising schemes. Risk averseness and time discount rate were related to the decrease in donation rates and amounts during the COVID-19 pandemic. The results also illustrate that empathy may affect different directions across types of organizations in the time of disaster.

Moreover, the current results emphasize the importance of potential donors' experience as food assistance recipients or disaster victims in terms of donation decisions, which did not get much attention from previous literature. Therefore, further study on the impact of experience on the giving patterns and its mechanism would advance charitable giving literature.

The current research focused on the changes in giving decisions at the time of the pandemic while the attention of the extant literature was mostly on the motivations or triggers of giving itself. Therefore, the present study may provide valuable knowledge for philanthropic organizations to promote efficiently their charitable giving when it is required the most. However, the present study has its limitation in the donation data such as yearly donation amount or donation rate during the COVID-19 pandemic because the survey was conducted less than a year after the COVID-19 outbreak. Therefore, there is a chance that the donation rate and the average donation amount during the COVID-19 pandemic were underestimated in the present research. These issues will be addressed in a further survey and study.

For a further study, it would be interesting to examine the changes in the donation share as a percentage of income in terms of other characteristics, once the annual income data during the pandemic is collected. It may produce more meaningful insights to compare donation shares before and after the COVID-19 rather than comparing the amount itself. In addition, it would be another valuable further study to see if there was a crowding-out out effect by the characteristics of NPOs during the pandemic, as the present study showed some differences in changes of the giving decision for food banks and other NPOs during the pandemic.

APPENDIX A

Table A.1. Cannabis legality and legalization year by state

State	MML year	RML year	Control(MML)	Treated	Donor
ALABAMA					*
ALASKA	1988	2014			
ARIZONA	2010	2020			*
ARKANSAS	2016				*
CALIFORNIA	1996	2016			
COLORADO	2000	2012		*	
CONNECTICUT	2012				*
DELAWARE	2011				*
D.C.	1998	2014			
FLORIDA	2017				*
GEORGIA	2015				*
HAWAII	2000		*		*
IDAHO					*
ILLINOIS	2013	2019			*
INDIANA					*
IOWA					*
KANSAS					*
KENTUCKY					*
LOUISIANA	2015				*
MAINE	1999	2016			
MARYLAND	2014				*
MASSACHUSETTS	2012	2016			
MICHIGAN	2008	2018			
MINNESOTA	2014				*
MISSISSIPPI					*
MISSOURI	2018				*
MONTANA	2004	2020	*		*
NEBRASKA					*
NEVADA	2000	2016			
NEW HAMPSHIRE	2013				*
NEW JERSEY	2010				*
NEW MEXICO	2007		*		*
NEW YORK	2014				*
NORTH CAROLINA					*
NORTH DAKOTA	2016				*
OHIO	2016				*
OKLAHOMA	2018				*
OREGON	1998	2015			
PENNSYLVANIA	2016				*
RHODE ISLAND	2006		*		*
SOUTH CAROLINA					*
SOUTH DAKOTA		2020			*
TENNESSEE					*
TEXAS					*
UTAH	2018				*
VERMONT	2004	2018			
VIRGINIA					*
WASHINGTON	1998	2012		*	
WEST VIRGINIA	2017				*
WISCONSIN					*
WYOMING					*

APPENDIX B

Questions measuring time discount rate, risk preference, food assistance recipient experience, and empathy

- **Time discount rate**

Now, **hypothetically,** suppose you have a choice of two payment options: receive a certain amount of money today, or receive a higher amount of money in one year. Please choose your preferred payment option in each row.

	Receive the money **today**	Receive the money **in one year**
$1,000 Today OR $1,010 in One Year	○	○
$1,000 Today OR $1,050 in One Year	○	○
$1,000 Today OR $1,200 in One Year	○	○

- **Risk preference**

Now, **hypothetically,** if you choose to play a gambling game, among Gamble 1 to Gamble 3, mark your most preferred one. (For example, if you choose Gamble 1, then you will earn $100 for sure. If you choose Gamble 2, then you will earn either $80 with 50% chance or $120 with 50% chance.)

○	Gamble 1	$100	100%		
○	Gamble 2	$80	50%	$120	50%
○	Gamble 3	$50	50%	$150	50%

Adapted from: Andersen et al. 2008; Eckel and Grossman 2008

- **Food assistance recipient experience**

Experience in any time of food assistance ('exper_foodassist') is measured by the sum of the answers to the following questions:

Q. Do you or any member of your household currently receive SNAP or Food Stamp benefits?

Q. Have you or anyone in your household acquired food from Food Banks in the past year **BEFORE the COVID-19 pandemic**?

Q. Have you or anyone in your household acquired food from Food Banks in the past year **DURING the COVID-19 pandemic**?

○ Yes (value: 1)

○ No (value: 0)

○ Not sure (value: 0)

○ Decline to answer (value: 0)

- **Empathy**

The following statements inquire about your thoughts and feelings in a variety of situations. For each item, indicate how well it describes you by choosing the appropriate one.

	Describes me very well	Describes me well	Describes me somewhat	Does not describe me well	Does not describe me at all
I am often deeply touched by what I see happening to others.	○	○	○	○	○
I find it easy to see things from other people's point of view.	○	○	○	○	○
Other people's misfortunes do not usually disturb me a great deal.	○	○	○	○	○

Adapted from: Schlegelmilch et al. 1997; Lee and Chang 2008

APPENDIX C

Table C.1. Probit model: Donation rate during the COVID-19 for previous donors

	Probit: Food banks		Probit: NPOs	
	(1)	(2)	(3)	(4)
high_empathy	0.018	0.163	0.197	0.296*
	(0.182)	(0.203)	(0.156)	(0.176)
belief_in_impact	0.075	0.075	0.077	0.104
	(0.095)	(0.100)	(0.078)	(0.084)
exper_foodassist	0.969***	0.594***	0.855***	0.518***
	(0.181)	(0.218)	(0.153)	(0.185)
high_timedis	-0.243	0.014	-0.343**	-0.062
	(0.178)	(0.212)	(0.156)	(0.179)
risk	0.339**	0.283**	0.203*	0.081
	(0.140)	(0.139)	(0.113)	(0.117)
female		-0.143		-0.195
		(0.187)		(0.158)
age		-0.010		0.000
		(0.009)		(0.007)
married		0.573**		0.578***
		(0.232)		(0.199)
children		0.045		-0.040
		(0.099)		(0.097)
employed		0.025		-0.019
		(0.384)		(0.284)
income		0.001		0.001
		(0.003)		(0.002)
conservative		0.033		0.032
		(0.047)		(0.040)
white		-0.277		0.232
		(0.231)		(0.182)
covid_self		0.710**		1.061***
		(0.280)		(0.284)
religion		0.174**		0.263***
		(0.083)		(0.073)
sti_check		-0.265		-0.230
		(0.217)		(0.185)
constant	0.021	-0.366	0.076	-0.992**
	(0.314)	(0.692)	(0.241)	(0.506)
N	363	363	452	452

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.2. Margins: Donation rate during the COVID-19 for previous donors

	Probit margins: Food banks		Probit margins: NPOs	
	(1)	(2)	(3)	(4)
high_empathy	0.004	0.032	0.051	0.063*
	(0.042)	(0.040)	(0.040)	(0.037)
belief_in_impact	0.017	0.015	0.020	0.022
	(0.022)	(0.019)	(0.020)	(0.018)
exper_foodassist	0.223***	0.116***	0.222***	0.110***
	(0.038)	(0.042)	(0.036)	(0.039)
high_timedis	-0.056	0.003	-0.089**	-0.013
	(0.041)	(0.042)	(0.040)	(0.038)
risk	0.078**	0.055**	0.053*	0.017
	(0.031)	(0.027)	(0.029)	(0.025)
female		-0.028		-0.041
		(0.037)		(0.033)
age		-0.002		0.000
		(0.002)		(0.002)
married		0.112***		0.123***
		(0.043)		(0.041)
children		0.009		-0.008
		(0.020)		(0.021)
employed		0.005		-0.004
		(0.075)		(0.060)
income		0.000		0.000
		(0.001)		(0.001)
conservative		0.006		0.007
		(0.009)		(0.008)
white		-0.054		0.049
		(0.045)		(0.039)
covid_self		0.139***		0.225***
		(0.053)		(0.061)
religion		0.034**		0.056***
		(0.016)		(0.015)
sti_check		-0.052		-0.049
		(0.042)		(0.039)
N	363	363	452	452

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.3. Probit model: Donation rate during the COVID-19 for previous non-donors

	Probit: Food banks		Probit: NPOs	
	(1)	(2)	(3)	(4)
high_empathy	-0.079	-0.179	-0.083	-0.172
	(0.251)	(0.309)	(0.332)	(0.388)
belief_in_impact	0.273***	0.112	0.064	-0.271
	(0.098)	(0.116)	(0.148)	(0.240)
exper_foodassist	1.188***	1.309***	0.993***	0.540
	(0.245)	(0.298)	(0.339)	(0.496)
high_timedis	-0.326	0.090	-0.247	0.062
	(0.253)	(0.294)	(0.332)	(0.479)
risk	0.256	0.216	0.213	0.854***
	(0.177)	(0.187)	(0.268)	(0.322)
female		-0.070		0.475
		(0.289)		(0.419)
age		0.019		0.020
		(0.017)		(0.018)
married		0.623*		0.597
		(0.361)		(0.466)
children		-0.062		0.014
		(0.120)		(0.169)
employed		0.000		-1.349
		(.)		(0.875)
income		-0.001		0.006
		(0.005)		(0.007)
conservative		0.015		-0.309***
		(0.083)		(0.117)
white		-0.133		-0.013
		(0.332)		(0.526)
covid_self		0.415		0.000
		(0.839)		(.)
religion		0.147		0.585***
		(0.105)		(0.182)
sti_check		-0.649**		-1.392***
		(0.299)		(0.507)
constant	-1.878***	-2.404***	-0.890*	0.062
	(0.394)	(0.820)	(0.512)	(1.267)
N	164	146	75	73

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.4. Margins: Donation rate during the COVID-19 for previous non-donors

	Probit margins: Food banks		Probit margins: NPOs	
	(1)	(2)	(3)	(4)
high_empathy	-0.018	-0.037	-0.026	-0.036
	(0.057)	(0.063)	(0.103)	(0.081)
belief_in_impact	0.062^{***}	0.023	0.020	-0.057
	(0.022)	(0.024)	(0.046)	(0.051)
exper_foodassist	0.269^{***}	0.269^{***}	0.308^{***}	0.114
	(0.044)	(0.052)	(0.086)	(0.101)
high_timedis	-0.074	0.018	-0.077	0.013
	(0.056)	(0.061)	(0.102)	(0.101)
risk	0.058	0.044	0.066	0.180^{***}
	(0.039)	(0.038)	(0.083)	(0.070)
female		-0.014		0.100
		(0.060)		(0.084)
age		0.004		0.004
		(0.004)		(0.004)
married		0.128^{*}		0.126
		(0.071)		(0.094)
children		-0.013		0.003
		(0.025)		(0.036)
employed		0.000		-0.284
		(.)		(0.178)
income		-0.000		0.001
		(0.001)		(0.001)
conservative		0.003		-0.065^{***}
		(0.017)		(0.023)
white		-0.027		-0.003
		(0.068)		(0.111)
covid_self		0.085		0.000
		(0.171)		(.)
religion		0.030		0.123^{***}
		(0.021)		(0.033)
sti_check		-0.133^{**}		-0.293^{***}
		(0.061)		(0.099)
N	164	146	75	73

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.5. Multinomial Probit model: Donation status changes

	Food banks (1)	NPOs (2)
1 (No – No)		
high_empathy	-0.368*	-0.416*
	(0.208)	(0.235)
belief_in_impact	-0.192*	-0.228*
	(0.103)	(0.117)
exper_foodassist	-1.813***	-1.460***
	(0.206)	(0.263)
timedis	0.217***	0.121
	(0.067)	(0.082)
risk	-0.334**	-0.043
	(0.147)	(0.172)
constant	0.603*	-0.220
	(0.346)	(0.401)
2 (Yes – No)		
high_empathy	-0.118	-0.292
	(0.218)	(0.199)
belief_in_impact	-0.110	-0.111
	(0.107)	(0.097)
exper_foodassist	-1.223***	-1.109***
	(0.215)	(0.199)
timedis	0.217***	0.259***
	(0.068)	(0.064)
risk	-0.441***	-0.242
	(0.168)	(0.152)
constant	-0.318	-0.507
	(0.378)	(0.326)
3 (No – Yes)		
high_empathy	-0.508**	-0.460
	(0.245)	(0.283)
belief_in_impact	0.059	-0.175
	(0.119)	(0.132)
exper_foodassist	-0.480**	-0.571**
	(0.241)	(0.278)
timedis	0.132*	0.026
	(0.072)	(0.079)
risk	-0.145	0.091
	(0.169)	(0.186)
constant	-1.312***	-0.934**
	(0.437)	(0.404)
4 (Yes – Yes) base category		
N	527	527

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.6. Multinomial Probit model margins: Donation status changes

	Margins: Food banks (1)	Margins: NPOs (2)
high_empathy		
1._predict (No – No)	-0.052	-0.032
	(0.035)	(0.026)
2._predict (Yes – No)	0.014	-0.030
	(0.030)	(0.034)
3._predict (No – Yes)	-0.037*	-0.024
	(0.022)	(0.020)
4._predict (Yes – Yes)	0.076*	0.086**
	(0.041)	(0.040)
belief_in_impact		
1._predict (No – No)	-0.032*	-0.021
	(0.018)	(0.013)
2._predict (Yes – No)	-0.006	-0.008
	(0.015)	(0.017)
3._predict (No – Yes)	0.012	-0.008
	(0.010)	(0.009)
4._predict (Yes – Yes)	0.026	0.037*
	(0.020)	(0.020)
exper_foodassist		
1._predict (No – No)	-0.267***	-0.122***
	(0.031)	(0.029)
2._predict (Yes – No)	-0.071**	-0.139***
	(0.028)	(0.033)
3._predict (No – Yes)	0.020	-0.006
	(0.018)	(0.018)
4._predict (Yes – Yes)	0.318***	0.266***
	(0.030)	(0.035)
timedis		
1._predict (No – No)	0.026**	0.003
	(0.012)	(0.009)
2._predict (Yes – No)	0.018*	0.044***
	(0.010)	(0.011)
3._predict (No – Yes)	0.003	-0.004
	(0.006)	(0.005)
4._predict (Yes – Yes)	-0.048***	-0.043***
	(0.012)	(0.012)
risk		
1._predict (No – No)	-0.034	0.004
	(0.026)	(0.019)
2._predict (Yes – No)	-0.047*	-0.046*
	(0.024)	(0.027)
3._predict (No – Yes)	0.002	0.012
	(0.015)	(0.013)
4._predict (Yes – Yes)	0.078***	0.030
	(0.028)	(0.030)
N	527	527

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$