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Pro-Social Behaviour in Times of Crisis and Uncertainty

An Empirical Study of Local COVID-19 Restrictions and the Donation Rate in the Norwegian Recycling Lottery

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Abstract

The purpose of this thesis is to investigate the relationship between local COVID-19 restrictions and the donation rate in the Norwegian recycling lottery, employing donations to the lottery as a proxy for pro-social behaviour. The thesis aims to study whether the enforcement of local restrictions has an impact on the donation rate and if separate categories of restrictions impact the donation rate differently. Additionally, the thesis explores whether the effect on the donation rate varies based on the duration of the local restrictions enforcement and whether there is a long-term impact after their termination.

The final dataset consists of 461,115 observations that contain data on recycling and the enforcement of local COVID-19 restrictions. The panel dataset also comprises information on municipal affiliation, total transactions, and infection numbers. Regressions on the data are conducted with fixed effects estimation with week and store fixed effects, and total transactions and the infection rate per 100,000 as control variables.

The findings reveal a positive effect of local COVID-19 restrictions on the donation rate. The results suggest that the enforcement of local restrictions will increase the donation rate by approximately 0.25 percentage points. Certain categories of restrictions, for instance, those related to travel and the ban on serving alcohol, are also found to have a greater effect than other categories. Furthermore, the thesis reveals that the duration of the local restrictions has a significant and increasing effect from the second week on. There is no evidence that local restrictions have a long-term impact on the donation rate.

An additional survey conducted on donation motivation demonstrates that there are diverse motives for contributing to the recycling lottery. Although local restrictions are found to have a positive effect on the donation rate, it remains undetermined whether these restrictions in fact have an impact on pro-social behaviour.

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1 Introduction

The COVID-19 pandemic has had a substantial impact on economies and societies all around the world. In response to the outbreak, several restrictions were introduced in Norway to prevent and control the spread of COVID-19, disrupting the lives of the population in the spring of 2020 and the years that followed. The implementation of restrictions caused major changes in society and daily routines. The crisis created a sense of unpredictability, and everyday life was characterised by uncertainty to a greater extent than before.

We find the impact the pandemic and the surrounding uncertainty had on society to be of great interest and relevance to discuss after the storm has passed. Such invasive restrictions have not been implemented within the lifespan of our generation, making their effects an interesting subject to delve deeper into. Furthermore, we believe that this could yield useful insights for the future. We particularly find it interesting to see how the pandemic affected social interactions, including those with acquaintances and strangers, and the willingness to support others financially. In connection with this, it is interesting to see whether the crisis motivated people to contribute more to society or whether it led to a more self-centred society where individuals prioritised personal security and well-being over societal welfare.

In this thesis, we study the potential impact of variations in local restrictions on the willingness to donate to charity. Specifically, we aim to explore whether variations in local restrictions are linked to differences in the donation rate in the Norwegian recycling lottery. The analysis is conducted using a large dataset consisting of recycling data in combination with a dataset of local COVID-19 restrictions in Norway. While variations in the donation rate can be influenced by several other factors, we make efforts to control for these variables. Our approach involves utilising the donation rate in the Norwegian recycling lottery as a proxy for charitable giving and pro-social behaviour in society. We believe that the donation rate is a good proxy for pro-social behaviour because it reflects the proportion of the deposit amount that people give away to benefit society and help people in need. The recycling lottery also contains a lottery component that can motivate people to donate, but we still believe that the donation rate can serve as a reasonable indicator. We discuss this in further detail later in the thesis.

Numerous restrictions were imposed on both the national and local level to prevent the spread of the virus. National regulations applied throughout the country, whereas local regulations applied in a specific area, such as a municipality, a county, or a region. The local restrictions in our dataset are structured at the municipality level. As a consequence of this thesis' delimitations, national restrictions are not the focus of this study because we assume that they have been practised equally throughout the country.

Local restrictions varied widely and included, for instance, limitations and prohibitions on the serving of alcoholic beverages, guidelines regarding the use of face masks, and shutdowns or limitations on businesses, schools, and workplaces. These restrictions had a limited duration and varied greatly across municipalities. Given a lack of standardised formulations for the various restrictions, identical restrictions could differ across municipalities. Consequently, several restrictions with similar names had different contents in different municipalities. Therefore, with the preparation of the data, we choose to categorise the different restrictions into 14 main categories.

In this thesis, we are interested in seeing whether different categories of local restrictions influence people's inclination to donate differently. Furthermore, we wish to investigate how long it takes for potential effects to become apparent. In connection with this, we want to gain a better understanding of whether the effect is smaller at the beginning of the restriction period or whether it diminishes over time as individuals become more accustomed to the restrictions. It is also of great interest to examine whether the behaviour remains unchanged after the restrictions are lifted or whether it reverts to pre-restrictions patterns.

In light of these thoughts, the research question this thesis seeks to answer is:

Do local COVID-19 restrictions have an impact on the donation rate in the Norwegian recycling lottery?

We have concretized the research question into the following sub-questions:

1. Do local restrictions affect the donation rate?
2. Do local restrictions in specific categories affect the donation rate?

3a. Does how long the local restrictions have been in force affect the donation rate?

3b. Do local restrictions have a long-term impact on the donation rate?

The analysis is conducted using multiple regressions with fixed effects to answer our research questions. We employ store fixed and week fixed effects to control for variables that may be constant for one store or over time. Our analysis suggests that local restrictions have an impact on the donation rate, with the effect varying with the category of restrictions examined. Furthermore, we observe that the duration of the restrictions appears to influence how big and significant the effect is. We do not observe any evidence that local restrictions have a long-term effect on the donation rate.

The remainder of this thesis is divided into nine chapters. Chapter 2 presents relevant literature on pro-social behaviour and lottery participation, followed by an introduction to the Norwegian recycling lottery and local COVID-19 regulations in Chapter 3. In Chapter 4, the hypotheses are presented. The collection and preparation of data, together with descriptive statistics, are presented in Chapters 5 and 6. Chapter 7 discusses the thesis' methodology. The main empirical findings and weaknesses of the analysis are presented and discussed in Chapters 8 and 9. Finally, we present a conclusion and make suggestions for future research in Chapter 10.

2 Literature Review

In this part, we summarise relevant literature on pro-social behaviour. It is essential to understand the relationship between times of crisis and pro-social behaviour. The focus of our thesis is whether local COVID-19 restrictions have an effect on the donation rate. Considering that the restrictions were implemented as a response to the pandemic, it is reasonable to view local restrictions as indicative of a crisis situation. The donation rate is also considered a proxy for pro-social behaviour. Consequently, we initially present previous literature on pro-social behaviour and times of crisis.

To the best of our knowledge, no research has yet been published on the effect of COVID-19 restrictions on pro-social behaviour in the context of supermarket bottle recycling. However, several studies of pro-social behaviour have been conducted on other topics in this setting. One study that provides us with useful contextual insights related to the seasonal effect in December and the use of donation rate as a proxy for pro-social behaviour is the study by Ekström (2018). The author studied altruism during the Christmas season by using data from recycling machines in Swedish supermarkets to discover that people showed more altruistic behaviour in December. He also found that this effect lasted into January.

It is key to understand what drives pro-social behaviour in order to provide context for our research question and thereby better comprehend which mechanisms underlie potential changes in the donation rate. Accordingly, we examine pure and impure altruism as well as other explanations for pro-social behaviour, including inequality aversion, reciprocity, self-identity, and the environmental setting. Because people may also partly regard the recycling lottery as a gamble, a potential change in the donation rate could be due to increased motivation for participating in the lottery. Therefore, we additionally provide brief literature on the motivation for lottery participation in this chapter.

2.1 Crises and Pro-Social Behaviour

Pro-social behaviour is behaviour intended to benefit another person. This behaviour is considered altruistic if it is driven by a genuine wish to benefit others without expecting any external reward in return (Eisenberg and Miller, 1987).

A crisis could change moral views, social norms, and behaviour. While stress might awaken selfish inclinations, the perception of a common threat could also unite people (Cappelen et al., 2021). Several studies have found that people become more solidary and altruistic during hard times. Voors et al. (2012) discovered that individuals who had been exposed to violent conflict in Burundi exhibited more altruistic behaviour. The authors suggest changes in preferences or, alternatively, social learning and social context as possible explanations. In another study, Gilligan et al. (2014) studied violence and conflict in Nepal. They also found that those exposed to violence showed more pro-social behaviour. Rodriguez et al. (2006) identified the same pattern of increased pro-social behaviour following Hurricane Katrina in the United States.

On the contrary, Fisman et al. (2015) found evidence that people became more selfish in times of crisis. They tested whether distributional preferences changed as a result of the Great Recession. Their findings revealed a link between recessionary circumstances and preferences for greater selfishness, suggesting that the thought of giving up money is more unappealing in times of scarcity (Fisman et al., 2015). Meer et al. (2017) studied charitable giving and also found that donations fell under this period. They argue that this could be due to changes in attitudes towards giving. As can be seen, there is some disagreement about whether or not crises make people more altruistic or selfish.

One crisis that could affect moral views and pro-social behaviour is the COVID-19 pandemic. Cappelen et al. (2021) performed an experiment on solidarity during the pandemic. Solidarity was referred to as the prioritisation of societal problems over individual self-interest. In the study, they compared people who were reminded of the pandemic to people who were not. The results showed that those who received a reminder were significantly more likely to be solidary. Shachat et al. (2021) investigated the impact of the pandemic on pro-social behaviour in China in another study. The authors discovered high rates of altruism right after strict lockdown measures were imposed. Furthermore, they argue that the results undermine the idea that social preferences could be influenced by crises and emergencies such as the COVID-19 pandemic.

2.2 Mechanisms behind Pro-Social Behaviour

This section seeks to enlighten motives for pro-social behaviour to better understand the underlying factors that may contribute to potential changes in the donation rate. Initially, we present the standard economic model, and subsequently, due to the deviation of people's behaviour from this model, we also provide explanations for pro-social behaviour. Factors that explain pro-social behaviour could be pro-social preferences, reciprocity, self-identity, and the environmental setting (Meier, 2006).

2.2.1 Standard Economic Model

The standard economic model argues that people act rationally and that individuals want to maximise their utility. According to the model, the utility of an individual is given by:

$$U_i = U_i(x_i) \tag{2.1}$$

x_i is the private consumption of individual i. Utility is solely a function of private payoff. Individuals are unconcerned about other people's consumption as long as it does not affect their own (Wilkinson and Klaes, 2012, p. 10). As a result, they will act selfishly and not engage in behaviour that only benefits others (Meier, 2006). However, this approach has failed to account for a variety of situations where people frequently participate in actions that positively affect others while having no impact on themselves.

2.2.2 Pure Altruism

Pure altruistic motives could explain why people donate to charity. Pure altruism assumes direct utility from the consumption of others (Ottoni-Wilhelm et al., 2017). The identity of the giver has no effect on personal utility from the consuming by others. In the model, individuals gain utility from private consumption x_i and a privately provided public good G (Becker, 1974):

$$U_i = U_i(x_i, G) \tag{2.2}$$

G is the total of all individual contributions (g_i) to the public good (Andreoni, 1988). The income of an individual can be spent on private consumption (x_i) or on charitable contributions (g_i). Individual contributions and donations from others are perfect substitutes (Ottoni-Wilhelm et al., 2017). As a result, they will have the same effect on the optimal amount of public goods donated. If the receiving party increasingly consumes more from other contributors, individuals will reduce their pro-social behaviour and donate less. According to Warr (1982), a specific amount of lump-sum tax allocated to charity would cause a decline in donations of the same amount from others, which is consistent with the pure altruistic model. Several empirical studies, however, have shown that crowding-out is incomplete, and thus they argue that pure altruism cannot fully explain why people behave pro-socially (Nyborg and Rege, 2003).

2.2.3 Impure Altruism

In a later paper, Andreoni (1989) extended the assumptions of pure altruism and introduced the concept of increased utility from the act of giving. The model of impure altruism states that people get a warm glow from giving. In addition to receiving utility from the consumption of others, individuals also experience a good feeling from donating per se (Andreoni, 1990). In the warm glow model, individuals gain utility from private consumption x_i, the privately provided public good G, and also the act of donating g_i:

$$U_i = U_i(x_i, G, g_i) \tag{2.3}$$

The variable g_i appears twice in the utility function: as part of the input in the privately provided public good and as a private good derived from the act of giving (Andreoni, 1989). When there is no warm glow, increased donations by others encourage people to minimise their own contributions (Andreoni, 1989). However, with the introduction of warm glow, personal contributions and donations from others are no longer perfect substitutes (Andreoni, 2006). This makes people less eager to reduce their own donations in reaction to higher overall contributions. In contrast to pure altruism, a complete crowding-out will not be experienced here because people derive utility from the act of giving, and they will continue to do so even if many others do the same (Ottoni-Wilhelm et al., 2017). All else being equal, people who are impurely altruistic will therefore prefer the option that gives them the warmest glow (Andreoni, 1990).

2.2.4 Inequality Aversion

Another explanation for donations is inequality aversion, which concerns differences between individuals (Charness and Rabin, 2002). If there are big variations in consumption, individuals could want to reduce the difference by donating. Fehr and Schmidt (1999) introduced a model that assumes inequality aversion:

$$U_i = (x_i - \alpha_i \frac{1}{n-1} \Sigma_{j \neq i} max[x_j - x_i, 0] - \beta_i \frac{1}{n-1} \Sigma_{j \neq i} max[x_i - x_j, 0]) \tag{2.4}$$

According to this model, an individual's utility is determined by private consumption x_i, disutility from disadvantageous inequality α_i, and disutility from advantageous inequality β_i. They also assume that $\alpha_i > \beta_i$. This implies that the utility loss caused by disadvantageous inequality is larger than the loss from advantageous inequality (Fehr and Schmidt, 1999). Even though individuals have a stronger aversion to being worse off, they also dislike having a material advantage, and they would therefore be more likely to donate to people who are worse off. Individuals who are deeply concerned about fairness would contribute because the benefit of reduced inequality surpasses the cost of decreased private consumption (Nyborg and Rege, 2003).

2.2.5 Social Norms and Self-Identity

Pro-social behaviour could also be connected to self-identity. Behaving in a certain way can positively contribute to people's self-identity by supporting them in developing a good self-image and restoring their identity (Akerlof and Kranton, 2000). In this scenario, people are more concerned with how their pro-social efforts affect their own self-image than the outcome of their actions (Meier, 2006).

What defines pro-social behaviour is determined by social norms. Krupka and Weber (2013) define social norms as "a shared understanding regarding the appropriateness of different behaviours". Acting pro-socially in terms of adapting behaviour to the social norms and behaviours of a reference group can improve self-image (Falk et al., 2013). People engage in activities perceived as good to self-signal their positive characteristics (Meier, 2006). The social norms of a situation can have a big impact on what behaviour is considered pro-social, and this can vary across contexts.

Social norms can also be linked to status-motivated pro-social behaviour (Ellingsen and Johannesson, 2008). It is natural to care about what other people think of us, and recognition from others and ourselves contributes to improving our self-image. Status can be achieved by portraying oneself as a person who behaves pro-socially (Guy and Patton, 1988). The awareness of others observing this behaviour can therefore be a motivator per se.

Holländer (1990) introduced a model where social norms and approval are considered in the choice of behaviour. The author claims that the expectation of social acceptance can be a driving force behind pro-social behaviour. In the model, the utility of an individual is determined by:

$$U_i = U_i(x_i, G, q_i) \tag{2.5}$$

, where

$$q_i = a(g_i) - \alpha * a(\bar{g})$$

$$0 \leq \alpha \leq 1$$

An individual gains utility from private consumption x_i, the public good G, and social approval q_i. In the function for social approval, individual contributions are represented by g_i, average contributions by $\bar{g}$, and a is the approval rate. Social approval is determined by the difference between approval from individual contributions and approval from average contributions multiplied by the coefficient α, which measures the strength of the negative externality from the average contribution (Holländer, 1990). Hence, an individual cares about social approval, which is positively related to how much a person contributes in comparison to others (Nyborg and Rege, 2003).

2.2.6 Reciprocity

Reciprocity's impact on pro-social behaviour is supported by several laboratory and field studies (Falk, 2007; Frey and Meier, 2004). Individuals will act in a way to reflect the behaviour or actions of others (Khadjavi, 2017). Falk (2007) found that including a gift in charity solicitations increased the number of donations. Pro-social behaviour can thus be explained by the desire to repay a favour. Individuals could also perform a good deed with the expectation of receiving something in return later (Zhang and Epley, 2009).

Reciprocity additionally involves conditionality. More people will want to behave pro-socially if they see others doing it (Fischbacher et al., 2001). They acknowledge others' good behaviour and want to contribute in a similar way. Furthermore, they do not want to be the only ones who do not behave pro-socially (Meier, 2006). A study by Frey and Meier (2004) finds that when students are told that most students contribute to the public good, their pro-social behaviour increases, and vice versa.

Rabin (1993) formalised a model that links pro-social behaviour with reciprocity. In the model, an individual has the following utility function:

$$U_i = U_i(a_i, b_j, c_i) = \pi_i(a_i, b_j) + \bar{f}_j(b_j, c_i) * [1 + f_i(a_i, b_j)] \tag{2.6}$$

In this model, a_i is the strategy of individual i; b_j is the strategy i thinks j chooses; and c_i is the strategy i assumes that j assumes i chooses. f_i represents i's kindness towards j, and $\bar{f}_j$ represents i's perception of how kind j is to him. π_i is the material payoff.

If i thinks that j treats him badly ($\bar{f}_j < 0$), i would want to pick a strategy a_i that will give a low f_i so that he returns the perceived bad behaviour. On the contrary, a positive perception of the behaviour of the other ($\bar{f}_j > 0$) will make i want to behave good towards j. However, the size of the material payoff π_i is important and may outweigh reciprocity issues (Rabin, 1993). Hence, the model claims that people care about responding to the behaviour of others in addition to their material payoff.

2.2.7 Environmental Setting

The environmental setting could also have an effect on donations. Social distance is an important factor here. Jenni and Loewenstein (1997) argue that reducing social distance seems to increase empathy for others. Consequently, people are more likely to help a specific human being than to donate to an anonymous crowd where they do not know who will receive their contributions (Bohnet and Frey, 1999). Anonymity is another relevant factor. People want to behave in accordance with social norms, and they want social approval of their actions. With no anonymity, others can approve of their behaviour, and pro-social behaviour is anticipated to increase (Andreoni and Petrie, 2004). In agreement with this, Soetevent (2005) found that people donated less when they gave anonymous contributions to collection bags.

Monetary incentives have an impact on donations in two different ways. In general, pro-social behaviour will be practised to a greater extent when it becomes cheaper (Arrow, 1972). Therefore, more donations are expected with the introduction of monetary incentives. One such incentive is tax deductions for charitable giving. In a meta-analysis, Peloza and Steel (2005) found that, on average, a one-percent increase in charitable deductions would increase donations by 1.44%. However, monetary incentives may also result in a decline in donations because they provide external rewards that can reduce the intrinsic motivation for giving (Bénabou and Tirole, 2006).

2.3 Lottery Participation

It is not necessarily the case that the recycling lottery is viewed as an opportunity to behave pro-socially and help those in need. Some may view the lottery solely as a means of gambling. The decision to donate the deposit from recycled cans and bottles may therefore be motivated by a desire to participate in the lottery. Lottery consumption can be understood by viewing the lottery as both an investment object and a consumption good (Kearney, 2005).

A lottery can be viewed as an investment with a small probability of a large return and a large probability of a small loss (Friedman and Savage, 1948), as the odds of winning a lottery are typically low and the likelihood of reward decreases as the prize size increases. In addition, lotteries are intended to entertain and bring joy regardless of the outcome. The act of entering the lottery itself could provide utility to the participant, as individuals gain utility from the joy of participating in addition to the expected value of the lottery (Markowitz, 1952). Conlisk (1993) argues that risk-averse individuals are approximately risk-neutral if the stake is sufficiently small. A risk-averse individual will therefore make risk-neutral decisions in a gambling situation with a small stake and choose to enter the lottery when the joy of participating outweighs the expected loss.

3 Setting

3.1 The Norwegian Recycling Lottery

The Norwegian recycling lottery is a charitable lottery established in 2008 (Pantelotteriet, n.d.). In 2021, there were approximately 3,400 deposit machines with the opportunity to donate in Norway (Pantelotteriet, 2022). The lottery is operated by Norsk Pantelotteri AS, which is jointly owned by the Norwegian Red Cross and the Olav Thon Group. 34.5% of the income is directly donated to charity, with the Norwegian Red Cross receiving the contributions. The Norwegian Red Cross has received over NOK 500 million in humanitarian aid since its establishment.

The only way to purchase lottery tickets is to recycle used cans and bottles. Small bottles and cans have a deposit of NOK 2, while containers larger than 0.5 litres have a deposit of NOK 3. After returning the old containers, you can choose whether to receive the deposit or participate in the lottery. Each lottery ticket costs NOK 0.50. A small bottle will thus provide 4 tickets, while a larger bottle will provide 6 tickets. The chances of winning are 1 in 467 (Pantelotteriet, n.d.). 35% of the income from the deposit machines is devoted to paying out prizes. It is possible to win either 50, 100, 1 000, 10 000, or one million Norwegian kroner.

In grocery stores, the donation process is anonymous and impersonal, and everyone is under the same amount of pressure to donate. Everyone is exposed to the same persuasion, which consists primarily of a note on the deposit machine informing them about the donation opportunity.

Donations to voluntary organisations may qualify for deductions from taxable income. In Norway, the minimum required gift amount is currently NOK 500, with a maximum deduction of NOK 25,000 (Skatteetaten, n.d.). However, gifts that have been received anonymously and without personal data accompanying them are not tax deductible (Røde Kors, n.d.). Røde Kors also specifies that donations to the Norwegian recycling lottery fall under this category and are not tax deductible.

However, because it is also a lottery, people may be financially motivated by the potential prizes. The question is whether the recycling lottery is primarily perceived as a charitable donation or a lottery by the majority of those who participate. To investigate this issue further, we conduct a brief, one-question survey that is presented in the results.

The recycling lottery takes place in an anonymous location. There is no relationship between the recyclers and the receiving organisation, and there is no expectation of a response to previous behaviour. Donations are made anonymously so that the decision to donate will not be announced and others will be unaware of the behaviour of the contributor.

3.2 COVID-19 Pandemic Regulations

During the COVID-19 pandemic, regulations were introduced that imposed various restrictions justified by the need to prevent the virus from spreading. The regulations related to the pandemic could be either national or local. The national regulations were applied throughout the country. Local regulations establish private persons' or businesses' rights and duties in a specific area, such as a municipality, a county, or a region, and can be given by the municipal council, the county governor, or the county council (Lovdata, n.d.a). According to the *Act relating to the control of communicable diseases* (*Smittevernloven*) § 4-1, the municipalities have the authority to implement local regulations if the regulation is necessary to prevent an infectious disease dangerous to the public from being transmitted (Statsforvalteren i Agder, 2021). Local restrictions must also be justified by a specific local need, such as a high level of pressure or a scarcity of resources in the area.

Due to the great number of different restrictions, the lack of standard formulations, and the wish to study the effect of different main categories, we categorise the restrictions into 14 main categories. The main categories concern different issues such as quarantine, private life, and public transport. The ones that are put in the same category pertain to the same area and are expected to have a similar effect on the donation rate. The categorisation is explained in more detail in Subsection 5.2.4.

4 Hypotheses

The main purpose of the thesis is to investigate whether there is a connection between local COVID-19 restrictions and the donation rate in the Norwegian recycling lottery. The hypotheses that will help us answer our research question are presented below. We develop three main hypotheses, the last of which is divided into two and addresses influence over time.

4.1 Hypothesis 1: Local Restrictions

We propose the following hypothesis to assess whether the imposition of local COVID-19 restrictions in general influences the donation rate in the recycling lottery:

$$H_0 = \text{Local COVID-19 restrictions } \textbf{do not affect} \text{ the donation rate}$$

$$H_A = \text{Local COVID-19 restrictions } \textbf{affect} \text{ the donation rate}$$

4.2 Hypothesis 2: Categorization of Restrictions

In order to examine the effect in further depth, we make use of the 14 different main categories of local restrictions. To determine whether the imposition of a specific category of local restrictions X impacts the donation rate, we formulate the hypothesis:

$$H_0 = \text{Restrictions in category } X \textbf{ do not affect} \text{ the donation rate}$$

$$H_A = \text{Restrictions in category } X \textbf{ affect} \text{ the donation rate}$$

4.3 Hypothesis 3A: Effect of Restrictions over Time

We also want to assess if the effect of local restrictions increases or decreases over time, that is, whether the effect is weaker or stronger in the first weeks compared to later in the restriction period. Therefore, we provide the hypothesis:

$$H_0 = \text{How long local restrictions have been in force } \textbf{does not affect} \text{ the donation rate}$$

$$H_A = \text{How long local restrictions have been in force } \textbf{affects} \text{ the donation rate}$$

4.4 Hypothesis 3B: Prolonged Effect of Restrictions after Termination

Furthermore, we want to investigate whether the local COVID-19 restrictions have any long-term effects after they have been lifted. The following hypothesis is proposed:

H_0 = Local restrictions **do not have a prolonged effect** on the donation rate

H_A = Local restrictions **have a prolonged effect** on the donation rate

We assume that the donation rate is an accurate measure of pro-social behaviour and that local restrictions reflect some of the uncertainty and stress associated with COVID-19. Similar to previous research on COVID-19 and pro-social behaviour, it could be that this crisis makes people more altruistic. The sense of a common crisis can motivate people to come together and support each other. Previous research on crises, however, also reveals that people can become more selfish in these situations. It is not inconceivable that stress causes individuals to think more about themselves, and as a result, they do not want to donate to others. Accordingly, it is also plausible that local restrictions could have a negative effect on people's altruism and that the donation rate would subsequently decrease. Consequently, we may be able to reject the null hypothesis, but whether the effect is positive or negative remains uncertain.

5 Data

Our empirical analysis is based on data from the Norwegian Recycling Lottery. We also use information on the imposition of COVID-19 regulations because we want to investigate the effect of local restrictions on the donation rate. In addition, to control for the infection rate, we retrieved relevant information from MSIS. To be able to merge the different datasets, we additionally obtain data on municipalities in Norway.

5.1 Data Collection

5.1.1 The Norwegian Recycling Lottery

Tomra provided data on the Norwegian recycling lottery. The dataset contains 481,507 different observations, which cover the time period from week 1 in 2019 until week 37 in 2022. The observations are from 3,289 different stores across Norway.

Each observation in the dataset is for a single store in a single week. There is also additional information on the locations of the stores, such as the postal code and county. Each week, information is provided for each store regarding the amount recycled and returned to the customers, as well as the amount recycled and donated to the Norwegian Red Cross. In the dataset, there is additional information concerning the number of deposit transactions and the number of donated transactions. Finally, there is data on the donation rate, which is calculated by dividing the donated amount by the total value of recycled cans and bottles. Stores opening or closing during the time period do not have observations for the full time period. Another explanation for missing observations in our sample is that new deposit machines with lottery participation options were installed later in some stores (Pantelotteriet, 2022).

5.1.2 Local COVID-19 Restrictions

Data on the local COVID-19 restrictions was retrieved from the Norwegian data base, Lovdata.no. We were interested in repealed local regulations, which totalled 838 (Lovdata, n.d.b). A student assistant began the task of collecting this data, by gathering data from the first 380 regulations. We continued the work and collected data from the remaining

458 regulations.

Each regulation offers information about restrictions imposed on a specific municipality for a certain period of time. If one regulation contains several restrictions, we divide the regulation into several observations. As a result, one observation includes information about one restriction and which municipality this restriction applied to. We obtain information about when the restriction was announced, when it entered into force, when it ended, and whether it was revoked before the end of the period. We also include whether the regulation has changed over the time period. Furthermore, we specify the type of restriction and provide a column with a more detailed explanation of the restriction.

5.1.3 Municipality Codes

To be able to merge the former datasets, we also need a third dataset containing information about the municipalities in Norway. This dataset is obtained from the Norwegian postal service, Bring. We gather information on postal code, postal address, municipality code, and municipality name from the dataset (Bring, n.d.).

5.1.4 Infection Rate

Data on COVID-19 cases were provided by the Institute of Public Health's (FHI) Surveillance System for Communicable Diseases (MSIS). We have weekly infection numbers at the municipal level in our dataset. In addition, we employ Stata to include a variable for the population of the municipalities. We obtain population data for the years 2020-2022 from Statistics Norway (2023) (SSB). This way, we can use the population for the respective year to construct the variable "Infection Rate", to include in our analysis for each municipality and week, as

$$\text{Infection Rate} = \text{Infection Numbers per 100,000} = \frac{\text{Infection Numbers}}{\text{Population}} \cdot 100{,}000$$

5.2 Data Preparation

Before we start our analysis, we need to prepare the different datasets. This includes, among other things, splitting observations so that we have week-level observations, categorising the multiple COVID-19 restrictions, and correcting county names.

First, we remove duplicates in the two datasets so that we do not have several identical observations. We also check for apparent mistakes. For example, there are some restrictions that have a negative timeframe, with the start date falling after the termination day. We discover that the dates have been written incorrectly and correct them by looking up the relevant restrictions in the original source. Moreover, some of the identical restrictions are labelled as distinct restrictions due to minor differences in how they are expressed. We modify the writing for these so that they all appear equal, reducing the number of distinct constraints.

5.2.1 Large Outliers

Because we might have some observations that could influence our results excessively, we decide to replace the most extreme variables in our recycling lottery dataset with values of less extremity. To accomplish this replacement, we employ Stata's function *winsor*. The function recodes the bottom and top 1% of the observed values of the variable "Donation Rate" to values corresponding to the 1st and 99th percentile values. The exclusion of large outliers is explained in more detail in Subsection 7.3.4.

5.2.2 Exclusion of Exceptions from Restrictions

In the dataset of local COVID-19 restrictions, we also have some restrictions that are not true restrictions. These restrictions concern general exceptions from quarantine regulations and special exceptions regarding camping sites, schools, and kindergartens. Since the restrictions represent exceptions rather than actual restrictions, they are not relevant to our analysis, and we choose to exclude them from our dataset.

5.2.3 Duration of COVID-19 Restrictions

The duration of the various restrictions must be determined in the dataset for local restrictions. A regulation was typically announced before it went into effect. We believe that a reasonable approach is to set the starting date as the date the restriction entered into force, assuming that when the restrictions were implemented, people truly understood the extent of the local infection situation. The regulation could either last until the announced period of time or until a potential termination before the end of the period.

The restriction would thus last until the first of these events occurred. We therefore create a variable that refers to the earlier of the announced ending date and a possible termination date.

5.2.4 Categorization of COVID-19 Restrictions

We categorise the local restrictions to be able to assess the impact of the different types of restrictions. There are 76 different restrictions in total, and because many of them concern the same thing, we expect a similar effect on the donation rate. We choose to categorise the restrictions depending on how related they are and how we assume they affect people. Placing several restrictions in one category entails accepting that the different restrictions within one group may pull the coefficient in different directions. However, we are primarily interested in the overall effect of a restriction category rather than the effect of each individual restriction. Therefore, we are mainly concerned with whether the classification is intuitive and provides a meaningful interpretation for the primary categories.

Based on this, we decide to group the restrictions into 14 categories, which are as follows:

1. Quarantine
2. Private life
3. Business
4. Closed schools
5. Ban on serving alcohol
6. Travel
7. Events
8. Use of face masks
9. Activities and sports
10. Public transport
11. Restrictions in health institutions
12. Restrictions in schools
13. Limited alcohol serving
14. Others

The complete list of restrictions included in the different categories is found in Appendix A1. In the following paragraphs, we describe the reasoning behind our categorisation.

The "Others" category contains restrictions that do not fit into any of the other 13 categories and that we are not interested in investigating further. Restrictions in category 14 concern, for instance, cruise ships and orders for expulsion from wharves. The alternative would be to remove these restrictions from the sample. For Models 1 and 3, however, we prefer to have every restriction in the sample. Consequently, we decide to put all of these restrictions into a separate category that is not central to our analysis.

Category 1 covers quarantine-related restrictions. These restrictions regard regulations for various types of quarantine, such as infection quarantine if you have had close contact with an infected individual, waiting quarantine if you have been in close contact with someone who has been in close contact with someone sick, travel quarantine, and isolation.

Restrictions that are assumed to intervene in people's private lives fall under category 2. This category primarily covers the number of guests that can stay in private residences as well as the number of social contacts a person can have. More specifically, it relates to regulations on whether guests can visit private homes or holiday homes, whether private events can be arranged in these locations, and how many people an individual can be in close contact with. It also considers what constitutes close contact and how much physical distance is required from others. These restrictions are grouped together with private life as a common denominator.

The grouping of category 3 is slightly less intuitive because these restrictions are more distinct from one another. This category includes, among other things, the closing of various types of businesses, mandated infection prevention measures in company settings, and visitor registration for specific service establishments and offices. The reason for combining these restrictions into one category is that they all affect business operations and their customers.

The distinction between categories 4 and 12 is dependent on whether kindergartens, schools, and offices are entirely closed to physical presence or if the activity is simply restricted to smaller groups and shorter periods of time. We distinguish between the two alternatives because we believe that completely closing down these institutions would be significantly more invasive in people's lives.

Similarly, the separation of categories 5 and 13 is based on whether there is a complete prohibition of, or limitations on, the serving of alcoholic beverages. We consider the severity level to be far greater if alcohol consumption in bars and restaurants is fully prohibited. However, it is unclear where the line should be drawn between total prohibition and restricted alcohol serving. In some cases, the limitations caused the serving of alcoholic beverages to close early, resulting in a complete prohibition after a certain hour. As an alternative, we could have drawn the line between the two groups at a specific time. Nonetheless, we wish to justify the separation between limitations on alcohol consumption and total prohibition because our main goal is to isolate the most invasive restrictions. Also, with serving restrictions, the alcohol service was typically closed late at night, which is less invasive than a total ban.

Almost every restriction that has a connection to travel is found in category 6. This includes limitations on residence and travel, as well as entry bans and entrance regulations. This category also includes the prohibition on staying overnight at a holiday property in municipalities other than the home municipality. Nevertheless, after-travel quarantine is governed by category 1 (quarantine).

Category 7, events, is similar to category 2, private life, except that it covers social life in public locations or at public events rather than in private houses. This category includes regulations for public events, such as limits on the number of participants and distance rules, as well as the prohibition of these gatherings.

The use of a mask to protect against infection is addressed in category 8. This category covers the requirement to wear a mask in public at all times, the obligation to use a mask in taxis and public transportation, and recommendations for wearing masks.

Category 9 deals with restrictions on activities and sports. This category includes various regulations on sports and leisure activities, as well as the closing of venues for sports, culture, entertainment, or leisure activities.

Regulation of public transportation and other related topics are covered in category 10. This category includes public transportation recommendations and requirements, requirements for registration when travelling with taxis, and commuter constraints.

We choose to group all regulations related to the health industry into one category. Category 11 covers health care institutions, and it comprises health facility restrictions, visiting limitations, and reduced activity offers for the elderly and those with limited functional capacity.

5.2.5 Transforming the Time Format

In the COVID-19 restriction dataset, each municipality has one observation for each restriction, with a start and a termination date. The information from the Norwegian recycling lottery, on the other hand, is provided by a single observation per store on a weekly basis. We want to transform the information from the restriction dataset into weekly observations to have the datasets in the same format. First, we have to compute the duration of the different local restrictions. We retrieve the week number from the start and end dates for each restriction before dividing the observations into the number of weeks that each of the restrictions spanned, resulting in one observation for each restriction for every week in each municipality. This implies that if there is a restriction at some point throughout the week, we consider the entire week to be treated.

5.2.6 Regional Structural Reform and Issues with Counties

To gain a better understanding of the variations in the donation rate and other key variables throughout the country, we wish to examine the descriptive statistics of counties. In the Norwegian recycling lottery dataset, the observations date back to 2019. However, the counties were reformed in 2020, decreasing from 19 to 11 (Regjeringen, 2019). Hence, some of the stores belong to different counties before and after 2020. To correct this, we update the old counties with the new ones in the dataset.

Nine observations also have missing county values. We look up each observation and add the missing counties. Moreover, we discover that some of the stores have been mistakenly registered with two different counties, which has nothing to do with the county reform. For the 27 affected stores, we change the county to the correct one.

5.2.7 Exclusion of Observations

We also exclude observations from stores that have been open for less than 52 weeks from our sample. The rationale behind this decision is to capture the variation caused by local restrictions. In order to do so, it is necessary to observe each store in a baseline setting without local restrictions imposed. We believe that having a time series spanning a certain period of time captures this more precisely. To create a dataset with only stores with 52 or more observations, we remove 18,832 observations from the sample.

5.2.8 Merging the Datasets

After preparing the datasets individually, we continue by merging them together. Every merger is performed with the function *joinby* in Stata, keeping the unmatched observations from the master dataset, the recycling lottery. First, we combine the municipality codes with the recycling lottery data. The recycling lottery dataset and the restriction dataset are then combined using the common variables "Municipality Code" and "Week". Subsequently, we merge the infection rate with the main dataset, yielding a complete dataset consisting of information on the recycling lottery, local COVID-19 restrictions, and the infection rate per 100,000.

6 Descriptive Statistics

In this chapter, we present descriptive statistics about the Norwegian recycling lottery and the local COVID-19 restrictions. We also compare the donation rate to the number of current local restrictions and the number of COVID-19-infected people.

6.1 The Norwegian Recycling Lottery

Our thesis is based on recycling data, where we received weekly data for each store. Table 6.1 summarises this information by store and week. Every week, the stores handle an average of 395 transactions. The overall amount recycled in each store averages NOK 18,867, and the average amount donated to the Red Cross every week is NOK 2,095. The donation rate is calculated by dividing the amount contributed by the total amount recycled. The overall average donation rate is 11.37%.

Variable	Mean	Std. Dev.	Min	Max	N
Total Recycled Amount	18,867.05	16,562.76	2	415,626	461,115
Deposit Amount	16,771.59	15,489.69	0	401,461	461,115
Donated Amount	2,095.47	1,625.41	0	25,773	461,115
Total Transactions	394.68	234.13	1	3,860	461,115
Deposit Transactions	277.37	166.56	0	2,643	461,115
Donated Transactions	117.31	76.61	0	1,277	461,115
Donation Rate (%)	11.37	4.69	2.49	25.61	461,115

Table 6.1: Descriptive Statistics of the Norwegian Recycling Lottery

We are also interested in seeing how the donation rate evolves over time. Figure 6.1 illustrates the average donation rate throughout time, beginning in January 2019 and ending in week 37 of 2022. The graph shows an increase in the average donation rate around the years' ends, implying seasonal altruism around Christmas, which is consistent with the findings of Ekström (2018). Over the measurement period, the donation rate also appears to be increasing from 2020 and on. This uptrend seems to have begun at the same time that COVID-19 restrictions were first implemented in Norway. Once the restrictions are repealed, the donation rate does not return to the pre-coronavirus average. If this is actually related to the COVID-19 restrictions is investigated deeper in the further analysis.

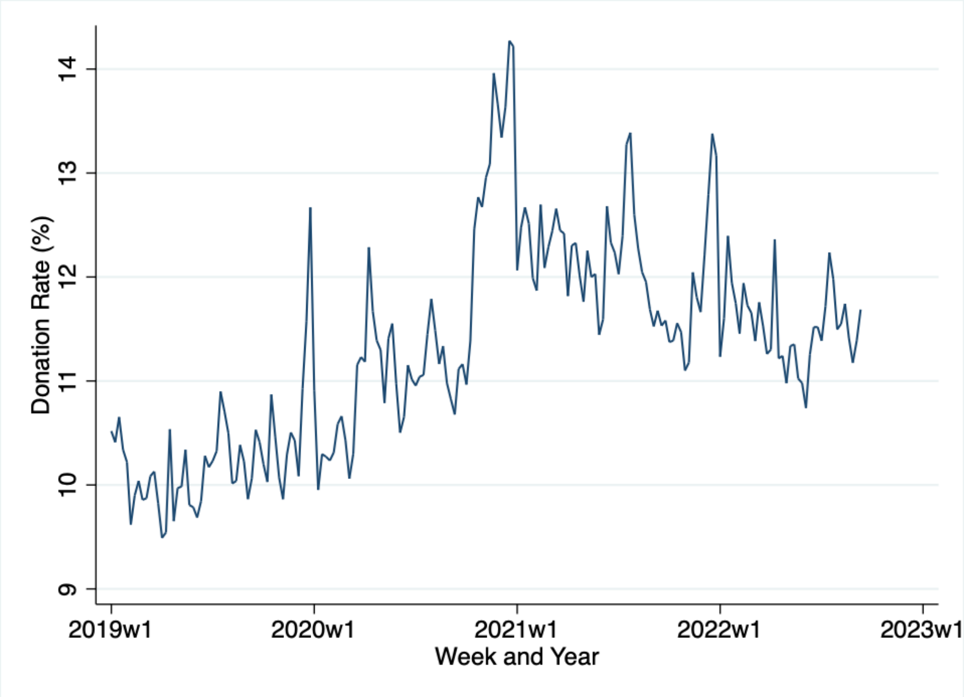

Figure 6.1: Donation Rate over Time

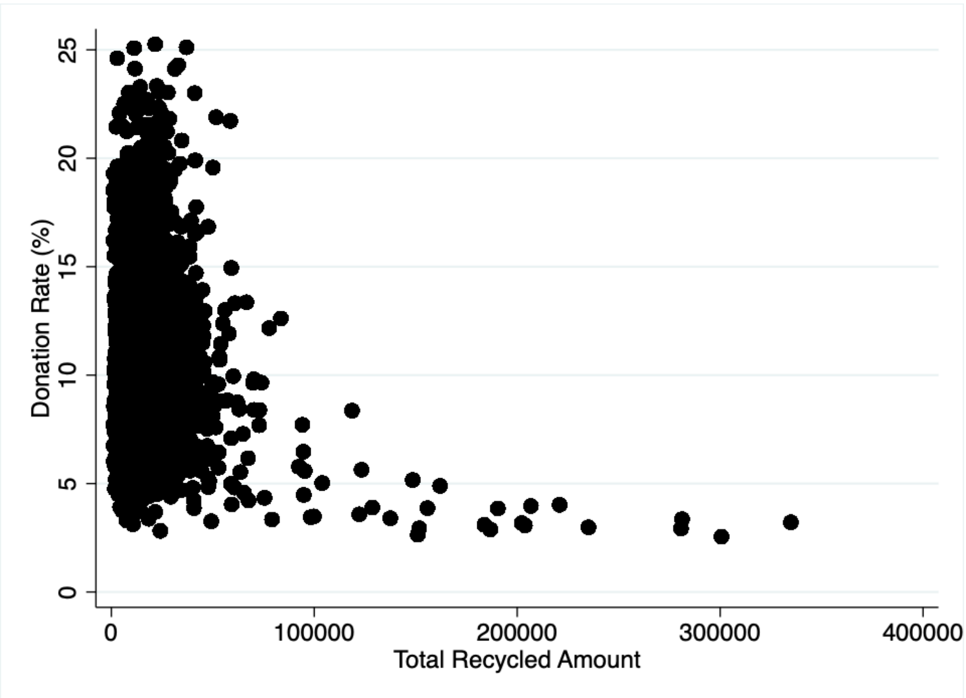

Figure 6.2: Store Heterogeneity: Donation Rate and Total Recycled Amount

Figure 6.2 illustrates the mean donation rate and the mean total recycled amount of the stores in our sample. One dot represents the means of one store. After winsorizing the data at the 1st and 99th percentiles, the figure shows that most stores have an average donation rate between 2.5 and 25% and that the majority handle recycled amounts ranging from 0 to 50,000 NOK on average. However, there are several stores with a higher weekly recycled amount, with the highest average nearly reaching NOK 350,000 weekly. The graph illustrates that, even though most stores have donation rates and recycled amounts within the same range, there are still differences among the various stores.

A further assessment of the donation rate is provided in Table 6.2, which presents the donation rate by county. Oslo has the highest average donation rate of nearly 15%, followed by Vestfold og Telemark and Viken, with average donation rates of 12.44% and 12.27%, respectively. In contrast, Troms og Finnmark exhibits the lowest average donation rate of 7.20%, followed by Nordland and Møre og Romsdal.

County	Mean	SD	p25	Median	p75	N	Unique Stores
Agder	10.68	4.21	7.74	10.20	13.07	32,291	202
Innlandet	9.92	3.79	7.34	9.49	11.96	39,422	247
Møre og Romsdal	9.09	3.56	6.67	8.77	11.09	23,989	160
Nordland	8.03	3.73	5.33	7.55	10.06	17,861	115
Oslo	14.88	5.50	10.97	14.84	18.82	52,441	309
Rogaland	11.01	4.27	8.12	10.50	13.35	38,020	243
Troms og Finnmark	7.20	3.56	4.68	6.64	8.92	17,900	127
Trøndelag	9.95	4.66	6.43	9.30	12.88	32,190	234
Vestfold og Telemark	12.44	4.10	9.62	12.07	14.79	43,083	242
Vestland	11.52	4.36	8.42	11.07	14.05	63,895	384
Viken	12.27	4.14	9.38	11.87	14.71	100,023	586
Total	11.37	4.69	8.04	10.85	14.10	461,115	2,849

Table 6.2: Donation Rate by County

It is also of interest to examine how the average donation rate is related to the different store chains. According to Table 6.3, the donation rate differs substantially between store chains. Jacobs has the highest average donation rate of 22.05%, followed by Meny with an average donation rate of 16.13%. On the other hand, Coop Obs has the lowest average donation rate of only 4.26%, followed by Coop Marked and Coop Prix.

From the statistics presented so far, it is evident that there are differences across stores. Stores located in Oslo have the highest average donation rate, while the average donation rates in Troms og Finnmark, and Nordland are the lowest. Furthermore, there appears to be a trend in which more expensive store chains exhibit higher average donation rates. Differences between stores, if they are constant, are accounted for in the regression models when we include store-specific fixed effects.

Store Chain	Mean	SD	p25	Median	p75	N	Unique stores
Coop Marked	6.91	4.32	3.61	5.88	8.96	3,136	54
Coop Mega	14.58	5.28	10.72	14.64	18.51	5,608	50
Coop Obs	4.26	2.14	2.79	3.51	4.84	1,794	29
Coop Prix	9.78	5.27	5.70	9.05	12.79	13,829	146
Extra	11.20	4.37	7.96	10.92	14.01	44,829	382
Jacobs	22.05	3.42	20.11	22.76	25.31	388	2
Joker	11.17	5.76	6.77	10.28	14.60	38,585	278
Kiwi	11.28	3.81	8.62	10.95	13.56	131,923	701
Matkroken	11.23	5.95	6.43	10.39	15.17	4,727	33
Meny	16.13	4.67	12.78	15.87	19.33	33,368	177
Nærbutikken	11.72	6.66	6.40	10.70	15.92	3,038	26
Rema 1000	10.64	4.12	7.73	10.13	12.97	124,678	673
Spar	11.14	4.66	7.74	10.58	13.96	55,212	298
Total	11.37	4.69	8.04	10.85	14.10	461,115	2,849

Table 6.3: Donation Rate by Store Chain

6.2 Variations in Local COVID-19 Restrictions

With the emergence of COVID-19, many national and local restrictions were enforced throughout Norway. Figure 6.3 illustrates current local COVID-19 restrictions in Norway at three different times during the last few years. The colour coding represents the number of restriction categories in force in each municipality. The lightest colour indicates that there were measurements in one to two categories; the second lightest colour shows that there were measurements in three to four categories; and the deepest blue colour indicates that there were measurements in five or more categories. No colour signifies that there were no local measures imposed at the time.

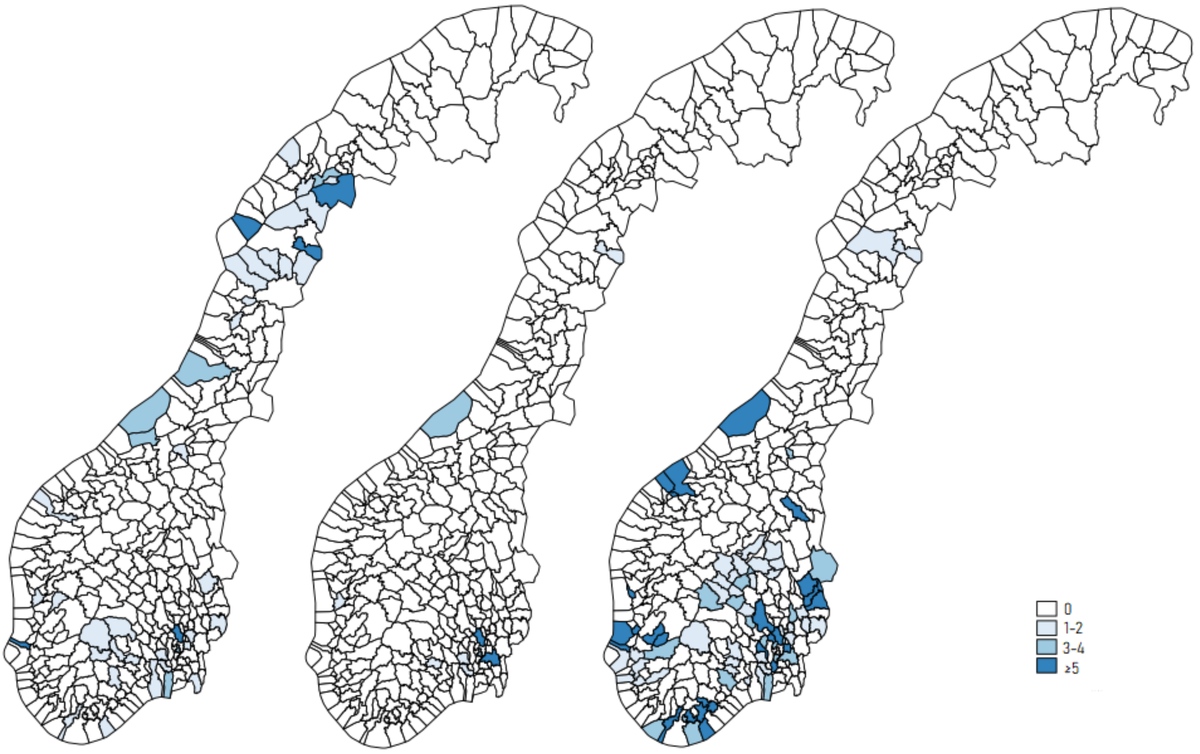

Figure 6.3: Local Restrictions: Week 14 2020, Week 33 2020, Week 13 2021

The first map displays the 14th week of 2020. This was during the first coronavirus outbreak in Norway, and we can see that various municipalities enforced local measures. The second map depicts the 26th week of 2020. This was a quieter period, with fewer occurrences of disease and fewer municipalities imposing local restrictions. The map to the right displays week 33 in 2021. Around this time, there were multiple outbreaks throughout Norway, and a total of 77 municipalities imposed local restrictions. The maps indicate that the amount of restrictions imposed at different times varied greatly. As a result, we believe there is enough variation in the dataset in terms of local restrictions to complete our intended analysis.

6.3 Local COVID-19 Restrictions

Table 6.4 presents summary statistics of the local COVID-19 restrictions prior to their classification into the 14 main categories. The table demonstrates that Oslo has the highest average of local restrictions, followed by Viken. In contrast, Troms og Finnmark and Nordland exhibit the lowest average of local restrictions.

County	Mean	SD	Min	Max	N
Agder	0.27	1.37	0	17	32,291
Innlandet	0.22	1.37	0	27	39,422
Møre og Romsdal	0.17	0.98	0	12	23,989
Nordland	0.10	0.61	0	10	17,861
Oslo	3.91	5.54	0	28	52,441
Rogaland	0.65	2.48	0	21	38,020
Troms og Finnmark	0.09	0.77	0	14	17,900
Trøndelag	0.36	2.07	0	23	32,190
Vestfold og Telemark	0.35	1.27	0	14	43,083
Vestland	0.59	2.12	0	23	63,895
Viken	1.23	3.66	0	40	100,023
Total	0.96	3.10	0	40	461,115

Table 6.4: Number of COVID-19 Restrictions by County

Figure 6.4 plots the average donation rate and the average number of current local restrictions at the time. We can see that around March 2020, the donation rate appears to be increasing in tandem with the average number of local restrictions. The average donation rate and the average number of restrictions appear to stay higher than normal simultaneously, and when the number of local restrictions decreases, the donation rate appears to remain higher than before the pandemic.

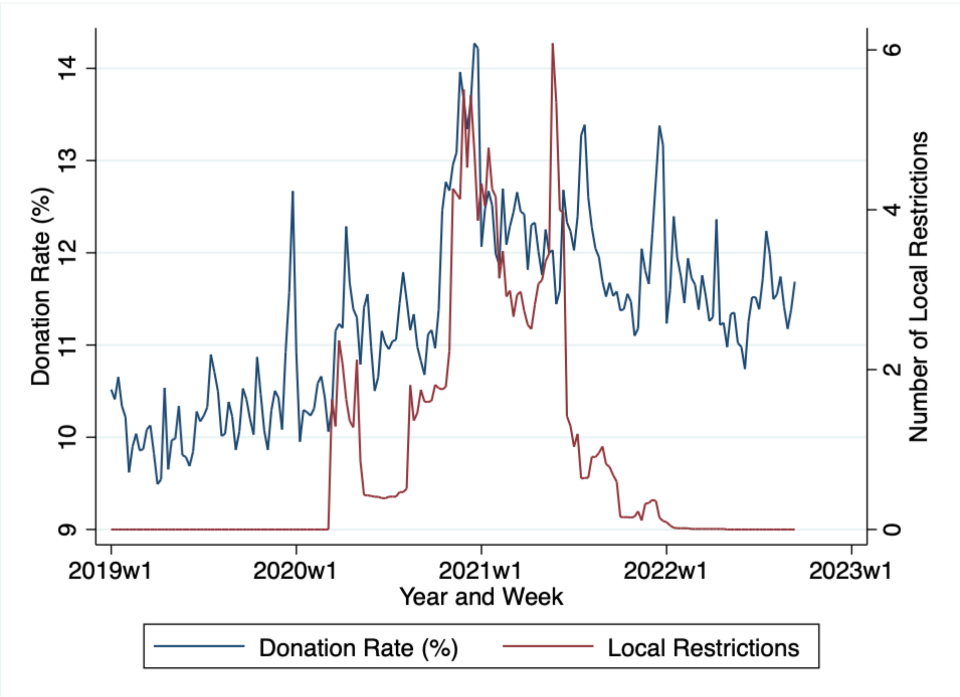

Figure 6.4: Donation Rate and Number of Current Local Restrictions

6.4 Infection Rate

It is also of interest to examine the relationship between the infection rate and the donation rate. Table 6.5 presents the infection rate per 100,000 by county. We see that Oslo has the highest average infection rate, followed by Viken. Nordland displays the lowest rate.

County	Mean	SD	Min	Max	N
Agder	155.03	497.31	0.00	7,863.85	32,291
Innlandet	124.96	429.40	0.00	5,891.72	39,422
Møre og Romsdal	135.39	458.19	0.00	8,206.41	23,989
Nordland	107.36	368.46	0.00	5,551.50	17,861
Oslo	210.74	535.44	0.00	3,520.30	52,441
Rogaland	154.19	487.18	0.00	5,821.06	38,020
Troms og Finnmark	133.70	412.75	0.00	5,421.69	17,900
Trøndelag	140.72	450.75	0.00	4,596.58	32,190
Vestfold og Telemark	131.34	411.62	0.00	4,841.40	43,083
Vestland	129.18	433.64	0.00	6,718.75	63,895
Viken	170.23	502.68	0.00	6,770.95	100,023
Total	151.53	468.70	0.00	8,206.41	461,115

Table 6.5: COVID-19 Infection Rate per 100,000 by County

In Figure 6.5, we observe the mean donation rate and average infection rate per 100,000. In comparison to the current local restrictions, we can see that the donation rate follows the pattern of the infection rate to a lesser extent.

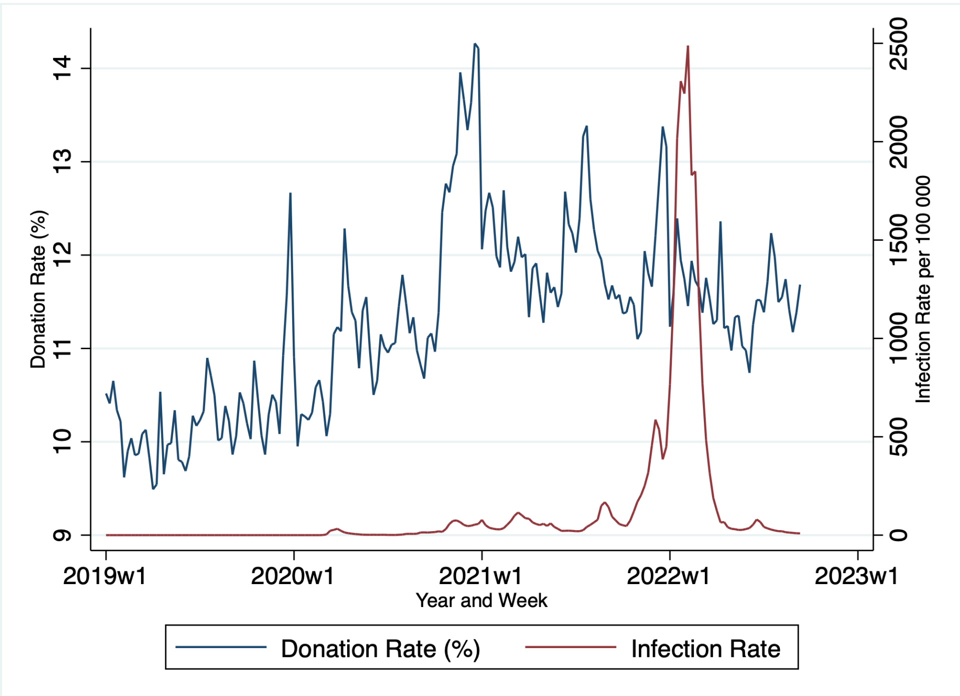

Figure 6.5: Donation Rate and Infection Rate per 100,000

7 Method

The primary purpose of many econometric studies is to determine whether a variable has a causal effect on another (Wooldridge, 2020, p. 10). Causality is the connection between cause and effect (Hicks, 1980, p. 1). In this thesis, we want to investigate whether there is a causal effect of local COVID-19 restrictions on the donation rate from the Norwegian recycling lottery, using the donation rate as a proxy for pro-social behaviour. To be able to say something about the effect of restrictions on the donation rate, all other relevant factors need to remain constant. This is referred to as Ceteris Paribus, which means "other factors being equal" (Wooldridge, 2020, p. 10). However, deciding which factors to include and whether enough factors have been held constant can be challenging.

From our data collection, we have an unbalanced panel dataset. The panel data is structured with a T*N dimension, where T represents the number of time observations and N represents the number of stores. In our dataset, there are more stores than time observations, so that N>T. Panel data has several advantages compared to pure time-series and cross-sectional analysis (Wooldridge, 2020, p. 427). More information is provided in panel data, which allows us to eliminate constant unobserved variables (Stock and Watson, 2020, p. 361). There are several methods for analysing panel data. Pooled OLS, fixed effects, or random effects can be used to estimate a panel data model. We perform two different tests to find out which method is most appropriate in our case and discover that the fixed effects model is the best fit.

7.1 Description of Models

In order to test our hypotheses, we need to formulate different econometric models. Our first hypothesis is whether local restrictions in general have an effect on the donation rate. Thus, the first model is presented by:

Model 1:

$$\text{Donation Rate}_{it} = \beta_1 \cdot \text{ Dummy(Local Restrictions)}_{it} + \beta_2 \cdot \ln(\text{Total Transactions})_{it} + \beta_3 \cdot \ln(\text{Infection Rate})_{it} + \alpha_i + \lambda_t + u_{it}$$

Our second hypothesis is whether different categories of restrictions have an effect on the donation rate. The second model is presented by:

Model 2:

$$\text{Donation Rate}_{it} = \beta_1 \cdot \text{Dummy(Restriction Category X)}_{it} + \beta_2 \cdot \ln(\text{Total Transactions})_{it} + \beta_3 \cdot \ln(\text{Infection Rate})_{it} + \alpha_i + \lambda_t + u_{it}$$

, where $X = 1, ..., 14$

In the variations of Model 2, we look at one restriction category at a time. Observations that include current restrictions but do not include category X are excluded. This way, we are able to compare stores with restrictions in category X against stores in areas with no restrictions imposed.

We are also interested in whether the donation rate is affected by how long the restrictions have been in place. This is expressed by:

Model 3A:

$$\text{Donation Rate}_{it} = \beta_1 \cdot \text{Dummy(First Week)}_{it} + \beta_2 \cdot \text{Dummy(Second Week)}_{it} + \beta_3 \cdot \text{Dummy(Third Week)}_{it} + \beta_4 \cdot \text{Dummy(Fourth Week)}_{it} + \beta_5 \cdot \text{Dummy(Week 5+)}_{it} + \beta_6 \cdot \ln(\text{Total Transactions})_{it} + \beta_7 \cdot \ln(\text{Infection Rate})_{it} + \alpha_i + \lambda_t + u_{it}$$

Ultimately, we want to study whether the effect of local restrictions persists after they are lifted. This is expressed by:

Model 3B:

$$\text{Donation Rate}_{it} = \beta_1 \cdot \text{Dummy(Local Restrictions)}_{it} + \beta_2 \cdot \text{Dummy(First Week After)}_{it} + \beta_3 \cdot \text{Dummy(Second Week After)}_{it} + \beta_4 \cdot \text{Dummy(Third Week After)}_{it} + \beta_5 \cdot \text{Dummy(Fourth Week After)}_{it} + \beta_6 \cdot \ln(\text{Total Transactions})_{it} + \beta_7 \cdot \ln(\text{Infection Rate})_{it} + \alpha_i + \lambda_t + u_{it}$$

Our dependent variable indicates the donation rate in store i at time t. The rate is calculated as the donated amount divided by the total amount recycled. α_i refers to the store fixed effects, which capture unobservable effects that are constant for each store over time (Stock and Watson, 2020, p. 368). For example, the availability of the establishment and the type of chain store could affect the donation rate. λ_t represents the week fixed effects (Stock and Watson, 2020, p. 372). They are separate dummies that capture effects that are equal for all stores in each week of each year. This implies, for instance, that there is one dummy for week 12 in 2020 and one dummy for week 12 in 2021. Week fixed effects allow us to account for time-varying factors that may influence the donation rate, such as larger donations in the weeks around Christmas (Ekström, 2018). u_{it} is the error term, varying between stores and time.

The different models contain a number of dummy variables. In the first model, there is a dummy variable that takes the value 1 if local restrictions were imposed in the municipality where the store is located within the current time period and the value 0 otherwise. In the second model, the dummy takes the value 1 if restrictions from category X are in force at the moment. X ranges from one to fourteen, referring to the different categories of restrictions. Model 3A includes several dummies. The first dummy represents the first week of restrictions, the second dummy represents the second week, and so forth. In model 3B, the second dummy is set to 1 if the restrictions were lifted the week before, the next dummy to 1 if the restrictions were terminated two weeks before, and so on.

We also include control variables for total transactions and the infection rate in the different models. While using the fixed effects estimation method, effects that are constant with the store or time dimension are taken into account (Stock and Watson, 2020, p. 373). Variables that do not remain constant within the store or week of the year, on the other hand, are not controlled for. Therefore, it is appropriate to include other variables that are not constant with store and time, which can be thought to influence the donation rate.

Total transactions are the number of transactions made in a store within a given week. In this context, a transaction refers to one individual's bottle recycling and the subsequent choice of whether to cash out or donate the deposit. We include total transactions in the model to account for the fact that the number of recycling transactions, which varies over time and between stores, could influence the donation rate. We additionally include the infection rate per 100,000 in our models. This, like the local COVID-19 restrictions, varies over time and between municipalities, and it may also have an impact on the donation rate.

To make the interpretation of the regressions more comprehensible, we employ the natural logarithm (ln) of the two control variables, total transactions and infection rate, in our models. However, since both control variables can have values of zero, we must address this issue before utilizing their logarithm values. Due to the fact that we recode outliers of our dependent rate variable in our sample, there are no zero observations of total transactions in our regressions, and this variable is not a concern. The infection rate variable, on the other hand, frequently has zero values. Excluding these observations is not an option because our analysis depends on observations from periods without COVID-19 cases. To resolve the issue, we increase the infection rate by adding the value one to every observation prior to its transformation into the natural logarithm value, which is referred to as the popular fix (Bellégo et al., 2022). Nonetheless, this practice can cause inconsistencies in our estimators, which is a weakness in our regressions.

7.2 Choice of Model

Because our sample contains data from a wide range of stores at different times, it can be classified as a panel dataset. Panel datasets provide a variety of estimation methods, the most well-known of which are pooled OLS, random effects (RE), and fixed effects (FE). In this section, we look closer at which model should be employed. Our choice of model is based on tests that help us determine what is the best fit, as well as a subjective assessment.

For the estimates to be unbiased, OLS estimating requires that the model's explanatory variables are not correlated with the residuals. If this is the case, omitted variables will take part in the residuals and yield biased estimates. Fixed effects estimation can help with this issue (Wooldridge, 2020, p. 463). FE estimation accounts for unobserved effects that give permanent differences in each observed store, resulting in more consistent estimators.

7.2.1 Breusch and Pagan Lagrange Multiplier Test

First, we conduct a formal investigation to determine which model of pooled OLS and random effects best fits our dataset. If each store in our sample has store specific noise $u_i = 0$, there is no need to correct for individual differences among stores using a RE or FE estimator. In this case, a pooled OLS model is sufficient for our analysis (Wooldridge, 2020, p. 473).

We perform a Breusch and Pagan Lagrange multiplier test to investigate this issue. The test determines whether the individual or time-specific variance equals zero, that is, $H_0 : S_u^2 = 0$. Rejecting H_0 implies that there exist random individual differences within our sample, and as a result, a RE model may be beneficial. The null hypothesis can be rejected if the test statistic is < 0.05.

We employ Stata to test our dependent variable against the explanatory variables in our different models. We discover that we can reject the null hypothesis in all cases, implying that pooled OLS is not the best model for our analysis. The complete result of the Breusch and Pagan Lagrange multiplier tests is found in Appendix A2.

7.2.2 Hausman Test

As previously mentioned, a fixed effects model accounts for endogeneity caused by unobserved effects. To formally investigate if a random effects or a fixed effects model best fits our sample, we further conduct the Hausman test. The Hausman test compares two versions of the same model, one of which is a random effect model and the other a fixed effects model (Park, 2011). The null hypothesis, H_0, is that the individual effects are uncorrelated with any of the explanatory variables in the model (Wooldridge, 2020, p. 475). If the null hypothesis is rejected, we can conclude that the individual effects are significantly correlated with at least one of the explanatory variables, and thus a random effects model may be problematic.

P-values less than 0.05 indicate systematic differences in the coefficient estimates, implying that fixed effects modelling is better suited to the data than random effects. On the other hand, P-values over this limit indicate that random effects modelling should be used. In our case, we get P-values < 0.05 for all our models, implying that fixed effects modelling is the better fit over random effects modelling. The result from the Hausman tests is presented in Appendix A3.

Based on the test results, we use FE estimators in our analysis. A similar empirical study by Ekström (2018) also supports our choice of fixed effects modelling.

7.2.3 Fixed Effects

FE estimation allows our sample to omit time-consistent variables that are correlated with x_i (Wooldridge, 2020, p. 440). The FE model controls for unobserved heterogeneity if it is constant over time. Even though it is reasonable that customer and store characteristics may change or evolve over time, we find it fair to assume that certain attributes impacting the donation rate persist over time. The fact that the number of stores in our sample is larger than the number of time periods (N>T) makes a FE estimator well suited to control for time-consistent effects (Wooldridge, 2020, p. 468).

When we use FE estimation, Stata performs a within-group transformation that takes advantage of the time dimension within our panel. This means that all store-specific effects are removed, and we are left with a regression model defined as the deviation from the store-specific mean (Wooldridge, 2020, p. 463). More precisely, the FE estimator looks at differences between the value of a variable in a given period and the mean value for each store. Because a_i is constant over time, the value in one period and the mean will be the same, and the difference will be 0. As a result, omitted time-consistent variables are not an issue in the estimation because they will be removed from the model.

Formally, Wooldridge (2020, p. 463) expressed the within-group transformation as:

The model with a single explanatory variable for each i can be considered as

$$y_{it} = \beta_1 x_{it} + a_i + u_{it} \tag{7.1}$$

, where

$$t = 1, 2, ..., T$$

Average this equation over time for each i

$$\bar{y}_i = \beta_1 \bar{x}_i + a_i + \bar{u}_i \tag{7.2}$$

Because a_i is fixed over time, it can be found in both (7.1) and (7.2).

By subtracting (7.2) from (7.1) for each t, we get

$$y_{it} - \bar{y}_i = \beta_1 (x_{it} - \bar{x}_i) + u_{it} - \bar{u}_i \tag{7.3}$$

$(y_{it} - \bar{y}_i)$ is the time-demeaned data on y, $(x_{it} - \bar{x}_i)$ is the time-demeaned data on x, and

$(u_{it} - \bar{u}_i)$ is the time-demeaned data on u. The unobserved effect, a_i, has now disappeared.

Other estimation methods, such as a RE estimator, consider a_i to be random. FE are therefore generally considered to have more convincing *Ceteris Paribus* effects than RE (Wooldridge, 2020, p. 473). One potential disadvantage of FE is that it removes time-consistent variables that are included in the model from the regression. By doing so, we run the risk of removing variables whose effects we want to investigate. However, this is not an issue in our case because the variable we are interested in varies across time and between stores.

7.3 Validity

A valid statistical study has the potential to provide answers to research questions concerning causal effects (Stock and Watson, 2020, p. 330). If the study is also externally valid, the answers can be generalised to other settings or populations than the ones studied. Internal and external validity differ in that in internally valid studies, the answers to the research questions are valid only for the population and setting in our studied sample, whereas external validity applies to populations of entities and settings in general (Stock and Watson, 2020, p. 331).

The inference of the analysis is only valid if all other variables remain constant, that is, if we have taken into account every possible variable that could influence the donation rate. Because we have fixed effects for store and time, the only remaining factors we need to consider are those that vary over time and across stores.

To ensure that FE estimation gives valid and unbiased estimates, we need to make sure certain assumptions are fulfilled. The relevant assumptions for FE estimators to be consistent and asymptotically normally distributed when N is large are (1) no omitted variable bias, (2) random sampling, (3) no perfect multicollinearity between the independent variables, and (4) no large outliers (Stock and Watson, 2020, p. 374–375; Wooldridge, 2020, p. 491–492). For more precise estimates and correct standard errors, we would also like the data in our sample to be homoscedastic and have no serial correlation. In the following paragraphs, we investigate these potential issues in more detail.

7.3.1 No Omitted Variable Bias

An omitted variable is a variable that is correlated with one of the included explanatory variables, has an effect on the dependent variable, and is omitted from the regression (Stock and Watson, 2020, p. 334). For the FE model to have no omitted variable bias, the value of the unobserved variable u_{it} must have an expected value of 0 for all values of t (Stock and Watson, 2020, p. 374).

The balance between omitted variables and too many included variables must be carefully considered, as including irrelevant variables can increase the variance of other explanatory variables, resulting in estimates with poorer precision.

As briefly addressed in the chapter on descriptive statistics, it is natural to speculate if infection rates in a given area can be as good a determinant of the donation rate as local restrictions. We visually compare the variation in the infection rate against the variation in the donation rate, and even though there appears to be little covariation between the two, we consider including the infection rate in our regression model to ensure that the potential effects are controlled for. Total recycling transactions in a store over a period is also an interesting variable to consider including in our regressions. To determine whether it is beneficial to include total transactions as a control variable, we examine whether including this variable results in better regressions. That is, we investigate whether the variable has a nonzero coefficient and whether including the control variable makes a meaningful change in the coefficient of interest (Stock and Watson, 2020, p. 335). We include these variables one by one in all our regressions to study the effect on our variable of interest. In Model 1, the regression results show that our coefficient of interest remains significant when the two control variables are included. The R-squared value is marginally increased, while the coefficient of interest decreases to some extent. Despite the fact that the infection rate variable has a fairly low coefficient, we believe that including these variables improves our regression sufficiently to include them in our analysis.

Other variables that we believe may affect the donation rate are part of the store fixed effects. This includes characteristics of the establishment, such as store location and availability, as well as attributes that are typical for its customers, such as wage, age, and gender. If these features remain constant for a store throughout time, they are accounted for in the store-specific fixed effects.

7.3.2 Random Sampling

Random sampling requires the entities to be selected randomly from the population. For this to be true, the variables of one entity need to be distributed identically to the ones of other entities while remaining independent from each other (Stock and Watson, 2020, p. 374). The assumption of random sampling ensures that the units in the sample do not differ systematically from the units in the population in general (Wooldridge, 2020, p. 315).

Our sample includes all of the recycling data compiled by the supplier Tomra, which has a large market share that includes various store chains (Tomra, 2022). In 2022, there were a total of 3,862 stores in Norway (Konkurransetilsynet, 2022). Our original dataset consists of observations from 3,221 different stores in 2022. We have no reason to believe that recycling data from other smaller providers differs significantly from this. As a result, we do not complicate this issue further. If this assumption is not satisfied, the results will not apply to entities outside of our sample, but they may still apply to entities that are (Stock and Watson, 2020, p. 331).

7.3.3 No Perfect Multicollinearity

Multicollinearity occurs when one of the regressors is a function of another regressor, and if there is an exact linear relationship between the regressors, the phenomenon is known as perfect multicollinearity (Stock and Watson, 2020, p. 226). Multiple regression models are used to estimate the impact of changes in individual regressors on the y-variable while keeping all other regressors constant. If two regressors capture the same effects, it becomes difficult to measure the effect of one regressor without also changing the other, and the purpose of multiple regression is lost. This issue usually arises as a result of a logical mistake in selecting the regressors for the model, and the regressors must be modified to resolve the issue.

The primary explanatory variables in our regressions are related to COVID-19 restrictions, while our control variables account for total transactions and the infection rate in each period. The variable "Total Transactions" is unrelated to the local restrictions. However, collinearity may arise between the "Infection Rate" variable and the restriction variables or between the different restriction variables themselves. We investigate the relationship between the "Infection Rate" variable and restrictions variables further by creating a correlation matrix. The results reveal that the correlation between the variables is sufficiently small to not pose any difficulties. The correlation matrix from Model 1 demonstrates a correlation of 0.238 between the dummy variable "Local Restrictions" and the control variable "ln(Infection Rate)". This is to be expected, and a slight degree of collinearity between variables is unlikely to have any adverse effects on our regressions. Presenting results both with and without "ln(Infection Rate)" allows us to ensure that the collinearity does not contaminate our regressions. Also, the regression coefficients cannot be estimated if perfect multicollinearity exists, and therefore the software will usually either warn the user or solve the problem itself by automatically removing perfectly correlated variables from the regression (Stock and Watson, 2020, p. 230).

Further, to avoid a potential multicollinearity problem between the different restriction variables, we only include one of the restriction-related explanatory variables at a time in Model 2. That is, we focus on one restriction category and exclude observations that only have restrictions from other categories imposed. Model 3 incorporates all of the restriction-duration dummies into the regression, but each observation has a maximum of one dummy equal to one.

7.3.4 No Large Outliers

Observations with values that deviate significantly from the typical values in the dataset should not be present because they could affect the estimators more than is beneficial. The FE coefficients can, just like the OLS coefficients, be sensitive to large outliers (Stock and Watson, 2020, p. 225). To ensure the accuracy of our results, we should therefore make every effort to exclude these observations from our sample when conducting the regression analysis.

We find it challenging to review what could be considered outliers in our sample because the variable of interest is always a proportion. As a result, the variable does not have extreme values below 0 or above 1, which tend to be what we first think of as outliers. However, the most extreme values in the dataset indicate that either nothing or everything is donated. This can, for example, be the case if a store hardly has any transactions during a period, and only one or a few transactions determine the value of the donation rate. With a closer look, we find that out of a total of 461,115 observations, 299 and 107 have a donation rate of 0 and 1, respectively. To handle these outliers, we recode the lowest and highest 1% as described in Subsection 5.2.1. As a result, we remove all observations with values of 0 and 1, as well as several observations in close proximity to these. The minimum and maximum values of the donation rate are now 2.49 and 25.61, respectively, as presented in Section 6.1. Figures 7.1 and 7.2 display histograms of the dependent variable "Donation Rate" before and after winsorizing. Despite the figures indicating that these outliers are of minor relevance, we choose to remove the most extreme values to be certain that they do not influence our analysis excessively.

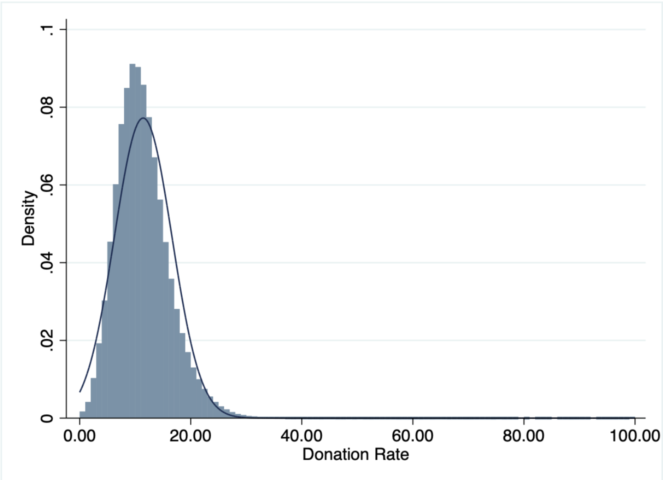

Figure 7.1: Distribution before Winsorizing

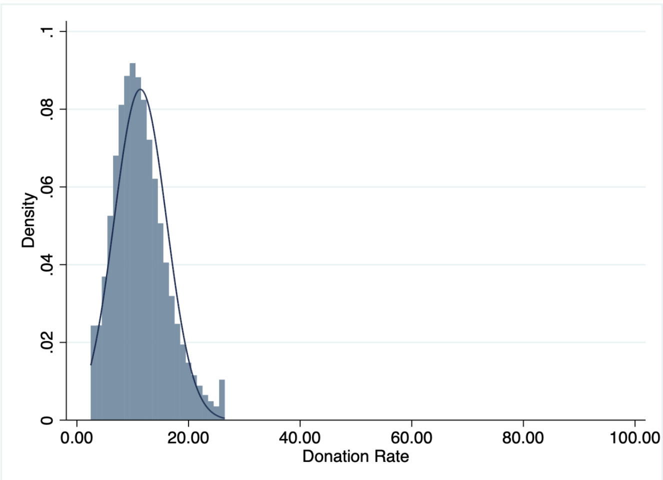

Figure 7.2: Distribution after Winsorizing

7.3.5 Standard Errors for Fixed Effects Regression

7.3.5.1 Assumption of Homoscedasticity

Homoscedastic errors require the variance of the conditional distribution of u_{it} for a given X_{it} to be constant for the different values of i and t and not depend on X_{it} (Stock and Watson, 2020, p. 188; Wooldridge, 2020, p. 492). Breusch and Pagan tests are performed to test for heteroscedasticity. The results indicate that heteroscedasticity is present in our sample. The test results are presented in Appendix A4.

7.3.5.2 Assumption of No Serial Correlation

In time series data, X_{it} tends to be correlated over time for a given entity. This is because what occurs in a specific store during one period of time naturally tends to affect subsequent periods. Similarly, if we assume that u_{it} comprises factors that both determine Y_{it} and vary over time, these omitted variables are likely to be correlated over time as well (Stock and Watson, 2020, p. 375). Consequently, autocorrelation errors could occur in our sample. We employ Woolridge tests to further investigate the potential issue of autocorrelation. Significant test statistics reveal serial correlation in our sample. Appendix A5 provides the results of the Woolridge tests.

7.3.5.3 Clustering

Regressions with panel data are assumed to have homoscedastic and uncorrelated errors. However, if the errors are in fact heteroscedastic and autocorrelated, the standard errors will not be valid as they were derived under a false assumption (Stock and Watson, 2020, p. 376). The results of the tests conducted reveal the presence of both autocorrelation and heteroscedasticity in our sample, which makes it highly probable that the validity of our standard errors is compromised.

To address this issue, we employ clustered standard errors in all our regressions. Clustering implies that regression errors are allowed for autocorrelation and heteroscedasticity within a cluster but not across clusters (Stock and Watson, 2020, p. 376). Clustered standard errors are robust to both heteroskedasticity and autocorrelation, which means they are valid even if u_{it} is potentially heteroskedastic and correlated over time within the clustered unit. There is no formal test for determining what level to cluster over, but the general agreement is to be conservative and employ larger clusters wherever feasible (Cameron and Miller, 2015). Therefore, we decide to cluster the standard errors by municipalities rather than stores. The treatment described in our analysis (local COVID-19 restrictions) is implemented at the municipal level. Clustering by municipality accounts for both autocorrelation within stores and autocorrelation within municipalities because each store is located within one municipality.

8 Results

8.1 Effect of Local COVID-19 Restrictions in General

Table 8.1 summarises the regression results of the analysis on whether local restrictions in general affect the donation rate. The results are shown in column 1 without any control variables. Column 2 displays the results with total transactions included, while column 3 presents the results controlling for total transactions and infection rate per 100,000. We account for store-specific effects that are constant throughout time and week-specific effects that are the same for all stores in each model.

VARIABLES	(1) Donation Rate	(2) Donation Rate	(3) Donation Rate
Local Restrictions	0.262***	0.262***	0.242***
	(0.0838)	(0.0818)	(0.0602)
ln(Total Transactions)		-0.376***	-0.376***
		(0.123)	(0.122)
ln(Infection Rate)			0.0207
			(0.0287)
Observations	461,115	461,115	461,115
R-squared	0.671	0.672	0.672
Number of Stores	2,849	2,849	2,849
Number of Municipalities	327	327	327
Store FE	YES	YES	YES
Week-Year FE	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8.1: Model 1

The coefficient in column 1 is positive. If local restrictions are imposed, the coefficient estimates that the donation rate will increase by 0.262 percentage points on average. For the mean value of the donation rate, this implies a 2.3% increase from 11.37 to 11.63. This coefficient is significant at the 1% level. As a result, based on column 1, we can reject the null hypothesis that local COVID-19 restrictions in general do not affect the donation rate.

Factors that vary between stores and across time are potential sources of error for the model in column 1. We incorporate total transactions and infection rate, both of which change over time and between stores, to account for potential errors in the regressions in columns 2 and 3. The coefficient of total transactions is negative and significant at the 1% level. A one-percent increase in total transactions would, on average, reduce the donation rate by 0.00376 percentage points. Like the coefficient of local restrictions, the coefficient of infection rate is positive, but the effect is small. The effect of the infection rate is also insignificant.

The coefficient for local restrictions is still significant at the 1% level when we include total transactions in column 2 and total transactions and infection numbers in column 3. The size of the coefficient does not change much either, so the effect of local COVID-19 restrictions on the donation rate remains roughly the same as before, with an increase of 0.262 percentage points in column 2 and an increase of 0.242 percentage points in column 3.

We employ clustered standard errors at the municipality level in our regressions, as described in Subsection 7.3.5.3. The standard errors are typically larger when robust standard errors are used. Nevertheless, we still find that our results are significant, allowing us to assert an increase in the donation rate as a result of local restrictions.

8.2 Effect of Local COVID-19 Restrictions in Categories

Based on hypothesis 2, we are further interested in which restrictions have the greatest impact on the donation rate. Table 8.2 presents the results when we divide the local restrictions into 14 main categories. Subsection 5.2.4 discusses this division in greater detail. The regressions include store- and week-fixed effects in addition to total transactions and the monthly infection rate as control variables. The number of observations varies because we exclude observations with current restrictions but without restrictions imposed in category X. This way, we can compare restrictions in category X to the case in which no local restrictions are imposed.

Table 8.2 shows that, with the exception of restriction category 12, all of the categories' coefficients are positive. Most of the categories have a greater effect on the donation rate than local restrictions in general, but there are also some categories that have a smaller impact. 11 out of 14 of the categories are significant at the 1% or 5% level.

Although restriction category 1 (quarantine) has a positive coefficient, it is not statistically significant. Category 12 (restrictions in school) has a negative coefficient and is also insignificant. The coefficient for category 13 (limited alcohol serving) is positive but not significant. As a result, we cannot reject the null hypotheses that quarantine, restrictions in school, and limited alcohol serving have no effect on the donation rate.

The coefficients indicate that categories 6 (travel) and 5 (ban on serving alcohol) have the greatest effect on the donation rate, with increases of 0.977 percentage points and 0.781 percentage points, respectively. The effects are significant at the 1% level. The impact is likewise relatively strong in categories 4 (closed schools), 7 (events), 9 (activities and sports), 10 (public transport), and 11 (restrictions in health institutions). All of these are significant at the 1% or 5% level. Furthermore, we see that categories 2 (private life), 3 (business), and 8 (use of face mask) have a lower but still significant influence on the donation rate.

We use standard errors that are clustered by municipalities. Most of the category coefficients are still significant, and we can conclude that the majority of restriction categories have an impact on the donation rate.

VARIABLES	(1) Donation Rate	(2) Donation Rate	(3) Donation Rate	(4) Donation Rate	(5) Donation Rate	(6) Donation Rate	(7) Donation Rate	(8) Donation Rate	(9) Donation Rate	(10) Donation Rate	(11) Donation Rate	(12) Donation Rate	(13) Donation Rate	(14) Donation Rate
Cat. 1: Quarantine	0.210													
	(0.153)													
Cat. 2: Private Life		0.361***												
		(0.130)												
Cat. 3: Business			0.265***											
			(0.0864)											
Cat. 4: Closed Schools				0.484***										
				(0.156)										
Cat. 5: Alcohol Ban					0.781***									
					(0.255)									
Cat. 6: Travel						0.977***								
						(0.167)								
Cat. 7: Events							0.431**							
							(0.178)							
Cat. 8: Use of Face Mask								0.226**						
								(0.106)						
Cat. 9: Activity, Sports									0.467**					
									(0.218)					
Cat. 10: Public Transport										0.616***				
										(0.103)				
Cat. 11: Health Institutions											0.536***			
											(0.0600)			
Cat. 12: School Restrictions												-0.168		
												(0.244)		
Cat. 13: Alcohol Regulation													0.169	
													(0.142)	
Cat. 14: Others														0.477***
														(0.0871)
ln(Total Transactions)	-0.363***	-0.368***	-0.360***	-0.342***	-0.342***	-0.350***	-0.388***	-0.367***	-0.372***	-0.352***	-0.340***	-0.350***	-0.371***	-0.351***
	(0.119)	(0.114)	(0.123)	(0.113)	(0.110)	(0.113)	(0.113)	(0.116)	(0.112)	(0.118)	(0.118)	(0.114)	(0.114)	(0.113)
ln(Infection Rate)	-0.00161	1.45e-05	0.0208	0.0119	0.00458	-0.000518	0.00905	0.0164	0.00557	0.00841	0.00119	-0.00408	-0.00385	0.00795
	(0.0136)	(0.0158)	(0.0275)	(0.0223)	(0.0163)	(0.0139)	(0.0201)	(0.0257)	(0.0193)	(0.0202)	(0.0152)	(0.0132)	(0.0137)	(0.0185)
Observations	403,805	423,587	446,332	431,112	417,256	400,965	433,355	441,221	422,460	414,181	408,077	398,205	409,119	411,822
R-squared	0.647	0.659	0.674	0.670	0.667	0.650	0.666	0.670	0.660	0.663	0.654	0.648	0.651	0.658
Number of Stores	2,849	2,849	2,849	2,849	2,849	2,849	2,849	2,849	2,849	2,849	2,849	2,849	2,849	2,849
Number of Municipalities	327	327	327	327	327	327	327	327	327	327	327	327	327	327
Store FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Week-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8.2: Model 2

8.3 Effect of Local COVID-19 Restrictions over Time

To assess whether the effect of local COVID-19 restrictions changes over time, we employ a regression model in which the duration of the restrictions is divided into five periods. Concerning the first week, the entire week is considered treated regardless of which day of the week the restriction comes into force. The variables "First Week of Local Restrictions" to "Fourth Week of Local Restrictions" represent local restrictions in force from week one to week four. The variable "Week 5+ of Local Restrictions" depicts the long-term effect beginning with week five. Each model employs store- and week-specific fixed effects, and columns 2 and 3 also include the total transactions and infection rate per 100,000 as control variables. We additionally use standard errors clustered by municipalities. The results are presented in Table 8.3.

VARIABLES	(1) Donation Rate	(2) Donation Rate	(3) Donation Rate
First Week of Local Restrictions	0.108	0.108	0.0924
	(0.0911)	(0.0891)	(0.101)
Second Week of Local Restrictions	0.121*	0.125*	0.111
	(0.0684)	(0.0672)	(0.0731)
Third Week of Local Restrictions	0.204**	0.210**	0.198**
	(0.0859)	(0.0853)	(0.0813)
Fourth Week of Local Restrictions	0.204**	0.211**	0.199**
	(0.0886)	(0.0881)	(0.0838)
Week 5+ of Local Restrictions	0.320***	0.317***	0.296***
	(0.110)	(0.107)	(0.0830)
ln(Total Transactions)		-0.375***	-0.375***
		(0.124)	(0.123)
ln(Infection Rate)			0.0193
			(0.0272)
Observations	461,115	461,115	461,115
R-squared	0.671	0.672	0.672
Number of Stores	2,849	2,849	2,849
Number of Municipalities	327	327	327
Store FE	YES	YES	YES
Week-Year FE	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8.3: Model 3A

The coefficients of interest in Table 8.3 are positive for each time period. The effect on the donation rate is the smallest in the first week before it gradually increases. In the first week with local restrictions, the average effect on the donation rate is an increase of 0.108 percentage points. The long-term effect from week 5 is the greatest, with an average increase of 0.320 percentage points. However, the effect of the first week is not significant. On the contrary, the effect is significant at the 10%, 5%, or 1% levels starting in the second week. The results remain about the same regardless of whether we include or exclude the control variables.

8.4 Effect of Local Restrictions after Termination

Table 8.4 presents the regression results of the prolonged effect of local COVID-19 restrictions after termination. The regressions include the period with local restrictions imposed and the four weeks following the termination. We account for store- and week-specific fixed effects, and control for total transactions and the infection rate in columns 2 and 3. Clustered standard errors are employed in the regressions.

The effect of local restrictions imposed on the donation rate remains similar to the results in Model 1. The weeks following the termination also have a positive effect on the donation rate. This effect is substantially smaller than the effect of present restrictions. These coefficients, however, are not significant. As a result, it cannot be claimed that local restrictions have any long-term influence on the donation rate after their termination.

VARIABLES	(1) Donation Rate	(2) Donation Rate	(3) Donation Rate
Local Restrictions	0.271***	0.270***	0.250***
	(0.0892)	(0.0873)	(0.0675)
First Week after Repeal	0.0507	0.0447	0.0384
	(0.0901)	(0.0879)	(0.0901)
Second Week after Repeal	0.00680	0.00313	-0.00184
	(0.101)	(0.0993)	(0.101)
Third Week after Repeal	0.0578	0.0561	0.0519
	(0.136)	(0.135)	(0.135)
Fourth Week after Repeal	0.126	0.126	0.121
	(0.0999)	(0.0992)	(0.0989)
ln(Total Transactions)		-0.376***	-0.376***
		(0.122)	(0.122)
ln(Infection Rate)			0.0202
			(0.0287)
Observations	461,115	461,115	461,115
R-squared	0.671	0.672	0.672
Number of Stores	2,849	2,849	2,849
Number of Municipalities	327	327	327
Store FE	YES	YES	YES
Week-Year FE	YES	YES	YES

Robust standard error in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8.4: Model 3B

8.5 Effect of Local Restrictions on Transaction Rate

In addition to the donation rate, we also employ the transaction rate as a dependent variable. The transaction rate is computed by dividing the number of donated transactions by the total number of transactions. The regression table with transaction rate as the dependent variable is presented in Table 8.5. We account for store- and week-specific fixed effects in each model. As with the other models, we employ clustered standard errors at the municipality level. The total amount and infection rate per 100,000 are included as control variables in columns 2 and 3.

VARIABLES	(1) Transaction Rate	(2) Transaction Rate	(3) Transaction Rate
Local Restrictions	0.000543	0.000362	0.00114
	(0.00196)	(0.00169)	(0.00155)
ln(Total Amount)		-0.0247***	-0.0247***
		(0.00124)	(0.00124)
ln(Infection Rate)			-0.000828**
			(0.000328)
Observations	461,115	461,115	461,115
R-squared	0.703	0.713	0.713
Number of Stores	2,849	2,849	2,849
Number of Municipalities	327	327	327
Store FE	YES	YES	YES
Week-Year FE	YES	YES	YES

Robust standard error in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8.5: Transaction Rate Model

Local COVID-19 restrictions have a low and insignificant coefficient in column 1. The coefficient remains insignificant and nearly unchanged when control variables are included. As a result, we cannot reject the null hypothesis that local restrictions have no influence on the transaction rate.

8.6 Survey on the Motivation Behind Donations

Prior studies of pro-social behaviour and bottle recycling have been performed in Sweden, where people do not have the possibility to participate in a recycling lottery (Ekström, 2012; Bergquist et al., 2020). Given that donations to the Norwegian recycling lottery may be driven by both the wish to donate to help others and the desire to participate in the lottery, we sought to gather additional insights on customers' donation motivations by conducting a brief survey. We received replies from 75 random respondents. The survey was conducted outside of different grocery stores and on the street in the city centre of Bergen. We asked potential respondents if they would be willing to complete a brief survey for our thesis. Those who accepted were instructed to scan a QR code and then answer one question on their mobile phones. This allowed them to respond anonymously, reducing the pressure to answer dishonestly in order to appear better.

In the survey, we asked the participants what their main motivation was for participating in the lottery when recycling. There were four answer options: "donate to the Red Cross", "participate in the lottery", "donate to both the Red Cross and participate in the lottery", and "I do not donate to the recycling lottery". The survey results are presented in Table 8.6.

Q: If you donate to the recycling lottery, what is your main motivation?	Freq.	Percent
Donate to both the Red Cross and participate in the lottery	24	32.00
Donate to the Red Cross	20	26.67
Participate in the lottery	18	24.00
I do not donate to the recycling lottery	13	17.33
Total	75	100.00

Table 8.6: Survey Results

From the results, we find that the most frequent reason among the respondents is a combination of the desire to donate to the Red Cross and participate in the lottery. However, donating to the Red Cross or participating in the lottery are also popular motives individually. The answers indicate that there is no apparent main motive. The complete survey format can be found in Appendix A6.

9 Discussion

9.1 Findings from Results

From the results of Model 1, we find that we can reject the null hypothesis that local COVID-19 restrictions in general do not have an effect on the donation rate. Hence, there is reason to assert that the enforcement of local restrictions does in fact have a positive effect on the donation rate. What might be the underlying mechanisms behind this increase are discussed later on.

In the analysis, we investigate whether the infection rate, rather than the local restrictions, is what determines the increase in the donation rate. This does not appear to be the case. The regression table shows that the coefficient for the infection rate is small and insignificant, so we cannot claim that it has any effect on the donation rate. One of the reasons why local restrictions seem to have influenced the lives of the population more than the infection rate could be that restrictions apply uniformly to everyone, regardless of their infection status. The infection numbers, on the other hand, may have been less noticeable, unless you were infected yourself, than the restrictions hindering the population's daily life.

In addition, local restrictions may provide a more accurate measure of the pandemic's severity in society than infection numbers. For instance, the situation was quite severe in the early stages of the pandemic, despite the fact that infection numbers were lower than later in the pandemic. Therefore, the infection numbers may not be as closely linked to individuals' perceptions of severity as local restrictions. Consequently, local restrictions may be a better indicator of the pandemic's gravity than infection numbers.

Model 2 produces more diverse results. We find that the majority of the categories have an effect on the donation rate, whereas a few have no significant effect. Furthermore, we discover that some categories have a considerably greater influence than others. Why some categories have a bigger impact than others cannot be determined from our data. Nonetheless, there may be indicators that the most severe categories have the largest effect on the donation rate. The most impactful categories are categories 6 (travel) and 5 (ban on serving alcohol), and those relating to closed schools, public transport, and health institutions also have a significant effect. Restrictions in categories 5 and 6 could make people stay at home and drink more, resulting in more bottles to recycle and potentially donate. However, the dependent variable as a fraction of the total recycled amount and the number of total transactions as a control variable will account for this potential problem. What is common to all of these influential categories is that they can be perceived as invasive to the daily lives of the population and signal a more serious infection situation. As a result, we may anticipate that these categories will have the biggest effect on the donation rate. However, which restrictions appear to be the most severe may differ from person to person. Although we cannot be certain, we believe that the severity of the various categories could be a possible explanation for the varying degrees of influence on the donation rate.

In Model 3A, we examine how the effect of local restrictions changes over time by dividing the timeframe into five periods. We discover that there is a positive effect on the donation rate in every time period. While not significant in the first week, we observe that the effect gradually increases over time. It is difficult to determine the reason for this. One possible explanation is that two opposing mechanisms are operating simultaneously. From Model 1, we find that the local COVID-19 restrictions in general have a positive impact on the donation rate. This effect may be present here, in addition to another component at work. Previous research on crises and pro-social behaviour suggests that people may become more altruistic or, on the other hand, more selfish in stressful situations. Hence, it is possible that the introduction of a restriction could act as a “shock” factor for customers, making them more selfish. Later, once the shock has faded, the general effect of behaving more altruistically towards others may become amplified because the selfish effect is reduced. It is also important to note that the entire week is considered treated when the restrictions come into force, regardless of which day they become effective. The fact that the first week is, in many cases, only partially affected by restrictions offers an additional explanation for the small and insignificant effect in the first week.

We investigate the effect of local restrictions after their termination in Model 3B. Our analysis reveals a positive effect on the donation rate, although the coefficients are not statistically significant. Consequently, we are unable to reject the null hypothesis that the local restrictions do not have a long-lasting impact on the donation rate. Our findings indicate that local restrictions only have an impact when they are put in place. This suggests that for the local restrictions to have an impact on the donation rate, individuals need to be reminded of the current stressful situation.

One of our models employs the transaction rate as the dependent variable. We find a small and insignificant effect of the local restrictions on the transaction rate. This finding implies that we cannot claim that the transaction rate is affected by the local COVID-19 restrictions. In other words, the proportion of overall transactions being donated is unaffected by the imposition of local restrictions. However, the earlier findings in our analysis support that the donation rate is influenced by local restrictions. Consequently, it is reasonable to assert that the introduction and existence of local restrictions only impact the donated amount and not the number of donations. That is, rather than the proportion of donations rising, we believe that local restrictions cause people to donate larger amounts to the Red Cross.

9.2 Donation Rate as a Proxy for Pro-Social Behaviour

In this thesis, we employ the donation rate in the Norwegian recycling lottery as a proxy for pro-social behaviour. Nevertheless, because the recycling lottery involves both a donation and a lottery component, we cannot be certain that the donations are made with the intention to benefit the Red Cross. Lottery participation could be motivated more by the investment opportunity or the entertainment value than by the desire to help the Red Cross. As a result, even though we have reason to assert that the local COVID-19 restrictions have a positive effect on the donation rate, we cannot claim that the local COVID-19 restrictions increase people's pro-social behaviour.

However, according to our survey, the majority of individuals who donate do so to contribute to the Red Cross or to both contribute to the Red Cross and participate in the lottery, rather than to only play the lottery. As a result, we have grounds to believe that many of the donors are at least partly motivated by acting pro-socially.

One factor to consider is that the motivation for lottery participation may remain constant. Even though many people choose to donate motivated by lottery participation, we do not know if individuals become more interested in the potential investment opportunity and entertainment of the lottery when local COVID-19 restrictions are enforced. Pro-social behaviour could increase, while motivation for lottery participation remains constant, because individuals donating primarily to support the Red Cross may increase their donation amounts, whereas those donating because of the lottery may not. However, we find no empirical evidence in the literature to support this issue.

With regards to the donation rate being a proxy for pro-social behaviour, it should be noted that our one-question survey has certain shortcomings that should be addressed. Firstly, because the survey had a small number of respondents, the answers cannot be representative of the entire population. Secondly, the answers may be somewhat skewed because the survey was not completely anonymous. Participants might have felt monitored and wanted to appear good, and thus modified their answers in another direction, even though they responded anonymously on their phones. Also, the sample may not have been random because the participants were in the city centre of Bergen on a regular day during working hours. This may result in an unequal distribution of participant characteristics such as age and occupation. Nevertheless, we believe that our survey can provide us with some indications of the motives for donating.

9.3 Mechanisms behind Pro-Social Behaviour

In this section, we assume that the implementation of local COVID-19 restrictions results in an increase in pro-social behaviour. That is, the donation rate is an adequate proxy for pro-social behaviour. According to the literature review, there are several motives for behaving pro-socially. The precise reason why the donation rate increases along with local COVID-19 restrictions is difficult to pinpoint. However, we believe some of the motives for pro-social behaviour can be eliminated due to the context of the recycling lottery.

It is also important to emphasise that we are interested in seeing what mechanisms may underlie the increase in the donation rate. What motivates pro-social behaviour in the setting of the recycling lottery at the baseline is difficult to determine, but that is not within our scope of interest. We are interested in understanding what may affect the change in the donation rate, not the mechanisms that constitute the donation rate per se.

When acting pro-socially becomes more affordable, pro-social behaviour is expected to increase. Deductions from taxable income are a potential factor that makes such behaviour cheaper. Tax deductions for charitable giving could thus provide a monetary incentive to donate. However, from Section 3.1, we know that donations from the recycling lottery do not qualify for tax deductions, and donating through the recycling lottery therefore does not become cheaper. Deductions are also unaffected by the implementation of local COVID-19 restrictions, and they remain constant over time. As a result, we can rule out tax benefits as a donation motive.

Social distance may also affect pro-social behaviour. A shorter social distance could increase pro-social behaviour because empathy towards those in need would rise. However, in the recycling lottery, there is no relationship between the individual recyclers and the people who would receive the contributions. The recyclers do not know who will receive their contributions, and they therefore would not feel any increased empathy towards them. However, during the pandemic, the perception of a common threat could unite people and thereby reduce social distance, even though the receiving party remains anonymous. Enforced restrictions indicating a more serious situation might therefore boost empathy, causing people to behave more pro-socially and donate more.

Following this concept, we can rule out reciprocity as a mechanism. The desire to mirror the behaviour of others and repay others' good actions is not present in a situation where there is no relationship between the individual recycling and the people receiving the contributions. As a result, there is no expectation from the receiving party to reciprocate previous behaviour. Nor is it reason to believe that one would wish to donate to expect something in return later from an anonymous second party. There is also no reason to believe that the desire to reciprocate increased with the implementation of local COVID-19 restrictions.

The anonymous environment of the recycling lottery also helps us eliminate status-motivated pro-social behaviour. The chance of receiving acknowledgement from others may enhance donations because people desire to be portrayed as selfless individuals who are more pro-social than the average and so get social approval. However, in this setting, recycling decisions are rarely observed by others. Recyclers cannot be criticised or approved for their choice of behaviour. As a result, we find donations to the recycling lottery unlikely to be motivated by status. Also, because the anonymous setting does not halt during the COVID-19 pandemic, it cannot be a mechanism underlying the increase in the donation rate.

Inequality aversion is another proposed factor underlying pro-social behaviour. If people believe they are better off, they may wish to donate to others who are worse off in order to reduce the disutility they experience as a result of their favourable inequality. During the COVID-19 pandemic, there was a greater focus on fairness and inequality. Many saw that the pandemic's health and economic consequences were unevenly spread, and the implementation of local restrictions could serve as a reminder of this. More attention to inequality may cause some people to become more aware of their fortunate position, causing them to donate more to others in a weaker position. As a result, we cannot rule out inequality aversion as a driving force behind the possible rise in pro-social behaviour.

Increased utility from the consumption of others could also explain pro-social behaviour. Individuals can benefit from others doing well, but we do not find any reason for this to become more prevalent with the pandemic. According to the extended assumption of impure altruism, individuals also benefit by contributing per se. It is difficult to assert whether pure or impure altruistic mechanisms underlie the rise in the donation rate. Nonetheless, it might be that people experience a warmer glow from donating when local restrictions are enforced because the situation is regarded as more serious and people are in greater need, so that the act of donating feels even better.

Self-identity and social norms may also influence pro-social behaviour. Individuals might choose to adjust their behaviour based on what is considered good in accordance with social norms to improve their self-image. It is possible that social norms changed along with the implementation of local restrictions that reflected the severity of the infection situation. During the pandemic, there was a stronger emphasis on standing together and assisting one another, and this team spirit may have had an impact on social norms at the time. At this time, people encouraged one another to contribute more and support those who were the most impacted. As a result, it is possible that changes in social norms are one of the mechanisms underlying the rise in the donation rate.

Whether it is a warmer glow of giving, increased inequality aversion, reduced social distance, or changes in social norms that cause people to become more pro-social, is difficult to say. We are able to rule out some motives, such as tax deductions, reciprocity, and status-motivated pro-social behaviour, but there still remain a variety of possible underlying reasons why people choose to donate more when local restrictions are enforced.

In addition, we cannot be certain that the increase in the donation rate is in fact due to an increase in pro-social behaviour and not to people becoming more interested in participating in the lottery.

9.4 Weaknesses with our Empirical Analysis

Our empirical analysis contains several weaknesses. One is related to the donation rate being a proxy for pro-social behaviour. People may be inspired to donate to the recycling lottery in order to support the Red Cross or to participate in the lottery. According to our survey, 71% of those who participated in the recycling lottery were motivated, at least in part, by donating to the Red Cross. However, we are unable to reach any firm conclusions. As a result, we cannot be certain that the donation rate in the recycling lottery is an accurate proxy for pro-social behaviour and thus that local COVID-19 restrictions have a positive impact on pro-social behaviour. This topic should be investigated further in order to gain a better understanding of the underlying motivations for participating in the recycling lottery.

Another weakness in our analysis is the uncertainty surrounding timing. In our dataset, we have two different start dates: the announcement date and the enforcement date. It is difficult to predict when the restrictions make an impact on the population. We assume that the restrictions will have an effect when they enter into force, but it is also possible that people are affected simply by knowing that they will enter into effect. Another potential drawback related to the start dates is that we recognise restrictions at the week level in our sample. This implies that a restriction applied on a Monday and a restriction applied on a Friday are assumed to have the same effect in a week, providing us with a possible time measurement error. This also applies to the repeal dates.

Furthermore, because there are no standard formulations of the different restrictions, restrictions primarily affecting the same aspects can be described in quite different ways across municipalities. As a result, our sample of local restrictions is somewhat imprecise. This is not expected to have a significant impact on our findings because we focus on whether or not restrictions in general, or the main categories of restrictions, are present at all. However, the likelihood of considerable differences in the actual content of the various local restrictions makes the dataset unsuitable for more detailed studies.

Another noteworthy shortcoming in our analysis is that the assumption that national restrictions are accounted for through time fixed effects can be violated in practise. As previously stated, our analysis is confined to studying the effects of local restrictions. We can do so because we presume that national restrictions have been consistent across the country and are accounted for through time fixed effects. This assumption is true in theory, but we lack sufficient information to determine if it holds in practice. The fixed effects only capture the part that affected the donation rate in the stores similarly at the same time. We do not know whether national restrictions have been practised equally strictly and experienced as equally invasive throughout the country. To conclude about the effect of local restrictions, the level of restrictions prior to introducing the local restrictions should be perceived as the same across municipalities.

10 Conclusion

The purpose of this thesis is to investigate the relationship between the donation rate in the Norwegian recycling lottery and the enforcement of local COVID-19 restrictions. The thesis seeks to provide an answer to the research question:

Do local COVID-19 restrictions have an impact on the donation rate in the Norwegian recycling lottery?

We find that local COVID-19 restrictions in general have a small positive effect on the donation rate. In this regard, because we find no effect on the proportion of donated transactions, we conclude that only the proportion of the amount donated would increase as a result of local restrictions being enforced. We also discover that some categories of local restrictions have a greater effect on the donation rate than others. The restriction categories with the strongest effect are discovered to be related to travel, the ban on serving alcohol, and public transport. Furthermore, there are indications that the impact on the donation rate increases with the duration of the local restrictions. This effect is not significant for the first week, but we find it to be significant for the subsequent weeks. In the study of the effect after the termination of local restrictions, we do not receive any significant results. Therefore, we can only assume that there is no effect, and we cannot assert that the local restrictions have a long-term impact on the donation rate after their repeal.

In conclusion, our thesis discovers that the donation rate increases as a result of the enforcement of local COVID-19 restrictions, but the effect is not prolonged after the termination of these restrictions.

The donation rate is chosen as our dependent variable because we believe it can be a good proxy for pro-social behaviour in society. However, whether the rise in donations is motivated by pro-social behaviour or the desire to participate in the lottery cannot be determined in our thesis. What might be the underlying mechanisms behind the increasing donation rate, if the increase is indeed a result of increased pro-social behaviour, is also unknown, although we believe it could be due to a warmer glow of giving, increased inequality aversion, reduced social distance, or changes in social norms.

10.1 Further Research

In this section, we present some ideas for further research that we believe could either strengthen our current analysis or provide additional insight in the field of pro-social behaviour, the COVID-19 pandemic, and the enforcement of restrictions on the population.

One limitation of our thesis is our choice of proxy for pro-social behaviour. Whether the donation rate in the recycling lottery is the best proxy for pro-social behaviour, as addressed in Section 9.4, warrants further investigation. We conclude that we cannot know for sure whether the donation rate in the Norwegian recycling lottery is an accurate proxy for pro-social behaviour. Further in-depth research is needed to gain a better understanding of this.

Another suggestion for further research is to compare the effect of local COVID-19 restrictions on pro-social behaviour in other countries to the effect in Norway. This requires access to data on COVID-19 restrictions as well as a suitable proxy for pro-social behaviour in the selected countries. For example, Sweden and Denmark have a similar choice between receiving the deposit or donating the amount when recycling bottles (Coop, 2019; Red Barnet, 2019), but without the lottery component, making it an even better proxy for pro-social behaviour. Studying other countries could provide us with insights on how different societies respond to the crisis and the surrounding insecurity related to the COVID-19 pandemic.

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Appendices

A1 Restriction Categories Overview

Table A1.1: Restrictions in each Category

Group	Group Name	Restrictions in the Group
1	Quarantine	Innreisekarantene Ventekarantene Smittekarantene Smittekarantene for husstandsmedlemmer Smittekarantene for personer under 18 år Reisekarantene Isolasjon Karantene Plikt til hjemreise ved sykdom og karantene
2	Private Life	Anbefaling om antall gjester i private hjem Regulering av private sammenkomster Antall nærkontakter Besøk i eget hjem/fritidsbolig Forbud mot private sammenkomster Begrensning av sosiale kontakter Påbudt med to meters avstand ved innendørs fysisk aktivitet Utvidet definisjon av nærkontakter
3	Business	Stenging av virksomheter og steder Stening av campingplasser Antallsbegrensning i butikker og på kjøpesentre Begrensning av aktivitet i butikker og på kjøpesentre Krav til smittevernfaglig forsvarlig drift i virksomhet Krav til smittevernfaglig forsvarlig drift ved serveringssteder Krav til smittevernfaglig forsvarlig drift ved visse typer virksomheter Krav til registrering av gjester ved serveringssteder Krav om forsterket smittevern for én-til-én-virksomheter Begrensninger i drift av campingsplasser Registrering av personer ved "drop in"-tilbud Krav til registrering av besøkende ved offentlige kontorer
4	Closed Schools	Stenging av barnehager, skoler og andre utdanningsinstitusjoner Rødt nivå på skoler og barnehager Rødt nivå på videregående skoler Krav til digital undervisning på universiteter, høyskoler og fagskoler Opplærings- og utdanningsinstitusjoner Hjemmekontor

Group	Group Name	Restrictions in the Group
5	Ban on Serving Alcohol	Skjenkestopp
6	Travel	Begrensning av opphold og ferdsel Innreiseforbud Innreiserestriksjoner Reise Forbud mot opphold eller overnatting på fritidseiendom eller camping i andre kommuner enn hjemkommunen
7	Events	Krav til smittevernfaglig forsvarlig gjennomføring av arrangementer Meldeplikt ved arrangementer Regulering av arrangementer Antallsbegrensning på arrangementer Forbud mot arrangementer Forbud mot russefeiring i form av "rulling" Forbud mot idrettsarrangementer
8	Use of Face Mask	Plikt til bruk av munnbind Anbefaling om bruk av munnbind Plikt til å bruke munnbind i taxi/kollektivtransport
9	Activities and Sports	Begrensning av idretts- og fritidsaktiviteter Stans av idretts- og fritidsaktiviteter Tiltak som gjelder lag, organisasjoner og private Fysisk aktivitet og kulturaktiviteter Avstandsreglar i skiheisanlegg Stengning av treningssenter, treningsparker, lekeplasser, svømmebasseng, idrettshaller Stenging av offentlige steder og virksomheter der det foregår kultur-, underholdnings- eller fritidsaktiviteter Krav til smittevernfaglig forsvarlig drift ved treningssentre ol.
10	Public Transport	Transport Krav til registrering av reisende med drosje Begrensninger i kollektivtransport Anbefaling vedr bruk av kollektivtransport Restriksjoner for pendlere
11	Restrictions in Health Institutions	Restriksjoner på helseinstitusjoner eller i hjemmehjelp Besøksrestriksjoner på helseinstitusjoner Aktivitetstilbud for eldre og mennesker med nedsatt funksjonsevne
12	Restrictions in Schools	Begrensning av aktivitet i skoler og barnehager Gult nivå på skole og barnehage
13	Limited Alcohol Serving	Regulering av lokale skjenketider
14	Others	Cruiseskip Kai, brygger og gjestehavner Privat næringsliv Påbud om begrensning i sosial omgang m.m. i båter Pålegg om bortvisning fra kai Smittevernfaglig drift på byggeplasser

A2 Breusch and Pagan Lagrange Multiplier Test for Random Effects

Table A2.1: BP LM Test for RE: Model 1

Breusch and Pagan Lagrangian multiplier test for random effects
Test: Var (u) = 0

chibar2 (01)	=	**2.5e+05**
Prob >chibar2	=	**0.0000**

Table A2.2: BP LM Test for RE: Model 2

Breusch and Pagan Lagrangian multiplier test for random effects
Test: Var (u) = 0

chibar2 (01)	=	**1.5e+05**
Prob >chibar2	=	**0.0000**

The table shows category 1. The other restriction categories give the same conclusions.

Table A2.3: BP LM Test for RE: Model 3A

Breusch and Pagan Lagrangian multiplier test for random effects
Test: Var (u) = 0

chibar2 (01)	=	**2.4e+05**
Prob >chibar2	=	**0.0000**

Table A2.4: BP LM Test for RE: Model 3B

Breusch and Pagan Lagrangian multiplier test for random effects
Test: Var (u) = 0

chibar2 (01)	=	**2.3e+05**
Prob >chibar2	=	**0.0000**

A3 Hausman Test

Table A3.1: Hausman Test: Model 1

Test of H0: Difference in coefficients not systematic		
chi2 (**3**)	=	(b-B)'[(V_b-V_B)^(-1)](b-B)
	=	**61.25**
Prob >chi2	=	**0.0000**

Table A3.2: Hausman Test: Model 2

Test of H0: Difference in coefficients not systematic		
chi2 (**3**)	=	(b-B)'[(V_b-V_B)^(-1)](b-B)
	=	**28.52**
Prob >chi2	=	**0.0000**

The table shows category 1. The other restriction categories give the same conclusions.

Table A3.3: Hausman Test: Model 3A

Test of H0: Difference in coefficients not systematic		
chi2 (**7**)	=	(b-B)'[(V_b-V_B)^(-1)](b-B)
	=	**57.58**
Prob >chi2	=	**0.0000**

Table A3.4: Hausman Test: Model 3B

Test of H0: Difference in coefficients not systematic		
chi2 (**7**)	=	(b-B)'[(V_b-V_B)^(-1)](b-B)
	=	**57.47**
Prob >chi2	=	**0.0000**

A4 Breusch and Pagan Test for Heteroscedasticity

Table A4.1: BP Test for Heteroscedasticity: Model 1

Breusch-Pagan/Cook-Weisberg test for heteroskedasticity
Assumption: Normal error terms

H0: Constant variance

chi2 (1)	=	**54.19**
Prob >chi2	=	**0.0000**

Table A4.2: BP Test for Heteroscedasticity: Model 2

Breusch-Pagan/Cook-Weisberg test for heteroskedasticity
Assumption: Normal error terms

H0: Constant variance

chi2 (1)	=	**1849.19**
Prob >chi2	=	**0.0000**

The table shows category 1. The other restriction categories give the same conclusions.

Table A4.3: BP Test for Heteroscedasticity: Model 3A

Breusch-Pagan/Cook-Weisberg test for heteroskedasticity
Assumption: Normal error terms

H0: Constant variance

chi2 (1)	=	**29.55**
Prob >chi2	=	**0.0000**

Table A4.4: BP Test for Heteroscedasticity: Model 3B

Breusch-Pagan/Cook-Weisberg test for heteroskedasticity
Assumption: Normal error terms

H0: Constant variance

chi2 (1)	=	**42.91**
Prob >chi2	=	**0.0000**

A5 Woolridge Test for Serial Correlation

Table A5.1: Woolridge Test: Model 1

Woolridge test for autocorrelation in panel data			
H0: no first-order autocorrelation			
F(1,	2848)	=	**49.384**
	Prob >F	=	**0.0000**

Table A5.2: Woolridge Test: Model 2

Woolridge test for autocorrelation in panel data			
H0: no first-order autocorrelation			
F(1,	2848)	=	**40.995**
	Prob >F	=	**0.0000**

The table shows category 1. The other restriction categories give the same conclusions.

Table A5.3: Woolridge Test: Model 3A

Woolridge test for autocorrelation in panel data			
H0: no first-order autocorrelation			
F(1,	2848)	=	**49.237**
	Prob >F	=	**0.0000**

Table A5.4: Woolridge Test: Model 3B

Woolridge test for autocorrelation in panel data			
H0: no first-order autocorrelation			
F(1,	2848)	=	**49.205**
	Prob >F	=	**0.0000**

A6 Survey

Table A6.1: Survey Question in English

Q: If you donate to the recycling lottery, what is your main motivation?
A: Donate to the Red Cross
B: Participate in the lottery
C: Donate to both the Red Cross and participate in the lottery
D: I do not donate to the recycling lottery

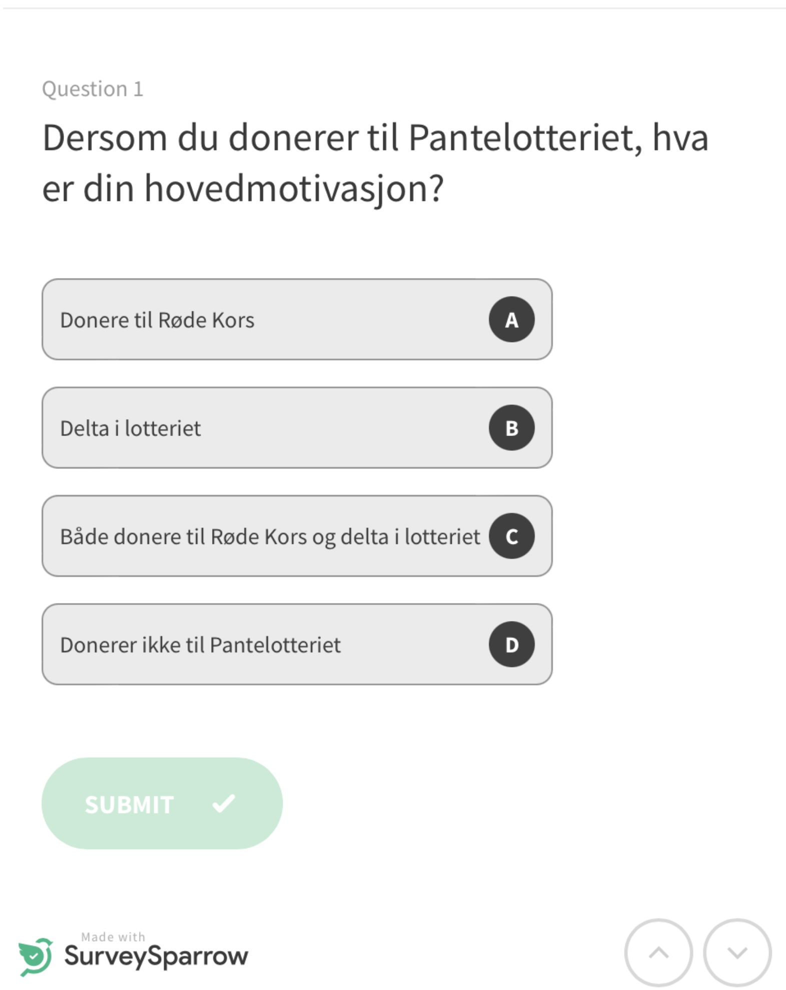

Figure A6.1: Survey Format