# Framing and Informing: Experiments in Donation Behaviour from the Lab and Field

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# Abstract

In this thesis we investigate charitable donation behaviour in the context of a food bank charity, which supplies support to those in crisis through the provision of food parcels.

In Chapter 1, we explore how worthiness framing influences donations to the FoodBank. There is contention around the worthiness of welfare recipients, and the majority of those in receipt of the FoodBank food parcels are welfare recipients on low incomes. As people prefer to donate to worthy causes, we challenged the stereotypes around the undeserving poor and measured the effect of this framing on donation level and rate. Our worthiness framing led to an increase in the size of cash donations made to the charity, but only from those whose perceptions were the most challenged by the framing. We add to the literature on the interaction between beliefs and donation behaviour.

In Chapter 2 we study the donation of tangible items to the FoodBank. Due to information asymmetry between the charity and potential donors about the specific items that are needed, there are inefficiencies. We conduct a novel experiment measuring in-store donations to the FoodBank in two stores of a large supermarket chain, and implement an information campaign to increase the donation of the most needed items. We show that reducing the information asymmetry increases the donation of the most needed items, but not systematically so. We add to the understudied field of in-kind donations with our rich dataset on donations in the field.

In Chapter 3 we further our exploration of tangible donations, with an expanded intervention in the form of a randomised control trial across 18 stores of a supermarket chain. We again measure in-store donation, but with a larger information campaign soliciting donations to the FoodBank. We find that highlighting the information campaign with posters and shelf-level signage is effective in increasing the donation of high demand products.

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# Introduction

Charitable giving is a broad and multifaceted topic, studied in a variety of fields and contexts, relating closely to distributive preferences and helping behaviour. Helping the disadvantaged is a social norm, and is therefore highly context-dependent (Schwartz, 1975). In this thesis, we collaborate with an anti-poverty charity which provides food for those in a crisis. We provide a first in-depth look at the donation patterns to an anti-poverty charity. We utilise varying beliefs about the origin of inequality in the UK to test the effect of recipient worthiness framing on donation level and rate. We further innovate in this field through the novel measurement of tangible donations, and explore how methods used in marketing apply to purchases as donations.

Donation behaviour depends on many things, one of which is worthiness of a cause (Body and Breeze, 2016). It is believed that the 'warm glow of giving' is a personal payoff experienced from donating to a cause (Andreoni, 1990). This would be reduced if the cause were not considered worthwhile. The worthiness of the recipient, then, affects a person's willingness to donate, and how much they might donate. We explore this explicitly in Chapter 1, as there exist contentious oppositions of opinion on the worthiness of FoodBank users. Where the effectiveness or efficiency of a cause has been previously studied (Gneezy et al., 2014), there exists little literature which explores the worthiness of the recipient (Fong, 2007). We therefore add to this relatively unexplored area and find that the use of framing can challenge the context sufficiently to induce larger donations from those who may think the poor undeserving. This has useful implications for the targeting and messaging of potential donors.

The FoodBank is an interesting cause which relies on tangible in-kind donations over pecuniary donations to provide the actual food that goes to recipients. This provided a unique opportunity to explore how tangible donations could be influenced in favour of more efficient donations. Although the most efficient way to donate is to give fungible pecuniary donations, part of the popularity of the FoodBank comes from the act of giving a tangible donation and the warm glow that comes from imagining it in use by a recipient (Cryder and Loewenstein, 2010). A smaller behavioural intervention is to encourage donors to switch their donation towards one which is more highly demanded by the FoodBank.

Tangible donations are harder to measure than pecuniary donations, which could account for their relatively under-studied status. For Chapter 2, we add a novel data collection method to the area of tangible donations, using a barcode scanner and weekly collections to record donations from two stores of a large supermarket chain. This also gave us a rich dataset of the types and numbers of items donated to the FoodBank, which would only usually measure the weight of donations. From this we are able to identify the relative popularity of donation items and how much this differed from the FoodBanks ideal ratios (Human Rights Watch, 2019). We discovered that the donations to the FoodBank are very diverse and highly variable across weeks. In our two-treatment quasi-experimental field trial, we learned that a larger number of more visible signs were more effective at increasing donations of the most needed items. As we believed that there could be additional factors affecting the donation of tangible goods, we explored how the products donated varied by quality (brands and luxury goods) over the course of the experiment. Though we did not identify clear trends in this area it is the first in-depth look of its kind into tangible donations.

Following on from our findings in Chapter 2, Chapter 3 uses a field experiment to measure the effects of an improved information campaign highlighting the most needed items in 18 small supermarket stores of a local chain. We did this to account for the highly variable nature of donations that we found in Chapter 2. We also drew on insights from Chapter 1 in the wording of the shelf-level signage. We add to the literature on generosity at Christmas (Müller and Rau, 2019; Birg and Goeddeke, 2016), as our intervention takes place in the lead up to the holiday, finding that the levels and types of products donated do vary at this time. We held store characteristic data which we used in exploratory analysis, which allows us to add to the literature on donation behaviour between socioeconomic status (Lee and Chang, 2007). As of yet, we have found no other research on how tangible donations differ between socioeconomic groups. Where we were restricted in the product data we had in Chapter 2, in Chapter 3 we were able to access data allowing us to do some preliminary investigations into the effect of price on donations.

We find that the effect of the intervention was non-homogeneous across product categories, but further investigation is required to shed light on the product characteristics which determine the success of this intervention. Our finding that donation patterns vary strongly between stores raises further questions about which store characteristics are important in affecting tangible donation behaviour. Although in this thesis we look at quantitative outcomes in terms of donations, qualitative research on the motivators of tangible donations could be revealing and help guide future research in the area. As online shopping has grown more popular as a result of the Covid-19 pandemic, bringing a small donation nudge to the online shopping process could lead to large improvements in the donation mix received by the FoodBank.

The rest of this thesis is organised as follows. In Chapter 1:

> We investigate the effect of worthiness framing on donation behaviour – both the propensity to donate and magnitude of donation. People prefer to donate to'worthy' causes. Prosocial behaviour is strongly influenced by value judgements based on the individual's perception of a situation and are therefore highly context-dependent. In this experiment, the target of manipulation is the context of a donation decision. We invited participants to donate to the local food bank and used selected questions from the World Values Survey to measure perceptions about the context of inequality. We find a treatment effect of worthiness framing–but only for those with certain beliefs about the context of inequality. We use hardworking and unlucky frames to highlight the worthiness of the recipient group and find this framing is only effective in increasing donations if it challenges an individual's prior beliefs. Framing a recipient as worthy only increases donations from those whose beliefs suggest they consider the poor less worthy.

In Chapter 2:

> An information asymmetry exists between charities and their donors: donors do not know exactly what a charity needs. Donations in tangible form can exacerbate the resultant inefficiency. Yet, in-kind donations persist as a popular method of donating. Efficiency and efficacy concerns could explain this persistence. We collect and analyse a novel dataset on tangible donations in supermarkets to a local food bank in a quasi-experimental setting. We show that an intervention to reduce the information asymmetry does increase the donation of the most needed items, but not systematically so.

In Chapter 3:

> Many charitable organisations rely on in-kind donations even though they are often less efficient than more fungible pecuniary donations. To increase efficiency, some charitable organisations therefore want to influence the types of in-kind donations they receive. We implemented a randomised control trial (RCT) in which we manipulated in-store signage soliciting donations to a local food bank, across locations of a supermarket chain. In some locations, we added shelf 'talker' signs adjacent to products which are in high demand at the food bank; in a further subset of locations we complemented the talkers with a poster campaign. We find that donations are not strongly affected by shelf talkers on their own, but that the use of posters highlighting the charity campaign increases the donation of in-demand items. Our estimates suggest the combined effect of using talkers with posters increases the donation of treated items by around 163%. Though the absolute increase is modest in size, if this intervention were rolled out more widely, there could be significant efficiency gains for the charity.

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# Chapter 1

# Are you worthy of my help? An experiment in worthiness framing on charitable donations

We investigate the effect of worthiness framing on donation behaviour – both the propensity to donate and magnitude of donation. People prefer to donate to 'worthy' causes. Prosocial behaviour is strongly influenced by value judgements based on the individual's perception of a situation and are therefore highly context-dependent. In this experiment, the target of manipulation is the context of a donation decision. We invited participants to donate to the local food bank and used selected questions from the World Values Survey to measure perceptions about the context of inequality. We find a treatment effect of worthiness framing– but only for those with certain beliefs about the context of inequality. We use hardworking and unlucky frames to highlight the worthiness of the recipient group and find this framing is only effective in increasing donations if it challenges an individual's prior beliefs. Framing a recipient as worthy only increases donations from those whose beliefs suggest they consider the poor less worthy.

**Keywords: prosocial behaviour, charity, worthiness, framing, deservingness**

## 1.1 Introduction

Donations to anti-poverty charities are akin to a redistribution of wealth. Previous work has found that support for redistribution correlates with subjective perceptions about the causes of inequality (Almås et al., 2020), such as whether the donor believes the recipient has invested effort into changing their situation (Aarøe and Petersen, 2014). Therefore, framing recipients from an anti-poverty charity as 'worthy' could increase donations, through changing the context of the inequality. For this experiment on worthiness framing we chose to use an anti-poverty charity due to debate around the worthiness of those in poverty in the UK. There is a large charitable sector in the UK, with donations totalling over £10.1 billion in 2018 (Charities Aid Foundation, 2019). However, charitable donations are concentrated towards larger, more popular charities (Body and Breeze, 2016). People like to choose the causes and how much they donate. Generally, there is a preference for causes perceived as 'worthy'. Charities which support causes which are perceived as less worthy can struggle to secure funds ahead of more popular causes (Body and Breeze, 2016).

In this chapter, we investigate whether worthiness framing can be used to elicit greater donations from donors, by challenging their perceptions about the context of inequality. The application of fairness principles depends strongly on the context: can contextual perceptions be manipulated to influence donation behaviour? We worked together with a local food bank (Norwich [UK] Trussel Trust FoodBank, henceforth FoodBank) which provides crisis provisions to those in need. We change the context of the donation by framing recipients as unlucky and hardworking in an attempt to increase their perceived worthiness in comparison to a neutral frame. The donors' donation and redistributive preferences were not targeted. We used two treatments of worthiness framing, changing only the wording about the recipients. After completing a real effort task (RET), participants were given the opportunity to donate money earned during the session, in cash, to the local FoodBank.

A key determinant of worthiness is perceived culpability: whether responsibility for the situation is attributed to the person in need. Konow (2000, p.1073-1074) describes the 'accountability principle': a rule of justice which requires "a person's fair allocation (e.g., of income) [to] vary in proportion to the relevant variables that he can influence (e.g., work effort) but not according to those that he cannot reasonably influence (e.g., a physical handicap)." According to this principle, the level of effort observed could influence the 'fair' distributive choice more than the absolute level of need. We use 'hardworking' and 'unlucky' frames to reduce perceived culpability and therefore increase worthiness and donations.

Framing is used extensively in charitable appeals in order to evoke empathy and thereby increase donations and is addressed in a variety of literatures (e.g. the identifiable victim effect (Schelling, 1968), valence of message used (Chang and Lee, 2009). Body and Breeze (2016) analysed determinants of the popularity of causes, but there is little research separating the worthiness of a cause from the worthiness of its recipients. In a lab experiment, Fong (2007) gave potential donors information about the level of effort and desire for employment of potential beneficiaries, and found such information significantly positively affects donation levels. However, the literature has not yet looked at using framing on the worthiness of the recipient.

We find some evidence, in line with previous research in this field, that there are correlations between donation behaviour and beliefs about the origin of inequality - henceforth we call these 'unworthiness' beliefs. Our findings suggest that there was a positive effect of the worthiness framing on donation behaviour, but only on those who held one or more unworthiness beliefs about those in need, as defined from our coding of responses. Finally, one third of the subjects participated in a competitive version of the RET, resulting in 'winners' and 'losers'. This allowed exploratory analysis of the effects of competitive outcomes on donation behaviour. We find that being in a competitive scenario alone does not affect donation behaviour, but experiencing a strongly positive or negative outcome both increase donation rates in comparison to those with overall neutral outcomes.

Policy applications include understanding how language and framing lead to greater pro-social outcomes. Particularly, we give insight into how charities and fundraisers could approach this aspect of their marketing. Challenging the context of a decision can lead to immediate changes in behaviour where changing preferences is not possible or would take much longer. The design of this behavioural 'nudge' has taken account of the idea that nudges should be low-cost and easy to implement in the long term.

This chapter is organised as follows: we begin with the literature review discussing determinants of donation behaviour and how these influences the subjective worthiness of the recipient in Section 1.2. Section 1.3 includes information on the political relevance of FoodBanks to worthiness perceptions. Section 1.4 describes the methodology and contains our hypotheses, design of the lab experiment, analysis strategy and descriptive statistics. Section 1.5 presents the results. Finally, in Section 1.6 we present the discussion and conclusion.

## 1.2 Related literature

### 1.2.1 Worthiness

There is a wide literature around the topic of worthiness in a variety of domains, but there is not yet a literature directly relating perceptions of worthiness to donation behaviour. We therefore observe the relationship between redistribution and donation to those in poverty in order to infer the relationship between worthiness and donation preferences.

Donors like to choose where their money is donated and prefer worthy causes. Charitable giving is a form of redistribution. Beliefs about the source, or context, of inequality correlate strongly with political and redistributive preferences (Almås et al., 2020; Alesina and Angeletos, 2005; Benabou and Tirole, 2006). Those who believe luck has a strong role to play in determining outcomes tend not to blame those in poverty for their situation. Conversely, those with "just world beliefs" - who believe that effort and hard work are the main determinants of success - tend to believe the poor could try harder in order to be relieved of poverty (Furnham and Gunter, 1984). These perceptions shape considerations of 'just deserts' – a fair allocation based on deservingness – and therefore influence if a cause is considered worthy.

Using an experimental method, Cappelen et al. (2007) suggest a mechanism in which context determines the application of fairness principles: highlighting egalitarianism, liberalism and liberal egalitarianism. They define liberal egalitarianism as a fairness principle by which "only inequalities that arise from factors under individual control should be accepted" (ibid, p.818), such as the choice of how much effort to expend. This idea resonates with the 'accountability principle' proposed by Konow (2000). Social norms of distributive fairness are found to be frequently governed by contextual factors such as perceived merit and opportunity or luck (Cappelen et al., 2017). Their study changed the context of the inequality to evoke different fairness norms by varying the influence of merit and luck on payoffs and measuring distributive preferences. However, in reality it is not always possible to change the context of the inequality. An easier task is to reframe the context of inequality to lead to the application of different fairness principles. Aarøe and Petersen (2014) discuss this point and name it the 'Deservingness Heuristic', finding that when cues about the deservingness of a welfare recipient are present, cross-country differences in opposition to welfare are diminished.

Beliefs about the context of poverty - how it came about and who might be to ‘blame’- can usually fall into one of two categories. Some criticise the structure of society as it leads to unfair inequality, whereas others criticise the individual and highlight personal responsibility. A robust finding is that individuals place relatively more responsibility on a person for their situation than they attribute to circumstance or luck (Cappelen et al., 2007). This is known as attribution error, and decreases the perceived fair allocation for the relief of poverty. Fong (2001) notes that a key factor in determining willingness to support the poor is “conditional on them [the poor] having industrious traits or intentions”. An experiment on donation to health causes showed that subjects were less willing to donate to causes for diseases that were more ‘controllable’. This effect is reported as being due to the subjects’ “tendency to blame people with more controllable health conditions” (Hsieh and Yucel-Aybat, 2018, p. 112). It is clear that whether an individual is at fault, or to blame influences whether they are perceived as a worthy recipient of charity.

The study which most closely reflects our own research questions is that of Fong (2007). Fong’s experiment used a novel social context in conjunction with a variant of the dictator game to investigate donation behaviour and measure the effects of conditional and unconditional altruism. The recipients of the donation were welfare recipients, with information on recipient characteristics provided to the donors in ‘industrious-recipient’ versus ‘lazy-recipient’ treatment conditions. Fong (2007: p. 1019) found that “Those who scored high on the HE [1] measure were highly responsive to the perceived worthiness of recipients.” That is, Fong found a worthiness treatment effect only on those who appeared to be unconditional altruists. She reconciles this counterintuitive finding by suggesting that self-defined unconditional altruists combine the desire to help others and the desire to reciprocate in one prosocial attitude termed ‘empathic responsiveness’. Fong’s experiment uses real information about specific people. However, there has not been an experiment that manipulates worthiness through framing, whilst holding the charity constant, nor the use of a group of beneficiaries instead of an individual.

### 1.2.2 Donation Determinants

Much research has sought to understand why people sacrifice their own welfare or payoffs for others. One explanation is that it is due to some form of altruism. A related explanation is inequality aversion. Having an outcome that is unequal produces negative utility for those with inequality aversion, though the aversion

[1] Humanitarianism-Egalitarianism scale created by Katz and Hass (1988)

is stronger for disadvantageous inequality than advantageous inequality (Fehr and Schmidt, 1999) therefore, highlighting inequality could lead to higher charitable donations to anti-poverty causes.

In-group bias is when individuals act in favour of their own in-group and those who comprise it, than those others who are in 'out-groups'. Research has found that trivial differences can create in-group bias, for example in seminal work by Tajfel (1970) on the minimal group paradigm. This bias can extend to more generous behaviour towards those in an in-group. Donations may therefore be higher when framed as within an in-group. Framing of charitable appeals often seek to elicit an emotional response in order to increase donations. Many studies have experimented with message framing factors - such as statistical, temporal and valence framing (Chang and Lee, 2009) – and found them to have significant effects on donation behaviour. Framing the beneficiary of a charity as a specific identifiable person has been found to increase generosity (Lee and Feeley, 2016). Research has consistently found that empathy is a strong predictor of donation behaviour (Klimecki et al., 2016; Penner et al., 2005). Medical literature has found that empathy releases oxytocin, which increases generosity (Zak et al., 2007). More recently, beliefs in conjunction with empathy have been found to moderate donation behaviour (Martinez, 2018). Whether empathy is the main driver of the identifiable victim effect[2] is contentious (Jenni and Loewenstein, 1997), but some argue that it is due to the 'vividness' of the victim which incites a greater emotional response (Small and Loewenstein, 2003). Inciting empathy leads to greater generosity and helping behaviour. There is little research on framing the attributes of recipients in comparison to framing of the cause itself, and such framing has not to our knowledge been tested experimentally.

Psychology research has long documented how affective state and emotion impact generosity (Underwood et al., 1976). The experience of winning or losing can evoke positive or negative emotions in an individual or group. This means that 'losers' display less pro-social behaviour due to their low mood. Underwood et al. (1976) replicated this finding that sadness or low-mood reduces generosity. Conversely, this could mean that winners could behave more pro-socially after experiencing a win (Kellner et al., 2019). Winning or losing can also affect the status of an individual. Liebe and Tutic (2010, p. 353) find that "the higher the status of the dictator, the more she donates", in a dictator game using German school children and the status that their school type confers. As yet, there is not known evidence on the effect of

[2]The 'Identifiable Victim effect' is the propensity for individuals to offer greater assistance to an identifiable, specific 'victim' than to an anonymous/statistical victim.

competitive outcomes on generosity.

## 1.3 The Politics of Food Banks

The cause chosen for this experiment was the local food bank. In the UK, those who find themselves in a crisis and lacking sufficient funds can access food banks. The majority of UK food banks are in a network operated by the Trussel Trust organisation. These 'Trussel Trust FoodBanks' require a voucher provided by a doctor, health professional or other service, in the event of a crisis. These are redeemed at a local FoodBank for 3 days' worth of food. The FoodBank also supports signposting to appropriate resources and organisations to help resolve the crisis. Trussel Trust statistics show that nationally, over 70% of referrals for the period 2017-18 were due to "'income not covering essential costs', 'benefit delays' and 'benefit changes'"(The Trussel Trust, 2020*b*).

This charity was chosen because opinions on the recipients' culpability for their situation often appears in media and political discourse. Some argue that food bank users may not be 'blameless' for their situation. Between 2014-2019, the number of food parcels distributed rose sharply (up 73%), in response to increasing demand (The Trussel Trust, 2020*b*). This increase in demand is a contentious issue for UK politics, as it could indicate the failure of the 'social safety net' and the effect of prolonged austerity on the most economically vulnerable. Members of the Conservative UK Government have sought to disassociate this increase in food bank users from their austerity policies, by implying that the increase in use is not due to a lack of funds, but opportunism to benefit from free food and laziness from those unprepared to find employment (Caraher et al., 2014). This relates to ongoing rhetoric about 'benefit scroungers' and laziness (Garthwaite, 2011), which seeks to highlight benefit fraud, despite its low incidence: estimated at 1.4% of the value of total benefits payments in 2019-2020 (Department for Work and Pensions, 2020).

Such depictions in the news and media influence perceptions about the context of inequality in the UK. The All Party Parliamentary Group on Hunger noted that many voters "no longer believe" evidence of increased demand for food banks (Forsey, 2016). Food bank users may be deemed culpable for their situation if they are not thought of as having put enough effort into finding a job, or if they own certain goods deemed as luxuries such as a car, mobile phone or television. However, common negative views about food bank users do not directly reflect reality: the majority of reasons people use food banks can be attributed to larger problems in the economy leading to structural and frictional unemployment, benefit delays/changes, low income, debt and mental illness (Loopstra and Lalor, 2017). Widespread financial insecurity even among the employed means that many are vulnerable to shocks such as bereavement, ill health and redundancy, while 60% of UK renting families "could be just one paycheck away from losing their home" (Shelter, 2019). For most, it is bad luck rather than lack of effort that leaves them in a crisis. These opposing discourses have led to an array of views about the worthiness of food bank donation recipients and makes this charity an ideal cause to use in this experiment.

## 1.4 Hypotheses and Methodology

### 1.4.1 Hypotheses

We investigate the effects of worthiness framing and subjective perceptions about income inequality on donation behaviour, as well as the interaction between the two. Framing the recipient of the donation as worthy changes the context of the decision, leading to the evocation of pro-social norms. We expected this to result in a higher frequency of donations, and donations of a larger size than in the unframed treatment. In a neutral frame, the subjects' own pre-conceived perceptions are used to fill in the context of the donation decision.

**Hypothesis 1.1** *A 'worthy' frame increases donations, as measured by rate and size of donation.*

If individuals have beliefs which attribute responsibility for poverty to those in poverty, they are less likely to perceive the recipients as worthy of help. As there is a preference for worthy causes, those who do not perceive the recipients of this charity as worthy are less likely to donate and any donation they do make is likely to be smaller than those without those views.

**Hypothesis 1.2** *Donation rate and level correlate with subjective perceptions about the determinants of income inequality, as measured by beliefs survey responses.*

If subjects believe that the poor are lazy, they are less likely to believe that a potential recipient of the food bank is worthy, and would therefore be less likely to donate.

**Hypothesis 1.3** *Donation level and rate will be lower in donors who believe that "Laziness" is why there are people in this country who live in need.*

If the donor believes that the government does not do 'the right amount' or more to aid those in poverty in the UK, then this would reduce the perceived culpability of the poor for their position, therefore increasing perceived worthiness.

**Hypothesis 1.4** *Donation level and rate will be lower in donors who believe that the government does "Too Much or About the right amount" for people in this country in poverty.*

If a larger income differential incentivises effort, this would imply that those in poverty have exerted low effort, and would therefore be perceived as unworthy.

**Hypothesis 1.5** *Donation level and rate will be lower in donors who believe "we need larger income differences as incentives for individual effort".*

If the donor holds the belief that hard work usually brings a better life, it implies that most people who are in poverty could be in a better position had they tried harder. This reduces perceived worthiness and thereby donations.

**Hypothesis 1.6** *Donation level and rate will be lower in donors who answer "in the long run hard work usually brings a better life".*

The size of the treatment effect depends on the beliefs held by the subject. The context of the decision will change more for those who do not perceive the recipients of the charity as worthy but will not change as much for those who already perceive the recipients as worthy. This means there will be a larger effect of worthiness framing on those who believe that those in poverty are responsible for their own situations.

**Hypothesis 1.7** *Worthiness framing interacts with beliefs to increase donation level and rate.*

In our experiment, there is a RET earnings phase, explained in more detail in the design section and in Nasamu (2020). In our analysis we control for differences in experiences that subjects had during this phase. The treatments were a Competition treatment (CT) or Non-Competition treatment (NC). Two thirds of participants were allocated to the NC. The remaining one third of subjects were allocated to the CT. Crucially, payoffs did not differ depending on the treatment. *Ex-post*, we have considered if the experience of winning/losing a competitive game could affect donation behaviour, as measured by donation rate and size. The experiment informed the subjects of their two competitive outcomes. Winning twice could increase positive affect, and losing twice could increase negative affect, and therefore influence donation behaviour (Weiss and Cohen, 2019). In addition, the most recent outcome could affect donation behaviour more than the first outcome. This experiment is not able to create a causal link between competitive outcomes and donation behaviour but could indicate areas for further research.

**Hypothesis 1.8** *'Winners' donate differently to 'non-winners'.*

**Hypothesis 1.9** *'Losers' donate differently to 'non-losers'.*

### 1.4.2 Experimental Design

We ran a lab experiment using the Laboratory for Economic and Decision Research (LEDR) labs at the University of East Anglia in January to March 2018. We designed three framing treatments displayed as a message soliciting donations at the end of an earnings task.

The participants first completed a RET to earn £15. Following the completion of this RET and a subsequent demographics survey, the subjects were then exposed to the messaging from one of the three framing treatments and given the opportunity to make a donation. They then completed the beliefs survey, at which point the session ended and subjects left one by one. To reassure them that the donations would really be made and the experiment was not deceptive, the subjects were given a choice to leave their contact details so they could be sent a video link to watch the donations they made be given to a representative of the local FoodBank. The subject recruitment criteria at LEDR required that the individuals were students or staff of the University of East Anglia. We therefore have a predominantly student-based subject pool. There was a further sign-up restriction that the participants must be a native English speaker. This was to ensure that the framing could not be misunderstood.

Subjects were seated in high-sided cubicles to maintain privacy and anonymity, in line with standard practice for the LEDR. Each cubicle had a computer - used for the RET, and for the display of the treatment message, as well as the post-experimental survey. In the cubicle there was also a white donation box and coin envelope (see Appendix 1.A).

#### 1.4.2.1 The Real Effort Task and Demographics Survey

The subjects completed a RET[3] in an unrelated experiment (Nasamu, 2020) lasting around 45 minutes, in order to earn their payoff and avoid the windfall effect (Clark,

[3]The real effort task used was a variant of the travelling salesman problem, called the 'Team Dispatching Problem' based on the original optimisation problem by Dantzig and Ramser (1959).

2002). Subjects either participated in a treatment with competitive feedback, or with no competitive feedback. Subjects received £15 in cash at their desks upon the completion of this task, regardless of which treatment they had been assigned to. After payment, subjects completed a brief demographics survey, which asked for gender, age, year of study, field of study and nationality.

#### 1.4.2.2 Framing Treatments

The display of the treatment message began after the RET had been completed and payments made. The subjects' computers displayed a screen explaining the collaboration with the local FoodBank, and an appeal for donations (Figure 1.1). This message varied depending on the treatment: baseline (B), Luck (L) or Luck and Effort (LE). Within each experimental session, all three treatments were implemented. The framing treatments differed in only one way: the message displayed to the subject. The message displayed was randomised but balanced within sessions to avoid session effects. The message displayed was as follows:

**Treatment 1:** Baseline: "Please help local people by donating today."

**Treatment 2:** Luck Frame: "Please help less fortunate local people by donating today."

**Treatment 3:** Effort and Luck Frame: "Please help hardworking, less fortunate, local people by donating today."

These messages were chosen to evoke the "accountability principle" (Konow, 2000) and the "deservingness heuristic" (Aarøe and Petersen, 2014): if someone has been unlucky or 'less fortunate' this is due to things outside of their control (luck), which makes the recipients appear more worthy. The use of the descriptor 'hardworking' indicates that the recipients are expending effort to extricate themselves from their situation and are therefore 'worthy', in contrast to stereotypes that depict those in poverty as lazy.

On each desk was an unmarked cardboard donation box. Next to this was an envelope in which to put a cash donation before sealing it and putting it in the donation box. As this step creates rustling and the sound of coins in the room, donors cannot be singled out as having made a donation or not. The denominations of the cash payments were such that any amount could be donated between 0-£15 in increments of 10p, see Appendix 1.B. The donation amount could not be changed after answering the beliefs questionnaire, as the donation had already been sealed

(cont..) The task requires 'visiting' up to 5 different 'checkpoints' on a virtual map. The participant's score is determined by the length of the route they construct, the aim being to minimise the length of the route. The task had two blocks of 7 rounds each.

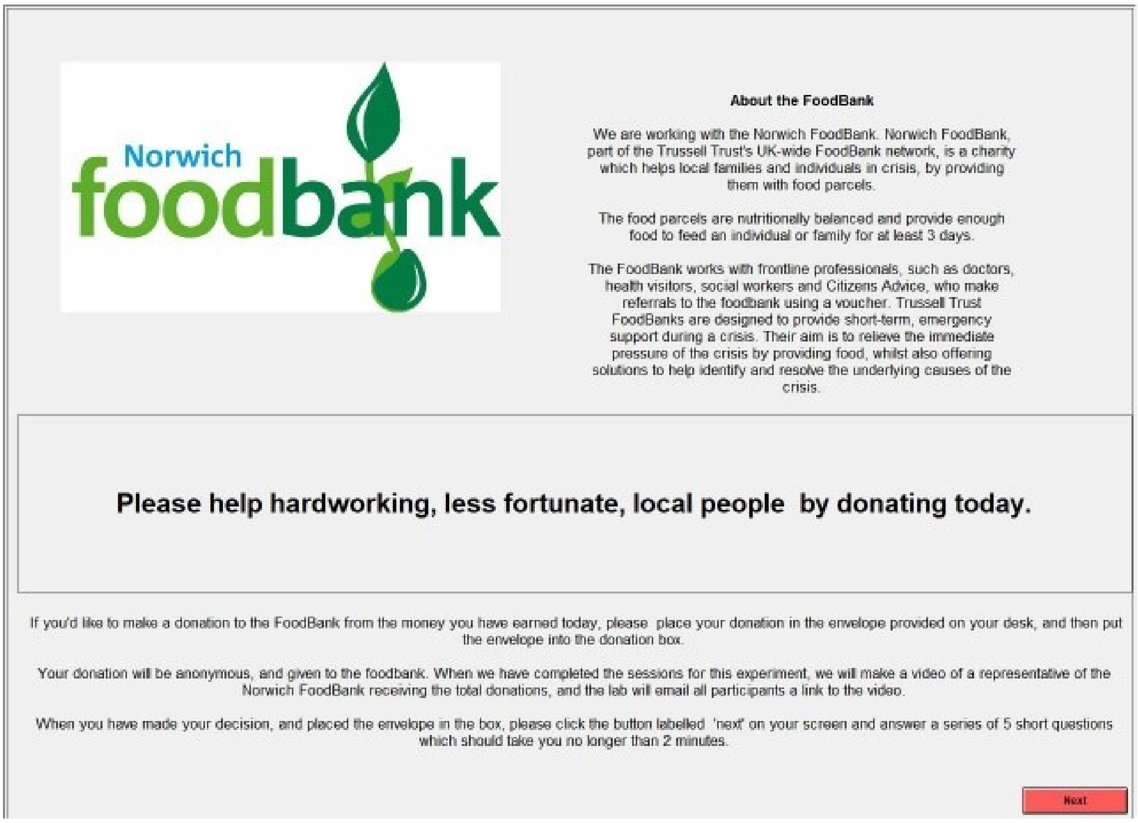


Figure 1.1: Screenshot of the donation solicitation page

Displaying FoodBank logo, information about the charity, treatment message (Treatment LE) and practical instructions.

and placed in the donation box.

#### 1.4.2.3 Beliefs Questionnaire

The final task was a beliefs questionnaire. These were selected and taken directly from the World Values Survey (2012). These questions were used to identify attitudes and beliefs, thereby allowing the differential effect of the treatment by belief to be measured. The subjects were asked to complete these final survey questions and then allowed to leave the experiment. It was possible to match the donation amount with the survey answers, and with the demographic data collected at the beginning of the experiment. The questions and their responses can be found in the descriptive statistics in Section 1.4.4. This survey also asked subjects to indicate their level of familiarity with the Norwich FoodBank, asking if they had previously heard of the charity.

### 1.4.3 Analysis

The two dependent variables in the experiment were the donation level (the amount donated) and the donation rate (the proportion of subjects who donated). The treatment effect on donation rate was tested using a Probit regression to estimate likelihood of donation. Although we look at the rate as a proportion, the underlying data is binary in nature: whether a donation is made or not. For the donation level variable, a Tobit regression was used. This was used due to natural censoring at £0 and £15, as donation amounts could not be outside of this range.

Perceptions about the origin of inequality were measured using the beliefs survey at the end of the experiment. A binary variable was created to indicate if the subject held one or more of these views. This allows us to estimate the interaction between treatment and beliefs. Norton et al. (2004) show that interpretation of the coefficients produced when using interaction dummies with non-linear models is not straightforward. We therefore show that the OLS model produces similar estimates to the simple Probit model, before estimating the interaction effects within the OLS model.

As a robustness check we change the level at which a view is coded as an 'unworthiness belief' for Questions 3 and 4. These questions required a response on a scale of 1-10, and initially a response of 7 or over was used to assign the binary unworthiness beliefs 3 and 4. We increase this to 8 in our robustness check to include only the strongest views.

To control for potential effects associated with participating in a competitive

Table 1.1: Demographics by Treatment.

| Treatment | Age | % Male | % Native English Speaker | % British | N |
|---|---|---|---|---|---|
| **Control** | 21.00 | 56% | 85% | 73% | 48 |
| **Luck** | 21.62 | 43% | 86% | 74% | 42 |
| **Luck+Effort** | 20.75 | 50% | 86% | 86% | 36 |
| **Total** | 21.13 | 50% | 86% | 80% | 126 |

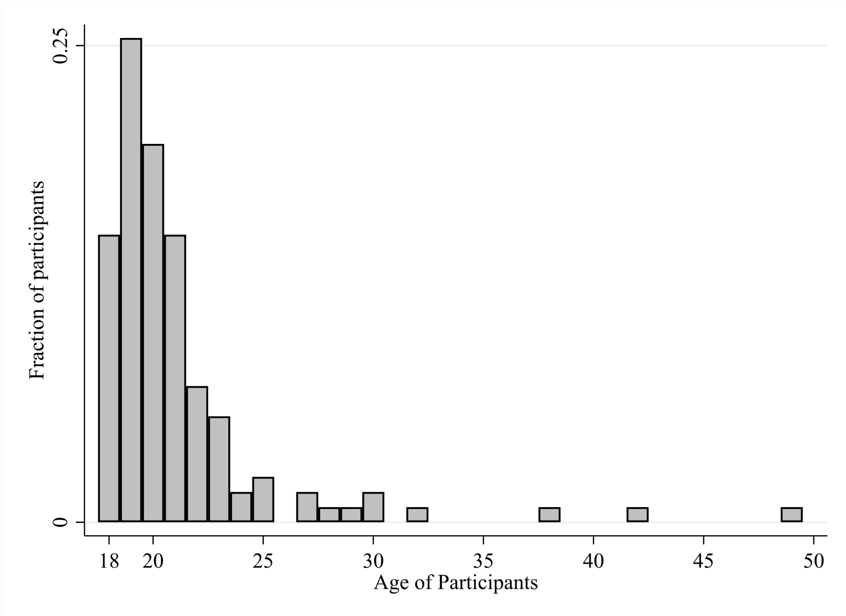


Figure 1.2: Histogram of age of participants, showing the majority are between 18-21

RET we have introduced a dummy variable. This takes the value of 1 if the subject had a particularly good or particularly bad competitive experience (winning twice or losing twice); or 0 if the subject did not compete in the competitive treatment (NC) or they had a 'neutral' competitive experience (in which they won one round and lost the other).

### 1.4.4 Descriptive Statistics

Table 1.1 shows the mean observed demographics of subjects by treatment. The results of an F-test show that the distributions between treatments were not statistically different. Figure 1.2 shows the fraction of participants in each age category. Our predominantly student-based sample is reflected in the fact that the majority of participants were between 18-21.

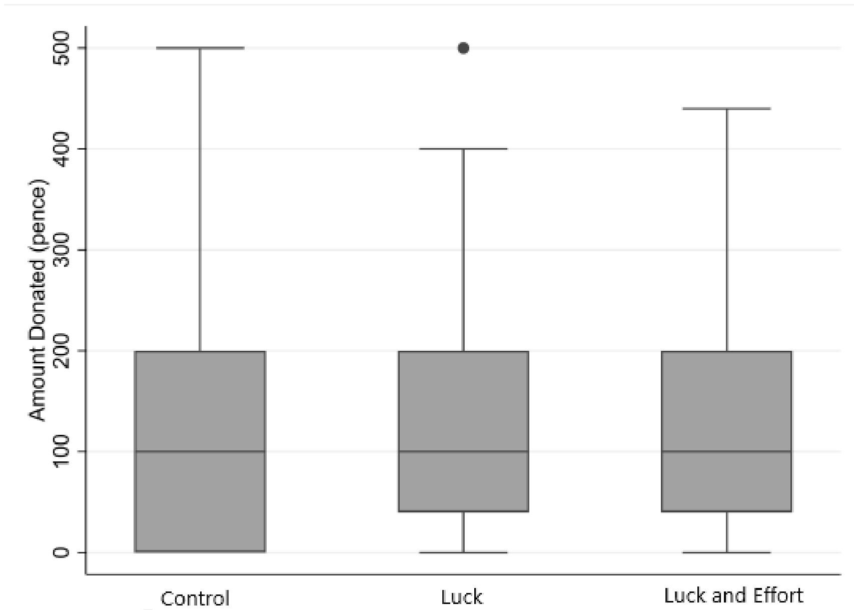


Figure 1.3: Box plot showing the amount donated by treatment in pence.

This shows that the distributions of donations were similar between treatments with most donations falling in the 0-£2 range. Note: the dot represents an outlier in the Luck Treatment.

Table 1.2: Summary statistics of amount donated by treatment in pence

| Treatment | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Control** | 48 | 134.17 | 162.56 | 0 | 500 |
| **Effort** | 42 | 132.33 | 138.38 | 0 | 500 |
| **Effort+Luck** | 36 | 124.72 | 116.73 | 0 | 440 |

Note: includes non-donors

#### 1.4.4.1 Donation Level

Across all treatments, the mean donation made was £1.31. This is very similar across treatments, as seen in Table 1.2. Table 1.3 shows the mean donation of only those who donated (removing the non-donors from the average), which shows the in Treatments 2 and 3 there is a lower mean donation than in the non-framed control treatment. This difference is not statistically significant using a Kruskal-Wallis equality-of-populations rank test. Figure 1.3 shows the median donation is the same across treatments: there is a cluster of donations at £1, the mode donation.

Table 1.3: Summary statistics of amount donated by treatment in pence, excluding non-donors

| Treatment | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Control** | 33 | 195.15 | 162.91 | 10 | 500 |
| **Effort** | 35 | 158.80 | 136.98 | 10 | 500 |
| **Effort+Luck** | 28 | 160.36 | 108.34 | 30 | 440 |

Table 1.4: Summary statistics: % of subjects who made a donation in each treatment

| Treatment | Obs | Mean | Std. Dev. |
|---|---|---|---|
| **Control** | 48 | 68.75% | 46.84 |
| **Effort** | 42 | 83.33% | 37.72 |
| **Effort+Luck** | 36 | 77.78% | 42.16 |

#### 1.4.4.2 Donation Rate

The overall frequency of donation was 76%. The donation rate was higher in the framed messages (80.8% v 68.6%) but this difference is not statistically significant using t-tests or a Kruskal-Wallis equality-of-populations rank test. Donation rate by treatment is presented in Table 1.4.

#### 1.4.4.3 Responses to Beliefs Survey

Question 1 asked for the participant's views on why people live in need in this country. They were asked to select answers for what they believed was the first and second most important reasons, with options for "Don't know" and "None of these'. Although the majority (59.53%) chose "because there is injustice in our society" for one of their two choices, 10.32% chose "because of laziness and lack of willpower" – however it is worth noting that only 1 of the 16 subjects who selected this response chose it as their first option (see Figure 1.4).

Question 2 asked for the subjects' views on how much the government does for those in poverty. The majority of respondents believed that the government does too little, with very few "too much" responses (see Figure 1.5).

Questions 3 and 4 asked for a response on a scale of 1 to 10, in line with the presentation of the questions in the World Values Survey 2012. Question 3 asked respondents to choose on a scale of 1-10 between "Incomes should be made more equal" and "we need larger income differences as incentives for individual effort"(see

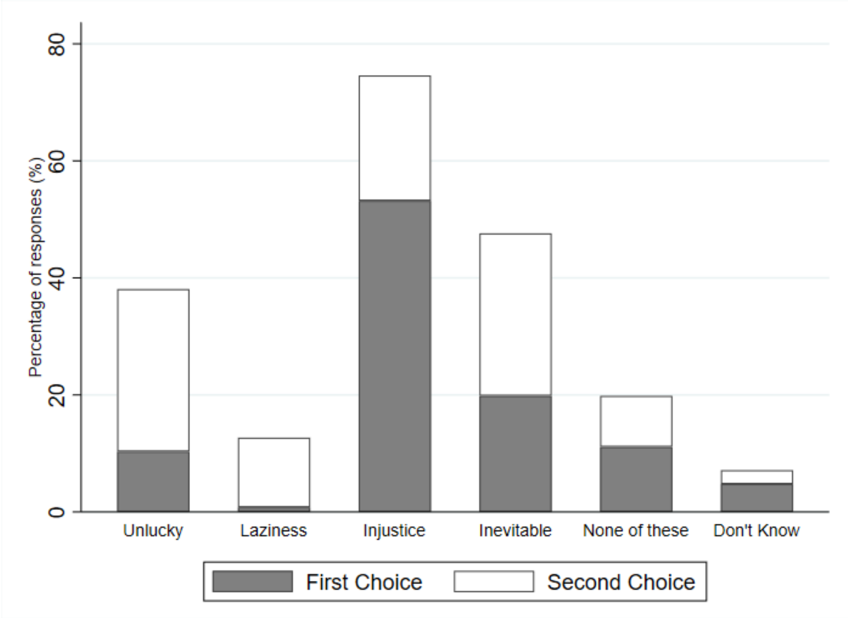


Figure 1.4: Responses to Question 1:"Why are there people in this country who live in need?"

The full responses to this question were: 'Because they are unlucky', 'Because of laziness and lack of willpower', 'Because there is injustice in our society', 'It is an inevitable part of modern progress', 'None of these', 'Don't know.'

Appendix 1.C). There was a slight clustering of responses near the middle – views which were more moderate. The results were similar for Question 4. Question 4 was a scale between "hard work doesn't usually bring a better life, it's more a matter of luck and connections" and "in the long run hard work usually brings a better life". There was a slight skew towards the latter but then with many less responses at 9 and 10 – indicating that extreme views were not preferred. Bar graphs showing the responses to Questions 3 and 4 can be found in Appendix 1.D.

The final question was not a beliefs question, but a question of the level of familiarity the subject had with the cause. The majority of the participants knew the FoodBank very well or a little, but a significant number had not heard of it at all. The responses can be seen in Appendix 1.D

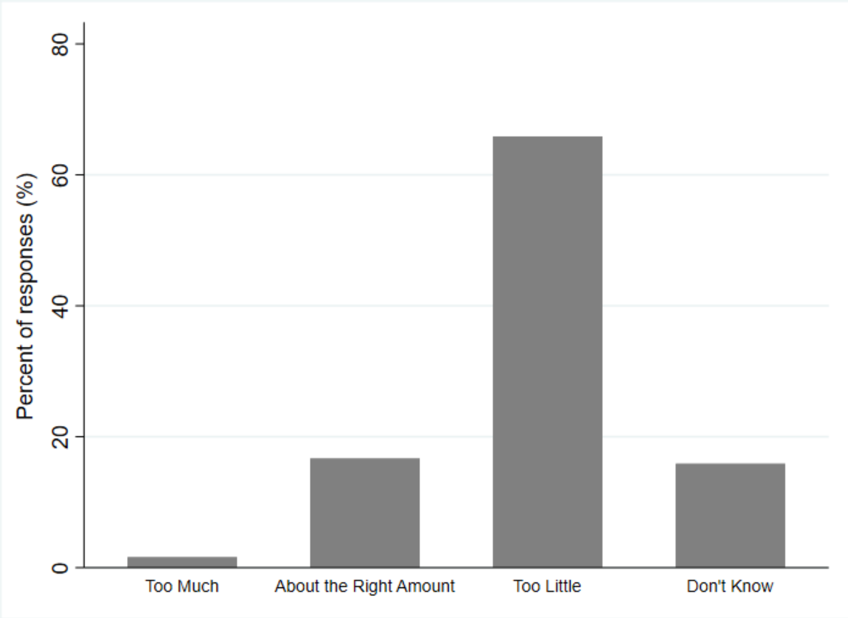


Figure 1.5: Responses to Question 2: "Do you think that what the government is doing for people in poverty in this country is too much, about the right amount, or too little?"

# 1.5 Results

## 1.5.1 Main Results

The main treatment effect was estimated using two dependent variables measuring the level and rate of donations.

**Result 1.1** *Worthiness framing does not affect the overall donation level.*

*Support:* We estimate the Tobit model:

$$Y_{\mathrm{a}} = \alpha + \beta_L L + \beta_{LE} LE + \theta \bullet \mathbf{V} + \beta_F F + \gamma \bullet \mathbf{C} + \varepsilon, \tag{1.1}$$

where $Y_a$ is the amount donated which is naturally censored at £0 (no donation) and £15 (the entire earnings from the RET), $L$ is the Luck treatment and $LE$ is the Luck + Effort treatment. **V** is the vector of coded responses to the beliefs survey, each a binary variable and F signifies whether the subject had heard of the FoodBank before. **C** is the vector of demographic controls.

Despite donation rates being higher in the E and E+L treatments, we are unable to find evidence that there is a statistical difference between the three treatments' mean donation levels. When looking only at subjects who made a donation, the mean donation in the unframed baseline is higher than in the framed treatments – in the opposite direction to the hypothesis. This however, is also not statistically significant. A Mann-Whitney test for the equality of distributions shows that there is not statistical difference between the treatments, even when looking only at non-zero donations.

The regression results confirm this – the treatments do not have a statistically significant effect in any specification of the model (see Table 1.5). This is not in line with the stated hypothesis.

**Result 1.2** *Worthiness framing may increase the donation rate.*

*Support:* The overall frequency of donation was 76%. The donation rate was higher in the framed messages (80.8% v 68.6%), This is in line with the hypothesis but is not statistically significant using a test of proportions.

We estimate the Probit model:

$$Y_{\mathrm{r}} = \alpha + \beta_L L + \beta_{LE} LE + \theta \bullet \mathbf{V} \ + \beta_F F + \gamma \bullet \mathbf{C} \ + \varepsilon, \tag{1.2}$$

Where $Y_r$ is the donation rate. When looking at the entire sample, Treatment L has weakly significant effect on the likelihood of donation, but Treatment LE does not have any statistically significant effect (Table 1.6).

**Result 1.3** *Donation level and rate are lower in donors who believe that "Laziness" is why there are people in this country who live in need.*

*Support:* Question 1 asked for the participant's views on why people live in need in this country. The selection of the 'laziness' option correlated strongly with donation rate: only 43.75% of these individuals made a donation, in comparison to 80.90% of the rest of the respondents. This was statistically significant using a test of proportions. However, when looking at donation level – adjusting for only those who donated – the mean amount donated was almost equal to those who did not choose this option (171.4p v 171.8p). In Table 1.5, the regression results show that there is a statistically significant coefficient on the variable indicating if the subject chose "laziness" as an answer to Question 1 – indicating they believe that those in poverty may be responsible for their own situation. The coefficient represents a reduction in donation amount of -108.7 pence, *ceteris paribus*. The Table 1.6 Probit regression on the propensity to donate also indicated that holding this view in Question 1 is statistically significant in the expected direction. The marginal effect of this coefficient implies that holding this view reduces the probability of donating by 0.315 [4].

[4]Calculated using the marginal effects command after a regression in Stata 16

Table 1.5: Tobit regression results on the amount donated.

| VARIABLES | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Luck Treatment | 14.61 | 5.429 | 8.631 | 11.18 |
| | (38.09) | (36.44) | (36.55) | (37.82) |
| Effort and Luck Treatment | 0.378 | -1.818 | 0.441 | 18.15 |
| | (39.88) | (38.17) | (37.93) | (38.24) |
| Holds 1+ 'unworthiness' beliefs | | -63.92 ** | | |
| | | (31.18) | | |
| Laziness Belief (1) | | | -108.7** | -139.8** |
| | | | (50.98) | (53.43) |
| Government Belief (2) | | | -49.84 | -38.74 |
| | | | (42.45) | (42.15) |
| Effort Belief (3) | | | 1.506 | -5.805 |
| | | | (46.20) | (45.19) |
| Hard Work Belief (4) | | | -47.56 | -43.51 |
| | | | (34.14) | (34.75) |
| Has heard of the Foodbank | | 72.55** | 73.71*** | 55.49* |
| | | (26.43) | (26.49) | (28.22) |
| Competition Treatment | | | | 7.866 |
| | | | | (31.41) |
| Demographic Controls included | No | No | No | Yes |
| var(e.amount) | 30,498*** | 27,184 *** | 26,351*** | 24,866*** |
| | (4,631) | (4,473) | (3,978) | (3,748) |
| Constant | 100.2*** | 23.54 | 22.65 | -90.39 |
| | (26.51) | (49.96) | (49.36) | (91.22) |
| Observations | 126 | 126 | 125 | 125 |
| Adjusted R-Squared | 0.000138 | 0.00339 | 0.0132 | 0.0186 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

'Belief' variables are dummy variables which are coded 1 if the subject gave a response associated with believing the origin of inequality to be within the control of the poor. The number of the belief refers to the question number in the survey. Controls include gender, age, year of study, subject studied and nationality. The number of observations is less in model 3 and 4 due to non-completion of the survey by one subject.

Table 1.6: Probit regression results on the donation rate.

| VARIABLES | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Luck Treatment | 0.479 | 0.511 | 0.668* | 0.701* |
| | (0.298) | (0.312) | (0.345) | (0.373) |
| Effort and Luck Treatment | 0.276 | 0.289 | 0.364 | 0.498 |
| | (0.300) | (0.304) | (0.317) | (0.332) |
| Holds 1+ 'unworthiness' beliefs | | -0.408 | | |
| | | (0.258) | | |
| Laziness Belief (1) | | | -1.193*** | -1.529*** |
| | | | (0.381) | (0.442) |
| Government Belief (2) | | | 0.159 | 0.225 |
| | | | (0.376) | (0.391) |
| Effort Belief (3) | | | -0.247 | -0.339 |
| | | | (0.371) | (0.384) |
| Hard Work Belief (4) | | | -0.348 | -0.287 |
| | | | (0.282) | (0.309) |
| Has heard of the Foodbank | | 0.123 | 0.163 | 0.112 |
| | | (0.220) | (0.231) | (0.250) |
| Competition Treatment | | | | 0.155 |
| | | | | (0.286) |
| Demographic Controls included | No | No | No | Yes |
| Constant | 0.489*** | 0.532 | 0.499 | -0.504 |
| | (0.189) | (0.416) | (0.423) | (1.361) |
| Observations | 126 | 125 | 125 | 125 |
| Adjusted R-Squared | 0.0196 | 0.0478 | 0.131 | 0.169 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

'Belief' variables are dummy variables which are coded 1 if the subject gave a response associated with believing the origin of inequality to be within the control of the poor. The number of the belief refers to the question number in the survey. Controls include gender, age, year of study, subject studied and nationality. The number of observations is less in model 3 and 4 due to non-completion of the survey by one subject.

**Result 1.4** *Donation level and rate do not appear to depend on whether donors believe the government does "Too Much or About the right amount" for people in this country in poverty.*

*Support:* Question 2 of the beliefs survey asked participants if they thought how much the government does for the poor was 'too much', 'too little' or 'about right'. There was not a statistically significant correlation found with donation rate or level, likely due to the low number of "Too much" responses (2 subjects, both of whom did not make a donation)(see Table 1.5 and Table 1.6). The coefficient for the amount donated is large and negative (see Table 1.5), which gives some reason to believe that this may lead to a significant result if there was a greater sample size with a greater number of subjects who held the 'too much' belief.

**Result 1.5** *Believing "we need larger income differences as incentives for individual effort" does not affect donation level or rate.*

*Support:* There is no statistically significant effect of holding the Question 3 belief on either donation amount or donation rate. However, in a robustness check we changed the level at which a response is coded as an 'unworthiness belief'. When the boundaries at which these responses were coded to include only the strongest views (these questions were answered using a scale of 1-10), there was still no significant effect on the donation amount. The regression results can be found in Table 1.7. The re-coded variable could not be used in the Probit model as it perfectly predicted donation: that is that none of the participants who held this view donated. However, this cannot be shown with any statistical significance due to the low sample size of those holding this strong belief.

**Result 1.6** *Donation level and rate may not be different for donors who answer "in the long run hard work usually brings a better life".*

*Support:* Table 1.6 and Table 1.5 both show no statistically significant effect of holding this (Question 4) belief. However, using the re-coded beliefs variables as explained above, the coefficients do become significant in the expected direction as shown in models 1 and 2 in Table 1.7. This implies that donation level and rate are affected only in those with the strongest views. This is logical given beliefs are stronger at the upper end of the scale, whereas a lower threshold includes some moderate views as well, for which we would not expect so strong an effect on donation level or rate. However, this result is not robust to the inclusion of all controls (Model 3). There is still no effect on donation rate when using the re-coded variables.

Table 1.7: Tobit regression on amount donated using re-coded variables for Question 3 and 4.

| VARIABLES | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Luck Treatment | 8.801 | 9.247 | 10.19 |
| | (35.90) | (35.94) | (37.19) |
| Effort and Luck Treatment | -9.230 | -8.490 | 8.319 |
| | (37.78) | (37.88) | (38.09) |
| Laziness Belief (1) | -89.52* | -89.13* | -119.9** |
| | (51.67) | (51.72) | (54.63) |
| Government Belief (2) | -61.35 | -61.54 | -49.33 |
| | (42.96) | (42.96) | (42.48) |
| Effort Belief (3) (recoded) | 100.6 | 98.44 | 97.65 |
| | (84.37) | (84.69) | (82.93) |
| Hard Work Belief (4) (recoded) | -89.45* | -88.83* | -84.47 |
| | (48.87) | (48.93) | (51.51) |
| Has heard of FoodBank | 68.27*** | 67.64** | 52.41* |
| | (26.06) | (26.15) | (27.55) |
| Competitive Treatment | | 8.784 | 7.970 |
| | | (30.17) | (31.29) |
| Demographic Controls | No | No | Yes |
| var(e.amount) | 25,813*** | 25,809*** | 24,410*** |
| | (3,892) | (3,891) | (3,675) |
| Constant | 27.41 | 23.42 | -71.30 |
| | (48.92) | (50.84) | (91.52) |
| Observations | 125 | 125 | 125 |
| Adjusted R-Squared | 0.0150 | 0.0151 | 0.0201 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

'Belief' variables are dummy variables which are coded 1 if the subject gave a response associated with believing the origin of inequality to be within the control of the poor. The number of the belief refers to the question number in the survey. Controls included are age, gender, year of study, field of study and nationality.

Table 1.8: Probit regression on donation rate using re-coded variables for Question 4.

| VARIABLES | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Luck Treatment | 0.713** | 0.708** | 0.740** |
| | (0.345) | (0.345) | (0.368) |
| Luck and Effort Treatment | 0.354 | 0.362 | 0.500 |
| | (0.317) | (0.318) | (0.333) |
| Laziness Belief (1) | -1.161*** | -1.144*** | -1.512*** |
| | (0.385) | (0.387) | (0.452) |
| Government Belief (2) | 0.148 | 0.129 | 0.216 |
| | (0.375) | (0.375) | (0.389) |
| Effort Belief (3) | -0.242 | -0.258 | -0.333 |
| | (0.371) | (0.371) | (0.385) |
| Hard Work Belief (4) (re-coded) | -0.417 | -0.403 | -0.330 |
| | (0.376) | (0.377) | (0.423) |
| Has heard of FoodBank | 0.137 | 0.116 | 0.0953 |
| | (0.230) | (0.234) | (0.248) |
| Competitive Treatment | | 0.145 | 0.154 |
| | | (0.270) | (0.285) |
| Demographic Controls | No | No | Yes |
| Constant | 0.473 | 0.432 | -0.501 |
| | (0.420) | (0.428) | (1.420) |
| Observations | 125 | 125 | 125 |
| Adjusted R-Squared | 0.129 | 0.131 | 0.167 |

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

'Belief' variables are dummy variables which are coded 1 if the subject gave a response associated with believing the origin of inequality to be within the control of the poor. The number of the belief refers to the question number in the survey. The recoded Question (Belief) 3 variable was not used as it perfectly predicted donation rate. Controls included are age, gender, year of study, field of study and nationality.

**Result 1.7** *The treatment effect interacts with the beliefs held: worthiness framing leads to higher donation rates in those with 'unworthiness' views about the poor.*

*Support:* We estimate the OLS model:

$$Y_{\mathrm{r}} = \alpha + \beta_L L + \beta_{LE} LE + \theta \bullet \mathbf{V} \ + \beta_F F + \gamma \bullet \mathbf{C} \ + \varepsilon, \tag{1.3}$$

and find that the estimates are similar to those found in the Probit model in direction and significance as can be seen in Table 1.9.

We therefore use interaction effects in the OLS model:

$$Y_{\mathrm{r}} = \alpha + \beta_L L + \beta_{LE} LE + \mu N + \beta_1 L \bullet N + \beta_2 LE \bullet N + \beta_{\mathbf{F}} \mathbf{F} + \gamma \bullet \mathbf{C} \ + \varepsilon, \tag{1.4}$$

where N is a binary variable indicating if one or more of the views indicated were 'unworthiness' beliefs towards the poor. $\beta_1$ and $\beta_2$ estimate the interaction effect between treatment and views. Using these variables, it was possible to isolate the treatment effect given these perceptions about the origin of inequality. This gives arguably the most interesting result in this study in which there was a positive effect of the treatment in the expected direction, but only on those who held 'unworthiness' perceptions about the origin of inequality as defined from our coding. In these regressions using interaction terms between the treatment and beliefs, holding a 'unworthiness' coded belief was strongly statistically significant at the 1% level in all specifications of the model, for both donation rate and level (see Table 1.10).

The 'unworthiness belief' variable, as previously mentioned, has a negative effect on donation amount. However, the interaction term with both treatments are positive. This is statistically significant for Treatment LE in all specifications, between 5 and 10% significance. The coefficient is of a similar size to the effect of holding an unworthiness coded belief. This result can be interpreted as that holding an unworthiness belief reduces your donation amount, but there is a positive effect of being in the two treatment groups on donation amount for those that hole one or more of these beliefs. The net effect of holding an unworthiness belief in the Treatment L framing is -44.5 pence reduction in the donation amount, *ceteris paribus*. In Treatment LE the net effect is positive: holding an unworthiness view in this framing leads to a 33 pence increase in donations *ceteris paribus*. This effect, although small in scale could have large implications and represents an increase of 42% in donation size compared to those with negative views in the control treatment.

The picture is the same when a Probit regression is used to estimate the propensity to donate Table 1.11: holding a unworthiness belief is statistically

Table 1.9: Probit and OLS comparison on donation rate

| VARIABLES | Probit Model | OLS Model |
|---|---|---|
| Luck Treatment | 0.701* | 0.174* |
| | (0.373) | (0.0934) |
| Luck and Effort Treatment | 0.498 | 0.161* |
| | (0.332) | (0.0930) |
| Laziness Belief (1) | -1.529*** | -0.456*** |
| | (0.442) | (0.123) |
| Government Belief (2) | 0.225 | 0.0442 |
| | (0.391) | (0.103) |
| Effort Belief (3) | -0.339 | -0.107 |
| | (0.384) | (0.109) |
| Hard Work Belief (4) | -0.287 | -0.0978 |
| | (0.309) | (0.0841) |
| Has heard of FoodBank | 0.112 | 0.0335 |
| | (0.250) | (0.0686) |
| Competitive Treatment | 0.155 | 0.0533 |
| | (0.286) | (0.0774) |
| Demographic Controls | Yes | Yes |
| Observations | 125 | 125 |
| R-squared | | 0.188 |
| Adjusted R-Squared | 0.169 | |

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

'Belief' variables are dummy variables which are coded 1 if the subject gave a response associated with believing the origin of inequality to be within the control of the poor. The number of the belief refers to the question number in the survey. Controls included are age, gender, year of study, field of study and nationality.

significant with a large negative coefficient, and the interaction term with treatment LE is also statistically significant. The size of the interaction coefficient is larger than the size of the coefficient for holding a unworthiness belief. However, the Treatment L interaction effect is not significant, and nor are the treatment effects on their own.

We gain further evidence for this result from regression results in Appendices 1.E and 1.F, using the combined treatment L and LE variable (both of the worthiness framing treatments). There is a statistically significant interaction effect and unworthiness coded belief effect found in the Tobit regression on the amount donated. However, in the Probit regressions on the rate of donation only the unworthiness coded belief was statistically significant. It seems that the framing leads to subjects donating a higher amount if their prior beliefs are challenged by the framing but it may not make them more likely to donate.

### 1.5.2 Robustness Checks

As a robustness check, we ran analysis in which the two treatments L and LE were combined into one 'Worthiness Framing' variable (Appendices 1.E and 1.F) (and the standard coding for unworthiness beliefs). We find further evidence that the coefficient on holding one or more unworthiness beliefs is negative, at the 1% level of confidence for all specified Tobit models on the donation amount. For donation rate, the models give statistical significance to this coefficient at the 10% level at a minimum in all specifications, unlike in the non-combined treatments. This is in support of our previous results.

When using the binary variable "Holds 1+ 'unworthiness' beliefs" and Model 2 in Table 1.5, to indicate if one or more of the views reported in the questionnaire was coded 'an unworthiness belief', there is a statistically significant negative effect on the amount donated. The estimates can be interpreted as a reduction in donations of around 64-68 pence if the subject holds one or more unworthiness beliefs, *ceteris paribus*. These estimates were robust to the inclusion of all controls. This pattern was not seen in the Probit regression on donation rate (Model 2 in Table 1.6). Though the coefficients were negative as expected, it was predominantly not significant in the models specified.

### 1.5.3 Extensions

**Result 1.8** *Outcomes of a competitive RET may affect donation level and rate.*

*Support:* In the RET, there was a treatment which included feedback on a

Table 1.10: Tobit regressions on donation amount with interaction terms

| VARIABLES | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Treatment L | -46.70 | -43.49 | -43.75 | -51.42 |
| | (49.13) | (47.51) | (47.50) | (47.97) |
| Treatment LE | -99.40 | -85.56 | -84.31 | -76.84 |
| | (60.27) | (58.42) | (58.48) | (58.42) |
| Holds 1+ 'unworthiness' beliefs | -156.8*** | -140.7*** | -140.3*** | -140.7*** |
| | (50.98) | (49.70) | (49.71) | (49.74) |
| Treatment L × Beliefs | 112.3 | 107.3 | 109.6 | 106.8 |
| | (74.36) | (72.85) | (73.06) | (72.33) |
| Treatment LE × Beliefs | 189.8** | 150.2* | 149.4* | 151.8* |
| | (79.08) | (78.08) | (78.08) | (77.50) |
| Has heard of the Foodbank | | 61.61** | 60.79** | 49.24* |
| | | (26.61) | (26.68) | (28.18) |
| Competitive Treatment | | | 12.36 | 14.65 |
| | | | (30.40) | (31.58) |
| Controls Included | No | No | No | Yes |
| var(e.amount) | 28,152*** | 26,337*** | 26,320*** | 25,174*** |
| | (4,260) | (3,980) | (3,977) | (3,801) |
| Constant | 179.9*** | 78.83 | 73.07 | -27.64 |
| | (35.62) | (55.89) | (57.68) | (95.05) |
| Observations | 126 | 125 | 125 | 125 |
| Adjusted R-Squared | 0.00791 | 0.0118 | 0.0119 | 0.0156 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Using interaction terms between beliefs and treatments. Controls included are age, gender, year of study, field of study and nationality.

Table 1.11: OLS regressions on donation rate with interaction terms

| VARIABLES | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Treatment L | 0.0939 | 0.0948 | 0.0928 | 0.0684 |
| | (0.121) | (0.120) | (0.120) | (0.126) |
| Treatment LE | -0.134 | -0.131 | -0.126 | -0.119 |
| | (0.145) | (0.145) | (0.145) | (0.150) |
| Holds 1 + ‘negative’ views | -0.266** | -0.262** | -0.261** | -0.270** |
| | (0.121) | (0.121) | (0.121) | (0.126) |
| Treatment L/Views interaction | 0.0520 | 0.0914 | 0.102 | 0.103 |
| | (0.178) | (0.180) | (0.181) | (0.186) |
| Treatment LE/Views interaction | 0.400** | 0.390** | 0.387** | 0.402** |
| | (0.188) | (0.191) | (0.192) | (0.197) |
| Has heard of the Foodbank | | 0.0171 | 0.0127 | 0.0144 |
| | | (0.0656) | (0.0661) | (0.0714) |
| Controls Included | No | No | No | Yes |
| Competitive Treatment | | | 0.0513 | 0.0733 |
| | | | (0.0756) | (0.0808) |
| Constant | 0.826*** | 0.798*** | 0.776*** | 0.745*** |
| | (0.0870) | (0.139) | (0.143) | (0.250) |
| Observations | 126 | 125 | 125 | 125 |
| R-squared | 0.085 | 0.086 | 0.089 | 0.104 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Using interaction terms between views and treatment. Controls included are age, gender, year of study, field of study and nationality.

competitive outcome. Graph 1.6 shows the mean amount donated, by competitive outcome. It shows that there is a statistically significant difference between the mean donated of those who won twice (WW) and those who lost then won (LW), with WW donating more. Compared to those who lost then won (LW) those who lost twice (LL) also donated statistically significantly more. These results were found using t-tests for equality of means. Graph 1.7 shows the proportion of people who donated, by competitive outcome. Again, those who both won twice and lost twice were more likely to make a donation than someone who did not have a clear competitive outcome, that is by winning one and losing one round.

We estimated models which controlled for whether the individual had had an experience of winning or losing which could have influenced their behaviour. Regression analysis on the amount donated shows that winning twice (WW) may upwardly affect the donation level. This is significant at the 10% level but does not retain significance when other control variables are included (see Appendix 1.H). We get a comparable result when looking at the likelihood of donation, where the coefficient is positive and significant at 10% but not robust to the inclusion of controls (see Appendix 1.G). For these Probit regressions, losing twice (LL) also becomes significant at the 10% level, and has a positive coefficient, but loses its significance when other controls are introduced. These regressions were run with the reduced sample of those who participated in the CT version of the RET.

To investigate if this finding could be due to a coincidental correlation between beliefs and winning outcomes, tests were run on the means and distributions of answers to the survey between these groups. No statistical difference was found. It is difficult to separate the effect of the treatment, the views held, and the competitive outcomes in their effect on the donation level and rate. The sample size for the regressions in this part of the analysis is small (n=58) so caution must be used when interpreting the significance of these results. We include the competitive treatment dummy variable for the RET in our main analysis as a control, and it does not significantly change our results. It therefore appears that having a competitive experience in of itself does not affect the situation, but the outcome may have an effect.

**Result 1.9** *Familiarity with a cause leads to larger donations.*

*Support:* In the majority of the models used to estimate a treatment effect, the variable "Has heard of the FoodBank" leads to larger donations (Table 1.5), if not more frequent (Table 1.6). Having heard of the FoodBank does not make you more likely to donate, but it does increase the donation you make.

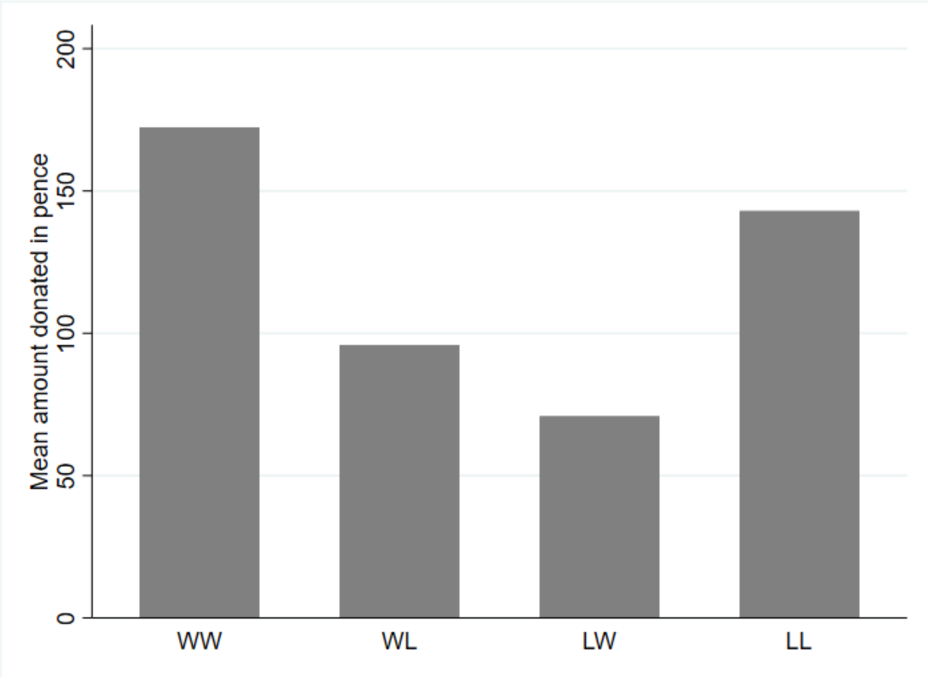


Figure 1.6: Bar graph showing the mean amount donated in pence by competitive outcome

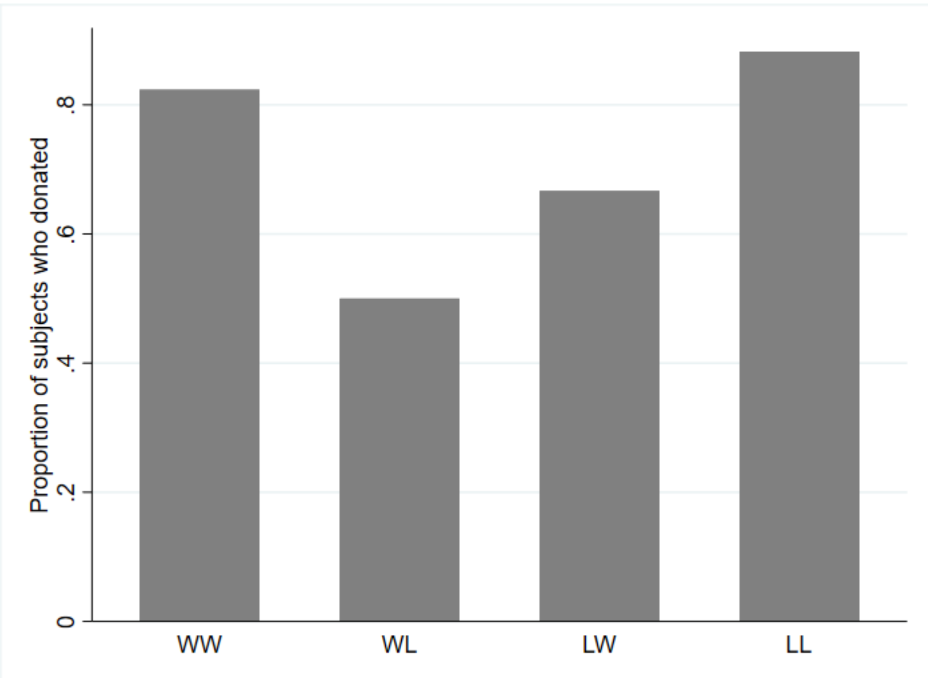


Figure 1.7: Bar graph showing the proportion of subjects who donated by competitive outcome

## 1.6 Discussion and Conclusion

The data suggests that overall, worthiness framing does not affect the donation level but may affect the donation rate. We found that beliefs about why people live in need had the strongest correlations with donation behaviour for both donation level and rate. Our study shows that familiarity with a cause can lead to large increases in the amount donated, but may not increase the rate of donation. Our analysis confirms that worthiness framing can change the behaviour of those with particular beliefs about the origin of inequality. Additionally, the study demonstrates a weak correlation between competitive outcomes and donation behaviour.

Initial results were surprising in the lack of a clear overall treatment effect, contrary to our hypothesis. However, when controlling for beliefs, it became clear that the treatment effect could only be observed on those whose views about the origins of inequality were most challenged. This makes sense, as the context remains unchanged for those who already believe those in poverty are unlucky and hardworking. For those who do not already consider the poor worthy, reframing the recipients as worthy changes the context in which they make their donation decision. Our results provide some evidence that beliefs correlate with donation levels, in agreement with previous literature on distributive preferences (Almås et al., 2020; Alesina and Angeletos, 2005; Benabou and Tirole, 2006). This is despite the treatment being designed to increase donations, which would reduce variation in donation levels by belief. Looking only at subjects in the unframed control treatment, beliefs about the causes of inequality (Question 1) held their significance in predicting both whether a donation was made and how much was donated.

One possible confounding factor could be that beliefs were asked for after the donation was made. The treatment was designed to affect only the context not the overall set of beliefs or preferences, but seeing the words 'unlucky' and 'hardworking' could have had a priming effect. An analysis of the responses by treatments show that there is no significant difference in the distribution of responses (or number of unworthiness beliefs held), which is evidence that, as intended, the treatment did not affect reported beliefs. However, for Questions 3 and 4 there is greater correlation for donation rate and level within the reduced sample (the unframed treatment) than in the whole sample. This could suggest that there was a priming effect on answers. We were limited in the methodology to asking only 4 questions in our survey, but given the opportunity it would have been preferable to administer an exit survey to determine how well the manipulation had worked: did subjects perceive the recipients as worthy? It is possible that we succeeded in changing the context for the subjects, but this did not instigate a donation or change in donation amount.

Despite the result in which framing was effective on those who had 'unworthiness' views about the context of inequality, there was still no overall treatment effect on those who did not. One possible reason for this could be that those who would already donate do not want to be persuaded further and did not like the emphasis on worthiness. This could be due to over-solicitation (Bekkers and Wiepking, 2011). It is also prudent to keep in mind that a limiting factor in this research is the sample used. The 'WEIRD' [5] student sample resulted in few participants who held strongly meritocratic or 'just-world' beliefs which are associated with more conservative populations. This resulted in a smaller sample than was hoped for when trying to find interaction effects between the treatment and beliefs.

Where Fong (2007) did not find that beliefs could be overridden by new information, this study finds the opposite. A treatment effect was found only for those who had certain 'anti-poor' beliefs about the causes of poverty, whereas Fong found a treatment effect only on those who are high scorers on the Humanitarian-Egalitarian (HE) scale. This was a surprising result for Fong, as it was expected that this type of person would donate irrespective of the worthiness information. Fong (2007, p.1009) gives an alternative hypothesis: "One possible explanation is that the attitudinal measure of unconditional altruism may be correlated with missing variables that may explain the results.". It is possible that the survey questions from the WVS that were asked in this experiment offer a more specific idea of the perceptions held about the origin of poverty than the HE scale.

These results highlight the importance of making the distinction between magnitude and incidence of donation when trying to increase donations. Though the treatments may have had a positive effect on those with unworthiness beliefs, increasing the rate of their donation, they had no statistically significant effect on the other subjects. These results should be taken into account when considering how an organisation could try to manipulate beliefs in such a way: they should be cautious to target their messaging effectively.

The reliability of these results is impacted by potential confounding factors in the competition element of the RET. However, the distribution of beliefs is not statistically significantly different between groups. Our results cannot confirm if the results found would be the same for other 'unworthy' causes. The issues around strong stereotypes might be more or less pronounced for a different

[5] Western, educated, industrialized, rich and democratic (WEIRD), (Henrich et al., 2010)

demographic. Future studies should take into account the familiarity of a cause when designing their studies – this was shown to have a large statistically significant effect on donation level and rate. An anonymised cause could eliminate this variation and may lead to clearer treatment effects. Though this experiment was not designed to understand the process through which competitive results can influence generosity, the data suggests there could be differences between how people behave after winning or losing, even if a competition does not have pecuniary repercussions. Further research is needed to establish if this is a replicable result, and to understand the channel through which this operates. This experiment took place in 2018. Since then, demand for food banks has continued to rise. At the point of writing during the Covid-19 pandemic, large increases in unemployment and a corresponding rise in demand for unemployment benefits have led to a further unprecedented demand on UK food banks. This has led to a huge rise in first-time users of the food banks (The Trussel Trust, 2020*a*). It is too early yet to say what effect this may have on future donation rates, or any effect this may have on long-term attitudes and beliefs about the origin of inequality – but this experience could potentially influence the beliefs of a generation in relation to support for redistributive welfare policies.

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# Appendices

## 1.A Cubicle Set-Up


Figure 1.8: The cubicle set up in the experimental lab, showing computer, donation box and envelope.

## 1.B Denominations of Payment


Figure 1.9: The denominations of cash given to participants

This totalled £15 and enabled the donation of any amount between 0 and £15 in 10p increments. The coin envelope displayed contains the same denominations inside.

## 1.C Beliefs Questionnaire Scale

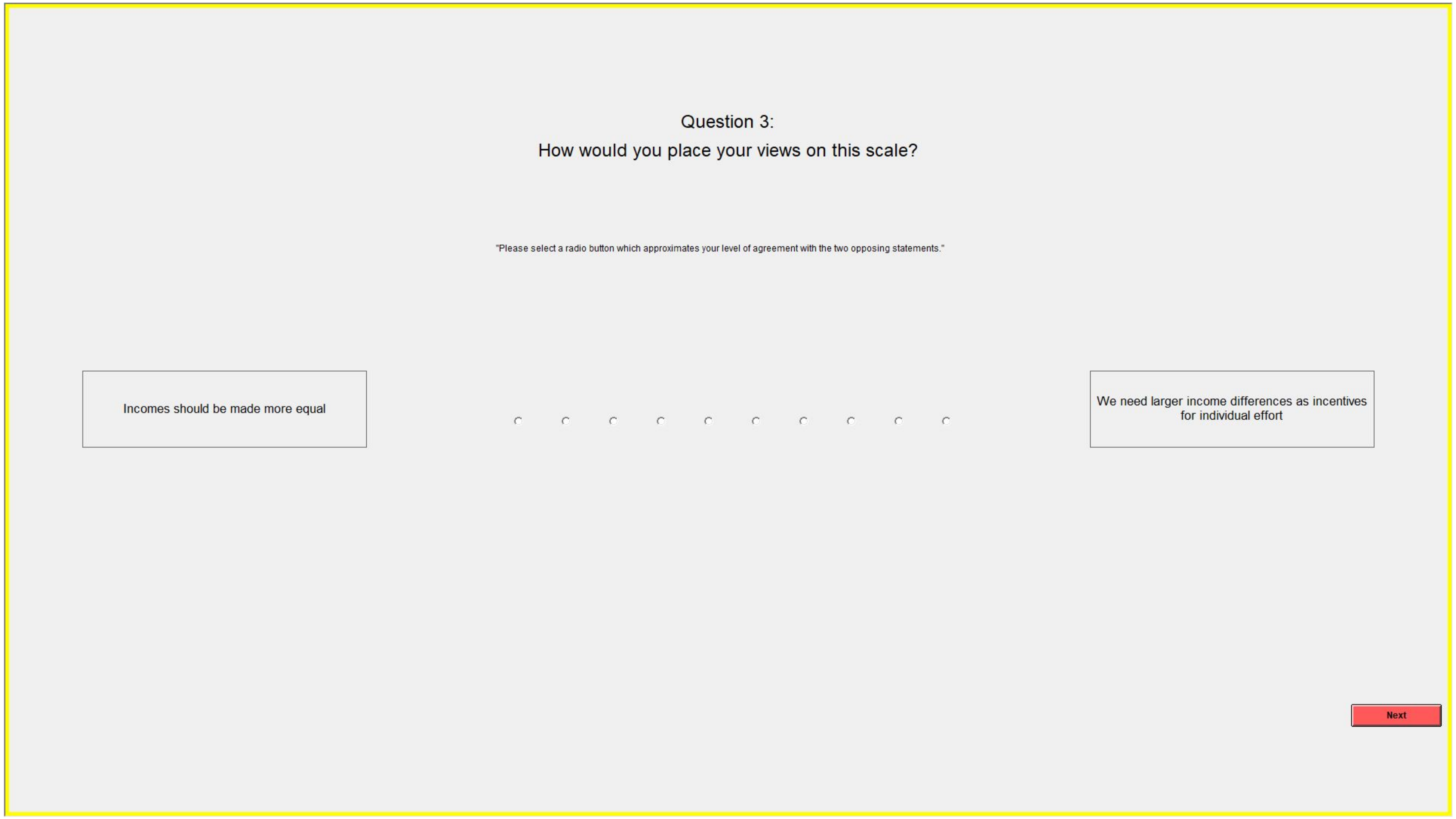


Figure 1.10: Screenshot of the presentation of Questions 3 and 4.

## 1.D Responses to Beliefs Survey

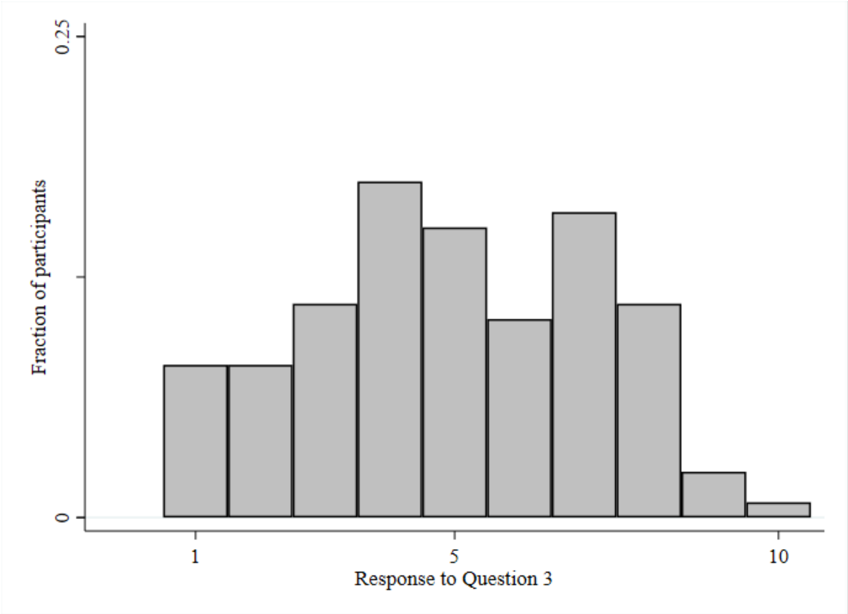


Figure 1.11: Bar graph showing responses to Question 3.

1 = Incomes should be made more equal, 10 = We need larger income differences as incentives for individual effort.

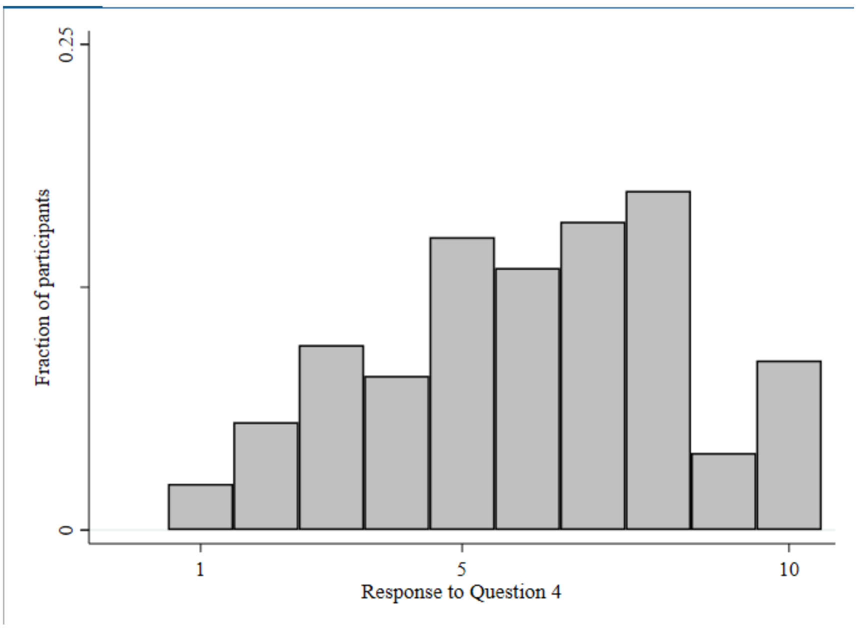


Figure 1.12: Bar graph showing responses to Question 4.

1 = In the long run, hard work usually brings a better life, 10 = Hard work doesn't generally bring success it's more a matter of luck and connections.

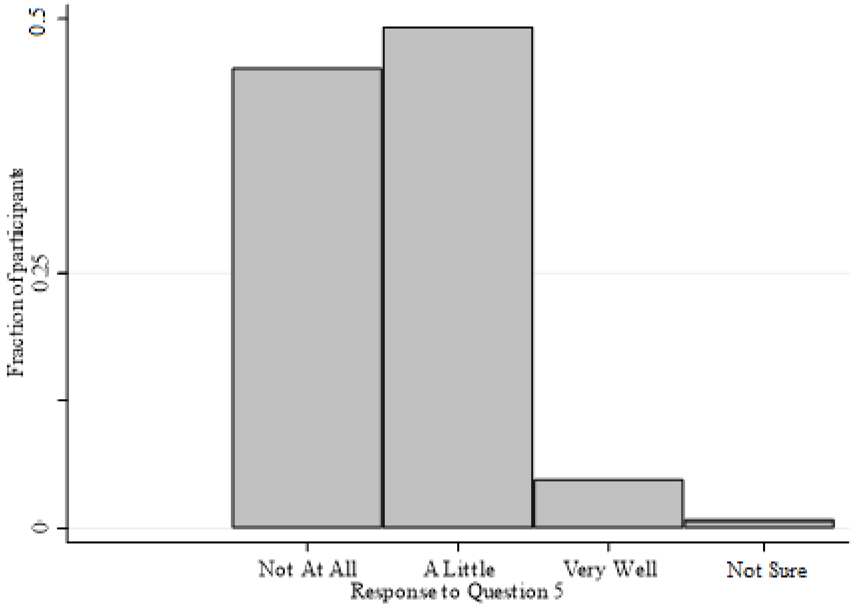


Figure 1.13: Bar graph showing responses to Question 5.
How well did you know the FoodBank before today?

## 1.E Combined Treatments Tobit Regressions

| VARIABLES | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Worthiness Framing | 6.588 | 4.318 | 3.505 | -13.10 |
| (L+LE Treatments) | (35.47) | (34.26) | (34.02) | (34.17) |
| Laziness Belief (1) | | | -107.4** | -136.9** |
| | | | (50.66) | (52.47) |
| Government Belief (2) | | | -50.89 | -39.58 |
| | | | (42.20) | (42.03) |
| Effort Belief (3) | | | 0.557 | -6.750 |
| | | | (45.99) | (45.04) |
| Hard Work Belief (4) | | | -48.42 | -45.19 |
| | | | (33.92) | (34.25) |
| Has heard of the FoodBank | | 72.76*** | 73.98*** | 56.41** |
| | | (26.38) | (26.45) | (28.03) |
| Holds 1+ ‘unworthiness’ views | | -64.39** | | |
| | | (31.01) | | |
| Competitive Treatment | | | | 8.190 |
| | | | | (31.37) |
| British | | | | -20.82 |
| | | | | (39.96) |
| ECO | | | | -40.81 |
| | | | | (37.81) |
| Male | | | | 11.75 |
| | | | | (30.54) |
| Age | | | | 6.209* |
| | | | | (3.565) |
| Year | | | | 9.468 |
| | | | | (11.59) |
| var(e.amount) | 30,471*** | 27,165*** | 26,324*** | 24,836*** |
| | (4,625) | (4,107) | (3,971) | (3,741) |
| Constant | 100.6*** | 21.69 | 23.16 | -73.16 |
| | (30.06) | (56.05) | (55.03) | (94.84) |
| Observations | 126 | 125 | 125 | 125 |
| Adjusted R-Squared | 2.61e-05 | 0.00864 | 0.0132 | 0.0185 |

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

‘ECO’ is a binary variable for if the participant was a student in the School of Economics. ‘Year’ refers to year of study.

## 1.F Combined Treatment Probit Regressions

| VARIABLES | Model 1 | Model 2 | Model 3 | Model 5 |
|---|---|---|---|---|
| Worthiness Framing | -0.0726 | -0.0823 | -0.107 | -0.224 |
| (L+LE Treatments) | (0.274) | (0.278) | (0.291) | (0.299) |
| Laziness Belief (1) | | | -1.047*** | -1.319*** |
| | | | (0.371) | (0.421) |
| Government Belief (2) | | | 0.0720 | 0.201 |
| | | | (0.367) | (0.387) |
| Effort Belief (3) | | | -0.342 | -0.407 |
| | | | (0.361) | (0.376) |
| Hard Work Belief (4) | | | -0.410 | -0.408 |
| | | | (0.276) | (0.295) |
| Has heard of the FoodBank | | 0.147 | 0.189 | 0.162 |
| | | (0.217) | (0.226) | (0.244) |
| Holds 1+ 'unworthiness' beliefs | | -0.446* | | |
| | | (0.255) | | |
| Competitive Treatment | | | | 0.192 |
| | | | | (0.282) |
| British | | | | -0.228 |
| | | | | (0.392) |
| ECO | | | | -0.449 |
| | | | | (0.325) |
| Male | | | | 0.153 |
| | | | | (0.283) |
| Age | | | | 0.0484 |
| | | | | (0.0509) |
| Year | | | | 0.0214 |
| | | | | (0.104) |
| Constant | 0.765*** | 0.804* | 0.854* | 0.0811 |
| | (0.233) | (0.463) | (0.472) | (1.261) |
| Observations | 126 | 125 | 125 | 125 |
| Adjusted R-Squared | 0.000511 | 0.0276 | 0.102 | 0.142 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

'ECO' is a binary variable for if the participant was a student in the School of Economics. 'Year' refers to year of study.

## 1.G Competitive Outcomes Regressions: Probit

Table 1.12: Probit looking at competitive outcomes

| VARIABLES | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Luck Treatment | 0.986** | 1.035** | 1.202** |
| | (0.500) | (0.515) | (0.610) |
| Effort Treatment | 0.714 | 0.766 | 0.931* |
| | (0.464) | (0.470) | (0.537) |
| Win Win | 0.887* | 0.939* | 0.699 |
| | (0.481) | (0.490) | (0.547) |
| Lose Lose | 0.930* | 0.893* | 0.530 |
| | (0.493) | (0.501) | (0.549) |
| Holds 1+ 'unworthiness' views | | -0.426 | -0.665 |
| | | (0.404) | (0.470) |
| Has heard of the FoodBank | | | 0.719 |
| | | | (0.444) |
| British | | | -0.712 |
| | | | (0.692) |
| ECO | | | -0.721 |
| | | | (0.576) |
| Male | | | -0.450 |
| | | | (0.485) |
| Age | | | 0.0285 |
| | | | (0.0910) |
| Year | | | 0.0253 |
| | | | (0.177) |
| Constant | -0.288 | -0.0702 | -0.615 |
| | (0.359) | (0.418) | (2.347) |
| Observations | 58 | 58 | 58 |

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Win Win and Lose Lose refer to subjects who were in the competitive RET, who either won twice or lost twice out of two rounds. Payoffs were not influenced by this outcome.

## 1.H Competitive Outcomes Regressions: Tobit

Table 1.13: Tobit model for competitive outcomes

| VARIABLES | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Luck Treatment | 71.17 | 52.64 | 73.73 |
| | (56.03) | (53.75) | (57.26) |
| Effort and Luck Treatment | 48.41 | 29.20 | 59.29 |
| | (56.55) | (55.26) | (54.67) |
| Win Win | 128.2** | 103.2* | 74.19 |
| | (56.11) | (55.27) | (53.09) |
| Lose Lose | 93.25 | 59.09 | 33.92 |
| | (55.89) | (54.49) | (53.25) |
| Holds 1+ 'unworthiness' beliefs | | -76.18 | -84.51* |
| | | (45.68) | (45.52) |
| Has heard of the FoodBank | | 86.61** | 89.74** |
| | | (42.18) | (42.51) |
| British | | | -39.88 |
| | | | (56.59) |
| ECO | | | -71.89 |
| | | | (63.64) |
| Male | | | -2.983 |
| | | | (46.34) |
| Age | | | 10.66* |
| | | | (5.905) |
| Year | | | 11.15 |
| | | | (17.42) |
| var(e.amount) | 28,014*** | 25,162*** | 22,030*** |
| | (6,342) | (5,670) | (4,944) |
| Constant | -5.364 | -68.85 | -267.4* |
| | (49.61) | (71.42) | (157.4) |
| Observations | 58 | 58 | 58 |

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Win Win and Lose Lose refer to subjects who were in the competitive RET, who either won twice or lost twice out of two rounds. Payoffs were not influenced by this outcome.'ECO' is a binary variable for if the participant was a student in the School of Economics. 'Year' refers to year of study.

# Chapter 2

# Reducing information asymmetry for the donation of tangible goods: Quasi-experimental data from food bank donations in supermarkets

An information asymmetry exists between charities and their donors: donors do not know exactly what a charity needs. Donations in tangible form can exacerbate the resultant inefficiency. Yet, in-kind donations persist as a popular method of donating. Efficiency and efficacy concerns could explain this persistence. We collect and analyse a novel dataset on tangible donations in supermarkets to a local food bank in a quasi-experimental setting. We show that an intervention to reduce the information asymmetry does increase the donation of the most needed items, but not systematically so.

**Keywords: efficiency, tangibility, charitable donations, messaging**

## 2.1 Introduction

To donate to a cause, one must first be aware of its existence. Awareness of need has long been understood to be a key prerequisite for the decision to make a donation (Richard et al., 1970). Research on donation behaviour has predominantly focused on pecuniary donations, however donations come in other forms: gifts in-kind. There has been research on two types of gifts in-kind: intangible gifts-in kind (such as professional services, volunteering (Lee and Chang, 2007)) and third-party payments (paying a creditor on an organisation's behalf) which pertain more to organisations than individuals. This chapter instead examines the donation of physical goods, an important but greatly understudied area. We use a novel experimental design in the context of in-kind donations to a food bank at in-store collection points. We look at physical donations of good for consumption by the recipient, henceforth referred to as tangible donations.

Charities have knowledge about their cause's needs, but this information is imperfectly communicated to donors: a costly information asymmetry. Awareness of need is crucial for tangible donations – fulfilling the charities' needs requires clear communication of specific demand to avoid inefficiencies. This chapter investigates how increasing awareness of need through reducing information asymmetries affects the type and level of tangible donations. Using a targeted information campaign in two large supermarkets, we examine how highlighting the charity's high-demand items affects the level of their donation. We also investigate if the information has a 'spillover effect' on donations of similar items or overall donations. Furthermore, we look at whether a change in the amount of high demand items affects the amount of low demand items donated- if there is a 'crowding out' effect.

The extent to which donors care about efficiency in donations is debated. Gneezy et al. (2014) provide evidence for 'overhead aversion', meaning a dislike of paying for overhead costs rather than what might be considered more core elements of a charity's work. On the other hand, donors have been found to spend little time researching the efficiency of a cause even if this is provided to them at a low cost (Wong and Ortmann, 2016). It is possible that the degree to which efficiency matters in making a donation depends largely on the context. If it were the case that donors care strongly about efficiency, the expectation would be that there would be a large increase in the donation of the highlighted items and a corresponding decrease in the donation of low demand items: we would find a crowding-out effect. The idea of a preference for choice is also a contested area of debate. If donors have a preference for choice, it could be observed in this study as an increase in the donation of items similar to the ones highlighted – a spillover effect.

In this context there are several arguments which could be made about how much donors care about efficiency. On one hand, donors are choosing to make tangible donations – this could indicate overhead aversion and a desire for efficiency or efficacy. The tangibility of the item also increases perceived efficacy – it is easy to imagine the recipient using the product donated (Cryder and Loewenstein, 2010). On the other hand, choosing to make a tangible donation instead of a pecuniary donation despite the inherent inefficiencies of transport, storage and unneeded product types could indicate no preference for efficiency or perceived efficacy. In this way, overhead aversion can represent both a desire for efficacy but a move toward inefficiency.

The difficulty of measuring tangible donations has likely been a reason for its current status as an understudied research area. This interesting and unique area is yet to be fully explored by behavioural economists. We use a novel dataset from a quasi-experimental design with two treatments. The treatments varied by the size, look and contents of the information campaign. The design allows us to study how the introduction of an information campaign affects the donation of various product types using a difference in differences (DiD) analysis.

The majority of the food banks in the UK are organised with the Trussel Trust. Trussel Trust [UK] FoodBanks receive around half of their total donations from donation points in supermarkets, so getting this element of their strategy right can have large effects on their overall stock levels. The idea of using in-store marketing in the form of "tickets" (shelf-level labels) next to item price tickets on shelves has already received some media attention. Such signage has been rolled out in some supermarkets and other food retailers have been keen to show their support for FoodBanks in this way. As of yet, the effect of these signs on donation rates has not been investigated.

Our results establish that the information campaign is not universally successful in increasing donation of high demand items, and effects found are small in magnitude. The analysis shows that mainly the treatment effect is observable at the product category level. From this we infer that donors value being able to choose the product they donate within a given category rather than the specific product requested. Our analysis shows that there are some small crowding-out effects on low-demand items, showing that overall donors changed their behaviour only slightly towards donating the high demand items. The findings can help inform how organisations attempt to influence donation behaviour, in an area with increasing political and social visibility.

The chapter is structured as follows: firstly, context on tangible donations and a literature review on awareness of need and efficiency concerns are presented in Section 2.2. The methodology in Section 2.3 then describes the design, descriptive statistics and method of analysis used. Section 2.5 presents the results of the analysis. Finally, the discussion and conclusion follows in Section 2.6.

## 2.2 Existing Literature

In this section, we first give some background on tangible donations, through a discussion of charitable giving more generally. We then focus on how awareness of need affects charitable giving, and why this is particularly relevant for tangible donations. Finally, we discuss the effects of efficiency and efficacy concerns of donations, and how this interacts with decision making behaviour. We conclude that tangible donations are often overlooked in the literature, resulting in many open questions in this domain. Our interest lies in how messaging at the point of purchase could influence donors to choose differently when making a tangible donation, in favor of more high-demand donations.

### 2.2.1 Tangibility

There are many ways to donate to charitable causes. The most common and straightforward is a pecuniary donation given directly to a cause. Pecuniary donations can also be given to be spent in certain ways, such as exclusively on core activities as opposed to administrative or overhead costs. A different variety of donation is that of 'in-kind' donations. These donations are goods or other commodities such as time or space that are donated to a cause. In-kind donations are frequently given by companies or businesses which have surplus resources. Examples include donating rental space or display models of items to charitable groups. A further example is the donation of items to charity shops which are then sold on to make profit for the cause – these are often items that the donor already owns but no longer wants. Another type of in-kind donation is the donation of blood for transfusion – though in this scenario it could be argued that it is actually time which is being donated, as well as a good which cannot be purchased in a store for donation.

In this chapter, we focus on tangible donations for consumption by the recipient. This type of donation occurs, for example, when causes appeal for help with specific items for the domestic homeless or refugees such as shoes, coats and tents. However, these often lack permanent collection points and are often situated where it is not possible to immediately purchase and donate the item required. One way this barrier to donation is overcome is through the use of online ‘wishlists’, where it is possible to donate specific items through an online retailer to be sent to the charity. This is an attempt to encourage donations despite the donation not being physically tangible to the donor. This situation is comparable yet distinct from the studied situation, as the tangibility of the donation is likely a key factor in the donation decision.

Tangible donations are still a popular way of donating to a charity or cause. This is evident in the response to humanitarian crises when lorry-loads of donations make their way to the affected areas. It is important to remember that donors may not realise that they are lacking information or making an inefficient donation. This means that donating the ‘right’ thing may still be important to them, and their actions could even be borne from efficiency concerns. Donors self-select into this tangible donation group based on unobserved characteristics. Their motivations and the types of information they respond to could be different than for pecuniary donations.

In their chapter on generosity, Cryder and Loewenstein (2010) present the argument that the ‘identifiable victim effect’ is the mechanism behind individuals choosing to giving more to a cause that supports someone you know (see Schelling (1968)). Cryder and Loewenstein (2010) suggest that this occurs through the channel of the increased tangibility of the recipient. They argue that the tangibility of the recipient causes an increase in generosity through making donating feel more effective. Specifically, they state that tangibility makes the donation more gratifying and increases the intensity of emotions.

It should be noted that there is a difference between tangibility of donation and tangibility of recipient/outcomes. By explicitly mentioning the potential recipient, charities try to make the recipient more tangible to the donor. Some charities run campaigns which explicitly convert pecuniary donations into tangible items, such as: “Your automatic monthly donation of $36.50 will provide your “new family” with enough groceries to get them through the end of the month” (family-to-family.org) or “£14 could protect 21 children from deadly measles - that’s just 66p per child” (unicef.org) and “This gift represents a donation to our health work, and could help five families sleep soundly under their own treated mosquito net.” (savethechildren.org). The “1 pack - 1 vaccine” Pampers’ matching programme was studied in the Cryder and Loewenstein (2010) chapter. The campaign’s success was attributed to its increased tangibility of the recipient (the baby) in comparison to the more general phrasing “help end world measles”.

However, in this study, tangibility relates to the physical tangibility of an item that is donated. This likely does make the donor also more tangible as one can imagine them using or holding the donation itself. There is little evidence to suggest how donors would react to an information campaign increasing awareness of need about items required by a charity, but we believe that it would have a similar effect to increasing the perceived efficacy of a donation: increasing charitable giving (Carroll and Kachersky, 2019).

### 2.2.2 Awareness of Need

Donation behaviour is affected by many factors and has been studied extensively in various fields. In their multi-disciplinary meta-analysis, Bekkers and Wiepking (2011, p. 927) summarise key insights and identify eight mechanisms, which determine and drive donation behaviour. These are: “(a) awareness of need; (b) solicitation; (c) costs and benefits; (d) altruism; (e) reputation; (f) psychological benefits; (g) values; (h) efficacy”. This list is not exhaustive, and many other determinants of donation behaviour have been observed.

The desire to help those in need is a social norm that individuals can feel compelled to adhere to. Schwartz (1975) described “awareness of need” in his psychology paper on social issues as the first step in norm activation: the norms of responsibility toward others, and the norm of altruism. Schwartz discusses prosocial behaviour as driven by some intrinsic desire for justice, through the perception of others’ needs and an attempt to fulfil them. Andreoni’s (1990) seminal theoretical paper presented an economic decision-making model of “the warm glow of giving”. Andreoni’s work explains how altruism has intrinsic benefits to an individual. Given these behavioural regularities, it logically follows that being aware of an other’s need makes one more likely to act to fulfil that need. Indeed, multiple experiments and surveys have found that perceived need is positively correlated with donation levels. Cheung and Chan (2000) used a survey to measure the contribution of a social cognitive theory framework in an attempt to reveal important factors in fundraising success. The authors find that awareness of need, along with beliefs such as outcome efficacy and moral obligation, were important elements when looking at intention to donate. More recently, Bekkers and Wiepking (2011) also reported that awareness of need is a pre-requisite for donations. There is plenty of evidence that awareness of need increases the frequency of donations. However, it is not clear if this is necessarily a relationship which would hold for tangible goods. The donor could be aware of the need, but unless there is only one item which is needed (somewhat comparable to a pecuniary donation) then a choice still must be made about which item to donate.

Bekkers and Wiepking (2011) find evidence in many studies that simply being asked to donate increases donations. They summarize this as: "the more opportunities to give people encounter, the more likely they are to give." Damgaard and Gravert (2018, p. 931) discuss an experiment using direct mail reminders to give to a charity. The authors find that online reminders can work to a point, but if too many are sent out then individuals may choose to unsubscribe from such direct mailing lists. The explanation given for an increase in solicitations leading to a decrease in donation level is 'empathy fatigue' or 'compassion fatigue'. Donors are indeed aware of the need for their donations but empathy is limited and individuals can become desensitised with multiple solicitations. Empathy fatigue has been researched with relation to professionals in "service-related activities in which they must be empathically available" such as doctors, counsellors, and carers (Stebnicki, 2000, p. 23). This has been applied to donation situations: as adverts become more and more shocking to try to induce empathy they may be having the opposite effect (Cockrill and Parsonage, 2016; Süssenbach, 2018). This concurs with research on the phenomenon of 'donor fatigue' in which empathy is limited (Andreoni, 2006). It is important not to go too far with messaging campaigns as this could create feelings of resentment or deter the individual from engaging with the messages.

### 2.2.3 Efficiency Concerns

Asymmetric information refers to when one party has more information than the other in an economic transaction. In this case, charities have more information about what is needed to further their cause. The charitable cause must inform potential donors about what it specifically needs rather than just what the cause provides, as with pecuniary donations. A separate but related issue is the inefficiency surrounding tangible donations. In most instances it is less efficient to donate goods/items to a charity instead of donating cash – the storage, transport, sorting and distribution costs are all much higher than if cash was given. Charities are also unable to take advantage of economies of scale in purchasing items when reliant on tangible donations – causing even greater inefficiencies.

There have been several high-profile cases that have caused a decrease in trust in some of the biggest charities, as noted by Body and Breeze (2016) in their work on marketing in the voluntary sector, concluding that even 'unpopular' charities can achieve success through framing and investment in fundraising. There has been considerable media attention around the pay levels of the directors of charities, which many deemed inappropriate and a misuse of the charities' money, which had been donated by the general public. This has increased the level of 'overhead aversion' experienced by potential donors. Gneezy et al.'s (2014) behavioural economics field-experiment compared 'matched'[1] donations to donations where a philanthropist had covered all overheads, finding that the rate and magnitude of donations increased under the covered-overheads treatment, indicating the presence of overhead aversion.

The most efficient type of donation is a pecuniary donation, as it is fungible. It would be expected that those most concerned with efficient donations would donate money to a cause, assuming that they realise this is the most efficient action. However, when there are concerns over the efficiency of a charity itself, for example through overhead aversion, giving a tangible donation may appear to be a more efficient solution. Therefore, those who choose to give tangible donations could be more susceptible to concerns about overhead aversion and the efficiency of a charity. A tangible donation can less easily be misused or directed into overhead costs. As of yet, efficiency considerations for tangible goods have not been studied in the literature.

The efficiency of donations refers to how effectively donations are used to further the charitable causes' aims. This tends to be interpreted as minimising other costs and ensuring as much of the donation going towards essential work as possible, achieved at the lowest price. In other words, a charitable cause getting as much value as possible out of a donation[2]. Some individuals may feel that the efficiency of donation is a key factor in their decision. Fundraising campaigns can use this bias to their advantage. An example of a campaign directed toward efficiency concerns of potential donors is matched donations, as this makes a donation by an individual more valuable. When charities give examples of what a donation could buy, they are also demonstrating their efficiency to a donor, as well as being a useful anchoring technique to increase donation levels, if not rates (Schwarzwald et al., 1983). The use of these mechanisms in the field implies that efficiency concerns are pervasive, and research in this field and others has generally supported this. However, the size of the effect and the contexts in which it comes into play are still contentious. Research has focused on reducing information asymmetries about the efficiency of a charity by highlighting relevant information for donors. These studies measure the responses to

[1]Matched donations refer to when an organisation or individual promises to also contribute to the cause if others do, and often will 'match' contributions 1 for 1, usually up to a predetermined amount.

[2]There is an argument that running charities more like businesses would lead to greater payoffs for the causes they support. This could mean that proportionally less of a donation goes directly to a cause, but could also mean that the overall income of the charity is increased, which is the more important factor from the point of view of the cause itself.

this information in terms of rate and magnitude of donation. Conveying information about the quality, efficacy (Vollan et al., 2017), and efficiency (Wong and Ortmann, 2016) of donations to a cause have found differing results, some finding an effect and others finding this only in certain contexts or not at all (Tinkelman and Mankaney, 2007).

Wong and Ortmann (2016) present an empirically motivated theoretical model of how donors choose which charity to donate to. The model shows a price-information trade off, based on 'charity price', defined as fundraising and overhead costs (here referred to as efficiency) and the costly gathering of such information. It posits that donors want their donations to 'maximise charitable output' but prefer not to spend time on researching efficiencies. The authors note that though there has been an increase in tools to help donors make decisions on this basis, that other research suggests it is not widely used in decision making – a clear point of contention in this literature.

Vollan et al. (2017) found that when including information about the quality of the outcomes provided by a charity there was a strong increase in donations. The authors found that there was a significant increase in donation magnitude when impact evaluations from an RCT were included in a campaign to raise donations, based on their survey experiment run in Austrian and German Universities. This is evidence that efficiency and quality of outcomes do play an important role in donation behaviour.

Reducing the information asymmetry has the effect of reducing the risk of donating to this particular cause. As shown by the variety of methods seen in the research, there are many ways that efficiency can be defined, from the proportion of donations that go on core activities to the quality of the outcomes observed. In summary, highlighting the most needed items for a charity to receive as donations will reduce the information asymmetry which leads to inefficiencies in tangible donations. Information asymmetry leads to costly inefficiencies when motivating pecuniary donations. If this is also the case for tangible donations, reducing the information asymmetry and increasing awareness of need would result in a higher donation rate of the demanded items. Efficiency concerns have been found to influence behaviour in pecuniary donations, albeit only in certain contexts. Given the presence of self-selection into a tangible donation behaviour, it could be the case that efficiency concerns are high for this type of donor. If this is the case, reducing information asymmetry about the efficiency of donations would result in an increased magnitude and rate of donating demanded items.

## 2.3 Methodology

### 2.3.1 Experimental Design

We had the unique opportunity of working with the Norwich [UK] Trussel Trust FoodBank, and one of the main national supermarket chains in the UK[3]. The design for this quasi-experimental field study used two treatments across two supermarket stores. Our design communicated to potential donors which items were in high demand for the FoodBank. Through shelf level signage, either smaller 'tickets' or larger 'talkers', we applied the information campaign to the two stores. The outcomes were measured at the same-shelf level, and the product category level, and for Treatment Talker, the image level.

Two similarly sized supermarkets in Norwich were selected, the only supermarkets of the chain in the area. Initially, our design had one treated store and one control agreed with the charity and supermarket management, however within weeks of the experiment commencing, a natural experiment took place as the supermarket put up their own, similar but larger shelf 'talker' signs in the control store. Though the original design was compromised, the opportunity was taken to measure both sets of interventions. In effect, the stores received separate treatments which started on different dates. The difference in differences (DiD) design controls for store-level differences in donation levels due to unobserved characteristics. The design also allows for a within-store analysis, using a group of untreated products with similar characteristics.

The data collection took place weekly from 3rd November 2018 to 20th December 2018. Baseline data collection commenced on the same day for both stores. The experiment lasted 7 weeks in total. Treatment Ticket had a baseline data collection period of 3 weeks, followed by 4 weeks of post-intervention data collection. Simultaneously, Treatment Talker had a baseline data collection period of 5 weeks followed by 2 weeks of post-intervention data collection.

The between-stores design allows for the two stores to serve as one another's control. Baseline data collection commenced on the same date, allowing for a comparison of pre-treatment trends. When Treatment Ticket commenced in Store A, no treatment had started in Store B, so we use between-store DiD estimation. Treatment Talker began 2 weeks later, on 8 different product types which were not treated in Treatment Talker. For the two product types which received treatment in both stores (milk and juice), the period for which the treatments overlap is dropped from analysis for Treatment Ticket, and a within-store DiD estimation

[3] J Sainsbury Plc, trading as Sainsbury's

Figure 2.1: The Treatment Ticket shelf ticket.


Figure 2.2: The Treatment Talker shelf talker.


used for Treatment Talker.

### 2.3.2 Treatments

Treatment Ticket received 'ticket' shelf-level signs: 8cm x 4cm labels placed directly underneath the item type they depicted. Four product types were treated chosen from the most highly demanded and low stocked products needed by the Norwich FoodBank: long-life milk, long-life juice, custard and microwave puddings. The tickets were white with a FoodBank logo in colour underneath (see Figure 2.1). They read "This item is currently needed by the Norwich FoodBank". In Treatment Talker, the shelf signs were larger, at 10cm x 21cm, known as shelf 'talkers'. They were placed under 10 different product types: tinned meat, tinned fish, coffee, tea, tinned vegetables, pasta, tinned beans, long-life juice and long-life milk. The talkers depicted two or three different items of that product type: usually the supermarket's own-brand product and a branded item. The talkers were orange and had text which read "Priority item for local charities, Donation point at checkout" (Figure 2.2).

Table 2.1: Treated Items and Categories, by Treatment

| **Treatment** | **Treatment Ticket** | **Treatment Talker** |
|---|---|---|
| **Treated Images** | n/a | 31 items |
| **Treated Shelves** | 4 (15 items) | 10 (19 items) |
| **Treated Product Categories** | 4 | 10 |
| **Items per Category** | Custard - 14<br>Milk - 17<br>Puddings-16<br>Juice - 20 | Fish- 34<br>Meat - 45<br>Beans - 32<br>Veg Tin - 40<br>Milk - 17<br>Juice - 20<br>Pasta - 63<br>Coffee - 13<br>Tea - 24<br>Soup - 70 |

Note: The shelf level products are not always the same products as those depicted on the talkers in Treatment Talker.

### 2.3.3 Data Collection

This experiment gathered data at the item level: each item donated in each store was scanned using a barcode reader. Donations were then dropped off at the FoodBank's warehouse for sorting and distribution. The collected barcodes were entered into a database to be matched with product information available online in order to determine trends in donation levels and types. Barcodes uniquely identify a product: all identical products share the same barcode, also known as a SKU (stock keeping unit). Therefore, the outcome variable is the number of times the treated barcodes appear per store per week in the collection baskets. Table 2.1 gives the number of different barcodes, or items, that were in each level of treatment. In the product categories, every item which was part of that product category (for example, every type of pasta) was included in the 'treated product' variable.

### 2.3.4 Hypotheses

Representatives from the FoodBank had informed us that the donations to the FoodBank did not reflect the proportions in which the goods were demanded and that there was therefore an inefficiency. In collecting these data we have been able to measure the extent of this inefficiency.

**Hypothesis 2.1** *Tangible donations to the FoodBank at in-store collection points do not match the ideal mix of donations.*

Due to the nature of this novel experiment, no previous data was available which could give an indication of the level at which a treatment effect might be observed. At the most specific level, the specific shelf that the ticket or talker is placed on could represent the set of products which are treated. The same could be said for the 2-3 products which are depicted on the talker in Treatment Talker. However, we could also see an increase in donations from the same category of product as the treated products.

**Hypothesis 2.2** *The information campaign increases donations of high demand items at the product level, shelf level and category level*

The information campaign could increase awareness of need for the FoodBank more generally and lead to an increase of non-treated items being donated.

**Hypothesis 2.3** *The information campaign increases the number of low-demand items donated (spillover)*

We may observe instead a decrease in the number of untreated items being donated. The information campaign could move donations away from untreated items towards high-demand treated items as donors seek to make a more helpful contribution to the FoodBank. In addition, the information campaign could signal that the untreated products are less desirable to the FoodBank and may decrease donations without a corresponing increase in the treated items being donated.

**Hypothesis 2.4** *The information campaign reduces the number of low-demand items donated (crowding-out)*

A regular pattern for the FoodBank is to see an increase in donations in the weeks preceeding Christmas, but this has not yet been quantified.

**Hypothesis 2.5** *Donation levels increase towards Christmas*

We aim to influence the types of products which are donated to the FoodBank, but we expect that there are seasonal changes in the pattern of donations which occur even in the absence of the intervention.

**Hypothesis 2.6** *The types of products donated changes towards Christmas*

## 2.4 Analysis

The outcome variable changes depending on the level of analysis: category, shelf or image level. The control group is used to compare the effect of the treatment. For the main analysis, a between-stores design is used. This comparison was used as there was reason to believe there could be spill-over effects to other categories or product types from the presence of the shelf talkers/tickets in the treatment. Within-store comparison groups are used to estimate the effect of treatment on milk and juice in Treatment Talker as they are treated simultaneously in both stores.

Due to the limited number of observations in our sample, we do not use a panel regression, and instead use the pooled negative-binomial regression, which accounts for the non-normal distribution of our dependent variables (see Appendices 2.D, 2.E, 2.F), which is particularly notable at the non-aggregated levels of analysis (individual product categories, shelves and images).

### 2.4.1 Estimating the Treatment Effect - Between Stores

We begin with a linear model using the difference in difference estimator and linear time trend:

$$y_{ist} = \beta_1 x_{time} + \beta_2 x_{treatment} + \beta_3 x_{time \bullet treatment} + \beta_4 W_n, \tag{2.1}$$

Where $i$ is the number of high-demand treated items donated in a collection in store $s$ at a given level of measurement (shelf, category, image). $Y_i$ is the latent outcome variable count of treated items donated, . Lowercase $t$ is time period dummy: before (0) or after (1) the treatment occurred. $W$ is the linear time trend estimator, with subscript $n$ as the week number.$\beta_1$ is the time trend estimator (common to both control and treatment groups). $\beta_2$ is the coefficient for the treatment group specific effect. $\beta_3$ is the effect of the treatment or the DiD estimator. However, our data is overdispersed and naturally censored at 0. There are many 0 values in our dataset as can be seen in the graphs in Appendix 2.D.

Therefore, for the main analysis we estimate the treatment effect using the following between-store difference in differences model. We estimate a pooled-model in which the probability of a given observation $y_{st}$ is:

$$y_{ist} \sim f\left(\exp\left(\beta_1 x_{time} + \beta_2 x_{treatment} + \beta_3 x_{time\bullet treatment} + \beta_4 W_n\right)\right), \tag{2.2}$$

where $f$ is assumed to follow a negative binomial distribution (Cameron and Trivedi, 2013), run as a random effects model with robust standard errors. $Y_i$ is measured in natural logarithm.

We also considered using week dummies for which the equation is:

$$y_{ist} \sim f\left(\exp\left(\beta_2 x_{treatment} + \beta_3 x_{time\bullet treatment} + \beta_{\mathbf{4n}} \mathbf{W_n}\right)\right), \tag{2.3}$$

omitting the previous $\beta_1 x_{time}$ due to multicollinearity with the week dummies given in the vector $\beta_{4n} W_n$. However, due to the limited number of data points we instead use a linear time estimator as in equation (2.2).

### 2.4.2 Estimating the Treatment Effect - Within-Store

As a robustness check, we estimate the within-store model:

$$y_{iat} \sim f\left(\exp\left(\beta_1 x_{time} + \beta_2 x_{treatment} + \beta_3 x_{time\bullet treatment} + \beta_4 W_n\right)\right) \tag{2.4}$$

The equation being used in this DiD estimation is similar to equation (1), however instead of the control group being the same set of items but in the control store, it is now a group of items with similar characteristics in the same store (subscript $a$). This eliminates variations due to unobservable store level characteristics. No evidence for spill over effects within the store from the treatment onto untreated goods were found (see Result 2.6), satisfying one of the key assumptions of the DiD estimation. To allocate the treated items a suitable within-store control group they have been distinguished by their YED (income elasticity of demand) – whether they are luxury or necessity items using research on income elasticities of demand. The control group for each product type will be the untreated items within the same store which are also of the same product type (luxury/necessity). For example, the control group for the within-store regressions for juice would be all non-treated luxury items. Where possible, data from culturally similar countries to the UK have been used, as food demand varies culturally. The data gathered is from separate sources and has inconsistencies in estimation strategies. Despite this, the allocation is binary, so finding simply whether the YED is positive or negative is required.

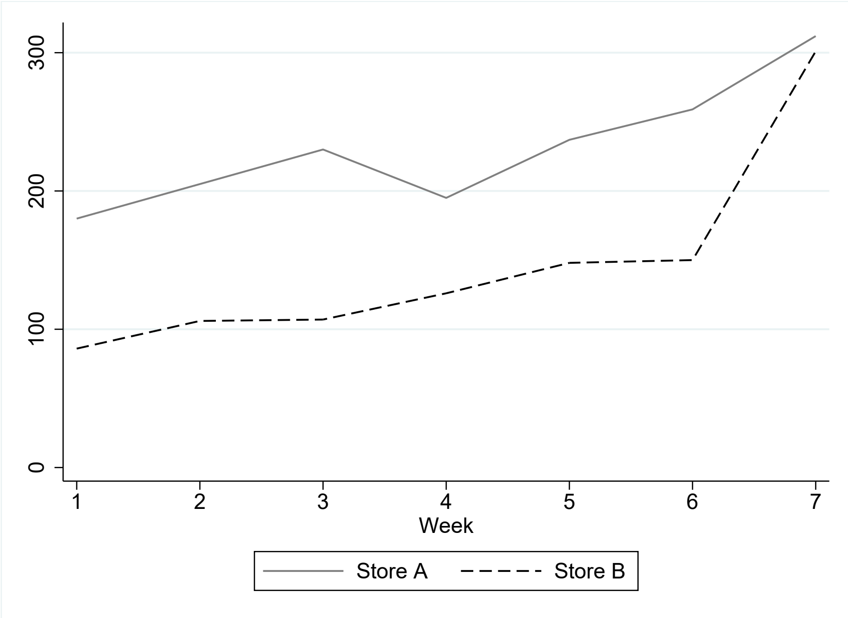


Figure 2.3: Total number of matched items donated in each store

### 2.4.3 Parallel Trends

Using the DiD estimation strategy, a key assumption is that of parallel trends in the pre-intervention period. Interventions took place in week 3 in Store A and in week 5 in store B. Figure 2.3 shows the total donations per week per store over the experiment.

The donation of treated items was highly variable both before and after treatment. Figure 2.4 shows the count of donations which were from the categories which were subsequently labelled in Treatment Ticket. Averaging across weeks to account for the high level of variation, we believe that the trend for both before intervention at week 3 is similar; a slightly increasing trend of donations. Taking into account this high variability, we believe that the stores show similar trends in this 3-5 week period: a moderate upward slope of donations. We therefore accept the parallel trends assumption and use this strategy in our estimation. Figure 2.5 shows the same variable but for items which were subsequently treated in Treatment Talker. Again, to account for the highly variable nature of the donations, we look at the averaged trend and believe that the trend was essentially flat for both stores before intervention.

### 2.4.4 Descriptive Statistics

**Variety of Products** A very wide variety of products were donated: for example, there were 71 types of chocolate donated and 63 types of pasta. A total of 1799

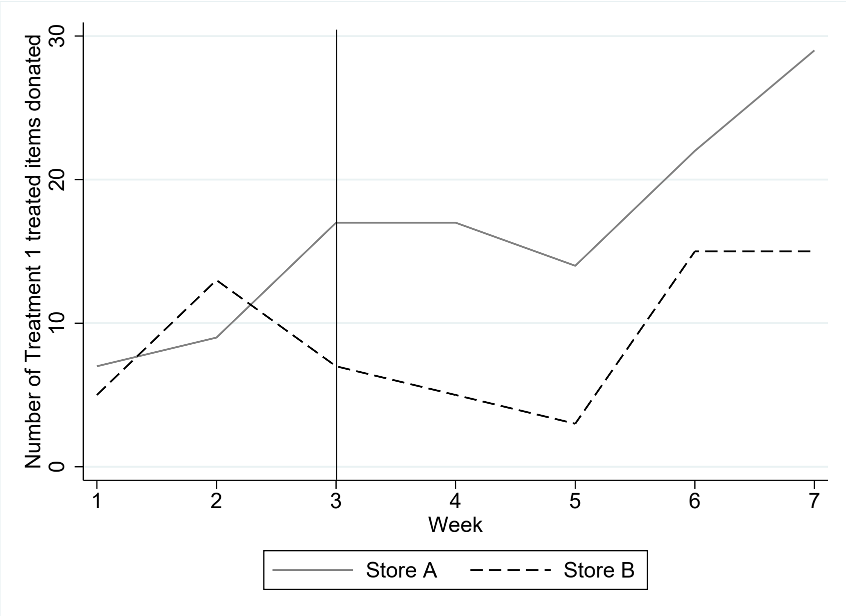


Figure 2.4: Number of items treated in Treatment Ticket donated in each store. The vertical line indicates the start of the treatment period for our analysis. The true start date is between week 3 and 4.

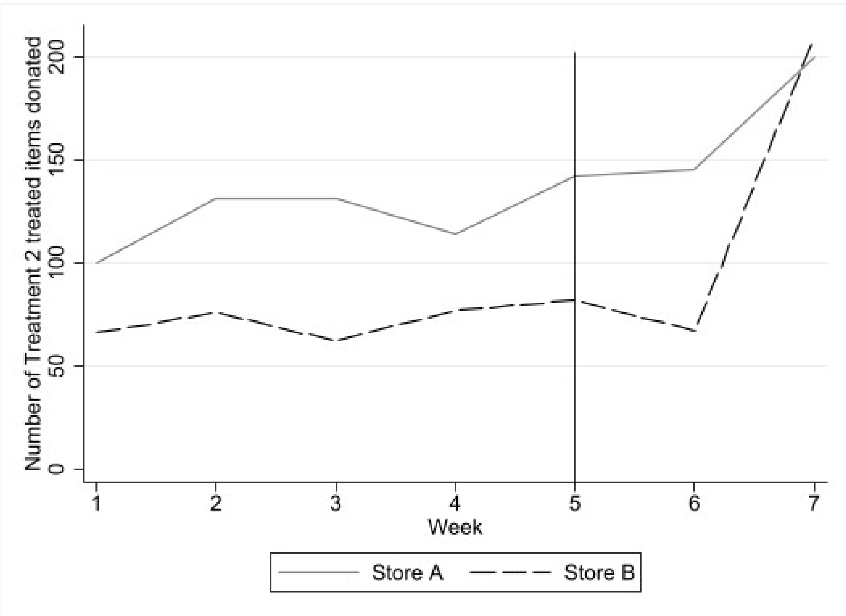


Figure 2.5: Number of items treated in Treatment Talker donated in each store. The vertical line indicates the start of the treatment period for our analysis. The true start date is between week 5 and 6.

Table 2.2: Summary statistics for the count of treated donations in each store

| Weekly Donations | | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| | Total | 7 | 231.14 | 44.64 | 180 | 312 |
| Shop A | Ticket Treated Items | 7 | 16.43 | 7.52 | 7 | 29 |
| | Talker Treated Items | 7 | 93.57 | 15.88 | 74 | 114 |
| | Total | 7 | 146.29 | 72.07 | 86 | 301 |
| Shop B | Ticket Treated Items | 7 | 9.00 | 5.16 | 3.00 | 15 |
| | Talker Treated Items | 7 | 55.00 | 26.65 | 20 | 92 |

Table 2.3: Summary statistics for the proportion of branded items donated

| **Variable** | Obs | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|
| Store A | 7 | 0.559 | 0.069 | 0.469 | 0.668 |
| Store B | 7 | 0.615 | 0.077 | 0.5 | 0.729 |
| Combined | 14 | 0.587 | 0.076 | 0.469 | 0.729 |

unique barcodes were recorded during the collection period. These were matched up to product characteristics online or manually from items in store. Around 121 barcodes could not be found, representing 9.64% of the sample. 38.64% of found barcodes were the supermarket's own brand products. 56.78% were other brands of products. This represents around 95% of the matched barcodes. The remaining 5% of barcodes came from other supermarket chains and are excluded from the analysis. 2630 items were branded or own-brand. 66 items were definitely from other supermarket chains. The items were classified into 1 of 57 product categories based on FoodBank product groups. The most popular product category for donation over the period is soup with 237 donations.

**Brands** Some items are branded items: they are an outside brand that the store buys in for retail, and the others are the store's own packaging and are "own brand" items. The former tends to be associated with more premium quality than the latter. Table 2.3 examines the number of donations which were branded as a proportion of the donations, as opposed to the supermarket's own-brand. The proportion of own-branded items donated varies from 0.47 to 0.73 during the collection period (see Figure 2.6). A Kruskal Wallis equality of populations test reports a p-value of 0.1797 indicating that there is no statistical difference between the two stores.

**Necessities** Product categories have been allocated into groups depending on whether they are luxury, normal or inferior goods (available in Appendix 2.B). This

Table 2.4: Summary statistics for the proportion of necessity items donated

| **Variable** | Obs | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|
| Store A | 7 | 0.600 | 0.045 | 0.536 | 0.672 |
| Store B | 7 | 0.527 | 0.078 | 0.407 | 0.643 |
| Combined | 14 | 0.563 | 0.072 | 0.407 | 0.672 |

tends to be a composite of both the product type and its branding. Some items are necessities such as shampoo, however if a shampoo is a premium brand it could be considered a luxury. It is also relative to a person's own income and wealth level – an item considered a necessity for some might be a luxury for others. In order to remove this level of subjectivity, where possible, income elasticities have been found for products to allocate them into the necessity group or non-necessity group, see Appendix 2.B. Table 2.4 shows the summary statistics for the proportion of necessity items donated in each store and Figure 2.7 shows how this changed over the course of the experiment.

## 2.5 Results

### 2.5.1 Characterising Donation Behaviour

Our first results section reveals our findings about the level and type of donations through this channel, and the effect of the lead up to Christmas on donations.

**Result 2.1** *There is a change in the types and number of items donated towards Christmas*

*Support:* Using a negative binomial regression, controlling for store and week, we estimated the Christmas effect as the time trend (in the approach to Christmas) on untreated product categories. We found a statistically significant positive time trend for biscuits, chocolate, rice and sanitary ware. Although festive items (i.e. advent calendars, Christmas puddings, mince pies) had the largest coefficient, is is not statistically significant (see Table 2.5). These results suggest that there is an increase in donations of sweet treats as well as an increase in donation of certain essentials. This could be interpreted as increasing motivations for donations in two ways: if it is a product that a donor would buy themselves and enjoy (such as a sweet treat), the warm glow of giving could well be higher when donating an treat-type item. Christmas is typically a time when consumers indulge in sweet items and gift giving behaviour. On the other hand, Christmas can also traditionally be a time to be reflective and thankful, which could make others' unfortunate circumstances more salient. This could motivate the increase donations of necessity items.

Table 2.5: Christmas Trend estimation for product categories

| VARIABLES | Baby | Biscuit | Chocolate | Condiment | Crisps | Deodorant | Drink | Festive | House | Oats | Rice | Snack | Sanitary |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Store A | -0.659 | -0.0166 | 0.964*** | 0.372 | -0.117 | 1.874*** | -0.629 | 0.0718 | 0.610 | 0.788*** | 1.223*** | 0.215 | -0.363 |
| | (0.722) | (0.279) | (0.330) | (0.380) | (0.557) | (0.636) | (0.419) | (0.878) | (0.511) | (0.305) | (0.319) | (0.475) | (0.312) |
| Week | 0.230 | 0.268*** | 0.294*** | -0.0745 | -0.0301 | -0.0885 | 0.0875 | 0.694 | 0.0463 | -0.0470 | 0.325*** | 0.156 | 0.143** |
| | (0.253) | (0.0654) | (0.0975) | (0.0823) | (0.137) | (0.0891) | (0.115) | (0.460) | (0.130) | (0.0585) | (0.0820) | (0.126) | (0.0714) |
| Lnalpha | 0.421 | -1.789** | -1.188*** | -1.145* | -0.365 | -1.592 | -17.07*** | -1.080 | -2.425 | -23.14 | -1.699*** | -0.951** | -24.49 |
| | (0.630) | (0.784) | (0.389) | (0.628) | (0.486) | (1.228) | (0.441) | (2.221) | (3.438) | (0) | (0.421) | (0.462) | (0) |
| Constant | 0.287 | 0.973*** | 0.207 | 1.705*** | 1.199* | 0.470 | 0.397 | -3.002 | -0.346 | 0.540* | -0.520 | 0.191 | 0.575 |
| | (1.043) | (0.257) | (0.438) | (0.312) | (0.694) | (0.700) | (0.602) | (2.400) | (0.645) | (0.287) | (0.449) | (0.535) | (0.357) |
| Observations | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The number of own-brand items donated was always higher than the number of other branded items donated, however the number of own-brand products donated in the week before Christmas increased sharply (as can be seen in Figure 2.6). There was a consistent increase in the number of branded products donated each week, but there was a larger increase in own-brand items.

An exploratory hypothesis is that donation behaviour could be different in relation to different product types, based on their characteristics, such as whether they are considered a necessity item.

To explore this 'Christmas Effect' of buying more treats and less necessities, the products donated were categorised into necessity or non-necessity items. Figure 2.7 shows that necessities are donated more often than non-necessities across all time periods, but the number of non-necessity goods donated increases sharply towards Christmas to where it makes almost 50% of donations. We do not have enough data to estimate an interaction effect of time and necessity product type, but we might expect to see a stronger time trend for non-necessity products as a result of the reduced time distance to Christmas.

This could be due to a change in preferences of individuals around Christmas time, tending towards less 'basic' items and more luxury or 'treat' items like biscuits and chocolates, mince pies and other traditional foods. People like to buy things that they themselves might like to receive at Christmas time and this could be an example of that. This may also reflect an increase in generosity towards Christmas.

**Result 2.2** *Some products are over-donated while others are under-donated, leading to an inefficient donations mix*

*Support:* The ideal proportions of a 'typical' nutritionally-balanced FoodBank parcel for one person for 3 days would contain the following: cereal (1) soup (2) beans (2) tinned vegetables (2) meat (2) fish (1) fruit (2) pudding/custard (1) biscuits (1) pasta (1) tea/coffee (1) juice (1) and milk (1). In addition, resources permitting it would include a sauce (1) and chocolate (1). This makes a parcel of 22 items. Table 2.6 gives the ideal proportion of donations versus the proportion of donations which were actually received over the duration of the intervention. The 'Difference' column shows that the product that is the most under-donated relative to the ideal proportions is fruit, followed by tomatoes. The most over-donated items is pasta and rice. The fact that so many of the products have a negative difference is a result of the many items donated which do not feature on the ideal parcel list.

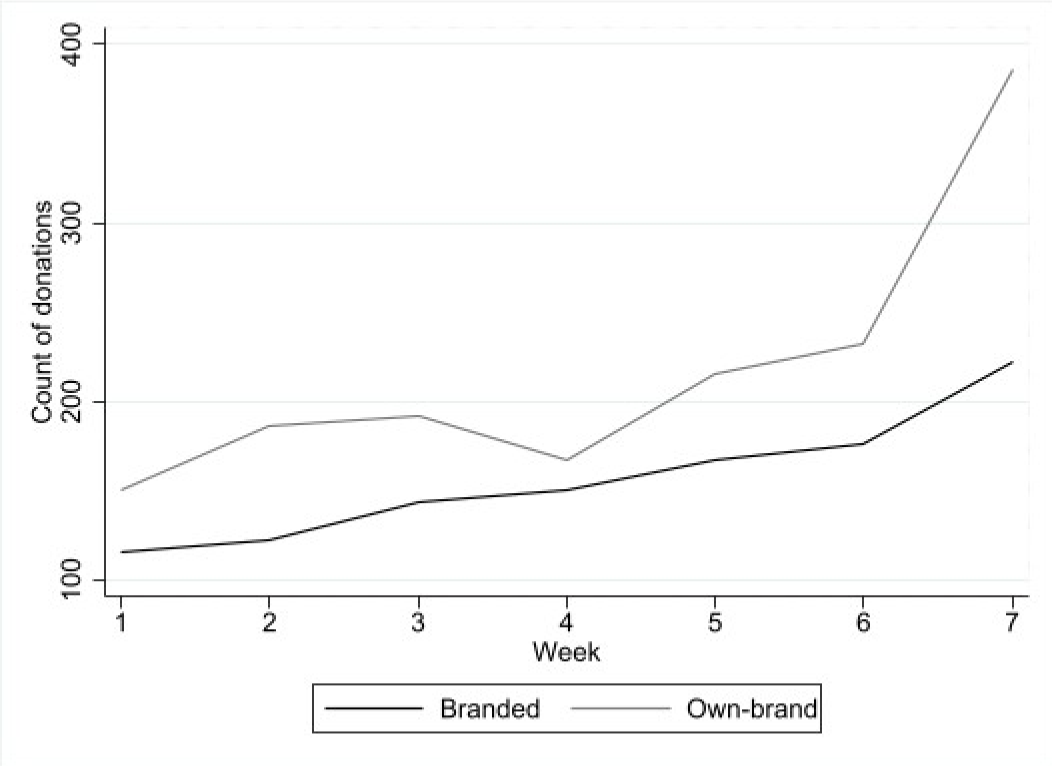


Figure 2.6: Line graph of weekly combined donations from both stores by brand

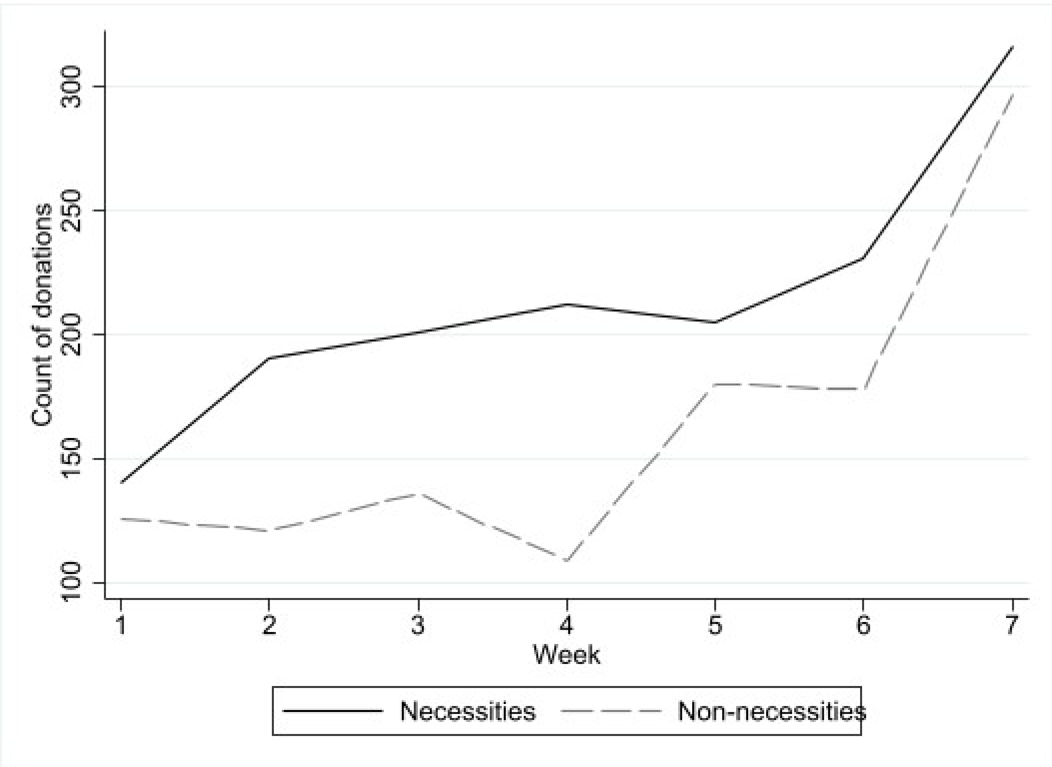


Figure 2.7: Line graph of combined donations to both stores by product necessity status

Table 2.6: Actual and ideal donation rates to the FoodBank

| Product | Ideal Units | Ideal (%) | Actual (%) | Difference |
|---|---|---|---|---|
| Cereal | 1 | 4.55 | 3.14 | -1.40 |
| Soup | 2 | 9.09 | 8.97 | -0.12 |
| Beans/hoops | 2 | 9.09 | 3.71 | -5.38 |
| Tomatoes | 2 | 9.09 | 2.23 | -6.86 |
| Vegetables | 2 | 9.09 | 6.93 | -2.16 |
| Meat | 2 | 9.09 | 6.43 | -2.66 |
| Fish | 1 | 4.55 | 2.42 | -2.12 |
| Fruit | 2 | 9.09 | 1.78 | -7.31 |
| Rice pudding/pudding/ custard | 1 | 4.55 | 5.83 | 1.28 |
| Biscuits | 1 | 4.55 | 4.69 | 0.15 |
| Pasta/rice | 1 | 4.55 | 9.95 | 5.41 |
| Tea/coffee | 1 | 4.55 | 3.26 | -1.29 |
| Juice | 1 | 4.55 | 1.40 | -3.15 |
| Milk | 1 | 4.55 | 2.65 | -1.90 |
| Sauces | 1 | 4.55 | 4.24 | -0.31 |
| Chocolate | 1 | 4.55 | 4.39 | -0.15 |
| Total | 22 | 100 | 72.03 | - |

Percentage of donations in each category received over the duration of the intervention across both stores.

### 2.5.2 Treatment Effects

We use DiD analysis to estimate the treatment effect sizes. The coefficient which gives the estimated treatment effect is 'DiD'.

**Result 2.3** *Both information campaigns increase the number of treated category items donated overall*

*Support:* In Treatment Ticket, there is an overall positive and statistically significant effect of the treatment at the aggregated category level as seen in Table 2.7. The effect size of this is comparable to being 4 weeks closer to Christmas, as estimated in the same table with the week coefficient. Also, for Treatment Talker, aggregating all 10 product categories, the DiD estimator is statistically significant (Table 2.8). The DiD estimator has a coefficient of 0.555. This means that for when the treatment occurs, the expected log count of the number of donations of treated items increases by 0.555. In count terms this implies an increase of 1.74 units per collection, post treatment.

**Result 2.4** *The information campaign has heterogeneous effects on the donation of treated high demand categories*

*Support:* In Treatment Ticket, no individual category can report a statistically significant treatment effect (Table 2.7).However, in Treatment Talker, 4 of the categories had significant positive treatment coefficients (see Table 2.8). The DiD estimator is significant in the Tinned Vegetables, Fish, Meat and Soup categories. For the milk and juice categories in Treatment Talker, a within-store estimation is used (see Section 2.4 for an explanation). We find a negative treatment effect on the donation of milk and juice at the category level from Treatment Talker, given in Table 2.9.

Table 2.7: Category level regressions for Treatment Ticket

| VARIABLES | Total | Milk | Juice | Pud | Custard |
|---|---|---|---|---|---|
| Treated | -0.201 | 1.614* | 1.386** | -0.697 | -0.767 |
| | (0.219) | (0.847) | (0.645) | (0.772) | (0.726) |
| DiD | 0.894*** | 0.951 | -0.288 | 0.623 | 0.607 |
| | (0.257) | (0.937) | (0.707) | (0.916) | (0.714) |
| Time | -0.729*** | 0.915 | 1.707** | -0.000354 | -2.895*** |
| | (0.250) | (0.878) | (0.758) | (0.639) | (0.830) |
| Week | 0.189*** | -0.256 | -0.298*** | 0.0194 | 0.565*** |
| | (0.0290) | (0.218) | (0.0898) | (0.199) | (0.155) |
| Lnalpha | -18.19*** | -4.074 | -17.19*** | -1.568 | |
| | (0.298) | (2.658) | (0.363) | (1.510) | |
| Constant | 2.110*** | -0.318 | -0.257 | 1.071*** | 1.007* |
| | (0.204) | (0.716) | (0.642) | (0.380) | (0.553) |
| Observations | 14 | 10 | 10 | 14 | 14 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: For the Milk and Juice regressions, the final two weeks of treatment were dropped from analysis due to the equivalent product categories being treated in Store B in those weeks. The All category does not drop these final weeks.

Table 2.8: Category level in Treatment Talker

| VARIABLES | Total | Pasta | Tin | Beans | Coffee | Tea | Meat | Fish | Soup |
|---|---|---|---|---|---|---|---|---|---|
| Time | -0.138 | 0.151 | -0.112 | -0.128 | -1.064 | 0.216 | -0.534 | 0.413 | -0.192 |
| | (0.170) | (0.369) | (0.454) | (0.217) | (1.252) | (0.417) | (0.374) | (0.457) | (0.271) |
| Treated | -0.841*** | 0.0486 | -1.306*** | -1.269*** | -0.693 | -0.999** | -0.434*** | -2.600*** | -1.161*** |
| | (0.128) | (0.219) | (0.353) | (0.425) | (1.020) | (0.419) | (0.163) | (0.596) | (0.220) |
| DiD | 0.555*** | -0.511 | 1.132*** | 0.629 | 1.674 | 0.464 | 1.018*** | 1.821** | 0.909*** |
| | (0.136) | (0.339) | (0.434) | (0.455) | (1.095) | (0.449) | (0.300) | (0.731) | (0.239) |
| Week | 0.111*** | 0.168** | 0.0255 | 0.154*** | 0.524 | 0.143 | 0.0575 | -0.0681 | 0.0972 |
| | (0.0386) | (0.0721) | (0.103) | (0.0584) | (0.353) | (0.0912) | (0.0758) | (0.155) | (0.0610) |
| Lnalpha | -49.89 | -4.186*** | -2.364*** | -21.40 | -17.00*** | -17.82*** | -40.65 | -4.054 | -17.95*** |
| | (0) | (1.194) | (0.893) | (0) | (1.117) | (1.238) | (0) | (3.361) | (0.808) |
| Constant | 4.139*** | 1.813*** | 2.797*** | 1.679*** | -2.167 | 1.187** | 2.457*** | 2.074*** | 2.784*** |
| | (0.104) | (0.260) | (0.405) | (0.157) | (1.489) | (0.536) | (0.182) | (0.562) | (0.150) |
| Observations | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 |

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: Milk and Juice categories cannot be analysed using the same control group as the other categories, as the Milk and Juice categories were simultaneously treated in Store A. Therefore, within-store analysis is given in Table 2.9

**Result 2.5** *The information campaign has heterogeneous effects on donations of high demand items on the treated shelves*

*Support:* At the shelf level, our analysis shows no overall treatment effect, but large negative treatment effects for Milk and Juice shelves for Treatment Ticket. The shelf tickets were displayed below long-life own brand 1 litre semi skimmed milk, and long life own brand orange juice with bits. There was no effect seen at the category level on these items, which indicates that there was a shift within the category away from the ticketed items towards other items in the same category.

For Treatment Talker, there is a strong negative effect on Pasta. Using the within-store analysis at the shelf level, there is a strong and large positive effect on Milk, the opposite to Treatment Ticket. There is no clear effect on Juice at the shelf level.

A partial explanation for the differences between product types is that there were many varieties of pasta so those on the shelf represent a smaller selection of the set of choices in the category than for milk. There were not many varieties of long-life milk and the talker was placed on the shelf of the type of long-life milk that is most often donated: semi-skimmed 1 litre own-brand. These two opposite directional effects mean that no overall effect can be found at the aggregated shelf level.

Table 2.12 shows the results of the analysis at the image level - the products depicted on the shelf talkers in Treatment Talker. There is generally a negative effect of the treatment. In the Pasta and Tea categories, there was a highly statistically significant negative effect of the treatment on the count of donations, of a magnitude larger than any other effect in the regressions. Looking at the within-store estimation for the milk and juice categories in Table 2.9 the regression output is very similar to that of the analysis at shelf level, due to the sets of items being very similar. We again find a large positive treatment effect for Milk, but no effect for juice. The size of the effect is very large, and therefore must be taken with caution.

**Result 2.6** *The information campaign had no spillover effects onto the donation of other products categories*

*Support:* As can be seen in Table 2.13, using the count of untreated items (at the category level) there is no positive effect of the Treatments. This implies that the information campaign did not lead to the donation of items which were not in the categories that they were highlighted. In fact, for Treatment Ticket there is a negative treatment effect on the number of untreated items donated - taken with the positive overall treatment effect of Treatment Ticket on the count of treated

Table 2.9: Within-store estimations for milk and juice shelf and image level for Treatment Talker

| VARIABLES | Milk (Shelf) | Milk (Image) | Juice (Shelf) | Juice (Image) |
|---|---|---|---|---|
| Time | -0.346*** | -0.346*** | 0.258 | 0.305 |
| | (0.131) | (0.131) | (0.423) | (0.409) |
| Treated | -21.37*** | -21.37*** | -5.256*** | -5.253*** |
| | (0.552) | (0.538) | (0.842) | (0.847) |
| DiD | 17.13*** | 17.13*** | 0.273 | 0.964 |
| | (0.638) | (0.638) | (1.215) | (1.050) |
| Week | 0.246*** | 0.246*** | 0.131 | 0.119 |
| | (0.0379) | (0.0379) | (0.110) | (0.106) |
| Lnalpha | -5.593*** | -5.593*** | -2.705*** | -2.701*** |
| | (1.826) | (1.826) | (0.382) | (0.384) |
| Constant | 3.380*** | 3.380*** | 3.529*** | 3.558*** |
| | (0.147) | (0.147) | (0.281) | (0.270) |
| Observations | 14 | 14 | 14 | 14 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Using the set of non-essential goods for juice and the set of essential goods for milk as the control groups.

Table 2.10: Regressions at Shelf Level for Treatment Ticket

| VARIABLES | Pud | Custard | Juice | Milk | All Shelves |
|---|---|---|---|---|---|
| Treated | 19.08*** | -0.693 | 17.55*** | 16.79*** | 1.381*** |
| | (2.478) | (0.567) | (0.953) | (0.933) | (0.268) |
| DiD | -0.319 | 0.470 | -16.67*** | -14.85*** | -0.206 |
| | (0.636) | (0.758) | (1.085) | (0.767) | (0.386) |
| Time | -1.326 | -2.272* | 16.78*** | 13.98*** | -0.497 |
| | (1.927) | (1.288) | (0.769) | (1.233) | (0.414) |
| Week | 0.373* | 0.573** | 0.101 | 0.644*** | 0.398*** |
| | (0.220) | (0.240) | (0.128) | (0.193) | (0.0832) |
| Lnalpha | -30.64 | -31.11 | -34.94 | -1.952*** | -3.842** |
| | (0) | (0) | (0) | (0.585) | (1.664) |
| Constant | -19.66*** | -0.900** | -17.29*** | -17.83*** | -0.615*** |
| | (2.112) | (0.447) | (0.673) | (0.633) | (0.196) |
| Observations | 14 | 14 | 14 | 14 | 14 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.11: Regressions at Shelf Level for Treatment Talker

| VARIABLES | Pasta | Soup | Milk | Juice | All Shelves |
|---|---|---|---|---|---|
| Treated | 15.81*** | -0.223 | -17.54*** | -1.099 | -0.635 |
| | (0.965) | (0.678) | (0.646) | (0.837) | (0.392) |
| DiD | -17.19*** | -1.163 | 15.81*** | 0.693 | -0.806 |
| | (1.312) | (0.762) | (0.817) | (1.209) | (0.653) |
| Time | 18.85*** | -0.116 | 0.445 | -0.547 | 0.519 |
| | (1.060) | (0.875) | (0.689) | (0.636) | (0.526) |
| Week | -0.191 | 0.255 | 0.397* | 0.243 | 0.274** |
| | (0.228) | (0.192) | (0.240) | (0.218) | (0.133) |
| Lnalpha | -109.6 | -16.33*** | -2.330*** | -21.41 | -3.376*** |
| | (0) | (0.439) | (0.678) | (0) | (1.240) |
| Constant | -16.74*** | -0.455 | -0.866 | -0.933 | 0.456 |
| | (0.676) | (0.745) | (0.867) | (0.804) | (0.436) |
| Observations | 14 | 14 | 14 | 14 | 14 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.12: Regressions at Image level for Treatment Talker

| Variables | Pasta | Tinned Veg | Fish | Meat | Tea | All Images |
|---|---|---|---|---|---|---|
| Treated | 17.25*** | -18.33*** | -14.89*** | -0.841 | 16.77*** | -1.127*** |
| | (0.542) | (1.029) | (1.079) | (0.610) | (0.698) | (0.343) |
| DiD | -17.94*** | -3.431*** | -1.598 | 1.402 | -36.50*** | 0.121 |
| | (0.959) | (1.218) | (1.336) | (0.901) | (1.306) | (0.514) |
| Time | 18.03*** | -0.582 | -0.242 | -0.0974 | 15.18*** | 0.229 |
| | (1.050) | (2.109) | (1.809) | (1.116) | (1.683) | (0.658) |
| Week | 0.142 | 0.280 | 0.484 | -0.0477 | 0.560 | 0.201 |
| | (0.265) | (0.576) | (0.377) | (0.266) | (0.369) | (0.133) |
| Lnalpha | -2.488 | -0.155 | -19.85*** | -2.739 | -22.28 | -2.962*** |
| | (4.955) | (1.099) | (0.564) | (3.835) | (0) | (0.754) |
| Constant | -17.90*** | -0.549 | -2.738** | 0.673 | -19.05*** | 1.400*** |
| | (1.057) | (1.647) | (1.390) | (0.819) | (1.311) | (0.304) |
| Observations | 14 | 14 | 14 | 14 | 14 | 14 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The treated product types which do not appear in this table were omitted either due to no donation of that product during the experiment or as the model could not converge to a solution due to the low amount of data. Milk does not appear here due to using a within-store control which did not yield significant results.

Table 2.13: Regressions for spillover effect on untreated items

| VARIABLES | T1 Total Spillover | T2 Total Spillover | All Shelves T1 | All Shelves T2 | T2 All Images |
|---|---|---|---|---|---|
| Treated | 0.752*** | -0.527*** | 0.688*** | -0.654*** | -0.641*** |
| | (0.0129) | (0.104) | (0.0262) | (0.0708) | (0.0674) |
| Did | -0.350*** | 0.194 | -0.276** | 0.376** | 0.359** |
| | (0.113) | (0.281) | (0.114) | (0.178) | (0.180) |
| Time | 0.00754 | -0.151 | -0.0323 | -0.200 | -0.197 |
| | (0.127) | (0.223) | (0.128) | (0.183) | (0.178) |
| Week | 0.155*** | 0.129** | 0.153*** | 0.126*** | 0.127*** |
| | (0.0464) | (0.0518) | (0.0462) | (0.0395) | (0.0387) |
| Lnalpha | -4.074*** | -3.138*** | -4.078*** | -4.116*** | -4.103*** |
| | (0.589) | (0.528) | (0.577) | (0.560) | (0.573) |
| Constant | 4.230*** | 4.459*** | 4.320*** | 4.980*** | 4.960*** |
| | (0.0705) | (0.122) | (0.0736) | (0.0838) | (0.0835) |
| Observations | 14 | 14 | 14 | 14 | 14 |

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

items donated, this gives some evidence that there is a crowding out of untreated donations.

**Result 2.7** *There is an increase in donation levels towards Christmas*

*Support:* The FoodBank usually receives an increase in donations in the lead up to Christmas. Looking at the week variable for the regressions on treated categories in Table 2.7 and Table 2.8, there is a relatively small but significant negative effect on the donation of the treated categories towards Christmas. For Treatment Talker, there is a small but positive effect of week on number of treated donations as was expected. In Table 2.13, there is a strongly significant effect of week on the number of items donated at both stores, for Treatment Ticket the coefficient represents a 4.7 unit increase per week, and for Treatment Talker a 3.6 unit increase per week. This positive time trend was expected, as donations increased in both stores over the experiment as can be seen in Figure 2.3.

### 2.5.3 Robustness Checks

As the treatment did not occur on a collection day, an additional robustness check is to use the week after as the starting point for the intervention in the estimation, rather than the week before. Our initial chosen start date was a cautious approach which would understate the effect of the treatment if there was one. In using the alternate start date, it is possible that the effect could be overstated.

Table 2.14: Alternate treatment start date regressions for Treatment Ticket Categories

| VARIABLES | Total | Pud | Custard | Milk | Juice |
|---|---|---|---|---|---|
| Treated | 0.278 | -1.205 | -0.579 | 1.891*** | 1.609*** |
| | (0.283) | (0.871) | (0.820) | (0.545) | (0.490) |
| DiD | 0.492 | 1.440 | 0.407 | 0.985 | -0.916 |
| | (0.344) | (0.983) | (0.911) | (1.134) | (0.631) |
| Time | -0.938** | 0.354 | -2.048 | -0.956 | -0.0331 |
| | (0.435) | (0.587) | (1.276) | (1.297) | (0.626) |
| Week | 0.298*** | -0.135 | 0.458** | 0.277 | 0.348** |
| | (0.0643) | (0.181) | (0.208) | (0.394) | (0.167) |
| Lnalpha | -20.58 | -3.087 | -0.966 | -1.688*** | -17.34*** |
| | (0) | (3.525) | (0.607) | (0.586) | (0.245) |
| Constant | 1.494*** | 1.469*** | 0.704 | -0.981 | -1.140* |
| | (0.288) | (0.375) | (0.718) | (1.013) | (0.674) |
| Observations | 14 | 14 | 10 | 10 | 14 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We estimate the effect at the category level, given that this is the level at which most treatment effects are visible. Table 2.14 has no statistically significant coefficient on the DiD estimators in Treatment Ticket. For Treatment Talker, the estimated coefficients support our previous results that Treatment Talker has a visible treatment effect at the aggregated category level but that Treatment Ticket does not. Further estimation at the shelf and image level removes the significance of surprising results such as the statistically significant negative effect for the depicted Tinned Vegetables and the very large significant negative coefficient for depicted Tea and pasta items. However, there are instead significant negative effects on the Fish and Meat categories. This shows that our results are very sensitive to changes in the week start date. This is likely because for Treatment Talker, moving the start date leads to there being only one post-treatment observation.

Table 2.15: Alternate treatment start date regressions for Treatment Talker categories

| VARIABLES | Total | Milk | Juice | Pasta | Tin | Beans | Coffee | Tea | Meat | Fish | Soup |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Time | -0.126 | 0.248 | 0.0744 | 0.355 | -1.244*** | -0.152 | -0.132 | 0.232 | -0.201 | 0.164 | -0.0411 |
| | (0.197) | (0.716) | (0.403) | (0.279) | (0.344) | (0.214) | (0.678) | (0.261) | (0.380) | (0.377) | (0.207) |
| Treated | -0.687*** | -2.330*** | -1.163*** | 0.0381 | -1.046*** | -1.030*** | -1.099 | -0.654* | -0.293* | -2.169*** | -0.981*** |
| | (0.119) | (0.519) | (0.340) | (0.172) | (0.288) | (0.301) | (0.991) | (0.373) | (0.163) | (0.489) | (0.196) |
| Did | 0.433*** | 0.907 | 0.652 | -0.689* | 1.083*** | 0.336 | 2.485** | -0.0837 | 0.986*** | 1.593** | 0.810*** |
| | (0.129) | (0.554) | (0.678) | (0.357) | (0.296) | (0.375) | (1.037) | (0.398) | (0.352) | (0.646) | (0.202) |
| Week | 0.116** | 0.182 | 0.109 | 0.136*** | 0.240** | 0.176*** | 0.193 | 0.180 | -0.00851 | -0.00851 | 0.0712 |
| | (0.0521) | (0.185) | (0.0782) | (0.0504) | (0.117) | (0.0588) | (0.225) | (0.122) | (0.0559) | (0.139) | (0.0544) |
| Lnalpha | -6.771 | -3.262 | -15.56*** | -5.465 | -2.603*** | -25.72 | -16.42*** | -15.99*** | -17.54*** | -3.671 | -27.42 |
| | (7.337) | (2.468) | (0.892) | (3.565) | (0.919) | (0) | (1.286) | (3.983) | (1.894) | (2.364) | (0) |
| Constant | 4.109*** | 1.243** | 0.824** | 1.895*** | 2.208*** | 1.570*** | -1.127 | 1.038 | 2.559*** | 1.971*** | 2.816*** |
| | (0.167) | (0.617) | (0.347) | (0.253) | (0.501) | (0.196) | (1.004) | (0.665) | (0.182) | (0.595) | (0.186) |
| Observations | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 |

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

## 2.6 Discussion and Conclusion

There are inefficiencies in the donation of tangible items to charities. As an organisation which relies on tangible donations, FoodBanks are susceptible to such inefficiencies. Ultimately this means that they cannot help people as effectively as they could otherwise. For potential donors, being unaware of what is needed can be an obstacle to donation. However, tangible donations are a popular method of giving. Shifting donations between categories of tangible donations is a smaller behavioural change than trying to move donations towards pecuniary donations. Reminders to give have been researched before but focused on cash donations. Their effects on tangible donations of in-kind goods has not been studied. Using a quasi-experimental design across two UK supermarket stores, we implemented a targeted information campaign. The two treatments differed by the size, colour, content and number of tickets/talkers placed in the supermarket. We estimate their effect on the type and level of tangible donations through a DiD analysis.

It was hypothesized that the information campaign would increase donations of the items they highlighted, but the level (category, shelf or individual item) at which this effect might be visible was unknown. It was also unknown whether there would be spillover effects of the treatment onto other items in store: if the information campaign was successful in reminding people about the existence of the FoodBank it is possible that overall donations of other products would also increase. An alternative hypothesis was that we would observe a crowding-out of other donations as donors moved towards the treated item types. We found that the effect of the information campaign was seen primarily at the product category level, as an increase in the overall level of high demand items donated. However, this effect was not seen on all of the categories which were treated - the treatment effect was heterogeneous across categories. We conducted robustness checks using an alternate week start date, which supported our findings that the treatment effect was heterogeneous across product types. No evidence for a spillover effect on donations of non-treated items was found. However, we did find evidence for crowding out of donations through a decrease in the number of untreated items donated and an increase in the number of treated items donated in Treatment Ticket.

The treatment effects, where found, were for the most part relatively small – this was surprising given the threefold increase in donations reported in national media for a similar scheme in Exeter (Amofa, 2018). The heterogeneous effects found on different categories was surprising - particularly the negative treatment effects. However, our robustness check of using the alternate start week eliminated the significance of most of these anomalous results - leading us to believe that the effect is not robust.

We find that proximity to Christmas changes the types of donations made, with a rise in chocolate, biscuits, sanitary ware and rice. We see an overall increase in donations, but see a larger increase in own-brand and non-necessity items towards Christmas.

It quickly became apparent that the variety of items donated to the FoodBank is incredibly wide and highly variable - this made the comparisons of trends difficult. As no research of this scope had previously been conducted at this level, the variability of donations was unknown.

Other control variables would make this analysis more robust, however, due to the superstore nature of these stores, local demographic data might not be representative of who shops there – customers likely travel to go to these stores. Data about the stores themselves is not publicly available.

Another measurement issue is the fact that some items donated came from outside of the store. When these are clearly not store-bought items (i.e. they are marked as from a different supermarket) they have been removed from the data, as this study is concerned with the effect of in store signage on in store donations. However, when these items were branded items which the supermarket also stocks, it is impossible to determine whether these have been bought inside the store or brought in from outside. This has the effect of potentially underestimating the effect of the treatment: as outside donations are assumed to be unaffected by the in-store information campaign. This was mitigated by removing the products which were definitely from outside the store (such as other supermarket own brands). There could be other exogenous effects from FoodBank promotional work in the run up to the Christmas period, such as the 'reverse advent calendar'[4] and their volunteer presence in other supermarkets.

The ideal dataset to test this would have a larger number of stores measured over a longer time frame. However, we were constrained by the fact that Norwich only has 2 comparable supermarkets of this chain and the presence of Christmas in the week of the final collection - it was expected that this would have strongly influenced the data.

The fact the supermarket did not share product information not only reduced the accuracy of included products, but also meant that other key variables such as price and weight/size of item were not recorded. This means that it cannot be known if the value of the items donated increased towards Christmas or if there was

[4]This was a set of posts on social media aimed at encouraging people to donate one item to the FoodBank each day during the period 1st December-25th December.

a treatment effect on the donation of multi-packs.

Having established that there were no within-store spillover effects of the treatment, a within-store control was used to meausre the treatment effect on milk and juice for Treatment Talker. This eliminated noise from store-level unobservable characteristics. The control used is based on product characteristics of the treated items: whether they are necessity or non-necessity items. The results indicated that the treatments have large negative effects on the number of donations of products from these categories. This unexpected finding reduces confidence in the within-store control method for this experiment.

The finding that any effect seen was at the product category level lends itself to the explanation that people desire to have some autonomy over the item they donate – whether this is due to price or personal preferences. The ability to choose could influence the utility derived from donating. Further investigations on the motivations of tangible donation behaviour could uncover interesting regularities in this under-researched field.

To counteract the uncertainty around whether customers saw the information campaign or not, a practical solution would be to use either smaller stores or bigger signs – or a combination of the two. Drawing more attention to the campaign during the store visit would also make the signs more salient and noticeable.

The field of tangible donations has clearly not yet been given the attention of its pecuniary counterpart. In a time where the 'sharing economy' is beginning to take shape and greater emphasis is put on reducing waste, reusing items and sharing resources, understanding what can influence tangible donation behaviour may be more important than ever. It appears that in this context, reducing information asymmetries about the most needed items has only a limited effect. Targeted messaging to those who are already interested in the cause might be of greater effect.

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# Appendices

## 2.A Proportions of Treated Donations Graphs

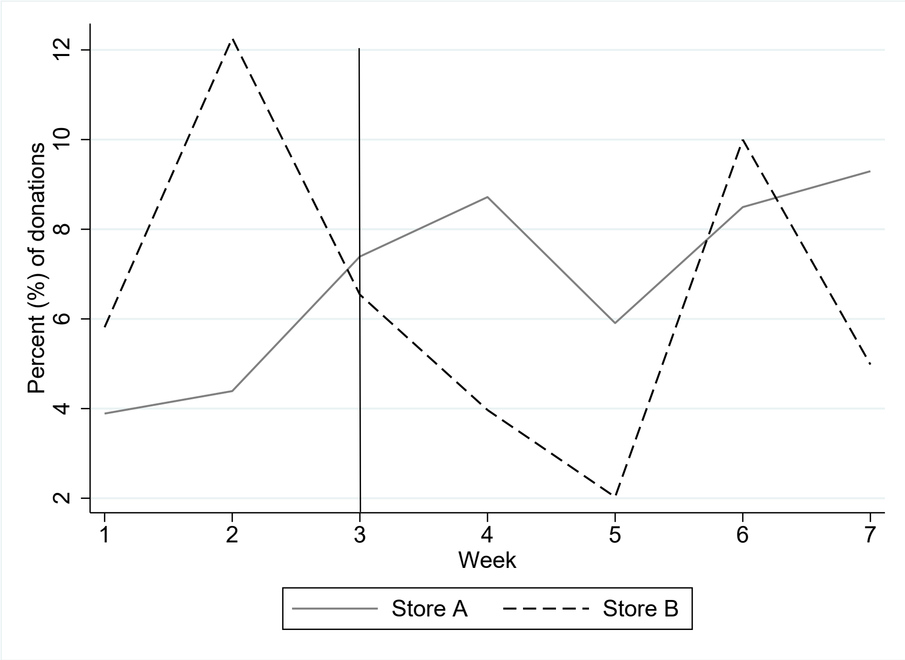


Figure 2.8: Percentage of items treated in Treatment Ticket donated.
The vertical line indicates the start of the treatment period for our analysis. The true start date is between week 3 and 4.

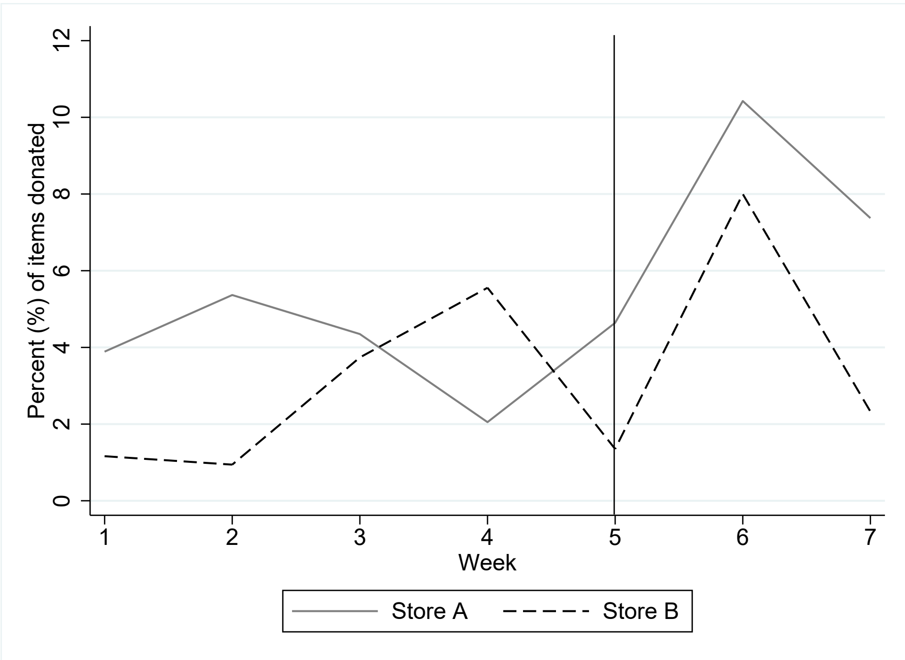


Figure 2.9: Percentage of items treated in Treatment Talker donated.
The vertical line indicates the start of the treatment period for our analysis. The true start date is between week 5 and 6.

## 2.B Allocation of products to necessity groups

Table 2.16: Elasticities of Product Categories

| Product Type | Estimated category | YED value | Implication | Source |
|---|---|---|---|---|
| Baby products (food, nappies) | | Inelastic | Necessity | |
| Tinned Beans | Beans | 0.7642 (0.2055) | Necessity | Yang et. al (2019) |
| Biscuits | Fats and starches (includes sweets) | 1.078 | Luxury good | Tiffin et al. (2011) |
| Bread Products | Bread in Slovakia | 0.9609715 | Necessity | Benda-Prokeinova & Hanová (2016) |
| | | Inelastic | Necessity | |
| Breakfast Cereal | | | Necessity | |
| Cheese Products | Dairy, egg and cheese | 0.896 | Necessity | |
| Chocolates | Sweets | 1.015 | Luxury good | Tiffin et al. (2011) |
| Coffee | Coffee | 1.019-1.167 | Luxury good | Tiffin et al. (2011), Klonaris (2011) |
| Condiments | Flavour in Slovakia | 0.7434021 | Necessity | Klonaris (2011) |
| Crisps | Chips | 0.132 | Necessity | Hoffer et al. (2015) |
| Custard | Sweets | 1.015 | Luxury good | Tiffin et al. (2011) |
| Deodorant | | Inelastic | Necessity | |
| | | Inelastic | Necessity | |
| Soft drinks | Cola | 0.042 | Necessity | Hoffer et al. (2015) |
| Festive Products | Candy | 0.105 | Luxury good | Hoffer et al. (2015) |
| Fish | Blue fish | 0.525 | Necessity | Tiffin et al. (2011) |
| Flour | Fats and starches | 1.074 | Luxury good | Tiffin et al. (2011) |
| Fruit | Fruit and nuts | 0.872 | Necessity | Tiffin et al. (2011) |
| Non- Food Household Items | | Inelastic | Necessity | |
| Instant mash | Potatoes in Slovakia | 0.478 | Necessity | Benda-Prokeinova & Hanová (2016) |
| Jelly | Candy | 0.105 | Necessity | Hoffer et al. (2015) |
| Fruit Juice | Juice | 0.717 | Necessity | Tiffin et al. (2011) |
| Kidney Beans | Beans | 0.7642 | Necessity | Yang et al. (2019) |
| Meat | Depends on quality | | Necessity | |
| Milk (Long-life) | Mixed evidence | | Necessity | |
| Nuts | Fruit and nuts | 0.872 | Necessity | Tiffin et al. (2011) |
| Oats | | | | |
| Pasta | | | | |
| Potato products | Potatoes in Slovakia | 0.478 | Necessity | Benda-Prokeinova & Hanová (2016) |
| Puddings | Candy | 0.105 | Luxury good | Hoffer et al. (2015) |
| Rice | Rice in Slovakia | 0.207 | Necessity | Benda-Prokeinova & Hanová (2016) |
| Rice pudding | Candy | 0.105 | Luxury good | Hoffer et al. (2015) |
| Cooking Sauces | Tinned fruit and veg | 0.377-0.578 | Necessity | Tiffin et al. (2011) |
| shampoo | | Inelastic | Necessity | |
| Snacks | Chips | 0.132 | Necessity | Hoffer et al. (2015) |
| Soap products | | Inelastic | Low YED | |
| Soup | Tinned fruit and veg | 0.377-0.578 | Necessity | Tiffin et al. (2011) |
| Squash (drink concentrate) | Cola | 0.042 | Necessity | Hoffer et al. (2015) |
| Sugar | Sugar in Iran | 0.8 | Necessity | Soleimany & Babakhani (2012) |
| Sweet milks | Fats and starches | 1.074 | Luxury good | Tiffin et al. (2011) |
| Sweets | Candy | 0.105 | Luxury good | Hoffer et al. (2015) |
| Tampons | | Inelastic | Necessity | |
| Tea | Black tea | 0.547 | Necessity | Klonaris (2011) |
| Dental Hygiene | | Inelastic | Necessity | |
| Tinned Goods | Tinned fruit and veg | 0.377-0.578 | Necessity | Tiffin et al. (2011) |
| Tomato (tinned and boxed) | Tinned fruit and veg | 0.377-0.578 | Necessity | Tiffin et al. (2011) |
| Sanitary Towels | | Inelastic | Necessity | |
| Wash products (shower gel etc.) | ‘ | Inelastic | Necessity | |

Where sources were not available, the closest alternative was found or otherwise the status of the product was chosen subjectively.

## 2.C An example of the products contained in a FoodBank parcel

**Food Allocation Form: One Person**

| Volunteer: | Voucher No: | Date: |
|---|---|---|
| | | |

| Item | Allocation | Amount given |
|---|---|---|
| Cereal | 1 small | |
| Soup (can/packet) | 2 standard | |
| Beans/spaghetti in sauce | 2 small | |
| Tomatoes/pasta sauce | 2 small | |
| Vegetables | 2 small | |
| Meat | 2 small | |
| Or Vegetarian | 2 small | |
| Fish | 1 small | |
| Fruit | 2 small | |
| Rice pudding/custard | 1 standard | |
| Biscuits | 1 small packet | |
| Pasta/rice/noodles | 500g | |
| Tea or coffee | 40 bags/small jar | |
| Long-life juice | 1 litre | |
| Milk UHT | 1 litre | |

**Extra items when available**

| | | |
|---|---|---|
| Sauces | 1 packet | |
| Chocolate | 1 small bar | |
| | | |
| | | |

| | |
|---|---|
| **Client signature to confirm food received:** | |

**Additional requests:**

| | COMMENTS |
|---|---|
| Cooking facilities? | |
| Vegetarian? | |
| Any other dietary requirements? | |
| Children's ages? | |

| ITEM | | REQUIRED | ISSUED |
|---|---|---|---|
| Cat/Dog? | Size? | | |
| Washing Powder? | | | |
| Washing up liquid? | | | |
| Toilet rolls? | | | |
| | | | |
| Toiletries | Soap or Shower gel? | | |
| | Deodorant? | | |
| | Toothpaste? | | |
| | Toothbrush? | | |
| | Shampoo? | | |
| | Feminine hygiene? | | |
| | Shaving foam? | | |
| | Razors? | | |

## 2.D Distribution Graphs - Totals

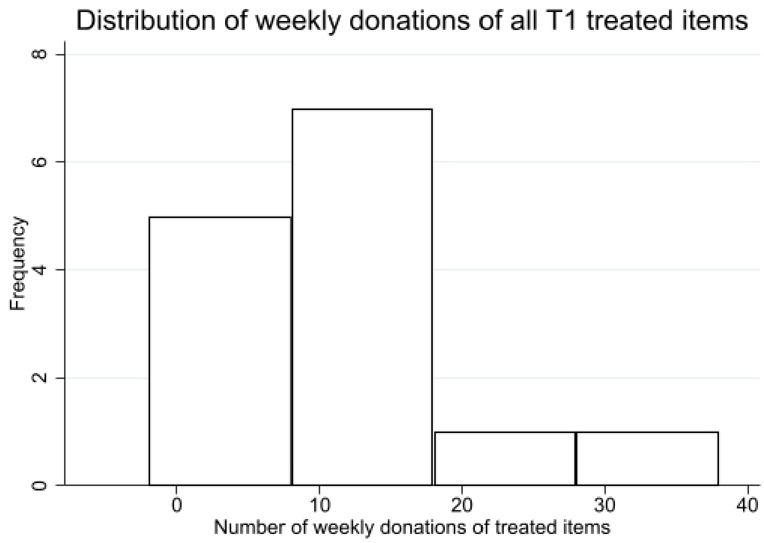


Figure 2.10: Histogram of weekly T1 treated donations (total)

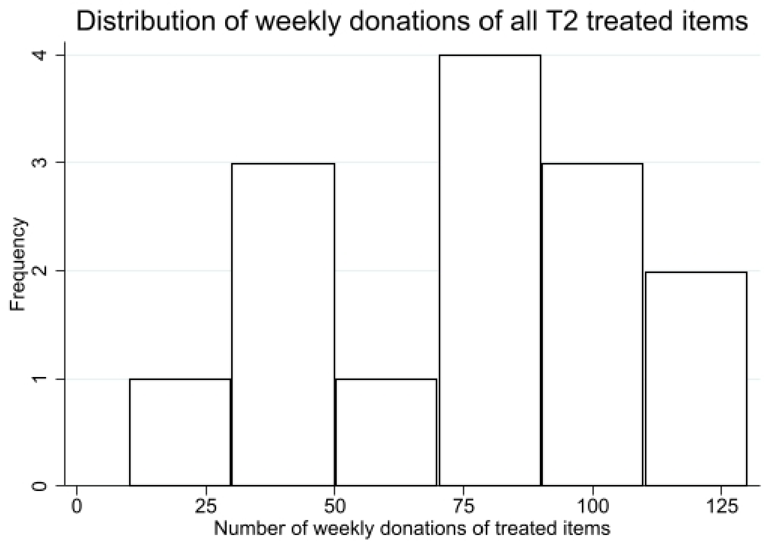


Figure 2.11: Histogram of weekly T2 treated donations (total)

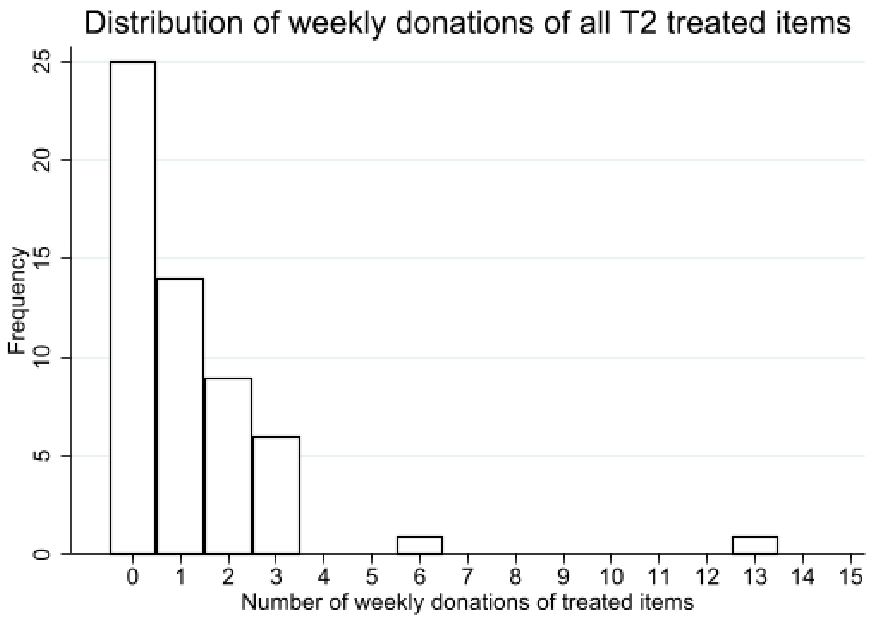


Figure 2.12: Histogram of weekly T1 treated donations (aggregated shelf level)

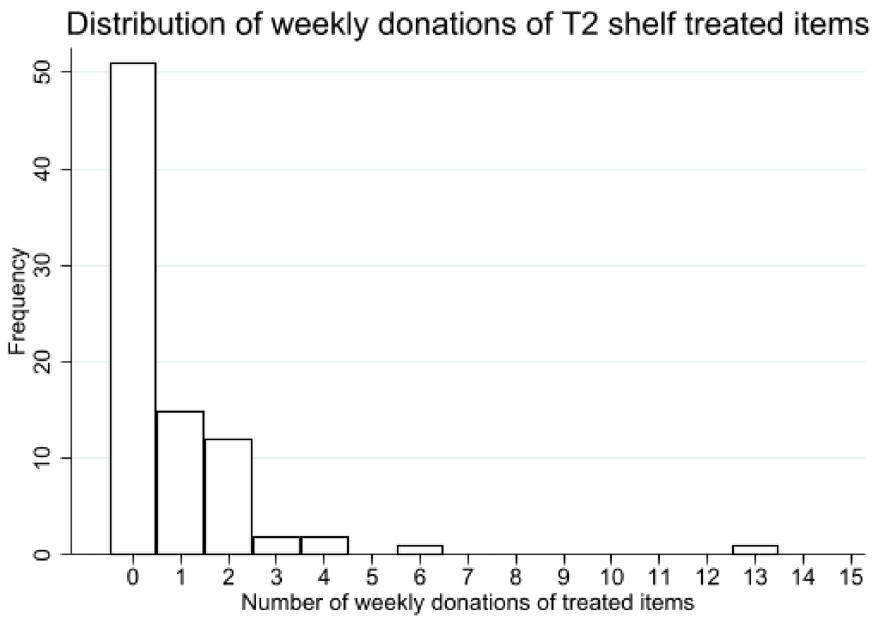


Figure 2.13: Histogram of weekly T2 treated donations (aggregated shelf level)

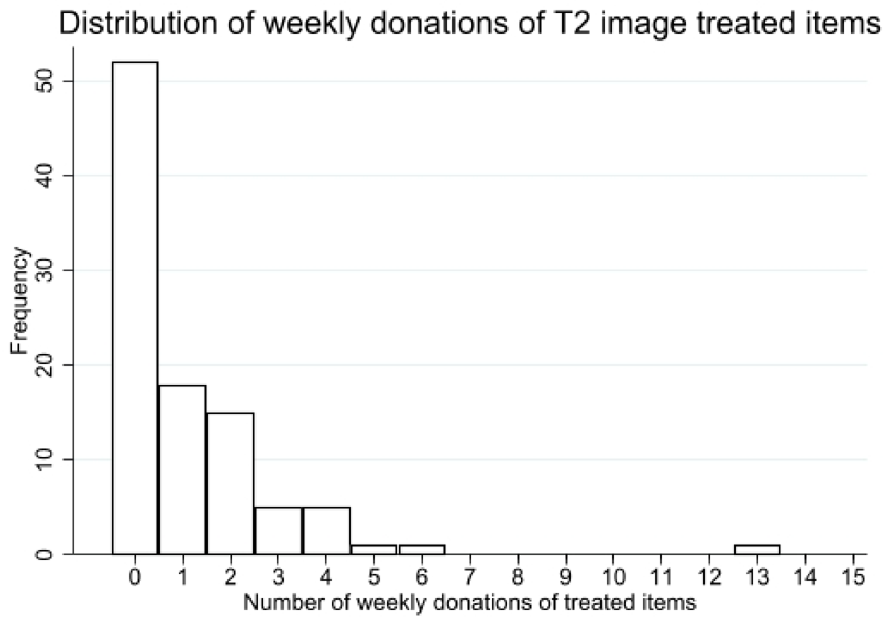


Figure 2.14: Histogram of weekly T2 treated donations (aggregated image level)

## 2.E Distribution Graphs - Shelf level

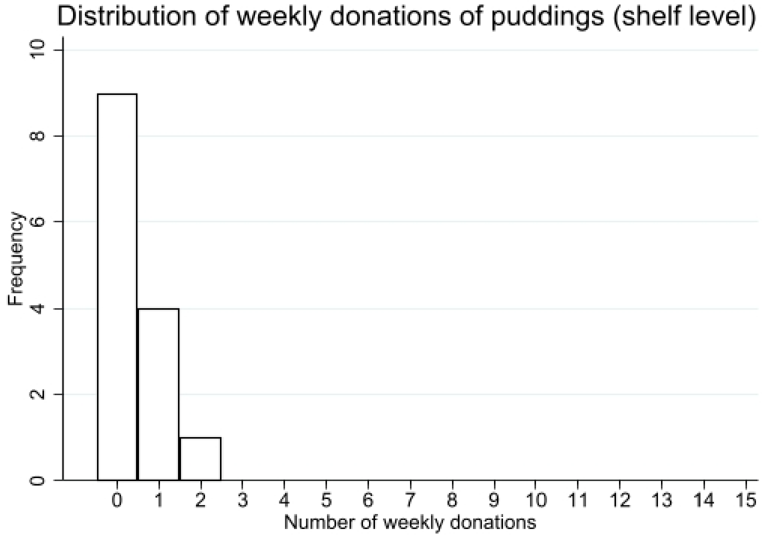


Figure 2.15: Histogram of weekly puddings donations (shelf level)

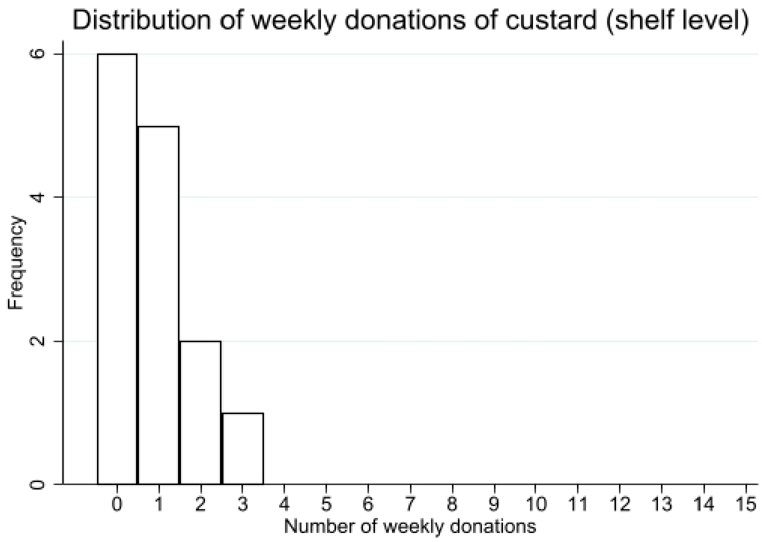


Figure 2.16: Histogram of weekly custard donations (shelf level)

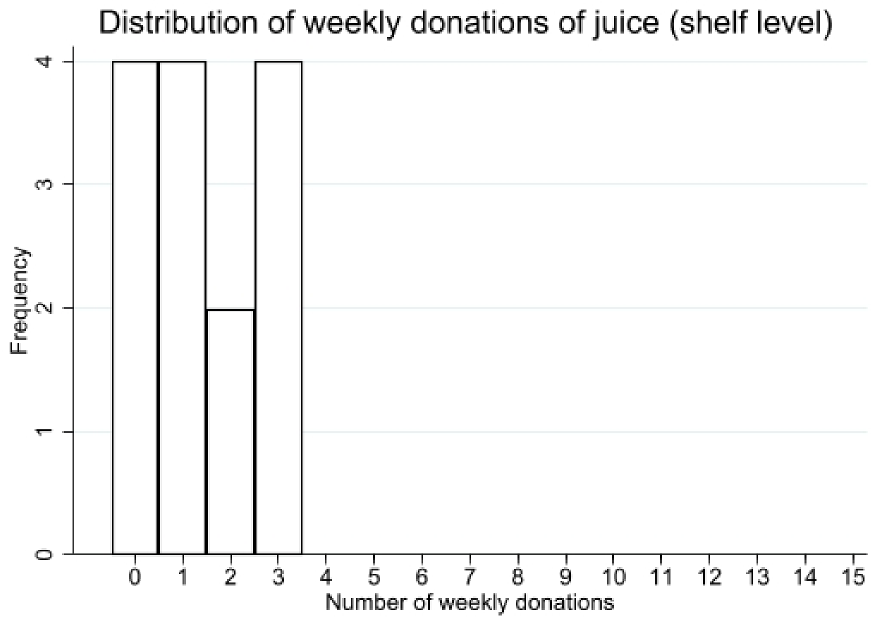


Figure 2.17: Histogram of weekly juice donations (shelf level)

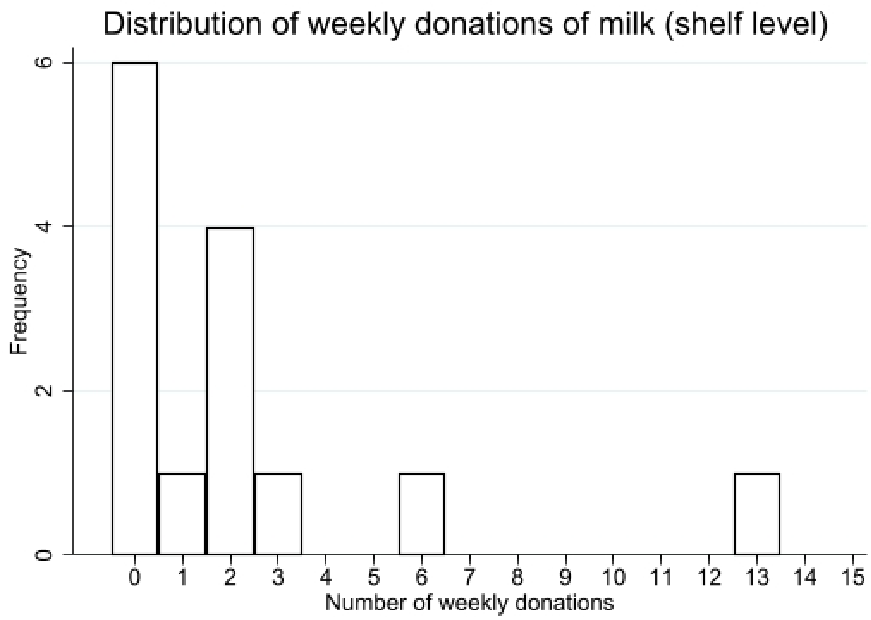


Figure 2.18: Histogram of weekly milk donations (shelf level)

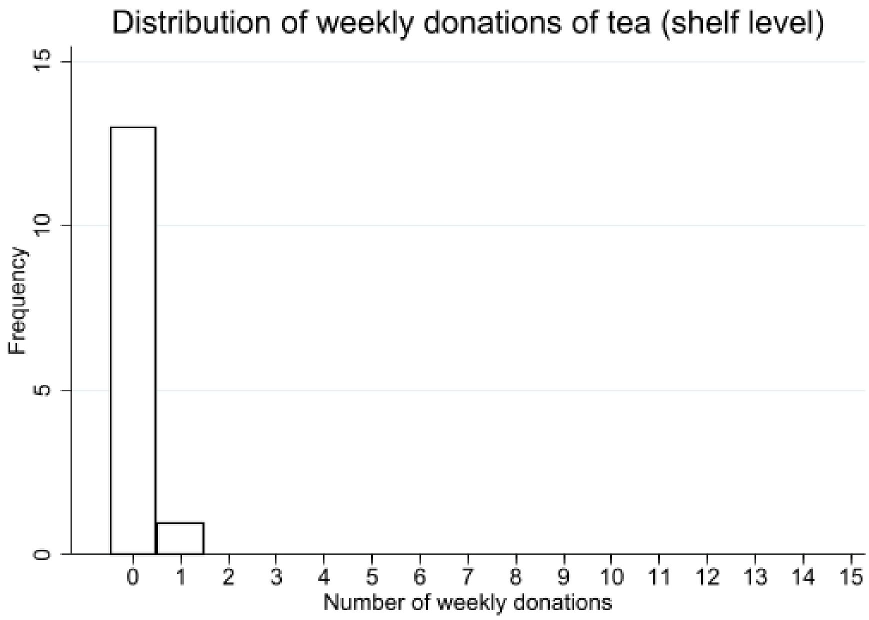


Figure 2.19: Histogram of weekly tea donations (shelf level)

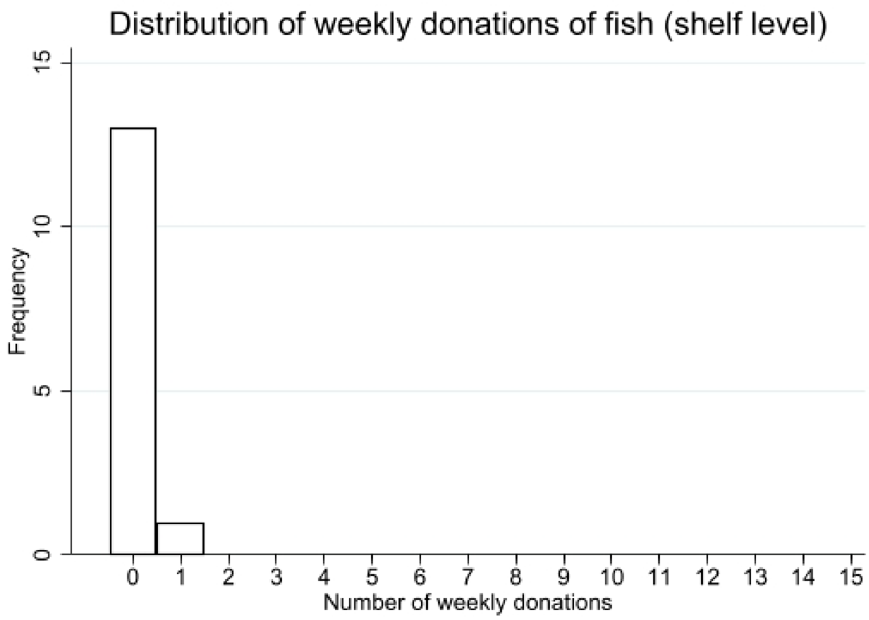


Figure 2.20: Histogram of weekly fish donations (shelf level)

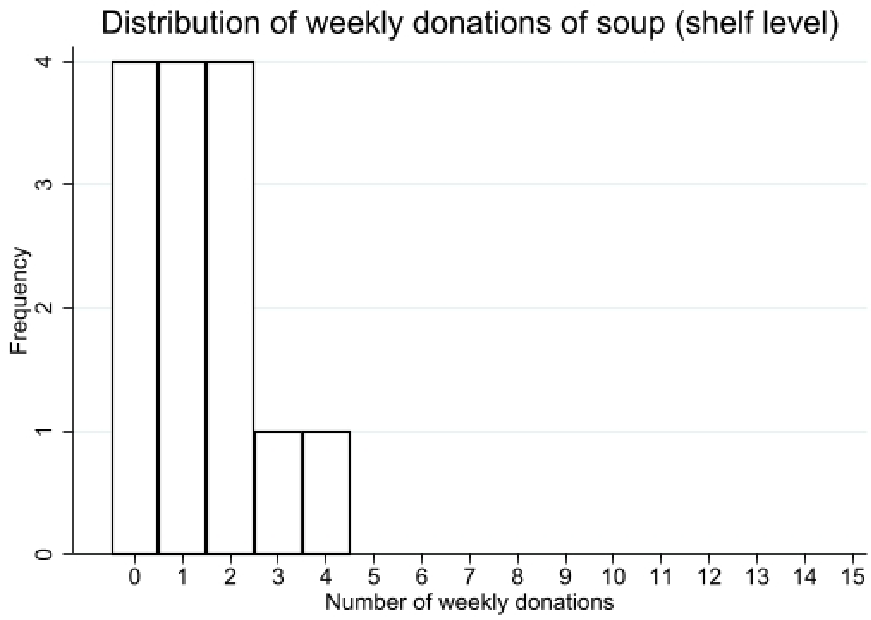


Figure 2.21: Histogram of weekly soup donations (shelf level)

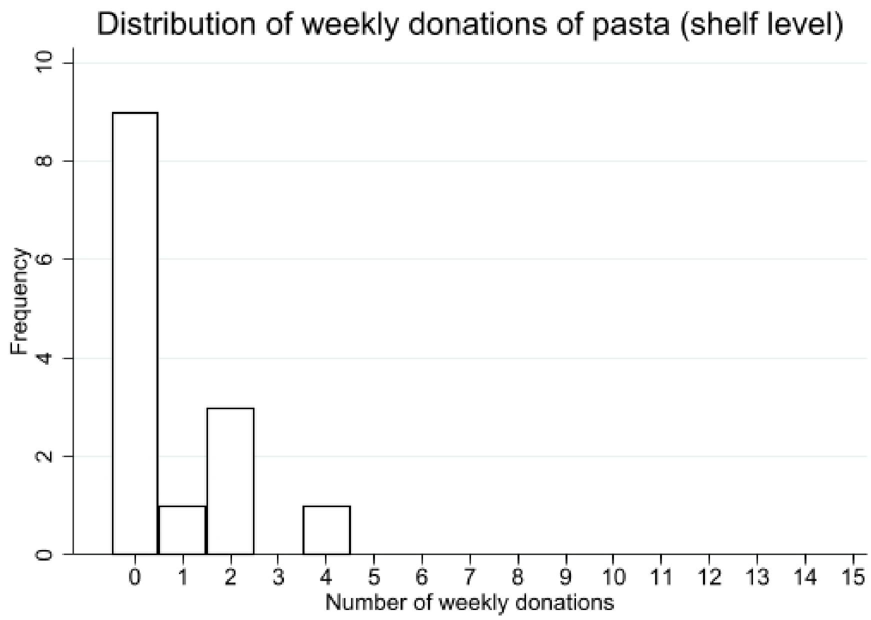


Figure 2.22: Histogram of weekly pasta donations (shelf level)

## 2.F Distribution - Category level

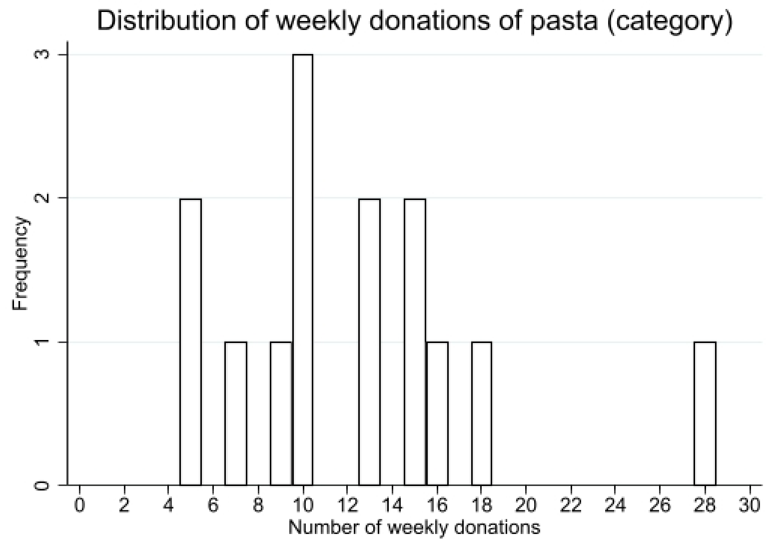


Figure 2.23: Histogram of weekly pasta donations (category level)

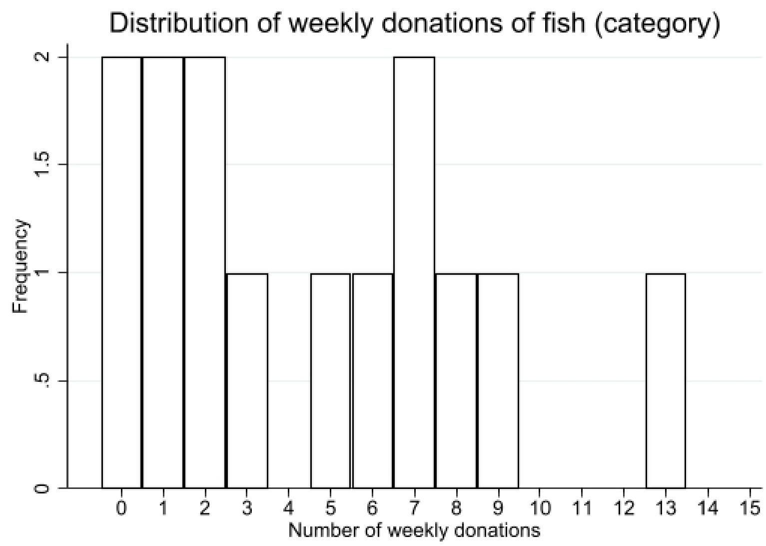


Figure 2.24: Histogram of weekly fish donations (category level)

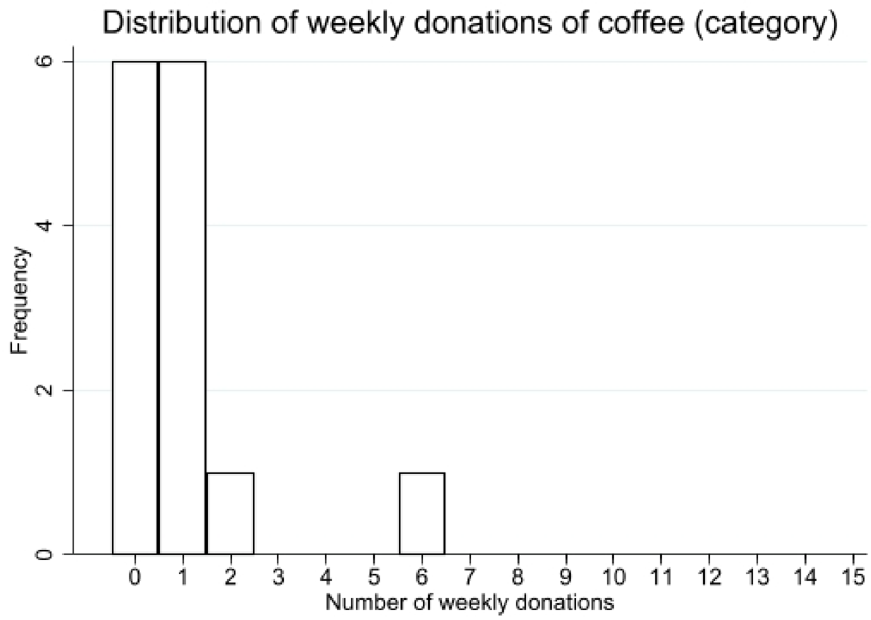


Figure 2.25: Histogram of weekly coffee donations (category level)

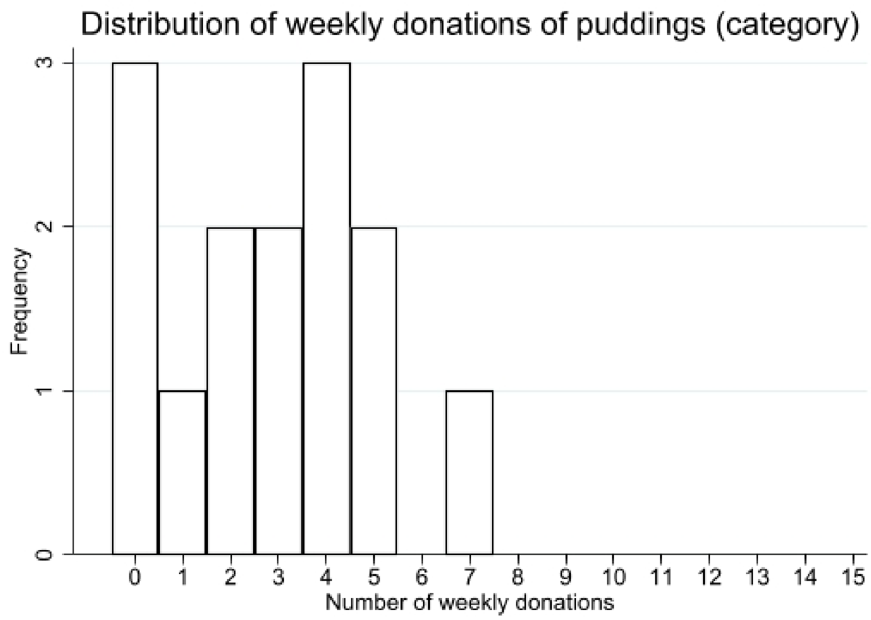


Figure 2.26: Histogram of weekly puddings donations (category level)

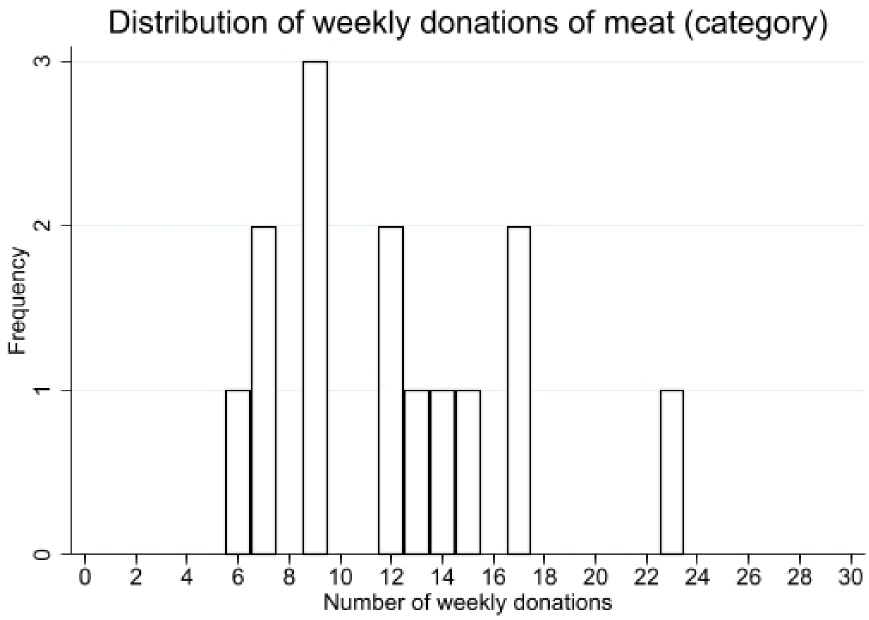


Figure 2.27: Histogram of weekly meat donations (category level)

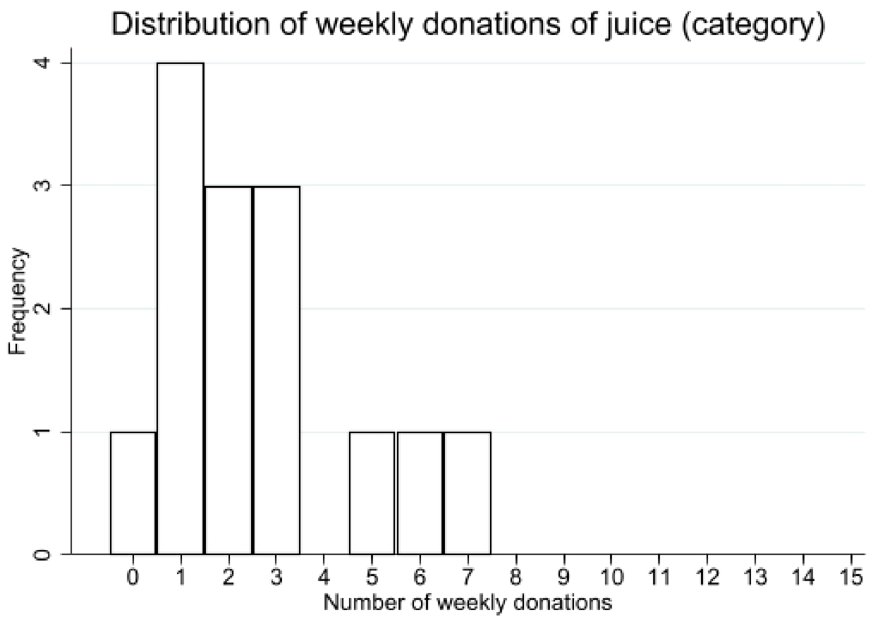


Figure 2.28: Histogram of weekly juice donations (category level)

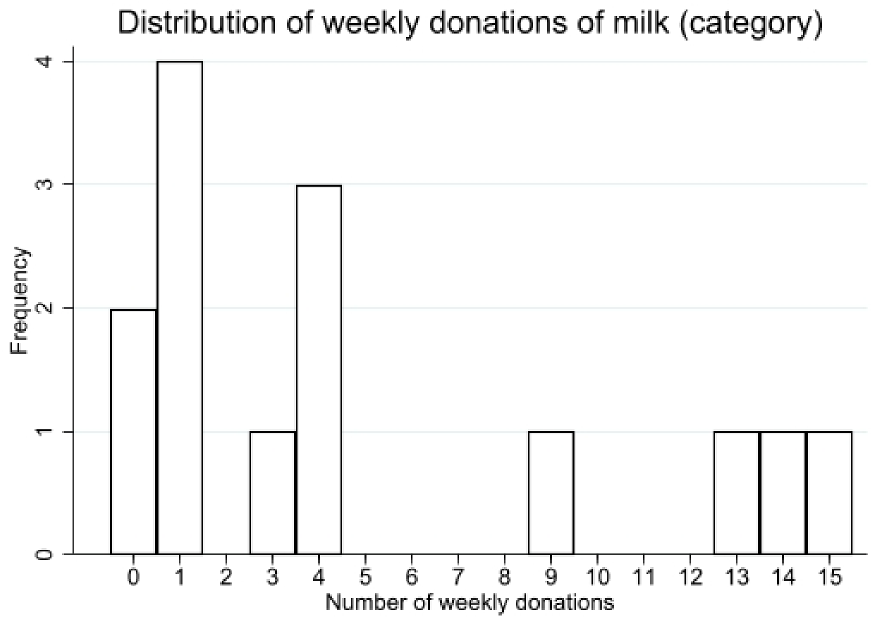


Figure 2.29: Histogram of weekly milk donations (category level)

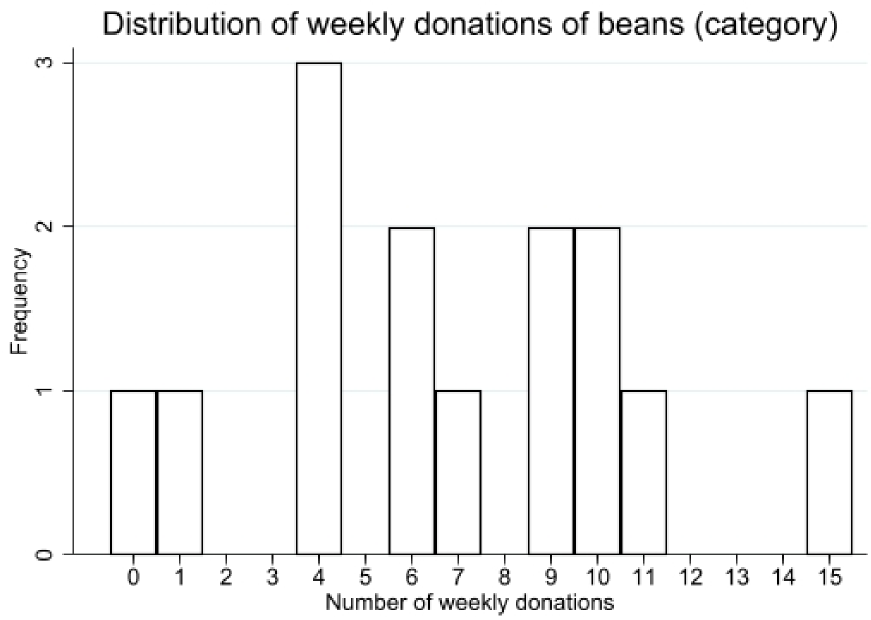


Figure 2.30: Histogram of weekly beans donations (category level)

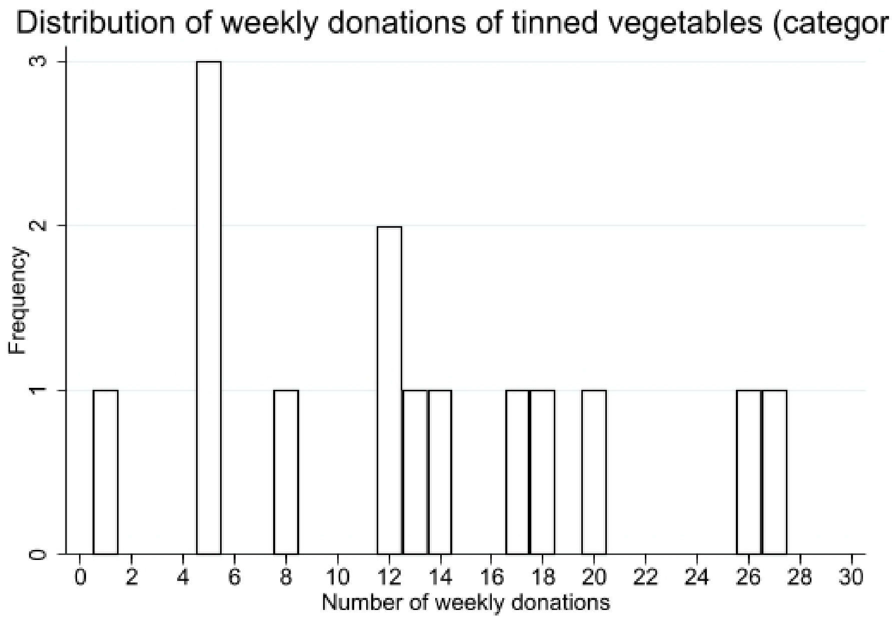


Figure 2.31: Histogram of weekly tinned vegetables donations (category level)

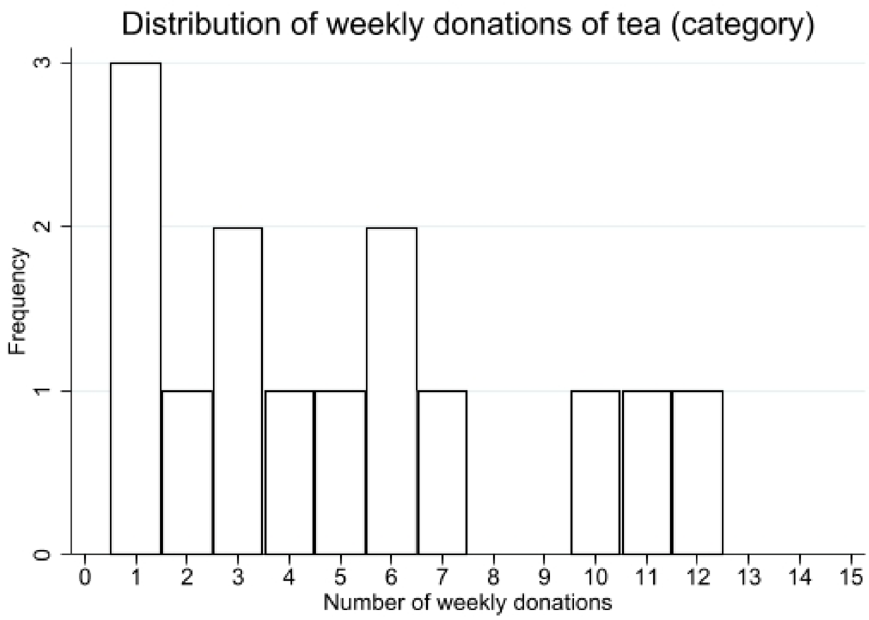


Figure 2.32: Histogram of weekly tea donations (category level)

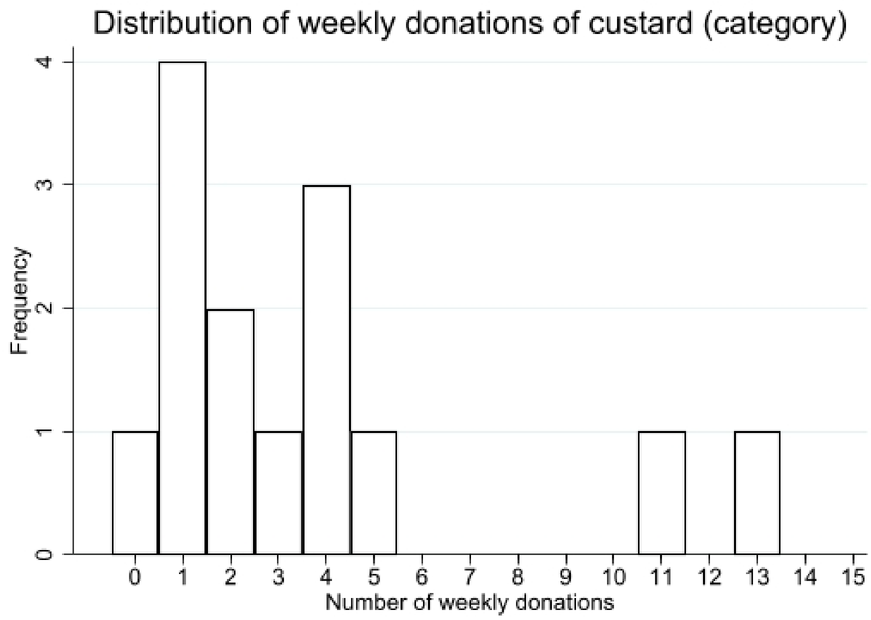


Figure 2.33: Histogram of weekly custard donations (category level)

## 2.G Within-Store Estimation

Table 2.17: Within-store estimation for Treatment Ticket at Category Level

| VARIABLES | Total | Milk | Juice | Pud | Custard |
|---|---|---|---|---|---|
| Treated | -2.205*** | -4.331*** | -4.554*** | -4.978*** | -3.186*** |
| | (0.0687) | (0.406) | (0.0344) | (0.688) | (0.295) |
| Did | 0.611*** | 1.266*** | 0.573*** | 0.868 | -0.364 |
| | (0.117) | (0.436) | (0.189) | (0.867) | (0.328) |
| Time | -0.165 | -0.119 | -0.108 | -0.178 | -0.157 |
| | (0.179) | (0.142) | (0.143) | (0.213) | (0.195) |
| Week | 0.127*** | 0.0933*** | 0.0904*** | 0.131*** | 0.125*** |
| | (0.0321) | (0.0309) | (0.0319) | (0.0412) | (0.0364) |
| Lnalpha | -6.371 | -6.302*** | -6.356*** | -5.529** | -5.768* |
| | (4.686) | (1.852) | (1.874) | (2.716) | (3.089) |
| Constant | 4.091*** | 5.106*** | 5.110*** | 4.087*** | 4.095*** |
| | (0.0706) | (0.0476) | (0.0493) | (0.0809) | (0.0744) |
| Observations | 14 | 14 | 14 | 14 | 14 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.18: Within-store estimation for Treatment Talker at Category Level

| VARIABLES | Pasta | Tin | Fish | Meat | Soup | Beans | Milk | Coffee | Tea | Juice | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Treated | -1.728*** | -2.472*** | -4.725*** | -1.861*** | -2.159*** | -3.219*** | -4.319*** | -5.277*** | -3.312*** | -3.869*** | 0.0613 |
| | (0.0950) | (0.228) | (0.476) | (0.0730) | (0.168) | (0.433) | (0.295) | (0.822) | (0.204) | (0.339) | (0.314) |
| Did | -0.284 | 0.611** | 1.495*** | 0.185 | 0.558*** | 0.538 | 0.638 | 1.666* | 0.469 | 0.139 | -0.308* |
| | (0.251) | (0.301) | (0.559) | (0.119) | (0.199) | (0.466) | (0.479) | (0.964) | (0.313) | (0.632) | (0.161) |
| Time | -0.282** | -0.268** | -0.366*** | -0.341*** | -0.359*** | -0.304** | -0.347*** | 0.0471 | 0.238 | 0.274 | 0.119 |
| | (0.117) | (0.125) | (0.140) | (0.117) | (0.131) | (0.119) | (0.132) | (0.501) | (0.383) | (0.402) | (0.248) |
| Week | 0.227*** | 0.223*** | 0.252*** | 0.245*** | 0.250*** | 0.233*** | 0.246*** | 0.185 | 0.137 | 0.127 | 0.185** |
| | (0.0388) | (0.0425) | (0.0375) | (0.0334) | (0.0346) | (0.0397) | (0.0377) | (0.129) | (0.0977) | (0.103) | (0.0718) |
| Lnalpha | -5.595*** | -5.414*** | -5.611*** | -6.557* | -6.219** | -5.583*** | -5.603*** | -2.632*** | -2.879*** | -2.711*** | -3.354*** |
| | (1.747) | (1.555) | (1.864) | (3.807) | (2.892) | (1.792) | (1.837) | (0.396) | (0.364) | (0.376) | (0.482) |
| Constant | 3.432*** | 3.443*** | 3.363*** | 3.382*** | 3.367*** | 3.413*** | 3.379*** | 3.402*** | 3.515*** | 3.539*** | 3.395*** |
| | (0.147) | (0.155) | (0.144) | (0.136) | (0.137) | (0.151) | (0.146) | (0.328) | (0.257) | (0.266) | (0.223) |
| Observations | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

# Chapter 3

# Reminders to give: a field experiment on in-kind donations in supermarkets

Many charitable organisations rely on in-kind donations even though they are often less efficient than more fungible pecuniary donations. To increase efficiency, some charitable organisations therefore want to influence the types of in-kind donations they receive. We implemented a randomised control trial (RCT) in which we manipulated in-store signage soliciting donations to a local food bank, across locations of a supermarket chain. In some locations, we added shelf 'talker' signs adjacent to products which are in high demand at the food bank; in a further subset of locations we complemented the talkers with a poster campaign. We find that donations are not strongly affected by shelf talkers on their own, but that the use of posters highlighting the charity campaign increases the donation of in-demand items. Our estimates suggest the combined effect of using talkers with posters increases the donation of treated items by around 163%. Though the absolute increase is modest in size (1.89 units per collection), if this intervention were rolled out more widely, there could be significant efficiency gains for the charity.

**Keywords: charitable donations, tangibility, customer behaviour, point of purchase.**

## 3.1 Introduction

Donating in-kind is a popular and engaging way in which people choose to support charities and other worthy causes. Many charities have come to rely on in-kind donations to support their missions. Food banks are an important type of charity which rely heavily on in-kind donations. In the UK, 1.9 million emergency food parcels were given out in the financial year 2019-2020 by Trussel Trust 'FoodBanks' alone, up 18% on the previous year (The Trussel Trust, 2020). Trussel Trust FoodBanks receive around half of their donations at donation points in grocery stores. Food banks operate by aggregating various foodstuffs and other common consumable household items into parcels, which are then distributed to users of the service. Food parcels such as those by the Trussel Trust FoodBanks must be balanced across food groups and appropriate for the size of the household[1]. If all parcels were completely identical, one could think of a food bank as having a Leontief-style fixed-proportions production function. Therefore, there is the potential for inefficiency if donations do not match the desired mixture of products in the ideal parcel. The consequences of this inefficiency can be so extreme that Ülkü et al. (2015, p.154) reports they are known as "aftershock disasters or 'disasters within disasters'", occurring when unhelpful tangible goods are donated in such volumes that they impede relief efforts.

Shoppers pay retail prices for the products they donate, whereas, given the scale at which many food banks operate, it would theoretically be more cost-effective for the food banks to purchase the required products more cheaply at wholesale prices. Despite this, it appears that many people have a preference for making in-kind donations, based on the popularity of such donations despite their higher transaction costs. One route to reducing this inefficiency would be to encourage a behaviour change away from tangible donations towards pecuniary donations. However, this would be a significant behaviour change and may reduce the appeal of donating. In contrast, a much smaller change in behaviour - simply donating different types of products - would address the inefficiencies arising from a food bank receiving a mix of in-kind donations which differs from their ideal proportions for their parcels.

In this chapter we conduct and evaluate the effects of a field experiment targeting which products people choose to donate at the in-store FoodBank donation points. This setting is unique in allowing us to influence real-life in-kind donation behaviour at the point of purchase. We reduce the information asymmetry between the charity and the potential donor in order to achieve a more

[1]See Appendix 3.A for an example list of items received in a one-person parcel.

efficient donation mix. Previous research using shelf-level messaging in two larger supermarket stores has suggested that larger, more visible shelf talkers – i.e., labels identifying individual items for sale on a shelf – are more effective in attracting attention and changing behaviour (Almond, 2021*b*), though this size effect is thought to be moderated by involvement (Kahneman, 1973; Han, 1992). Moreover, Almond (2021*a*) provides evidence that messaging using a 'local' frame is most effective at increasing donations, a result that we exploit in the specific message wording in our intervention on the talkers and posters. We worked with the Norwich FoodBank (UK) and a chain of small, local supermarkets (the East of England Co-Operative Society, or Co-op) in and around the city of Norwich. The small-store setting is also interesting because individuals are more likely to walk through every aisle and notice the shelf talkers, potentially making the intervention more visible and therefore more effective. Such talker signage has been rolled out in other UK supermarkets (The Guardian, 2018), but the effects of these signs on donation mix have not been systematically investigated to our knowledge.

Using an RCT design to test two treatments against a control, we find that the shelf talkers alone do not increase the level of high demand items donated. However, when used in conjunction with the posters, there is an increase in the donation of high demand items. We found that stores with low levels of donations do not respond significantly to the treatments, from which we infer that it is easier to get donors to change their donation type than to become a donor. The level of donations of treated items is relatively low throughout the course of the intervention, but this means that modest increases in the donation rate lead to large percentage increases in donations. An increase of 1.89 units per collection of in-demand items due to the intervention equates to roughly a 163% increase in the rate of donations of this type. Our analysis is however limited by the highly variable nature of donations and unobserved store characteristics leading to differences in donation behaviour between stores.

This chapter is structured as follows: Section 2 discusses related literature from the fields of marketing and donation behaviour. Section 3 describes our experimental design, along with hypotheses and estimation strategy. Section 4 contains descriptive statistics. The results are presented in Section 5 and Section 6 concludes.

## 3.2 Related Literature

The intersection of donation behaviour and purchasing behaviour represents an unexplored gap in the marketing and behavioural literature. To our knowledge, there has not been any research specifically on purchasing items for donation rather than for consumption by the purchaser. The decision-making processes for the two types of purchases, and their determinants, may differ substantially. There is a wealth of literature analysing the effectiveness of marketing techniques to increase purchases for consumption. Optimisation of marketing strategies can lead to increased profits (Assmus et al., 1984), through increased sales. There is also a vast, multi-disciplinary literature on determinants of donation behaviour. However, these contributions often focus on pecuniary donations. Although there is a literature on tangible donations such as organ and blood donations, little literature affords attention to other types of in-kind donations – in this chapter we focus on the purchase for donation of tangible goods intended for consumption by the donation recipient. Firstly, we explore the literature on in-store advertising on purchasing behaviour including visual aspects of the marketing material and their efficacy. Secondly, we look at the wide literature on pecuniary donation behaviour and discuss the possible implications for tangible donation behaviour.

Businesses spend large sums on marketing and advertisement in order to increase sales, profits and market share. For this review we focus on physical adverts aimed at the purchase of a consumable product, particularly at the point of purchase (within a store). Marketing practice has shown that the purchasing decision is frequently made when adjacent to the product in-store. In-store adverts, therefore, are very important. Aspects such as the size, colour, placement and number of adverts have all been studied and shown to affect purchasing decisions (Sparkman Jr, 1985; Han, 1992; Chandon et al., 2009; Huddleston et al., 2015). However, purchasing for personal consumption may differ significantly to purchasing with intent to donate. We are yet to learn if these marketing techniques also work to increase the purchase of products intended for donation.

Advertising products for purchase and subsequent donation raises the question of potential externalities: could there be crowding-out of other donations, or spillover effects to other product types? It is hard to draw general conclusions as much of the research in the marketing field is highly product specific, for example Brester and Schroeder (1995) – which focusses solely on meat products. Seiler (2017) finds no advertising spillover effects onto other brands and products but the research focusses on brand recall rather than purchasing decisions. It is unknown if there would be either crowding out or spillover effects for purchases as donations.

There is often a time-lag between seeing an advert and making a purchase. In marketing, the 'effective frequency' of an advert describes how many times an advert must be seen to lead to a change in behaviour. Schmidt and Eisend (2015) present a meta-analysis concluding that repetition is important for brand recall, but that these effects were non-linear. However, whether these patterns differ for purchases as donations has not yet been studied. In a related area of the donation literature, there is evidence that the number of solicitations affects donation behaviour (Bekkers and Wiepking, 2011; Bekkers, 2005).

Bekkers and Wiepking (2011, p.931) find evidence that simply being solicited, or asked, increases donations: "the more opportunities to give people encounter, the more likely they are to give." However, they find that this trend is also non-linear as too many solicitations may induce "donor fatigue" (Van Diepen et al., 2009). So far, the effect of repeated solicitation on tangible goods is unclear. It is likely that more solicitations are required for tangible donations than for pecuniary donations due to the increased distance between solicitation and donation: physically moving an item from one place to another rather than the transfer of funds electronically. Though pecuniary and tangible donations are not directly comparable, we might expect the same positive, non-linear effect of solicitations on donations (Damgaard and Gravert, 2018).

Awareness of need is a pre-requisite for donations (Bekkers and Wiepking, 2011). Multiple experiments and surveys have found that perceived need is positively correlated with donation levels (Cheung and Chan, 2000; Schwartz, 1970). Tangible donations require awareness of both the cause and of the specific items required. Donors have imperfect information about the needs of the cause and may have concerns about donating the 'wrong' thing (i.e. being ineffective)[2]. Information on required donations helps overcome this barrier to donation. Experimental studies have found that information on the effectiveness of donations affects donation choices (Bekkers and Wiepking, 2011). It appears that individuals (at least sometimes) care whether their donation will be effective. We expect donors may hold similar preferences for tangible donations. It is worth noting the relationship between efficiency (maximum productivity with minimal waste) and effectiveness (producing the intended result) from the point of view of a donor. If a donation is ineffective then it is also clearly inefficient, as it is a wasted resource. However, a donation could be effective but inefficient: as tangible donations often are. In choosing to make a tangible donation, they may therefore be valuing effectiveness over efficiency.

Costs and benefits of donation also play a part in the decision process. Donors may seek to make a donation with the lowest cost for which they can still gain the

[2]These efficiency and effectiveness concerns are discussed more extensively in the literature review of Almond (2021*b*).

benefits of self-image and the “warm glow of giving” (Andreoni, 2006). The price of a product purchased for donation may be important in two ways here: if an individual wishes to make a donation, they might donate the cheapest item available. In doing so, they will gain the utility associated with making a donation. Secondly, if the donor cares about efficiency but is uncertain about which items are in demand by a cause, the donor take a risk by donating a tangible good. The size of that risk is minimised when a cheaper product is donated. There are also other transaction costs associated with donating, such as time and effort (Huck and Rasul, 2010).

The effects of income, wealth and socioeconomic status on donation behaviour are highly debated in the literature. Those who have less disposable income have a higher relative cost of donating – this could decrease the size of their donations. On the other hand, those who live in areas with more deprivation are more likely to be aware of need by virtue of proximity – this could increase donation rates. There is experimental evidence to suggest that those of different socioeconomic status donate at differing rates (Manstead, 2018), while other studies suggesting that there is an “essentially flat relationship between income and percentage donations to charity” (Mayo and Tinsley, 2000). Those with lower incomes are more likely to attribute success to luck – favouring structural causes, whereas the rich are more likely to attribute success to hard work – favouring individualistic causes (Bullock, 1999; Kluegel and Smith, 1986; Mayo and Tinsley, 2000). These beliefs can influence whether a cause is deemed worthy of support and thereby donations. However, little information has been recorded on how tangible donations differ across these demographic variables.

Many charities increase their solicitations towards Christmas, due to a perceived increase in generosity. They employ a variety of strategies to increase donatios such as donation buckets, additional mailings and advertisements. Several studies find that people are more generous at the Christmas festive period in a variety of domains from church collections to tipping behaviour (Cairns, 2011; Greenberg, 2014). However, Müller and Rau (2019) finds the opposite, citing “increased stress” and “saving behaviour” as factors leading to reduced giving in Germany compared to summer.

In summary, we identify a gap which exists in the overlap between two areas of research: marketing of consumables and influences on donation behaviour. Advertisements often aim to increase recall (Danaher and Mullarkey, 2003) and desire whereas adverts for charities often aim to evoke empathy and awareness of need (Fisher et al., 2008). Understanding if in-store marketing techniques can increase not only the purchase, but also the donation of items is important to

NGOs (non governmental organisations) who rely on donations of tangible goods.

## 3.3 Design

In partnership with Norwich (UK) FoodBank, (henceforth named the FoodBank) we designed and carried out a randomised control trial[3] in a local supermarket chain[4] which hosts donation baskets for the FoodBank. With the cooperation of the chain, we varied the design of messaging advertising the opportunity to make in-kind donations across individual stores. This messaging targeted customers who could potentially donate to the FoodBank by purchasing items during their shop, and depositing them in the donation baskets before leaving. *A-priori* it was assumed that the majority of donations to the FoodBank in these baskets are purchased during the same visit to the shop.

According to the marketing literature and practice in the supermarket industry a key decision point for customers when making purchases for themselves, or on behalf of their households, is when they are standing next to a product display. Targeted messaging located at that decision point is influential in shaping purchasing decisions. This suggests that a similar use of messages targeted at this point of decision could be effective in influencing which products a potential donor purchases for donation to the FoodBank. The design aimed to use a low-cost intervention as a nudge for donation behaviour, which if successful could be rolled out to further stores and used more widely.

However, there are practical limits on how large targeted message signage can be on a supermarket shelf, and therefore the existence of these message signs might not be salient to potential donors. Furthermore, some product categories, such as long shelf-life milk, are product types which are 'high-demand' for the FoodBank, but are less typically purchased by individual shoppers for themselves. Supermarkets are able to draw attention to products through means such as end of aisle displays, distinctive decorations of shelves, or placement near check-out tills. These are not viable interventions to influence purchase-for-donation decisions: these are valuable strategies and using them for lower profit margin items may harm the profitability of the store in the long run. Instead, in selected locations, we complement the use of targeted messages at the purchase decision points with signage in the form of posters near the entrance of the store telling shoppers to look out for signs on shelves indicating products which are in high demand at the FoodBank.

[3]This design was pre-registered with the AEA RCT Registry number AEARCTR-0004894.

[4]The East of England Co-operative Society, or Co-op

We conducted the intervention across 18 stores of the supermarket chain for 10 weeks from 10$^{\text{th}}$ October to 19$^{\text{th}}$ December 2019. All 18 stores already collected donations to the Norwich FoodBank prior to our intervention. The in-store donation baskets had a small sign listing items which were regularly required by the FoodBank. However, there was no additional signage or messaging about donating to the FoodBank beyond the presence of the basket. We randomised the stores into three groups of 6, using a procedure we describe in more detail below, and randomly assigned treatment to the groups.

### 3.3.1 Randomisation procedure

Selection of stores depended on the store being a donor to the Norwich branch of the Trussel Trust FoodBank. One store, located at the city's train station, was not included as the demographic served was likely significantly different to other stores.

One advantage of working with small local supermarkets is that their customer base tends to be very local, too, allowing us to control for – or block on – important expected customer characteristics. To allocate the 18 stores into three treatment groups, we used block randomisation[5]. Block randomisation allows the even spread between groups of observable characteristics that we believed *ex-ante* were likely to influence store footfall and customer profile, and potentially donation behaviour. First, we expected that average income level of customers would influence donation behaviour (Manstead, 2018), though the directional effect is still contested. We used the percentage of free school meal (FSM)[6] recipients at the nearest state-funded infant or junior school as a proxy for average local income level. The data was transformed to rank the stores into 6 strata. The allocation rule to treatments was that there would be one store from each stratum in each treatment. Second, we anticipated that the presence of a Post Office[7] or Subway[8] could have a potential influence on store footfall and therefore donation behaviour. The direction of the relationship is hard to determine ex ante, given that some customers may enter the store with the sole purpose of using the Post Office or purchasing a takeaway

[5]Power analysis was conducted which showed that the sample we used would have adequate data points to make inference with statistical significance. Size of the effect has been taken from an earlier experiment in this field, conducted in two superstores in 2018 (Almond, 2021*b*).

[6]Free School Meals (FSM) have a means tested eligibility criteria, which supplies children from lower income households, as well as all children in years 1 and 2, with meals at school free of charge. This measure has been widely used as a measure of disadvantage in educational settings, but may understate the true level of disadvantage of those in the school (Kounali et al., 2008)

[7]Post Office® Ltd, retail post office company.

[8]Subway ®, takeaway restaurant franchise.

meal from the in-store Subway counter, and not purchase any supermarket items. The randomisation procedure ensured that the number of stores with Post Offices would be distributed evenly between treatments, and that the two stores with a Subway would not receive the same treatment. The final blocking variable was the location of the donation basket: we created a dummy variable to indicate if the donation basket is clearly visible at the checkout or upon entry to the store[9]. We randomised the allocation of stores to treatment groups based on these constraints, and also randomly allocated the groups to treatment arms[10]. The analysis of equality of means of these store characteristics in Table 3.1 shows that the randomisation process was successful. ANOVA and Kruskal-Wallis tests show that none of the observable characteristics are significantly different between the arms.

[9]Other less-accessible locations of the donation baskets included at the far end of the store, in a corner of the store or behind an object which impeded the view of the basket.

[10]Randomisation used a Python code with a set seed and is replicable.

Table 3.1: Table showing all observable variables at store-level and ANOVA test of equivalence p-value

| Treatment | Control | | | | Talker | | | | Talker+Poster | | | | ANOVA/Kruskal-Walli |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Mean | Std.Dev | Min | Max | Mean | Std.Dev | Min | Max | Mean | Std.Dev | Min | Max | |
| Population of LSOA | 10092.33 | 3437.628 | 5120 | 14405 | 8134 | 2251.07 | 5606 | 11123 | 9956.333 | 2921.356 | 4163 | 12114 | 0.2995 |
| Square Foot of Store | 2867.833 | 534.4969 | 2099 | 3433 | 3128 | 1251.182 | 1645 | 4757 | 2347.333 | 668.231 | 1540 | 3010 | 0.3722 |
| Turnover (Low) | 28993.5 | 7551.929 | 20573 | 38302 | 31461.17 | 7151.688 | 20949 | 40246 | 25524.17 | 8542.874 | 12444 | 36300 | 0.4336 |
| Turnover (High) | 42030.67 | 10375.08 | 29766 | 54569 | 42340.83 | 8612.298 | 29531 | 51539 | 39996.5 | 15342.99 | 20708 | 59853 | 0.9327 |
| Turnover (Mean) | 35630 | 9244.992 | 24691 | 46838 | 36382.83 | 7660.418 | 25871 | 46022 | 32250 | 11121.43 | 17643 | 44514 | 0.7508 |
| Average Transactions | 5236 | 1162.683 | 4029 | 7070 | 5222.167 | 889.9821 | 4231 | 6254 | 4731.167 | 1413.758 | 2874 | 6525 | 0.9265 |
| ATM | 0.833333 | 0.408248 | 0 | 1 | 0.666667 | 0.516398 | 0 | 1 | 0.5 | 0.547723 | 0 | 1 | 0.5207 |
| Post Office | 0.333333 | 0.516398 | 0 | 1 | 0.333333 | 0.516398 | 0 | 1 | 0.333333 | 0.516398 | 0 | 1 | 1 |
| Subway | 0.166667 | 0.408248 | 0 | 1 | 0.166667 | 0.408248 | 0 | 1 | 0 | 0 | 0 | 0 | 0.6163 |
| Car Parking | 0.833333 | 0.408248 | 0 | 1 | 0.666667 | 0.516398 | 0 | 1 | 0.666667 | 0.516398 | 0 | 1 | 0.7911 |
| Parking Nearby | 0.666667 | 0.516398 | 0 | 1 | 0.833333 | 0.408248 | 0 | 1 | 0.833333 | 0.408248 | 0 | 1 | 0.7613 |
| PayPoint | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0.666667 | 0.516398 | 0 | 1 | 0.1156 |
| Collect+ Point | 0.333333 | 0.516398 | 0 | 1 | 0.5 | 0.547723 | 0 | 1 | 0.5 | 0.547723 | 0 | 1 | 0.8271 |
| Customer Service Desk | 0 | 0 | 0 | 0 | 0.166667 | 0.408248 | 0 | 1 | 0 | 0 | 0 | 0 | 0.3911 |
| UberEats | 0 | 0 | 0 | 0 | 0.166667 | 0.408248 | 0 | 1 | 0 | 0 | 0 | 0 | 0.3911 |
| Amazon Locker | 0.333333 | 0.516398 | 0 | 1 | 0.333333 | 0.516398 | 0 | 1 | 0 | 0 | 0 | 0 | 0.3147 |
| Lotto | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | n/a |
| % Free School Meals | 21.93333 | 13.28724 | 8.1 | 41 | 21.96667 | 13.4809 | 7.7 | 41.9 | 23 | 14.01242 | 7.2 | 41.9 | 0.9898 |
| IMD Rank | 17761.17 | 9624.593 | 7285 | 28519 | 13554 | 12655.78 | 2268 | 30078 | 20349.17 | 8357.96 | 6020 | 29670 | 0.6116 |
| Income Rank | 16186 | 9067.345 | 5861 | 26598 | 12493.67 | 11555.71 | 2290 | 28500 | 17629.33 | 8197.296 | 5628 | 30142 | 0.6482 |
| Income Decile | 5.5 | 2.880972 | 2 | 9 | 4.166667 | 3.544949 | 1 | 9 | 5.833333 | 2.639444 | 2 | 10 | 0.6146 |
| Income Score | 0.119667 | 0.070848 | 0.048 | 0.214 | 0.174 | 0.11193 | 0.04 | 0.297 | 0.104667 | 0.063026 | 0.033 | 0.218 | 0.3542 |
| Employment Rank | 15303.67 | 6820.617 | 5476 | 22742 | 11339 | 10732.13 | 1711 | 25668 | 19770.5 | 9146.235 | 6200 | 32635 | 0.3002 |

Table 3.1: Table showing all observable variables at store-level and ANOVA test of equivalence p-value

| Treatment | Control | | | | Talker | | | | Talker+Poster | | | | ANOVA/Kruskal-Walli |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Mean | Std.Dev | Min | Max | Mean | Std.Dev | Min | Max | Mean | Std.Dev | Min | Max | |
| Employment Decile | 5 | 2.097618 | 2 | 7 | 3.833333 | 3.311596 | 1 | 8 | 6.5 | 2.810694 | 2 | 10 | 0.2811 |
| Employment Score | 0.093667 | 0.041812 | 0.056 | 0.163 | 0.14 | 0.079765 | 0.047 | 0.236 | 0.0725 | 0.046801 | 0.014 | 0.154 | 0.3719 |
| Education Rank | 12413.33 | 7497.572 | 1567 | 24375 | 9760.5 | 6354.802 | 1440 | 15974 | 13175.33 | 9722.043 | 1550 | 31088 | 0.7433 |
| Education Decile | 4.333333 | 2.33809 | 1 | 8 | 3.333333 | 1.861899 | 1 | 5 | 4.5 | 2.949576 | 1 | 10 | 0.7164 |
| Health and Disability Rank | 15379.33 | 11416 | 3315 | 30402 | 11085.17 | 11954.24 | 1001 | 28307 | 15229.67 | 6343.952 | 5549 | 23324 | 0.5314 |
| Health and Disability Decile | 5.333333 | 3.444803 | 2 | 10 | 3.833333 | 3.488075 | 1 | 9 | 5.166667 | 2.228602 | 2 | 8 | 0.6648 |
| Crime Rank | 19978 | 10235.56 | 8980 | 30254 | 17491.17 | 13704.66 | 1056 | 32153 | 24679.5 | 4691.834 | 15584 | 28207 | 0.8843 |
| Crime Decile | 6.5 | 3.209361 | 3 | 10 | 5.833333 | 4.167333 | 1 | 10 | 8 | 1.549193 | 5 | 9 | 0.495 |
| Barriers to Employment Rank | 26787 | 4323.205 | 18987 | 30872 | 26034.67 | 5206.404 | 15869 | 30008 | 26460.67 | 3826.859 | 19892 | 31338 | 0.9586 |
| Living Environment Rank | 21906.33 | 3725.882 | 16369 | 27525 | 22765.33 | 3854.161 | 17453 | 28592 | 20710.67 | 3693.762 | 16236 | 26618 | 0.5472 |
| Living Environment Decile | 7.166667 | 1.32916 | 5 | 9 | 7.5 | 1.048809 | 6 | 9 | 7 | 1.414214 | 5 | 9 | 0.7898 |
| IDACI Rank | 16134.17 | 10938.38 | 3658 | 28754 | 14831.17 | 11332.51 | 4034 | 29012 | 12935.67 | 7120.989 | 3488 | 22094 | 0.8571 |
| IDACI Decile | 5.5 | 3.209361 | 2 | 9 | 4.833333 | 3.430258 | 2 | 9 | 4.5 | 2.073644 | 2 | 7 | 0.8395 |
| IDAOPI Rank | 16465.33 | 9712.617 | 4024 | 25948 | 12985.5 | 11821.44 | 1997 | 29674 | 13845.67 | 4228.044 | 7604 | 19226 | 0.7937 |
| IDAOPI Decile | 5.333333 | 2.804758 | 2 | 8 | 4.5 | 3.674235 | 1 | 10 | 4.666667 | 1.21106 | 3 | 6 | 0.8592 |
| Donation Easy | 0.666667 | 0.516398 | 0 | 1 | 0.666667 | 0.516398 | 0 | 1 | 0.666667 | 0.516398 | 0 | 1 | 1 |
| Week 0 Treated Donations | 0.333333 | 0.816497 | 0 | 2 | 1 | 1.264911 | 0 | 3 | 1.166667 | 2.401388 | 0 | 6 | 0.6548 |
| Week 0 Total Donations | 17.5 | 17.46711 | 4 | 45 | 15.33333 | 21.27596 | 0 | 58 | 8.166667 | 3.763863 | 3 | 13 | 0.307 |

The data for the lower super-output areas (LSOA) each store was situated in comes from the Index of Multiple Deprivation (IMD) 2019 (Ministry of Housing, Communities & Local Government, 2019). The Income Deprivation Affecting Children Index (IDACI) measures the proportion of all children aged 0 to 15 living in income deprived families. The Income Deprivation Affecting Older People Index (IDAOPI) measures the proportion of all those aged 60 or over who experience income deprivation.

### 3.3.2 Treatments

In the **Control group**, we made no changes to the existing status quo.

In **Treatment T**, we placed 7cm x 21cm signs (called 'talkers' or 'barkers' in the retail industry) directly underneath the product they depict. These talkers featured the message, "Please help local people by donating this item today", in conjunction with the Norwich FoodBank logo and images of the item in demand at the FoodBank. See Figure 3.2 for an example of the talker design.

In **Treatment T+P**, we complement the use of talkers with posters at or near the entrance to the store. The posters featured the messages, "Please help local people by donating today!", and "Look out for these labels around the store to find the most needed items!", in conjunction with the Norwich FoodBank logo and a picture of one of the shelf talker labels. See Figure 3.3 for the full poster design.

The **Treated Items** were 5 product types chosen by the FoodBank, selected from their most in-demand products at the time. The product types were: microwave desserts, tinned vegetables, deodorant, long-life milk and long-life fruit juice.

Figure 3.1 shows the spacial distribution of stores across the city and its outskirts.

The donation baskets were emptied of any previous donations before the experiment began. We recorded the weekly baseline donations made to the FoodBank from each store during one week of pre-intervention data collection. Treatment began on the day that the pre-trial collections were made. Following this, donations were measured weekly for a 10-week period. Each store was visited on the same day each week. We used a barcode scanner to record the items donated ensuring the donation baskets were emptied, then delivered the donations to the FoodBank warehouse.

## 3.4 Hypotheses

The shelf talkers highlight individual items which are in demand at the FoodBank. The information that an item is in demand would tend to encourage a potential donor to purchase and donate that item. In addition, the items treated with talkers become more salient, and therefore more likely to be selected. Both these considerations suggest that treating an item with a talker will increase donations of that item.

**Hypothesis 3.1** *Shelf talkers increase donations of the treated product categories.*

The talkers are placed adjacent to in-demand items. We can think of a shopper as deciding how to allocate their budget among donations of in-demand items,

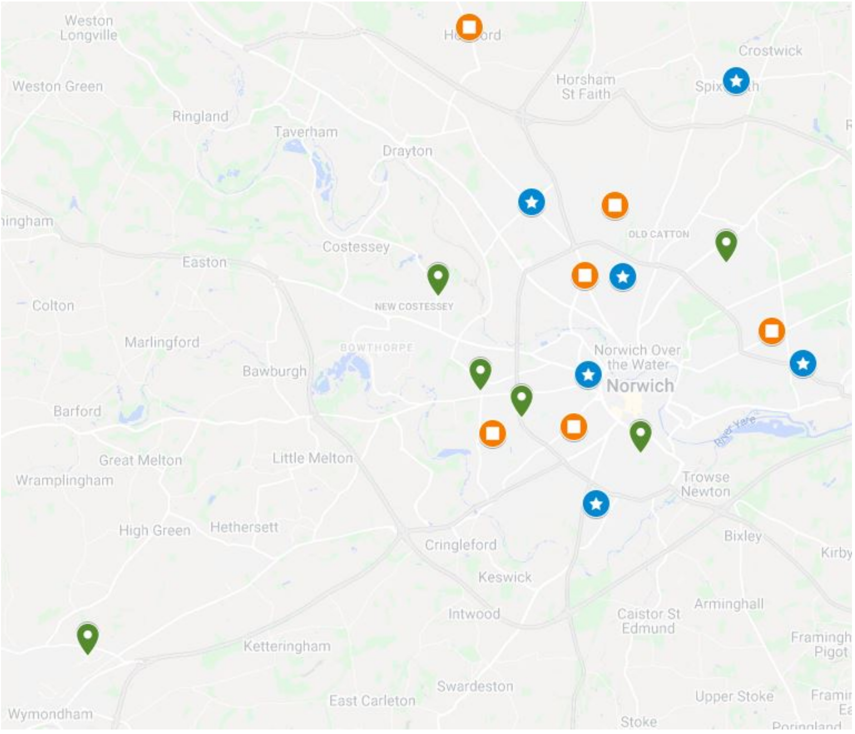


Figure 3.1: Map showing the location of all 18 stores.

Star (blue) markers indicate Treatment T, square (orange) markers indicate Treatment T+P and circle (green) markers indicate the control group.


Figure 3.2: Shelf talker used in treatments T and T+P.


Figure 3.3: Poster used in Treatment T+P (A3 size).

donations of other items (not in-demand), and personal consumption. Any increase in donations of the in-demand items must come from a decrease in either donations of other items or personal consumption. Consider the case of a shopper who is already aware of the FoodBank and possibly intending to make a donation. In this case, it seems plausible that the effect of the targeted shelf talkers would be to lead the shopper to substitute towards donations of the in-demand item, away from donations of other items, whether for informational or saliency reasons.

**Hypothesis 3.2** *Shelf talkers decrease the donations of non-treated product categories.*

Alternatively, shelf talkers may incite a donation from those without a prior intention to donate by informing or reminding them of the FoodBank's existence and more generally the need for donations. If this is the primary channel through which the talkers operate, we would expect to see donations of both in-demand and other items to increase jointly when in-demand items are treated with talkers.

**Hypothesis 3.3** *Shelf talkers increase the donations of non-treated product categories and treated product categories*

The marketing literature suggests that there is a positive relationship between advertising and sales (e.g. Assmus et al., 1984). In the context of donations, Van Diepen et al. (2009) find that increased solicitations generally lead to increased donations. In Treatment T+P, the posters at the entrance to the shop would complement the use of talkers and increase their salience, and the talkers reinforce the reminder given by the posters. Therefore, we expect that the donation of treated items will be greater when talkers are used in conjunction with posters.

**Hypothesis 3.4** *The addition of posters to the campaign increases the donation of treated products.*

The design of the posters both increases the shoppers' awareness of the FoodBank, and also informs them to look out for the talkers indicating the in-demand items. If the reminder of the existence of the FoodBank is the main driver, converting those with no prior intention of donating into donors, we expect that donation levels overall would increase in the presence of the generic reminder of the poster.

**Hypothesis 3.5** *the addition of posters to the campaign has a positive effect on the donation of untreated items.*

The posters in Treatment T+P were additional to the signage and branding of the existing FoodBank donation baskets. The baskets themselves are another form of solicitation, and the location of the baskets varies across stores. In some stores, the donation basket is located near the entrance, or next to the checkout, either (or both) of which increase the salience of the basket and reduce the transaction costs associated with donation (Knowles and Servátka, 2015). In other stores, the donation baskets are less visible and placed away from the checkout, requiring the donor to return to the basket to make a donation.

**Hypothesis 3.6** *Donations are higher in stores with the donation basket close to the entrance or checkout.*

We expect to see larger effects of the talkers on items which are cheaper to purchase than items that are more expensive. Shoppers are more likely to allocate part of their budget to low cost donations, as the overall costs of donation are smaller.

**Hypothesis 3.7** *The effect of the shelf talkers is stronger on cheaper items.*

The FoodBank consistently receive more donations in the run up to Christmas, but the size of this effect is yet to be quantified.

**Hypothesis 3.8** *Donations increase as Christmas gets closer.*

## 3.5 Estimation strategy

The analysis is described in terms of 'collections' which refers to one week's worth of donations in one store. We gathered data at the item level: we scanned every item donated in each store with a barcode scanner, resulting in a time-series panel data structure. The East of England Co-op shared product characteristic data with us for use in our analysis, allowing us to identify the products donated by their barcode. We used these data to determine trends in donation levels and types. We excluded items which were not bought from an East of England Co-op store. The product data also allowed us to measure the value[11] and weight of the collections.

Figure 3.4 presents the distribution of the counts of treated items donated by collection, showing that the dependent variable is not normally distributed and has a strong skew towards 0. This makes our data unsuitable for the assumptions required to perform OLS regressions. The unconditional mean of the count of treated items

[11] Prices are a snapshot given at 1st January 2020 and do not include information on promotions.

Table 3.2: Mean of treated items donated per collection by Treatment

| Treatment | Mean | Variance | N |
|---|---|---|---|
| Control | 0.818 | 3.259 | 66 |
| Treatment T | 1.409 | 6.430 | 66 |
| Treatment T+P | 1.652 | 6.446 | 66 |
| Total | 1.293 | 5.447 | 198 |

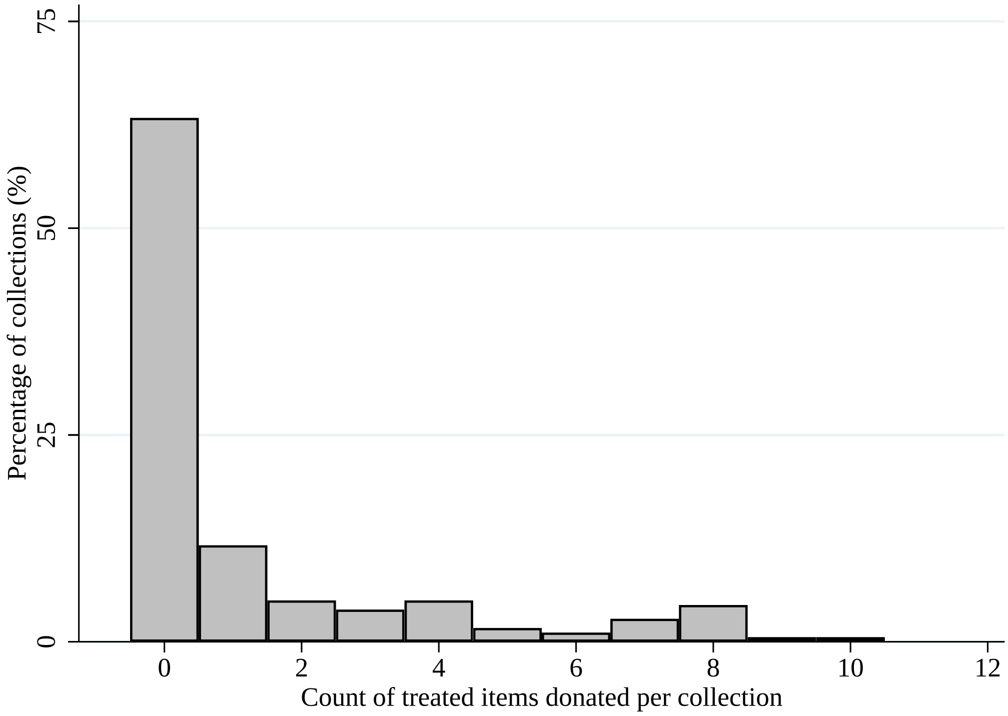


Figure 3.4: The distribution of counts of treated items donated per collection

donated is 1.29 per collection. The unconditional variance is higher than this, at 5.45. The mean, conditional on treatment, is given in the Table 3.2 which shows all have conditional variances larger than their conditional means. This suggests that the data are over-dispersed. To adequately capture the characteristics of our data structure we therefore use a negative binomial model in our analysis, with 18 groups at the store level (Bell et al., 2019).

## 3.6 Descriptive statistics

### 3.6.1 Donated products

We begin with a description of the items donated, broken down by various categories. In total 3609 individual items were donated over the course of the 10 weeks. As we do not observe the donations being made, there is unfortunately no way to know how many different people donated at least one item, or if people donated on multiple trips over the course of the study.

**Brands:** The FoodBank *a-priori* believed that a majority of their donations come from shoppers who purchase items and leave them in the donation baskets on the same visit. We matched the scanned barcodes against a product list provided to us by the supermarket chain. We were not able to match 38.6% of the items donated, indicating they must have been brought into the store from elsewhere with the intention to donate them. Among the items that we could match, 28.1% were 'own-brand' products offered by the supermarket chain, and therefore it is likely most of these items were purchased and donated on the same visit. The rest of the matched items were branded items which may or may not have been purchased from a Co-op store, as they are also sold elsewhere. As the intervention was intended to target shoppers to encourage them to purchase and donate on their current visit, we exclude unmatched items from the analysis.

**Product categories:** We classified the matched items based on the needs of the FoodBank for products of various types to comprise the parcels they produce. Table 3.3 lists the 10 most frequently donated categories, by item count. Non-food items such as household goods, nappies, shampoo, deodorant, sanitary ware and cleaning products comprise 8.0% of the donated items. Approximately 27% of the donations were sweet items such as biscuits, sugar, chocolate, custard and puddings.

**Prices:** The prices of the donated items ranged from 25p to £11. The mean price was £1.55 and the standard deviation was 1.16, with a long right tail of higher prices (Figure 3).

**Baseline Collections:** For each store $s$, we compute the proportion of items donated in the baseline week $w = 0$ which were among the items subsequently treated, $D$, where $U$ is the count of untreated items: $Y_{D,s,0}/Y_{D+U,s,0}$. Using Kruskal-Wallis tests, the pre-treatment distibutions of the counts and proportions are not different between the treatment arms, at p=0.528 and p=0.370 respectively. Looking at Figure 3.7, there appear to be no high-donation stores included in the Treatment T+P, which has a much smaller distribution of baseline donations than the other treatment groups.

Table 3.3: The 10 categories of items that were most frequently donated.

| Category | Count of donations | % of total donations |
|---|---|---|
| **Veg** | 398 | 17.73% |
| **Soup** | 287 | 12.78% |
| **Biscuit** | 198 | 8.82% |
| **Chocolate** | 182 | 8.11% |
| **Pasta** | 129 | 5.75% |
| **Sweet** | 127 | 5.66% |
| **Sauce** | 109 | 4.86% |
| **Meat** | 99 | 4.41% |
| **Cereal** | 66 | 2.94% |
| **All other categories** | 650 | 28.95% |
| **Total matched donations** | 2245 | 100.00% |

Counts refer to the subset of donated items which were sold in East of England Coop stores (matched items).

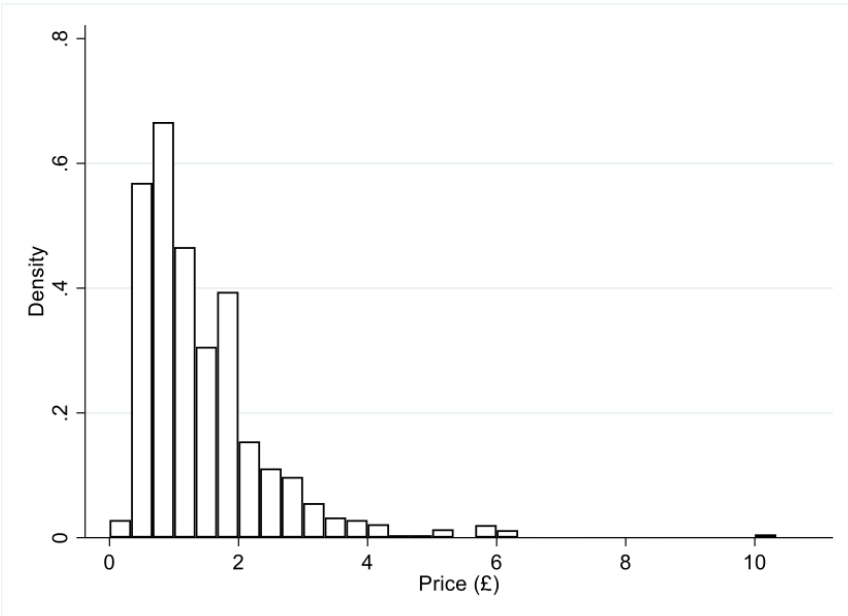


Figure 3.5: Distribution of prices of donated items.

Table 3.4: Summary statistics on the treated items donated by treatment arm, collection level.

| | Baseline Mean Items | Intervention Mean Items | Mean % | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Control | 0.33 | 0.87 | 6.36% | 11.97% | 0% | 58.33% |
| Treatment T | 1.00 | 1.43 | 8.38% | 14.10% | 0% | 66.67% |
| Treatment T+P | 1.17 | 1.70 | 14.97% | 17.68% | 0% | 60.00% |

Table 3.5: Summary statistics on the total value of collections made from each store.

| | Stores | Mean | Std. Dev. | Min (£) | Max (£) |
|---|---|---|---|---|---|
| Control Group | 6 | £176.30 | 110.36 | 61.40 | 355.77 |
| Treatment T | 6 | £209.36 | 172.71 | 40.86 | 543.17 |
| Treatment T+P | 6 | £129.68 | 101.29 | 18.40 | 277.28 |
| Combined T and T+P | 12 | £169.47 | 141.24 | 18.40 | 543.17 |

### 3.6.2 Dependent variables

**Treated Items**: Across all weeks and all stores, an average 7.2% of donations were treated items, ranging from 0% to 67% of a collection. The standard deviation of this proportion is 0.13 (N=152, excluding collections in which no items were donated). Table 3.4 shows summary statistics on treated items donated in each of the treatments. This percentage was 6.36% in the control group, 8.38% in Treatment T, and 14.97% in Treatment T+P. However, Kruskal-Wallis tests using the overall proportions across the 10 weeks for each of the 18 stores (n=18), show that there is not a statistical difference between them. Treatment T+P has a lower number of treated item donations made than the other two arms during the experiment (89 compared to 118 in the control group and 145 in Treatment T), but this difference is not statistically significant using Kruskal-walllis tests.

**Collection Value:** The total price of items donated in a single collection ranged from £0 to £130.24[12](Table 3.5). The arms do not differ in terms of the value of the treated items donated or the collection values based on results from t-tests.

[12]A 0 price in the data could be due to promotional activity by the East of England Coop during the intervention

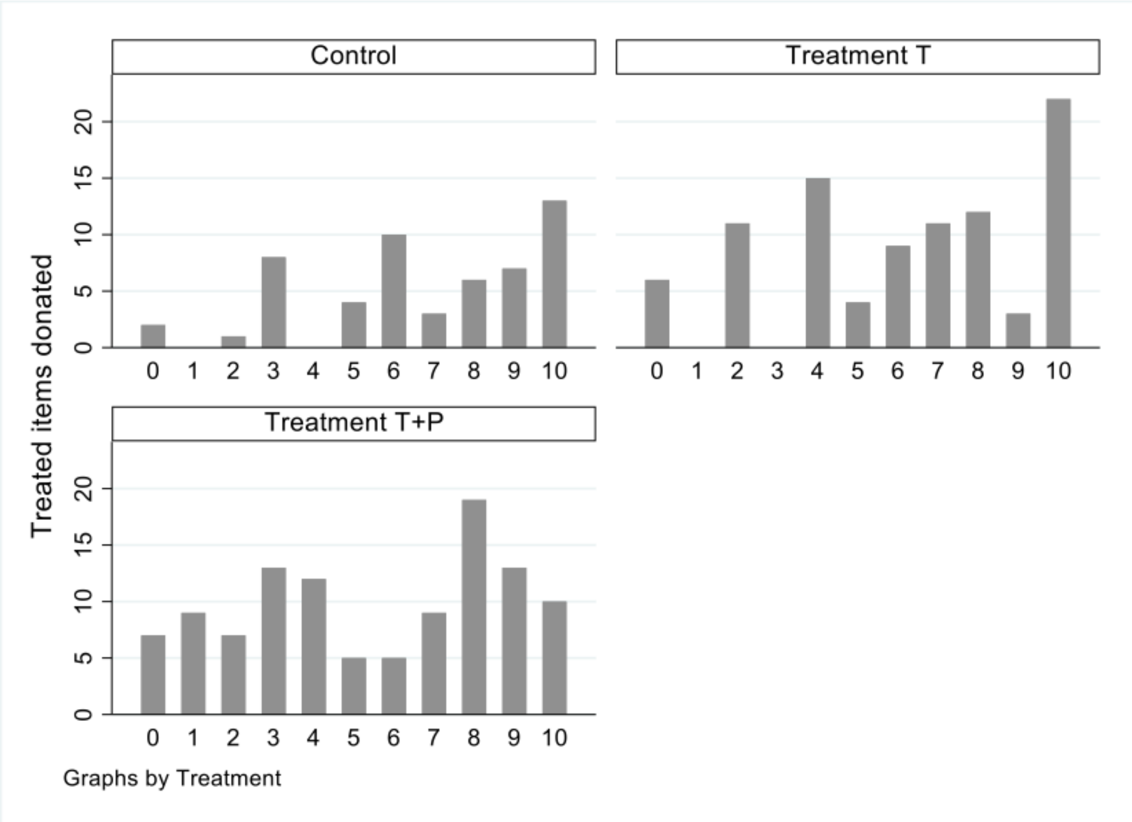


Figure 3.6: Bar graphs showing the weekly count of treated item donated by Treatment

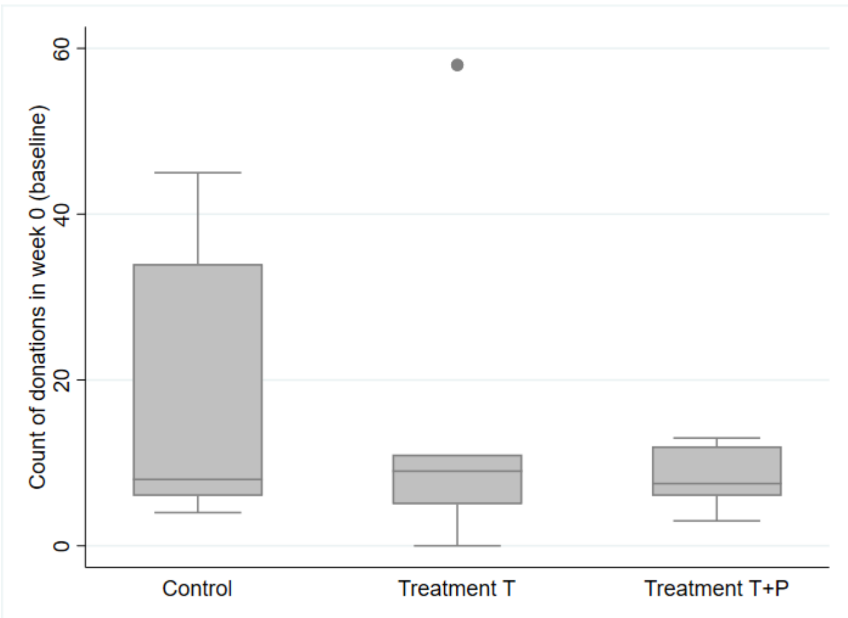


Figure 3.7: Box plot showing the distributions of counts of total donations in week 0 (baseline) collections.

### 3.6.3 Observable store characteristics

Information was provided by the East of England Coop on the weekly average transactions, store size and and turnover of each store we included in experiment. This information was given prior to the start of the experiment. As seen in Table 3.1 there were over 44 variables associated with each store. Due to insufficient data points, not all of these could be included to avoid over-fitting the model. Also, almost all of the variables we had for the stores did not correlate with donation rate, so they were not included to avoid over-specification.

**Further Facilities:** 4 stores had an Amazon Locker and 8 stores had a Collect+ service. 8 stores had neither of these services. 12 of the stores had an ATM either within the premises or directly outside the store. 16 of the stores had a 'PayPoint' facility for prepaying an electric meter. 13 stores had their own designated parking areas. 1 store had a 'customer service point'. These characteristics did not correlate with the number of items donated in stores, and were therefore left our of the estimation model.

**Average Turnover:** Turnover is the value of the sales made in each store per month. The maximum average turnover was over 2.6 times the amount of the lowest average turnover. This characteristic did not predict the number of items donated in a store and was therefore left out of the estimation model.

**Size of Store:** The store size varied from 1540 sq. ft to 4757 sq. ft. The mean was 2781 sq. ft, and the standard deviation was 887 sq. ft. This characteristic could influence how easy it was for customers to see the shelf talkers in the store, and is therefore included in our estimation models.

**Average Transactions**: The mean is approximately 5000 transactions per week per store with a standard deviation of 1100. This factor weakly predicted variations in the number of items donated, and is included in our estimation models.

**Deprivation of Area**: To assess the socioeconomic characteristics of the neighbourhoods surrounding the stores, we use the Index of Multiple Deprivation Ranking (Ministry of Housing, Communities & Local Government, 2019) for the surrounding Lower Layer Super Output Area (LSOA), the smallest unit available for population statistics in England and Wales. There was at least one store in every decile of the ranking. Having assessed the different measures, listed in Table 3.1, and as there is a high correlation between the various rankings, we decided to use the general IMDR and not include any others in the regression (See Figure 3.8). Further exploration of the variables which most closely correlated with donation rate is given in section 3.7.2.

**Donation Easy**: This binary variable describes the location of the donation

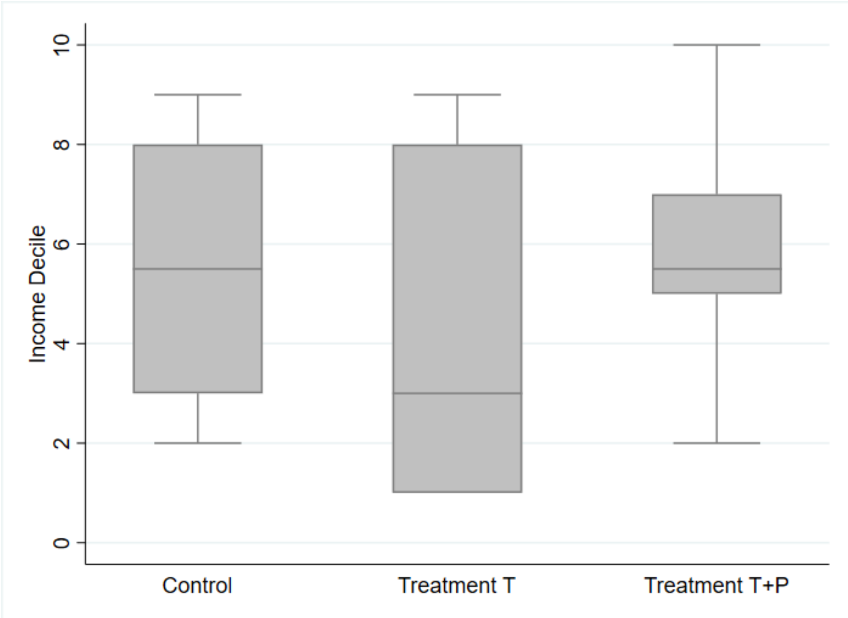


Figure 3.8: Box graph showing the distribution of stores by Index of Multiple Deprivation decile (2019) for each of the Treatments.

point in the store, if it was near the checkout/on the route out of the store it is defined as 1, otherwise 0. Two thirds of the stores had a donation point which was classified as 'Donation Easy'. We anticipated that this would have a significant effect on the rate of donations, and block randomised on this variable, we therefore include it in our regressions.

## 3.7 Results

### 3.7.1 Targeted Reminders

**Result 3.1** *Shelf talkers do not increase donations of specific (treated) item types to the FoodBank.*

*Support:*

We estimate a fixed-effects model. There is within-panel serial correlation in the error term $\epsilon_{it}$, so we use with cluster–robust standard errors for panels nested within the cluster by store.

$Y_{it}$ is the number of treated items donated, where $i$=store and $t$=week number. $T_{it}$ represents a binary variable indicating if the store $i$ was treated with Talkers (T) at time $t$. $T_{it}$ represents a binary variable indicating if the store $i$ was treated with Talkers (T) at time $t$. $\beta$ are the coefficients for the independent variables. $u_{it}$ is the error term. $\beta_t W_t$ is the set of dummy variables for each week-level effect. **Z** is a vector of store-specific characteristics.

$$y_{it} = \beta_1 T_{it} + \beta_2 P_{it} + \beta_{\mathbf{3}} \mathbf{W_t} + \beta_{\mathbf{k}} \mathbf{Z_i} + \epsilon_{it} \tag{3.1}$$

However, this model does not fit the data we have: the conditional variance exceeds the conditional mean. We therefore have over-dispersed count data. The negative binomial model is a generalisation of the Poisson model- often used for count data, but with an extra parameter to model the over-dispersion.

We therefore estimate a model in which the probability of a given observation $y_{it}$ is:

$$y_{it} \sim f\left(\exp\left(\beta_1 T_{it} + \beta_2 P_{it} + \beta_{\mathbf{3}} \mathbf{W_t} + \beta_4 x_{DE} + \beta_{\mathbf{k}} \mathbf{Z_i}\right)\right), \tag{3.2}$$

where $f$ is assumed to follow a negative binomial distribution (Cameron and Trivedi, 1998), run as a random effects model and $y_{it}$ is the number of high-demand treated items donated in a collection in store $i$. We include the indicator variables for if the store had talkers $T$ or posters $P$. We do this as in our design, there is no instance in which there are posters without talkers, so therefore we measure the additional effect of the Posters when we interpret the coefficients from this model. We also include the 'Donation Easy' $DE$ dummy variable and a vector of store-specific characteristics $\mathbf{Z}$[13]. The model is estimated as time series data, where $t$ is the week number of the intervention. Table 3.6 displays the estimated parameters for the full model as well as several restrictions. We have no evidence that the Talkers alone increase the donation of treated items. The sign of the coefficient is negative - an unexpected but weak result.

**Result 3.2** *Shelf talkers do not change amount of non-treated donations to the FoodBank.*

*Support:* We estimate a negative binomial regression on the count of non-treated items donated, where $y_{it}$ in (2) is the number of untreated items donated in a collection in store $i$. The full model and several restricted models are shown in Table 3.7. There is no significant effect of the talkers on the count of untreated items donated.

**Result 3.3** *Posters used in conjunction with shelf talkers on increase the donation of treated items.*

[13]The store characteristics included were: the presence of a Post Office, the average number of transactions per week, the size of the store in square feet and the Index of Multiple Deprivation Ranking. These variables were included as they had the strongest correlation with donation rate, and also did not lead to multicolinearity or uniquely identify any of the stores - which due to the distribtuion of characterisitcs between stores would have been caused by including the Subway variable for example

Table 3.6: Negative-binomial time-series regression models on the count of treated items donated.

| VARIABLES | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Talker | -0.355 | -0.374 | -0.914 |
| | (0.501) | (0.540) | (0.672) |
| Poster | 2.179*** | 2.150*** | 1.891** |
| | (0.673) | (0.756) | (0.934) |
| Week 1 | | -0.676 | -0.716 |
| | | (0.682) | (0.680) |
| Week 2 | | 0.0826 | 0.167 |
| | | (0.499) | (0.490) |
| Week 3 | | 0.105 | 0.100 |
| | | (0.518) | (0.510) |
| Week 4 | | 0.429 | 0.369 |
| | | (0.468) | (0.473) |
| Week 5 | | 0.0229 | 0.0408 |
| | | (0.496) | (0.489) |
| Week 6 | | 0.182 | 0.0921 |
| | | (0.495) | (0.492) |
| Week 7 | | 0.304 | 0.359 |
| | | (0.475) | (0.470) |
| Week 8 | | 0.834* | 0.872** |
| | | (0.436) | (0.431) |
| Week 9 | | 0.509 | 0.459 |
| | | (0.456) | (0.461) |
| Week 10 | | 0.811* | 0.818* |
| | | (0.445) | (0.438) |
| Donation Easy | | | 0.698 |
| | | | (0.953) |
| Post Office | | | 1.012 |
| | | | (0.790) |
| Average Transactions | | | -0.000489* |
| | | | (0.000290) |
| Square Foot | | | 0.000117 |
| | | | (0.000453) |
| Index of Multiple Deprivation Ranking | | | -6.54e-05** |
| Constant | -0.566 | -0.690 | 1.957 |
| | (0.403) | (0.549) | (1.772) |
| Observations | 198 | 198 | 198 |
| Number of stores | 18 | 18 | 18 |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Donation Easy describes the location of the donation point in the store, if it was near the checkout/on the route out of the store it is defined as 1, otherwise 0. The store characteristics included were: the presence of a Post Office, the average number of transactions per week, the size of the store in square feet and the Index of Multiple Deprivation Ranking.

Table 3.7: Negative-binomial time-series regression models on the count of non-treated items donated.

| VARIABLES | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Talker | 0.221 | 0.353 | 0.194 |
| | (0.205) | (0.251) | (0.242) |
| Poster | -0.0490 | -0.356 | -0.176 |
| | (0.255) | (0.251) | (0.265) |
| Week 1 | | -0.0881 | -0.0276 |
| | | (0.287) | (0.274) |
| Week 2 | | -0.461 | -0.177 |
| | | (0.312) | (0.286) |
| Week 3 | | -0.777** | -0.759** |
| | | (0.341) | (0.334) |
| Week 4 | | -0.0370 | 0.0216 |
| | | (0.293) | (0.276) |
| Week 5 | | -0.277 | -0.234 |
| | | (0.318) | (0.304) |
| Week 6 | | -0.178 | -3.53e-05 |
| | | (0.301) | (0.282) |
| Week 7 | | 0.170 | 0.336 |
| | | (0.283) | (0.267) |
| Week 8 | | 0.388 | 0.539* |
| | | (0.297) | (0.279) |
| Week 9 | | 0.598** | 0.766*** |
| | | (0.270) | (0.256) |
| Week 10 | | 0.709*** | 0.866*** |
| | | (0.266) | (0.253) |
| Donation Easy | | | -0.163 |
| | | | (0.308) |
| Post Office | | | 0.168 |
| | | | (0.248) |
| Average Transactions | | | -0.000264** |
| | | | (0.000104) |
| Square Foot | | | -5.53e-06 |
| | | | (0.000170) |
| Index of Multiple Deprivation Ranking | | | -6.79e-05*** |
| | | | (1.28e-05) |
| Constant | 0.0751 | 0.349* | 2.915*** |
| | (0.154) | (0.211) | (0.716) |
| Observations | 198 | 198 | 198 |
| Number of stores | 18 | 18 | 18 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Donation Easy describes the location of the donation point in the store, if it was near the checkout/on the route out of the store it is defined as 1, otherwise 0. The store characteristics included were: the presence of a Post Office, the average number of transactions per week, the size of the store in square feet and the Index of Multiple Deprivation Ranking.

*Support:* The coefficients for the Poster variable in Table 3.6 show that there is a strongly significant and positive effect of posters on the number of treated items donated when used in conjunction with talkers, robust to the inclusion of all controls. the size of the effect is still smaller than the size of the positive, statistically significant coefficient for the inclusion of posters alongside the talkers in the intervention. The Posters variable is significant and robust to the inclusion of all controls. The size of the coefficient is larger than the size of the negative coefficient on talkers, indicating a net positive effect on donation levels. In the full model, the marginal effect of the posters in combination with the talkers is an increase of 1.89 treated items donated per collection. This is a 163% increase on the level of treated items seen in the baseline week in the treatment T+P stores.

**Result 3.4** *Using a poster does not change the number of non-treated items donated.*

*Support:* The Poster variable in Table 3.7 indicates no significant effect of the posters on the number of untreated donations made, robust to the inclusion of all controls.

**Result 3.5** *The location of donation point does not affect the donation of treated or untreated items.*

*Support:* The ease of donation dummy indicates if the donation basket was placed in a location which was near the checkout/entrance or not. It has no significant effect on the count of treated items donated (Table 3.6), or on the donation of untreated items (Table 3.7). This is a surprising result, as in our experience in working for the FoodBank and conducting this experiment, a commonly cited reason for not donating is not seeing the donation basket until leaving the store.

**Result 3.6** *The effect of the shelf talkers does not differ predictably by price.*

*Support:* We estimated 5 models, each using one treated product type within the set of 5 treated product types. The posters in conjunction with the talkers had a statistically significant effect on the donation of vegetables and milk. Vegetables did have the largest and most significant treatment effect, as the cheapest item, and the most expensive item, puddings, did not have a statistically significant treatment effect. The results do not demonstrate a clear correlation between price and the effect of the intervention, but could indicate further room for studies in this area.

Table 3.8: Treated product individual regressions.

| Mean Price | £0.73 | £1 | £1.31 | £1.79 |
|---|---|---|---|---|
| **VARIABLES** | **Vegetables** | **Juice** | **Milk** | **Puddings** |
| Talker | -0.241 | -1.099 | 0.546 | -1.892 |
| | (0.684) | (1.372) | (1.051) | (1.310) |
| Poster | 1.994** | 1.609 | 1.784* | -1.396 |
| | (0.824) | (1.322) | (0.978) | (1.404) |
| Week Dummies Included | Yes | Yes | Yes | Yes |
| Constant | -0.617 | 13.17 | -2.330* | -21.48 |
| | (0.663) | (1,412) | (1.378) | (37,923) |
| Observations | 198 | 198 | 198 | 198 |
| Number of store | 18 | 18 | 18 | 18 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Deodorant had a mean price of £2.03, but the regression did not converge using the parameters listed. Donation Easy describes the location of the donation point in the store, if it was near the checkout/on the route out of the store it is defined as 1, otherwise 0. The store characteristics included were: the presence of a Post Office, the average number of transactions per week, the size of the store in square feet and the Index of Multiple Deprivation Ranking.

### 3.7.2 Exploratory Analysis

Due to the highly variable nature of donations both within and between stores, we use outlier analysis to check the robustness of our results. This was not part of our pre-registered plan with the AEA. In our exploratory analysis (see Figure 3.9) we found that donation patterns differed considerably by store, in ways which did not strongly correlate with the observed characteristics. In Graph A, we observe that two shops in Treatment T+P are outliers in that they have a much higher number of treated items donated, and those treated items form a much larger proportion of the total items donated at those shops, compared to other shops. Meanwhile the other four shops in T+P are among the lowest in both total donations and treated item donations. In Graph B it is clear that there is an outlier of one store in treatment 1 (T), which has the largest number of items donated by far. The relationship appears to be that the more deprived the area is, the higher the total donations made. A lower ranking indicates the area is more deprived. This correlation is controlled for through inclusion as a variable in the regression analysis.

In Graph C of Figure 3.9 we show the relationship between FSM% and number of donations made in total. We used the FSM % as a proxy for income level. This agai shows a trend of higher donations in areas with higher rates of deprivation.

In Graph D we can see the relationship between the Health and Disability ranking and the total donations in each store, in which we observe a negative relationship between ranking and donations similar to in Graph B.

Using the total count of donations per collection as the dependent variables, Table 3.10 in Appendix 3.B shows the coefficients of the store-level characteristics which were included as controls. The two controls which have statistical significance are Average Transactions and IMDR. Average transactions has a negative coefficient - this is surprising as one would assume that more transactions in store would mean higher footfall and therefore a higher number of donors. IMDR has a negative coefficient, which indicates that as the relative deprivation of an area increases, so do donations. This is in line with Manstead (2018), who found that those in different socioeconomic strata donate at different rates. The controls in the treated items regressions (Table 3.6) are statistically significant for Average transactions, again in the negative direction, and for IMDR again in the negative direction. The controls for the untreated items regressions (Table 3.7) are highly significant for both average transactions and IMDR, again in the same negative direction. It is hard to interpret the IMDR coefficient or marginal effect, as it is an ordinal variable, but as the area becomes relatively more deprived, donations increase.

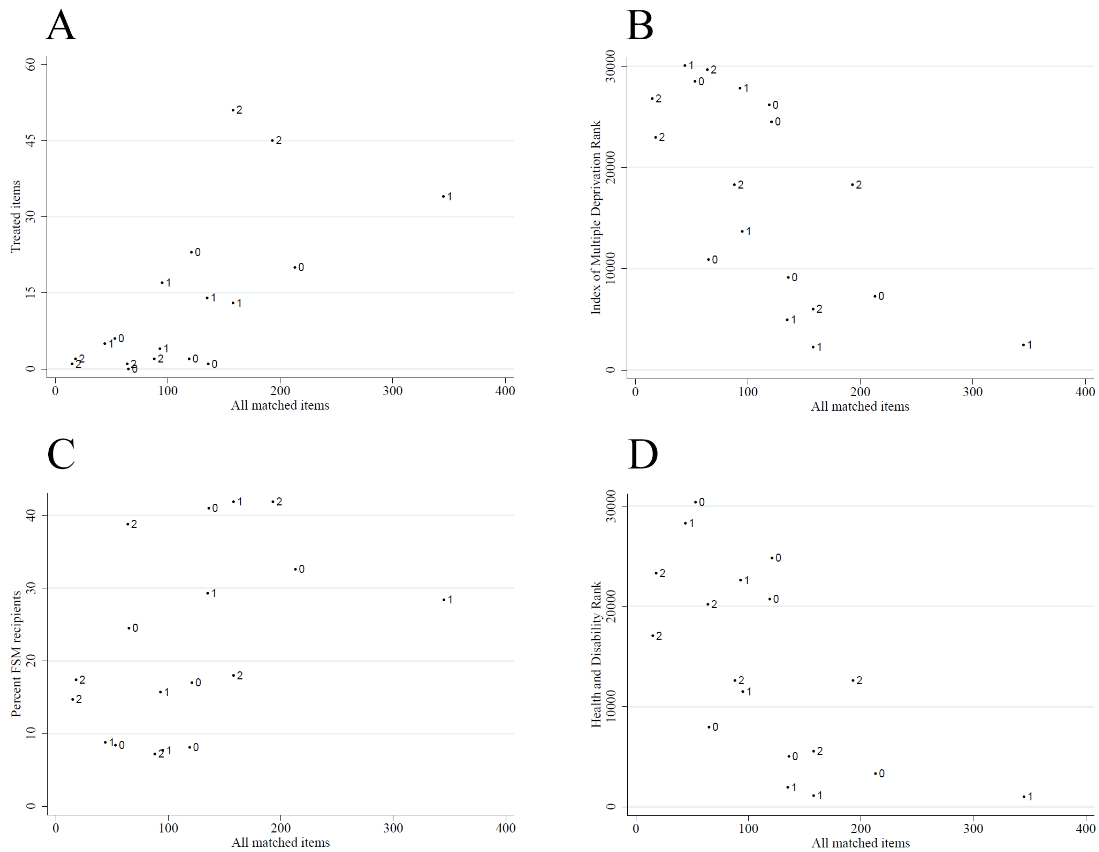


Figure 3.9: Scatter graphs showing individual store attributes for outlier analysis.

Labelled with treatment number: 0=control, 1=T, 2=T+P. All graphs share the x-axis of total donations made across the duration of the intervention. Graph A shows the number of treated items donated across the duration of the intervention. Graph B shows the stores' Index of Multiple Deprivation Ranking Score 2019. Graph C shows the percentage of FSM recipients in each store's nearest infant or primary school, which was used as a proxy variable for local deprivation levels when assigning stores to treatment groups. Graph D shows the Health and Disability Ranking (Ministry of Housing, Communities & Local Government, 2019).

### 3.7.3 Robustness Checks

As a robustness check we investigated the effect of time on donations. We anticipated an increase in donations as the week number increased due to the intervention's proximity to Christmas. The number of treated and untreated items donated each week can be seen in Figures 3.10 and 3.11. This also shows the results of a simple estimation of week and week squared on items donated. The week variable is significant in the regressions estimating the donation of both treated and untreated items (see Table 3.6 and Table 3.7). We investigated if there was a non-linear time trend for treated, non-treated and all donations, the results are displayed in Table 3.9, in columns 1, 3 and 5. We can see that for treated items there is no significant coefficient on either week or the week squared variable. For non-treated and total donations, there is a negative coefficient for week, but a positive coefficient for week squared, which are all statistically significant. This indicates a U-shaped time trend with donations increasing at an increasing rate closer to Christmas. This can be seen by the reasonably good fit in Figure 3.11. We investigated if there were divergent time trends in the donation of items by treatment, through the estimation of an interaction term between week and treatment (see Table 3.9, columns 2, 4 and 6). No such effect was found for treated items, however, a small negative effect was found on the interaction between treatment T+P and week for untreated and total donations, relative to the control. This effect was only slightly statistically significant, and had a negative coefficient, which would indicate shops with talkers and posters experienced a smaller time trend increase than the control group. This effect, although small, was unexpected, but could be driven by the inclusion of stores with lower baseline levels of donations in Treatment T+P (see Figure 3.7). As the time trend is not perfectly captured by either linear or quadratic estimations, we use week-dummies in our main analysis. The coefficients for the talker and poster variables in this robustness check support the previous finding that there is a strongly significant positive effect of using the posters in conjunction with the talker on the donation of treated items. In these regressions, the talker coefficient is again negative, but this time achieves statistical significance where it did not in Table 3.6. Again, there is no statistically significant effect on the level of non-treated items donated.

To account for the possibility of outliers based on our exploratory analysis in Section 3.7.2 we drop those stores with overall donation levels that are more than 1 standard deviation above (over) the average donation level and find that the poster variable retains its high statistical significance, and a similar effect size. The talker coefficient remains insignificant. The poster variable remains highly statistically

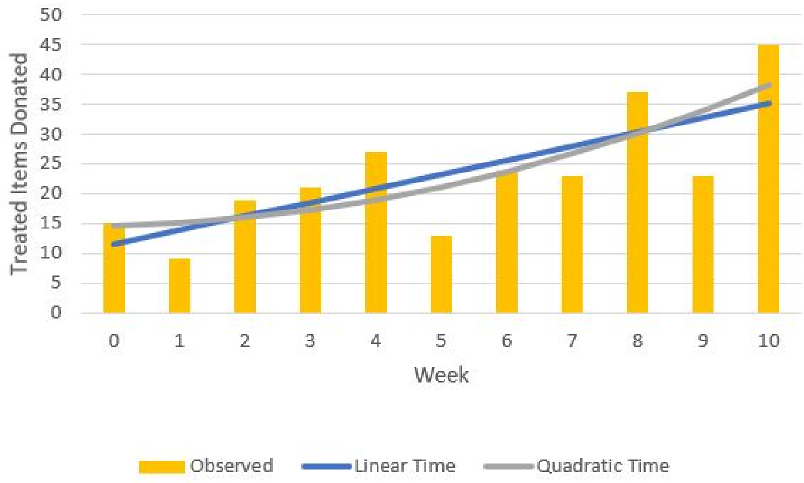


Figure 3.10: Graph of Treated Donations by Week

Graph includes the actual number of treated items observed each week, with estimates from linear and quadratic equations overlaid.

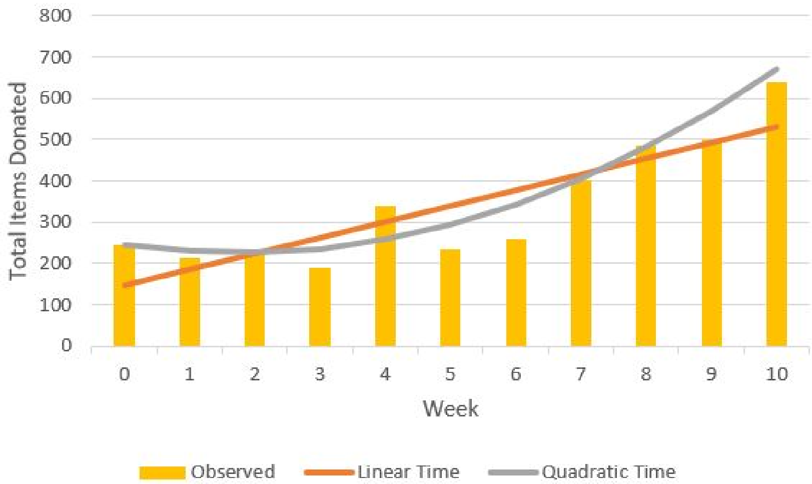


Figure 3.11: Graph of Treated Donations by Week

Graph includes the actual number of untreated items observed each week, with estimates from linear and quadratic equations overlaid.

Table 3.9: Estimating the effect of time.

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| VARIABLES | Treated | Treated | Untreated | Untreated | Total | Total |
| Talker | -1.099** | -1.237* | 0.342 | -0.233 | 0.282 | -0.252 |
| | (0.485) | (0.676) | (0.261) | (0.332) | (0.260) | (0.330) |
| Poster | 2.450*** | 3.185*** | -0.0644 | 0.573 | 0.0297 | 0.643 |
| | (0.577) | (0.796) | (0.302) | (0.418) | (0.303) | (0.416) |
| Week | 0.0982 | 0.185*** | -0.156** | 0.113*** | -0.144** | 0.117*** |
| | (0.138) | (0.0613) | (0.0741) | (0.0293) | (0.0734) | (0.0289) |
| Week Squared | 0.000847 | | 0.0240*** | | 0.0229*** | |
| | (0.0120) | | (0.00649) | | (0.00642) | |
| Talker × Week | | -0.0361 | | 0.0404 | | 0.0337 |
| | | (0.0973) | | (0.0476) | | (0.0471) |
| Poster × Week | | -0.108 | | -0.0937* | | -0.0909* |
| | | (0.0891) | | (0.0518) | | (0.0508) |
| Constant | -0.708* | -0.881** | 0.192 | -0.162 | 0.210 | -0.134 |
| | (0.406) | (0.436) | (0.188) | (0.201) | (0.188) | (0.201) |
| Observations | 187 | 187 | 198 | 198 | 198 | 198 |
| Number of stores | 17 | 17 | 18 | 18 | 18 | 18 |

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Negative binomial regressions testing for a non-linear effect of time on donations (columns 1, 3 and 5) and for divergent time trends on donations between treatments (columns 2, 4 and 6) significant and larger than the absolute coefficient size of the talker variable, as seen previously, meaning that there is still a net positive effect of the intervention in the Treatment T+P on the treated items. There is no statistically significant effect on the untreated items - again in agreement with our main results (see Appendix 3.C: Over, Treated and Over, Untreated columns[14].)

We drop those stores with overall donation levels that are more than 1 standard deviation below (under) the average. A regression on the treated items donated shows that the poster variable is still highly significant and in the expected direction, though its magnitude is reduced with respect to our initial results (1.765 in comparison to our earlier 2.150), reflecting a smaller marginal effect (net of the talker variable) of 1.49 increase in treated items donated per collection in comparison to our previous result of 1.89. The talker variable is still insignificant. Looking at the effects of these variables on the untreated items, there is one difference in that the talker variable whilst remaining positive, becomes significant. There are no other significant effects on the donation of untreated items (see Appendix 3.C, Under, Treated and Under, Untreated columns).

We drop both stores with overall donation levels 1 standard deviation above and below the average and find that the poster variable is again positive highly significant and the talker variable is not significant. Our results therefore appear to be robust to outlier analysis, and the positive effect of Posters on the donation of treated items in conjunction with talkers is supported further by this evidence (see Appendix 3.C, Both, Treated and Both, Untreated columns).

## 3.8 Discussion and Conclusion

In-kind donations are popular despite being less efficient than pecuniary donations. NGOs that rely on in-kind donations would benefit from a donation mix that converts to their outputs more closely. This chapter has investigated the effect of point of purchase messaging on the product mix of donated items. We used shelf talkers, in addition to poster signage to highlight products most needed by a local FoodBank.

We found that shelf talkers did not increase the donation of in-demand items when used alone. However, when posters were used in addition to talkers, the net effect was an increase of donation of high demand items. We contribute to the marketing literature in finding that marketing materials may work best in

[14]'Over' and 'Under' refer to the outliers dropped in the analysis that were either 1 standard deviation *over* or *under* the mean

conjunction with one another as part of a strategy rather than in isolation. We contribute to the donation behaviour literature in showing that such an intervention has the potential to influence donations in favour of the treated items - but that this effect does not change the level of other donations made. We found that increase deprivation in the local area was correlated with higher donation levels - contributing to the literature in the effects of wealth and income on donation levels and rates.

The treatment effect is non-homogenous across product types. This could result from differences between the product categories. One difference we investigated was price. We hypothesized an individual might choose the cheapest item to donate among a selection of goods. We did not find a correlation between price and the effect of the talkers. Due to the lack of available data, the results cannot specifically investigate the effect of price on donations: the prices used in this analysis were a snapshot of prices as valued in January 2020, and did not take into account any promotions that took place during the experiment.

The novel nature of this field experiment and data collection method means it was subject to some limitations. The variation in donation patterns was such that some stores received almost no donations for the entire duration of the experiment. A larger sample size and more information of customer intentions (e.g. via a customer survey) would allow a better understanding of the mechanisms driving in-kind donations, as well as provide more information on store-level characteristics. The posters may have alerted donors to the need for specific products, shifting donations towards the treated items without an overall increase in donations, but donations could equally have come from someone who did not intend to donate until they saw the intervention. In our experiment, we are only able to observe outcomes.

This study is highly context specific, and we recognise that the factors involved in donation behaviour are also context specific - so the results of this study may not be highly generalisable. However, this context was chosen to reduce the distance and noise between the solicitation and the action of donating a tangible good. Moreover, the use of food banks has been on the rise in the UK, particularly in the wake of the Covid-19 pandemic, making this particular context highly relevant for the charity involved. We found in the exploratory study that the combination of general reminder (i.e. posters at the store entrance) and targeted product solicitation (i.e. talkers) could be a simple and cost-efficient way of increasing the share of high-demand items in total donations. A related design might introduce the ability to purchase high demand items during the online shopping experience.

Our results highlight the importance of small factors in design when looking at changing in store behaviour, such as location and visibility (Dalton et al., 2015). Changing elements of the environment in which tangible donations are made can lead to greater donations – but further work remains on achieving a more efficient mix of donations. This exploratory study raises further questions about how responsive consumers are to the changing needs of the charity and what role price plays in the donation of tangible items.

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# Appendices

# 3.A An example of the products contained in a FoodBank parcel

**Food Allocation Form: One Person**

| Volunteer: | Voucher No: | Date: |
|---|---|---|
| | | |

| Item | Allocation | Amount given |
|---|---|---|
| Cereal | 1 small | |
| Soup (can/packet) | 2 standard | |
| Beans/spaghetti in sauce | 2 small | |
| Tomatoes/pasta sauce | 2 small | |
| Vegetables | 2 small | |
| Meat | 2 small | |
| Or Vegetarian | 2 small | |
| Fish | 1 small | |
| Fruit | 2 small | |
| Rice pudding/custard | 1 standard | |
| Biscuits | 1 small packet | |
| Pasta/rice/noodles | 500g | |
| Tea or coffee | 40 bags/small jar | |
| Long-life juice | 1 litre | |
| Milk UHT | 1 litre | |

**Extra items when available**

| | | |
|---|---|---|
| Sauces | 1 packet | |
| Chocolate | 1 small bar | |
| | | |
| | | |

| | |
|---|---|
| **Client signature to confirm food received:** | |

**Additional requests:**

| | COMMENTS |
|---|---|
| Cooking facilities? | |
| Vegetarian? | |
| Any other dietary requirements? | |
| Children's ages? | |

| ITEM | | REQUIRED | ISSUED |
|---|---|---|---|
| Cat/Dog? | Size? | | |
| Washing Powder? | | | |
| Washing up liquid? | | | |
| Toilet rolls? | | | |
| | | | |
| Toiletries | Soap or Shower gel? | | |
| | Deodorant? | | |
| | Toothpaste? | | |
| | Toothbrush? | | |
| | Shampoo? | | |
| | Feminine hygiene? | | |
| | Shaving foam? | | |
| | Razors? | | |

Figure 3.12: Packaging slip for a 3-day single-person FoodBank parcel
Source: Human Rights Watch (2019)

## 3.B Extensions

Table 3.10: Regression models on the count of total items donated.

| VARIABLES | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Talker | 0.217 | -0.0201 | -0.131 |
| | (0.231) | (0.250) | (0.244) |
| Poster | 0.288 | 0.0359 | 0.0694 |
| | (0.291) | (0.304) | (0.330) |
| Donation Easy | | -0.113 | -0.314 |
| | | (0.286) | (0.427) |
| Week | | 0.110*** | 0.128*** |
| | | (0.0199) | (0.0182) |
| Post Office | | | 0.0783 |
| | | | (0.336) |
| Average Transactions | | | -0.000300** |
| | | | (0.000136) |
| Square Foot | | | -0.000271 |
| | | | (0.000230) |
| IMDR | | | -7.87e-05*** |
| | | | (1.61e-05) |
| Constant | 0.00646 | -0.0843 | 3.704*** |
| | (0.164) | (0.272) | (0.895) |
| Observations | 198 | 198 | 198 |
| Number of stores | 18 | 18 | 18 |

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

## 3.C Outlier Analysis

Table 3.11: Regressions using outlier analysis

| VARIABLES | 1<br>Over<br>Treated | 2<br>Under<br>Treated | 3<br>Both<br>Treated | 4<br>Over<br>Untreated | 5<br>Under<br>Untreated | 6<br>Both<br>Untreated |
|---|---|---|---|---|---|---|
| Talker | -1.062 | -0.385 | -0.997 | 0.444 | 0.508** | 0.487*** |
| | (0.675) | (0.531) | (0.688) | (0.276) | (0.214) | (0.173) |
| Poster | 2.297*** | 1.765*** | 2.492*** | -0.317 | -0.0718 | -0.132 |
| | (0.608) | (0.573) | (0.617) | (0.255) | (0.232) | (0.165) |
| Week 1 | -0.256 | -0.990 | -0.335 | -0.0485 | -0.261 | -0.129 |
| | (0.874) | (0.770) | (0.842) | (0.317) | (0.284) | (0.309) |
| Week 2 | 0.306 | -0.130 | 0.161 | -0.569 | -0.371 | -0.358 |
| | (0.771) | (0.602) | (0.757) | (0.349) | (0.290) | (0.321) |
| Week 3 | 0.234 | -0.145 | 0.137 | -0.651* | -0.910*** | -0.673* |
| | (0.793) | (0.648) | (0.770) | (0.357) | (0.336) | (0.348) |
| Week 4 | 0.748 | -0.0835 | 0.323 | -0.0670 | -0.166 | -0.0912 |
| | (0.736) | (0.603) | (0.746) | (0.329) | (0.286) | (0.313) |
| Week 5 | 0.180 | -0.183 | 0.0201 | -0.323 | -0.264 | -0.170 |
| | (0.796) | (0.612) | (0.782) | (0.352) | (0.297) | (0.318) |
| Week 6 | 0.331 | 0.00113 | 0.169 | -0.253 | -0.261 | -0.227 |
| | (0.824) | (0.624) | (0.808) | (0.334) | (0.289) | (0.314) |
| Week 7 | 0.422 | 0.0873 | 0.288 | 0.117 | 0.152 | 0.214 |
| | (0.762) | (0.582) | (0.747) | (0.315) | (0.269) | (0.294) |
| Week 8 | 1.164 | 0.544 | 0.962 | 0.308 | 0.367 | 0.429 |
| | (0.731) | (0.562) | (0.720) | (0.335) | (0.277) | (0.297) |
| Week 9 | 0.815 | 0.197 | 0.577 | 0.616** | 0.479* | 0.613** |
| | (0.767) | (0.596) | (0.761) | (0.301) | (0.261) | (0.281) |
| Week 10 | 0.918 | 0.569 | 0.677 | 0.666** | 0.629** | 0.696** |
| | (0.759) | (0.589) | (0.752) | (0.297) | (0.255) | (0.276) |
| Constant | -0.728 | -0.333 | -0.591 | 0.219 | 0.486** | 0.336 |
| | (0.542) | (0.441) | (0.544) | (0.229) | (0.216) | (0.238) |
| Observations | 176 | 165 | 143 | 176 | 165 | 143 |
| Number of Stores | 16 | 15 | 13 | 16 | 15 | 13 |

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The 'Over' columns refer to when stores with a total donation level 1 standard deviation above the mean were dropped from the analysis (stores 1 (Talker) and 2(Control)). 'Under' refers to the stores with total donations 1 standard deviation below the mean being dropped from the analysis (store number 3 (T+P), 17 (T+P) and 16 (T)). 'Both' refers to stores with total donations 1