# Vaccine sharing behaviour in the COVID-19 pandemic: the impact of narratives and peer effects

## Pre-analysis plan

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**Abstract**

We conduct a virtual lab experiment to understand individuals' vaccine sharing attitudes and behaviour in the context of altruistic and self-interest narratives, with and without peer effects. A 2-by-3 factorial design is used to determine the isolated impact as well as the interaction of these treatments on vaccine sharing with resource-poor countries, which is approximated by monetary donations from subject payments to the vaccine access initiative COVAX. The main interventions are complemented by detailed socio-economic surveys, including attitudes towards vaccines and vaccine history.

# 1 Introduction

Understanding the inclination of resource-rich countries to share is essential for ensuring that vaccine redistribution policies are accepted among the general public. On a population level, we know that people give more in times of economic prosperity [List and Peysakhovich, 2011], and are equally willing to give to their community and outside of it [Candelo et al., 2018]. The COVID-19 pandemic, however, is unprecedented. Our study will collect data to understand individuals' willingness to share after nearly two years of physical, financial and emotional hardship. This is particularly pertinent as vast amounts of private and public money are spent on global vaccine distribution initiatives while many low-and-middle-income countries (LMIC), especially on the African continent, have fully vaccinated only a single digit share of their population and half of all African countries 2% or less [WHO Africa, 2021a]. At the same time, new data reports that only one in seven infections in Africa are detected [WHO Africa, 2021b]. In contrast, the willingness to get vaccinated against COVID-19 is much higher in LMICs with an average of 80.3% compared to only 64.6% in the US and 30.4% in Russia [Solís Arce et al., 2021]. For these reasons, our research aims to establish a more coherent picture of individuals' attitudes and sentiments towards vaccine sharing, establishes individual-level data. We believe that, in hindsight and the future, this data is crucial to evaluate and guide public policy and vaccine investments abroad.

In our study, we conduct an online experiment to determine influencing factors on vaccine sharing behaviour of individuals in resource-rich countries. The experiment investigates the role that narratives play in how people consume and react to information. Narratives generate long-run beliefs about a subject matter [Eliaz and Spiegler, 2020, Shiller, 2017], and provide motivation for choices and actions taken when it is cognitively exhausting to differentiate between facts and hearsay. In the charitable giving literature, narratives

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have historically been part of the design of information provision to increase donors' pledges, and framing can be decisive for donation behaviour [see, e.g., Merchant et al., 2010, Metzger and Günther, 2019]. We introduce a $3 \times 2$ factorial design, where subjects are randomly assigned to one of six experimental conditions. In the first dimension, we present our subjects with facts appealing to either altruism or self-interest (plus control group) as a narrative for sharing vaccines. Subjects then have the opportunity to share any amount of their earnings from the experiment as a donation to the vaccine access initiative COVAX. In the second dimension, we observe peer effects: after learning the average sharing behaviour of their peer group, subjects can revise their pledge. For all subjects, we also collect relevant covariates such as data on vaccine history, exposure to hardship during the pandemic, risk attitudes, baseline level of altruism, and standard demographics.

Vaccine donation behaviour differs from traditional charitable giving. Because of the ongoing pandemic, there is a sense of urgency in handling the redistributional process. Subjects may be quick to empathise with other people going through their same struggles who are, to a certain degree, in a more precarious situation due to their geographical location. On the other hand, they may be discouraged from donating if they believe that their own needs have not yet been met, regardless of how comparatively worse-off someone else is. Eliciting sharing behaviour in the context of controlled information narratives may shed light on how to encourage a cooperative global society through public policies.

# 2 Experimental conditions

In a $3 \times 2$ experimental design, we randomise subjects into two narrative conditions and a control group, and further split these three groups into isolated decision makers or agents who are exposed to peer effects. The two narratives we present are grounded in facts about vaccination and inequities worldwide, with the first narrative appealing to subjects' altruism and the second narrative appealing to self-interest. Table 1 shows the matrix of our factorial design, with the experimental conditions and the interaction between the narratives (experimental conditions) and peer effects.

## 2.1 Altruism narrative

It is a long-established concept that people are altruistic because they experience 'warm glow' by helping others [Andreoni, 1989]. We also know that altruistic behaviour in times of crisis may be encouraged by policies, an experienced life shock [Ashraf and Bandiera, 2017] and the actions of others [DellaVigna et al., 2012, Martin and Randal, 2008]. That is, people enjoy giving, and all the more so when exogenously encouraged by design or through social interaction that may result in self-image concerns or social expectations. This line of research motivates the altruism-narrative experimental condition, and further suggests the question of whether subject donation behaviour will differ in isolation that in a social setting. To answer this, we randomise subjects in the altruism-narrative condition into two groups: subjects who donate in isolation, and subjects who are exposed to their peers' average donations: The latter are shown their session and treatment group's total and per-person average donations before being asked whether they wish to revise their donation amount.

## 2.2 Self-interest narrative

Self-interest, beyond the utility derived from a warm glow, may also be a strong argument in favour of donation. While donating may be perceived as inherently altruistic, the case of vaccine donation during a global pandemic can be framed as a necessary action to aid oneself, one's family and one's country. For example, the longer it takes to inoculate the world, the higher the probability of viral mutations which citizens in resource-rich countries are not protected against. Consequently, it may be in the best interest of subjects to cooperate and help citizens of resource-poorer countries. While people do derive some utility from helping others, there is also evidence that we try to avoid being asked to donate [Andreoni et al., 2017, DellaVigna et al., 2012] because there is a cost to experiencing empathy for others. A self-interest narrative allows us to understand donation behaviour in the absence of exogenous empathic stimuli, and therefore separate and illuminate some of the correlates to donation that have previously been conflated with altruism. As with the altruism narrative, we also randomly divide the subjects in the self-interest narrative condition into two groups that are, and are not, exposed to their session and treatment group's per-person average donation before they are asked whether they wish to revise their donation amount.

### 2.3 Control group

Finally, we have a control group where subjects are not exposed to any narrative. This group defines a baseline for the information that exists in the world and how it is consumed and processed by people when there is no direct(ed) narrative. The control group is also randomly divided into peer exposure and no-peer exposure subgroups. In the absence of a donation ask, evidence shows that people are more likely to engage in altruistic behaviour in social settings as a result of social-image concerns [Partika, 2017], or as a form of conditional cooperation [Wiepking and Heijnen, 2011]. The choices we make are subject to social scrutiny, whether that be from our family, or in a public environment. Therefore, any true control group would also have to vary social exposure as is captured by the experimental conditions.

To ensure comparability of the choice architecture between treatments, all groups without peer effects will also be given the chance to revise their pledged donation (without additional information in before this choice).

| | **Control** | **Altruism narrative (A)** | **Self-interest narrative (S)** |
|---|---|---|---|
| **No peers** | C | A | S |
| **Peers (P)** | P | PA | PS |

Table 1: The $3 \times 2$ factorial design of our experiment.

## 3 Power and sample size determination

We perform a simulation-based, between-subject ANOVA[1] power analysis in order to estimate the minimum sample sized needed to minimise the probability of incurring a Type II error. Our a priori calculation uses Caldwell and Läkens' Superpower R package [Lakens and Caldwell, 2021], whose algorithm relies on 10,000 Monte Carlo data set simulations with attributes specified by the researcher. We have defined the input parameters, $\mu = \{2, 1, 4.5, 2.5, 5.5, 4.5\}$[2] and $\sigma = 2.89$, based on a linear approximation of Metzger and Günther's experimental *pooled* mean and standard deviation [Metzger and Günther, 2019], whose design is similar to ours[3]. We adapt these numbers to our hypotheses, developed in the next section.

| | **power** | **partial $\eta$ squared** | **cohen f** | non-centrality |
|---|---|---|---|---|
| **Narrative** | 100 | 0.1981 | 0.4971 | 369.1686 |
| **Peer effects** | 100 | 0.0507 | 0.2311 | 79.8202 |
| **Narrative + Peer effects** | 81.3681 | 0.0066 | 0.0817 | 9.9775 |

Table 2: Power analysis, performed using the Superpower R package.

With a power score of 100 for the narrative factor, 100 for the peer effects factor, and 81.4 for the interaction between these two factors, a sample size of $n = 250$ per experimental condition suffices to reach

[1]We choose to focus on causal claims for the sample size justification, as opposed to the correlational claims stated in the hypothesis section. Therefore, the MANOVA variation of the power calculation is not relevant for this analysis.

[2]Each mean corresponds to the following condition, respectively: P, C, PA, A, PS, S.

[3]Their subjects donate between 0 and 100 cents of one USD. They have a pooled mean of 0.3443 cents and a pooled standard deviation of 0.3620. In our experiment, subjects donate on a scale between 0 and 8 GBP, the linear adjustment for the pooled mean is therefore $\mu = 0.3443 \times 8$, and the linear adjustment for the standard deviation is $\sigma = 0.3620 \times 8$.

the recommended power level [Cohen, 1992] with a significance level of 0.05. Cohen's $f$ estimates of 0.5, 0.23 and 0.08 coincide with benchmark big, medium and small effect sizes (0.4, 0.25, 0.1), and with other online experimental studies on charitable giving (e.g. [Sisco and Weber, 2019]).

# 4 Hypotheses

Our experiment is designed to understand donation behaviour among subjects when faced with different information, and subjected to peer effects. In these regimes, we propose to find evidence in favour, or against, the following main and secondary hypotheses.

## 4.1 Main hypotheses (causal effects)

**H1: The altruism and self-interest narratives both increase willingness to give.** We expect that being exposed to a directed narrative changes subjects' perception of their real-world environment which, in turn, increases their donation amount. Both narratives are grounded in factual information, and, it is known that, independently from the narrative, information provision provides an exogenous shock to the belief formation processes of subjects [Haaland et al., 2020].

**H2: Self-interest is a stronger motivator than altruism.** In times of economic and medical hardship, it is plausible for individuals to choose to focus on themselves, their family and their close social circle. It has been shown that individuals give more to close family and less to community members and strangers, demonstrating that the willingness to donate is linked to social distance [Candelo et al., 2018].

The COVID-19 pandemic has resulted in unexpected and sudden hardships, as well as uncertainties for a large proportion of the population, even in resource-rich countries. Given these circumstances, we hypothesise that self-interest, rather than altruism, is a stronger motivator for donating COVID-19 vaccine resources. Altruism and self-interest are outlined as two mechanisms driving charitable giving by Bekkers and Wiepking [2011]. We expect our hypothesis to manifest itself in higher (initial or revised) donation amounts from subjects in the treatment arms subjected to self-interested motivators (arms 5 and 6), as compared to the treatment arms subjected to altruistic motivators (arms 2 and 3).

**H3: Peer effects increase willingness to give.** When individuals interact in social settings and observe decisions by their peers, they are motivated to maintain a positive self-image and converge to a consensus [Martin and Randal, 2008]. Peer effects in charitable giving can be considerable [Smith et al., 2014]. In the treatment arms with altruistic motivators, we expect subjects to increase their contribution if it lies below their group's average in response to perceived social pressure. This aligns with literature that demonstrates increased charitable giving in the presence of social pressure, or conditional cooperation, [DellaVigna et al., 2012, Wiepking and Heijnen, 2011] and in the presence of social comparison [Partika, 2017].

In the self-interested treatment arm, on the other hand, we expect a similar trend for a different reason: a group average higher than the subject's contribution indicates a greater group confidence in the benefits of donating, suggesting that the subject should align their beliefs (and their donation) with that of the group. We evaluate this by comparing the (revised) donation amounts between the treatment arms with, and without, peer effects.

**H4: The interaction of peer effects and self-interest is greater than the interaction of peer effects and altruism.** Peer effects have a different effect when combined with altruism than when combined with self-interest. That is, the interaction of those two treatments differs. We hypothesise that seeing others' (average) donation doesn't encourage 'more altruistic' behaviour as much as it encourages 'more self-interested' behaviour. The rationale behind this is that distributing vaccines around the globe is a public good. The more people donate, the more effective action can be taken and the better the outcome for the subject. That is, seeing others donate will motivate a self-interested individual even more [Frey and Meier, 2004]. An altruistically motivated subject, however, may feel less 'in the ask' to give (as someone else is already helping), if they see high average donations. While subjects may also feel the need not to 'fall behind other's generosity', we hypothesise that these effects combined are weaker than the interaction between self-interest and peer effects.

### 4.2 Secondary hypotheses (heterogeneous effects and correlational claims)

**Vaccine history and perceived safety affects giving behaviour.** While we expect individuals to take care of themselves, their families and their immediate social circles first [Candelo et al., 2018], it is plausible that this effect is correlated with the perceived safety, and in particular vaccine history, of the subject and their close social network. In particular, we hypothesise that individuals who are vaccinated, and whose close family and friends are too, are more willing to donate. The extent to which our hypothesis holds will be evaluated by analysing the survey data in conjunction with each subject's initial donation amount (for all treatment arms).

**Hardship affects willingness to give.** There is evidence in the literature that hardship leads to increases in the willingness to donate due to an increased awareness of need [Bekkers and Wiepking, 2011]. It is plausible that the need for increased vaccines, applied domestically and internationally, is felt more acutely if the subject has personally experienced COVID-19-induced hardships first-hand. Likewise, List and Peysakhovich [2011] suggest that individuals do not significantly reduce their charitable giving when faced with economic downturns. Based on this literature, we hypothesise that a correlation between hardship and willingness to give can be observed under both altruistic and self-interested motivators.

**Inequity aversion correlates with willingness to give.** Finally, we hypothesise that willingness to give towards COVID-19 vaccinations is correlated with inequity aversion, in accordance with the literature [Derin-Güre and Uler, 2010]. We anticipate that this correlation will be stronger in the altruistic treatment arm, as the narrative reinforces the need for equitable vaccine distribution. However, as the self-interested motivator can be seen as a complementary narrative to altruism, we expect subjects with higher inequity aversion to be motivated partly by equity considerations when submitting their donation amounts. Inequity aversion will be determined for each subject through a survey measure.

## 5 Metrics and methods

In this section, we formulate the metrics and methods used for evaluation of our study. We refer to the six experimental conditions as $C$ (control), $P$ (peer effects), $A$ (altruistic narrative), $S$ (self-interested narrative), $PA$ (peer effects + altruistic narrative) and $PS$ (peer effects + self-interest narrative). This notation is also reflected in Table 1. For convenience, let $\mathcal{T} := \{P, A, S, PA, PS\}$ be the set of treatments. For the full sample of subjects, we collect our main variables of interest and a number of relevant covariates. For each subject $i$, the dependent variables are:

- The initial amount $y_i^0$ that subject $i$ agrees to donate to COVAX (in GBP).
- The revised amount $y_i^1$ that subject $i$ agrees donate to COVAX (in GBP).
- From $y_i^0$ and $y_i^1$, we compute a binary variable $y_i^R = [\![|y_i^0 - y_i^1| > 0]\!]$, which indicates whether subject $i$ has revised their initial amount.

### 5.1 Methodology

We propose an experimental design that randomly assigns subjects to one of six groups. Randomisation ensures that, on average, experimental groups do not differ from each other in observed and unobserved dimensions, leaving the treatment status as the only source of exogenous variation. We adopt a standard identification strategy, where the average initial and revised amount donated, as well as the revision indicator, given by $y_i^* \in \{y_i^0, y_i^1, y_i^R\}$ is a linear[4] function of the subject's treatment status described by binary treatment dummies $T_i^A, T_i^S$ and $T_i^P$, which indicate whether subject $i$ received treatment $P$, and $A$ or $S$. Hence, the saturated model is

$$y_i^* = \alpha + \beta_P T_i^P + \beta_A T_i^A + \beta_S T_i^S + \beta_{PA} T_i^P T_i^A + \beta_{PS} T_i^P T_i^S + u_i, \tag{1}$$

where $\alpha$ denotes a constant (the average donation of the control group), while $\beta_P$, $\beta_t$ and $\beta_P + \beta_t + \beta_{Pt}$ denote the differential between donations in the control group and donations under treatment $P$, $t$, and $Pt$, where $t \in \{A, S\}$. Finally, $u_i$ is an error term. This allows us to express our four main hypotheses H1-4 from Section 4.1 as follows: H1 corresponds to $\beta_A > 0$ and $\beta_S > 0$; H2 corresponds to $\beta_S > \beta_A$; H3 corresponds to $\beta_P > 0$, $\beta_{PA} + \beta_P > 0$ and $\beta_{PS} + \beta_P > 0$; H4 corresponds to $\beta_{PS} > \beta_{PA}$.

We also include the following robustness check for the randomisation by controlling the relation between the outcome $y_i^*$ and the treatment statuses with a row vector of covariates $X_i'$ (described in Section 5.2) to obtain the corresponding coefficient vector $\gamma$. The saturated model with covariates is:

$$y_i^* = \alpha + \beta_P T_i^P + \beta_A T_i^A + \beta_S T_i^S + \beta_{PA} T_i^P T_i^A + \beta_{PS} T_i^P T_i^S + X_i'\gamma + u_i \tag{2}$$

Finally, we present a model with interaction terms to explore heterogeneous effects within treatment groups (in reference to the secondary hypotheses outlined in Section 4.2). We introduce a row vector $C_i'$ which contains four covariates corresponding to the secondary hypotheses: vaccine history, perceived safety, hardship, and inequity aversion, and interact it with subjects' treatment statuses $T_i^A$, $T_i^S$ and $T_i^P$ together with additional dummy variables $\mathfrak{T}_i^t$, which indicate whether subject $i$ belongs to *treatment cell* $t \in \mathcal{T}$, to obtain corresponding coefficient vectors $\delta_t$.

$$y_i^* = \alpha + \beta_P T_i^P + \beta_A T_i^A + \beta_S T_i^S + \beta_{PA} T_i^P T_i^A + \beta_{PS} T_i^P T_i^S + X_i'\gamma + C_i' \left( \sum_{t \in \mathcal{T}} \mathfrak{T}_i^t \delta_t \right) + u_i. \tag{3}$$

In the analysis of the linear models, we follow Angrist and Pischke [2008] and use bootstrapped H2C standard errors, as they reduce finite-sample bias in the estimators, and because the sampling-distribution for the bootstrapped test statistics is closer to the finite-sample distribution. That is, the H2C standard errors better reflect the variation that we may expect from (randomly) assigning a fixed number of subjects to 6 experimental conditions. To assess the veracity of our hypotheses, we choose a significance level of 0.05.[5]

## 5.2 Covariates

We collect the following additional explanatory variables. The purpose of these variables is to check for group balance on a host of relevant economic, social, and psychological attributes. Moreover, they allow us to explore heterogeneous effects within groups, and shed light on the underlying mechanisms influencing the impact of the narrative shocks on sharing behaviour.

- Socio-economic attributes: gender, age, ethnicity, education, perceived socio-economic status, income bracket.
- Self and other regarding preferences: sociability, risk aversion, altruism, optimism, inequity aversion.
- COVID-19 specific: Pandemic experience (perception of pandemic management), health concerns during the pandemic, financial impact, vaccine history of self and inner social circle, attitude towards national vaccine policy.

The measurement strategy for each covariate can be found in **??**.

[4]We use a linear model for both the continuous and binary outcomes. As established by Gomila [2021], linear models are a good strategy for the estimation of causal effects (in an experimental setup with binary outcomes), both for interpretation purposes and to deliver unbiased estimates.

[5]Despite recent calls to abandon the notion of statistical significance [Amrhein et al., 2019] as our only means to determine association, a 0.05 significance level remains the standard in the experimental evaluation literature.

### 5.3 Data sources and attrition

The experiment will be performed in an online format, in collaboration with the Centre for Experimental and Social Sciences (CESS) at Nuffield College, Oxford. CESS guarantees a diverse sample of English-speaking citizens from the UK in the subject pool that accept payment in GBP. The online experiment runs in sequential small-group sessions of at least 30 participants per session and will be run until our sample size of $n = 250$ per treatment (see Section 3 for the determination of this sample size) has been reached in order to achieve 80% power. Throughout the duration of these sessions, recruited participants are allowed to withdraw from the study at any point (as stated in the consent form). In each small-group session, unfinished or declined surveys will be discarded from the minimum sample size count. However, these surveys will remain in the sample for a brief period to guarantee that consent withdrawal is not correlated to any experimental condition, after which these data will be deleted.

CESS guarantees the integrity of the obtained data by requesting all studies obtain approval from CESS's independent ethics review board. The review board confirms that all subjects consent to participating in the study, are not deceived in any way by the experiment(ers), and that the final data set is correctly anonymised.

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