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Sharing the cake during a crisis: The impact of the COVID-19 pandemic on intertemporal altruism and efficiency concerns[☆]

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A R T I C L E I N F O

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A B S T R A C T

This study examines inter-temporal distribution decisions on private payments and donations during the coronavirus pandemic. We simultaneously measured individual efficiency concerns, altruism and time preferences in an online experiment conducted among US residents during different stages of the crisis. Participants were asked to distribute money between different dates and recipients, that is, today versus in two weeks and private payouts versus donations to fight against the pandemic. To assess participants' affectedness by COVID-19, we collected data on participants' employment status and financial situation, as well as their individual vulnerability to COVID-19. We identify a decrease in individual preferences for efficiency over the progress of the pandemic. The reduction of efficiency concerns is driven by self-reported financial affectedness, but accompanied by an increase in altruism. Our results point at the crucial role of financial security for both efficiency-seeking behaviour and the willingness to provide support during the crisis.

1. Introduction

COVID-19 left its footprints everywhere in our society. As of September 30, 2022, over 96 million people were infected in the US alone (Centers for Disease Control and Prevention, 2022). Besides the enormous medical consequences of the pandemic, the economic consequences are also significant: economic activities and global trade slowed down considerably, generating a worldwide rapid growth of people in need. By January 2021, in the US, 48 percent of all households reported job or income loss (Root and Simet, 2021). These findings are not restricted to the US but also affect citizens of low- and middle-income countries (Egger et al., 2021).

In addition to immense state aid programs enormous private contributions to the common health system were provided. In the US alone donations in 2020 reached a record high of over 471 billion USD (USA, 2020), despite donors themselves often being medically and financially affected by the coronavirus pandemic. Even at height of the pandemic, the health system functions as an impure public good (Lange et al., 2017). That is, impure public goods have both, a private good component (e.g., the private benefits contributing individuals extract from a strengthened health system) and a public component (e.g., the public benefits the society extracts from a strengthened health system). The emphasis which potential donors put on each of the two components may vary depending on their personal background: individuals in good health conditions may consider, for instance, the public health

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system as a public service for other society members stressing its public component. In turn, individuals in rather poor economic conditions may rely with their personal health care entirely on the public health system implying that voluntary donations to this system enhance their private health cover.

Provided that personal background and external factors influence the importance of public and private components for the donations, our study investigates whether those factors also emphasise efficiency-seeking and patience. That is, we ask whether the severeness of the pandemic in the personal environment of the potential donor changes the willingness to give altruistically. We will pay particular attention to the trade-off between efficiency considerations and the timing of the donation. In other words, do people opt for less efficient, but immediate giving when the pandemic rages in their near environment? In turn, do people prefer later donations (when it yields higher benefit for the recipient) especially in times of minor medical and financial consequences of the pandemic? The COVID-19 pandemic will not be the last global challenge. Our simultaneous analysis of altruism, efficiency and time discounting provides a meaningful insight, since shifts in these preferences can have persistent welfare consequences. Developing an understanding of behavioural patterns provides an important tool for the future optimisation of crisis management at the economic and political level.

Throughout our study, we apply a two stage analysis strategy: in the first stage, we experimentally measure three key economic preferences among our participants on the individual level. These are: the inter-temporal discount factor for private payments, a time-independent degree of altruism that weights donations relative to own income, and a variable measuring the importance of individual efficiency concerns. In addition, we separate the preferences between allocation decisions for the same recipient and decisions with differing recipients. In the second stage, we estimate whether the three parameters vary systematically to a degree by which the pandemic influences the individual environment of subjects. For this, we use data collected in spring and summer 2020, from an online experiment with American participants. During that time, the COVID-19 crisis progressed, creating a natural variation of the impact of the pandemic on participants' lives.

The effect that COVID-19 can have on an individual can broadly be separated into two categories. Firstly, the pandemic can directly affect an individual's health. This can be either through infection or being under a specific risk of infection. Secondly, COVID-19 can impact wealth and income. This includes changes in employment status, wages and economic prospects. We include variables that reflect the two categories of impact into our analysis and investigate how they in turn influence altruism, efficiency concerns and the willingness to postpone consumption.

In the long run, economic preferences are assumed to be stable (Stigler and Becker, 1977; Krupka and Stephens, 2013). However, a more recent strand of the literature finds that events potentially alter preferences, for example (Schildberg-Hörisch, 2018) on risk preferences. Negative experiences, such as wars or natural disasters, are likely to cause a substantial change in behaviour (Haushofer and Fehr, 2014), for example increasing individual acceptance of risk taking (Malmendier and Nagel, 2011; Guiso et al., 2018; Eckel et al., 2009; Dohmen et al., 2016). Literature on the malleability of time preferences is scarce: while some studies show systematic changes in time preferences (Ifcher and Zarghamee, 2011; DeSteno et al., 2014), amplifying impatience over time (Meier and Sprenger, 2015), the potential effect of extreme events caused by nature on time preferences is far less settled (Cassar et al., 2017; Bauer and Kramer, 2016). Psychologists refer to intensified pro-social behaviour in the face of negative circumstances as 'catastrophe compassion' (Zaki, 2020). There is mixed evidence regarding catastrophe compassion, particularly regarding stronger altruism; some studies identify more (Voors et al., 2012), others less (Fisman et al., 2015) altruism in the aftermath of the crisis. Schwirplies (2023) explores changes in charitable giving after being hit by hurricane Sandy. Total donations increase significantly in the immediate aftermath of the hurricane. In affected regions, the changes in charitable giving appear to be more pronounced than in regions further away. The systematic increase of altruism as a consequence of experience of extreme events like civil war or natural disasters is reported elsewhere (e.g., Bauer et al., 2016; El-Bialy et al., 2022; Li et al., 2013).[1] Other scholars analyse the effect of natural disasters on reciprocity (Cassar et al., 2017; Picozzi et al., 2014; Fleming et al., 2014) and public good contributions (Whitt and Wilson, 2007).

Regarding the catastrophe compassion of COVID-19, there is also mixed evidence: Grimalda et al. (2021) find that personal exposure to COVID-19 increases donations relative to those not exposed. The study by Fridman et al. (2022) shows that individuals exhibit greater financial generosity when their county experienced COVID-19 threat. Likewise, Adena and Harke (2022) demonstrates in a real-donation online experiment that including the reference to COVID-19 in the appeal increased donations. Moreover, their results indicate that both higher local severity and more related articles in the local media increase giving of participants in the respective areas. Finally, Shachat et al. (2021) analyse altruism and ambiguity aversion before and after the breakout of COVID-19 in China. They find high levels of altruism and risk taking during the crisis relative to the pre-crisis. Particularly, they observe a move towards risk neutrality both in the gain and loss domains. In a similar framework, Cappelen et al. (2021) demonstrate that increasing the salience of the pandemic positively impacts altruism but also tolerance of inequalities due to luck. Alsharawy et al. (2021) demonstrate that self-reported individual fear of the pandemic is an important factor for increasing altruism and decreasing risk tolerance. Overall, the meta analysis of Umer (2024) on 24 dictator games conducted during COVID-19 shows that dictators give significantly more of their endowment revealing relatively higher altruism when compared with pre-pandemic studies.

Contrasting the former studies, Campos-Mercade et al. (2021) identify no systematic change in the degree of prosociality between the time prior to and past the pandemic (i.e., in 2018 and 2020, respectively). Similarly, Bokern et al. (2023) do not observe significant differences in elicited preferences for risk, time, ambiguity, and social preferences when comparing them just before

[1] Notice that the latter paper test altruism of 6- and 9-years-old children after experiencing an earthquake. While 6-years old-children show lower degrees of altruism, 9-years old-children show higher degrees of altruism. Thus, the mental development of participants could play a role for the adjustment of preferences.

the start and during the crisis. Casoria et al. (2023) also find stable prosocial preferences in a longitudinal online experiment in France, despite being exposure to long-lasting social distancing. Kiss and Keller (2022) cannot show changes in generosity among school children during the crisis. In turn, Lohmann et al. (2023) show that participants who were more intensely exposed to the virus outbreak became more anti-social than those with lower exposure. Branas-Garza et al. (2022) observe decreasing generosity during the coronavirus pandemic, while Buso et al. (2020) demonstrate that social isolation influences the degree of selfishness in ultimatum bargaining and public good games: fairness and cooperation fade out with prolonged lockdown.

In an online donation experiment, Abel and Brown (2022) primes participants with examples of private citizens and public officials acting in ways that either increase or decrease the spread of the coronavirus. Watching positive private role models leads to an increase in donations compared to negative examples, while watching negative public role models lead to an increase in donations and volunteering compared to positive examples. Those patterns may result from different norm activation: positive private role models increase norms of trust, while negative public role models increase a sense of responsibility. Thus, the consequences of COVID-19 appears unstable and highly context dependent.

Other studies test the influence of the COVID-19 on health relevant behaviour. Even though participants in the experiment by Leder et al. (2020) consisted mostly of prosocially oriented students, the researchers show that, above all, participants use protective measures that protects themselves rather than measures that have higher protective value for the public. With respect to the effects of lockdown measures, there is evidence towards behaviour shifts following the implementation and abolition of social distancing rules (Casoria et al., 2021). Behaviour changes quickly when norms change. Hence, there is already some evidence on the potential effects of COVID-19 on preferences, but the previously mentioned studies miss the, from our perspective, important effects of the pandemic on efficiency concerns.

To provide a complete picture of the potential preference shift, we adapt the state-of-the-art approach to measure time preferences (Frederick et al., 2002; Cohen et al., 2020), efficiency concerns and altruism simultaneously based on convex time budget decisions (Andreoni and Sprenger, 2012; Augenblick et al., 2015; Andreoni et al., 2018). In earlier studies, when exploring the interplay between time preferences and altruism (i.e., when dividing money between oneself and another person), subjects are substantially more selfish with immediate consequences, in comparison to delayed consequences (Kölle and Wenner, 2021). While giving to others decreases with delay (Kovarik, 2009; Buser and Dreber, 2016), the relation may not be monotonic (i.e., altruism increases between a one and two month time gap of charitable giving in Breman, 2011).

Our results show that in general individuals predominantly consider efficiency when they distribute money between the same recipient (themselves versus themselves or charity versus charity). As soon as money is allocated between different recipients, efficiency plays a minor role. This suggests that pro-sociality considerations overrules efficiency concerns. With respect to the impact of the pandemic, we find that the preference for efficiency decreases with the progression of the pandemic. Individuals who are more financially affected by COVID-19 are less concerned about efficiency and more about altruism. When choosing between personal income now or later, efficiency is (slightly) less important for individuals who have been infected by COVID-19. However, most measures of the pandemic's severity like the number of cases per capita and lockdown stringency do not coincide with a change in behavioural parameters.

2. Analysis

We will proceed as follows: Firstly, Section 2.1 gives a detailed description of the experimental design and procedures. Then Section 2.2 presents the general behaviour in the overall allocation decisions. Further, Section 2.3 reports the methodology used to generate the structural estimates we use to capture individual preferences. Section 2.4 introduces expectations regarding changes in the structural estimates in the course of the pandemic, followed by a discussion of the distribution and averages in 2.5. Finally, Section 2.6 presents the empirical strategy applied to determine the impact of COVID-19 on the estimated preferences and the corresponding results, which we consider the main contribution of the paper.

2.1. Design and procedures

We conducted an online experiment to measure altruism, time preferences and efficiency concerns simultaneously in individuals. The online questionnaire was generated using SoSci Survey (Leiner, 2018) and was made available to users via www.soscisurvey.de. We executed the experiment in three cohorts initially planned for 300 participants each via Amazon Mechanical Turk (MTurk). In total, 886 MTurkers participated in April, May, and July 2020.

Recruiting

We decided to recruit participants from the pool of MTurk which is an online labour market for virtually performed tasks following earlier studies on social science and economic research (Paolacci et al., 2010; Kuziemko et al., 2015). It enabled us to swiftly enlist many participants and ensured the anonymity of participants from implementation through to payment. Furthermore, MTurk allows online experiments to be conducted even under pandemic restrictions, circumventing COVID-19 related problems such as lockdowns and enabling the invitation of participants from the US and different states.[2]

[2] The recruited MTurk workers agree to the use of their information when they register on the site. Details of the MTurk Participation Agreement are available at: https://www.mturk.com/worker/participation-agreement (last updated 17 October 2017). In line with the common procedure in behavioural experiments, the participants are already anonymised to the experimenter when they are recruited. For this study only the MTurk worker ID could be recorded, and no personal details such as name or address. In addition, the payment of participants is done through the MTurk platform, so there is no record of a bank account, which provides further anonymity.

Table 1
Overview over blocks.

Block	Left option		Right option	
	Recipient	Time	Recipient	Time
Self	Private	Now	Private	In two weeks
DonationLate	Private	Now	Donation	In two weeks
SelfLate	Donation	Now	Private	In two weeks
Donation	Donation	Now	Donation	In two weeks
BothNow	Private	Now	Donation	Now
BothLate	Private	In two weeks	Donation	In two weeks

To keep as many variables constant as possible, we only selected participants from the US. This allows to concentrate on one country, which was affected differently by the pandemic in the various states at the beginning of the study. We aimed at recruiting participants from both weakly and strongly affected states, to have enough variation in the impact of COVID-19 between cohorts and to increase representativeness. We considered the different dynamics of the pandemic and the size of the participant pool (so that all three cohorts from this state can be examined if possible) in our selection. During the progress of the experiment, we noticed low participation numbers from New Mexico, potentially due to the MTurk pool being particularly small in this state. We aimed to counteract this by opening the experiment to participants from Colorado and Nevada in cohorts 2 and 3.[3] We also control for a wide array of COVID-19 indicators on the state level, such as the cases per capita and the stringency index. Fig. 9 in the Appendix gives a graphical overview of the number of participants per state.

Conducting the experiment at different points in time allows different levels of severity of the pandemic to be analysed: At the time of the first cohort, the medical impact of the pandemic represented by the number of COVID-19 cases was at a high plateau, while the economic impact peaked, represented by high rates of unemployment. In the second cohort, the economic impact slightly decreased, and the medical aspects were at a moderate level. At the time of the third cohort, the medical impact of the coronavirus pandemic had increased sharply respectively achieved a high level while economic impact still decreased somewhat. To make sure that the level of information about the progression of the pandemic is aligned between participants, we required participants to look up and report the current number of cases in their state,[4] based on an online source we provided. We use the difference between actual case numbers and the number reported by participants to analyse differences in beliefs/information processing behaviour about the pandemic in Section 2.5. We decided not to repeatedly measure the same participants' preferences for two main reasons: Firstly, repeated choices suffer from endogeneity and researcher demand issues. Secondly, the MTurk pool is difficult to maintain in a long-term panel. That prevents the number of participants from shrinking across different cohorts. Thus, participants were allowed to participate in this study only once.

Task description

The experiment consists of a series of 36 allocation questions similar to convex time budget decisions introduced, for example, by Andreoni and Sprenger (2012) and Kölle and Wenner (2021). The answers inform the estimation of participants' preferences for an immediate payment, efficiency, and a donation. For each question, we endow participants with ten experimental tokens, each worth 25 US Cents, and ask them to divide the endowment between two options by using a slider. The questions are organised into six blocks with six questions per block. In these blocks, we vary the recipient of allocation and timing of payment for the two options. In some blocks, participants divide money between themselves and a charity supporting medical facilities in their fight against the coronavirus pandemic. One time of payment is directly after the experiment and the other 14 days past the experiment.[5] In one block, the participant's payout is delayed and in another block the charity's payout. In other two blocks, participants allocate money only for themselves or only for the charity, with the same difference in payment timing. Finally, we featured two blocks allowing participants to allocate tokens between the participant themselves and the charity, but no time difference between payments. We randomised the order of the blocks for each participant, to control for any order effects.

Table 1 summarises the variations between the six blocks. We denote the option of the left side of the slider as "left option" and the option on the right as "right option" without intending to give a rating of the options. Notice that we refer to the decisions in blocks Self and Donation "intrapersonal" decisions as the receiver is the same, while we refer to the other blocks as "interpersonal". The main reasoning for this separation is that the types of decisions are substantially different, which is why we assume different underlying utility functions in the structural estimations.

For each combination of recipient and timing, the participants choose six allocations. That is, we vary the efficiency (i.e., the multiplier) for the right option for each question per block. Tokens allocated to right option are multiplied with a factor, R, which can take values 0.6, 0.8, 1.0, 1.2, 1.4 and 1.6 . Multipliers smaller than 1.0 lead to smaller payouts for money allocated to the right option. Multiplier higher than 1.0 raise money allocated to the right option. The multiplier of the left option is kept constant at 1 (i.e., each token allocated to option one yields one token). Thus, allocating tokens onto the right option leads to efficiency losses

[3] We replicate the main results from Section 2.6 for a subset of our data that excludes participants from New Mexico, Colorado and Nevada in Appendix Tables A5 and A9.

[4] However, we did not require the number to match the actual number, since the numbers continuously changed at the time and the requirement to be correct potentially would have resulted in frustration on the side of participants. Overall, the majority of participants (82%) are within a 20% margin of error.

[5] Due to the setup of the MTurk platform there is a delay of payments of up to one day.

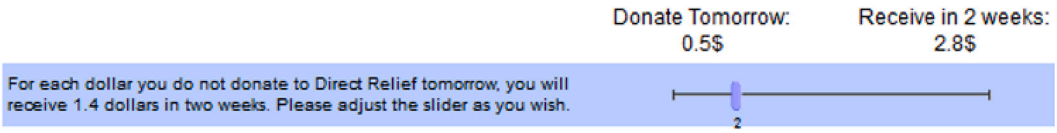

Fig. 1. Screenshot sample slider.

with the first two multiplier ($R < 1.0$), and efficiency gains with the latter three multiplier ($R > 1.0$).[6] That means, the distribution amount is the same for each question, but the distribution mass can change due to an efficiency parameter.

To summarise, the allocation tasks vary the recipient, time of payment and a multiplier for the right option. The allocation of tokens is later used to determine real money payouts to participants and real donations and reveal selfish and altruistic behaviours. Different timing of the payout allows to identify the impatience for the payout and possible influence on the other parameters. The multiplier helps to capture both the exact level of impatience and the concern for efficiency of distributions in the face of a crisis.

A single decision may be, for example, as follows: the participant receives ten tokens. She chooses to donate none, some or all of those tokens to the charity directly the next day, while she receives 1.4 times the number of tokens not donated after 14 days. In this case, we denote the right option to be 1.4 times more efficient than the left option, defining an increase in total monetary payments as a raise in efficiency. Fig. 1 illustrates this example. The corresponding amounts paid out are displayed next to the sliders (here 0.5 and 2.8) to eliminate any need for calculation on the participants' side. To keep biases as low as possible, no values are entered by default.

Participants also filled in an extensive post-experimental survey. The aim was to capture the financial and medical effects of COVID-19 in individual variables to analyse how they influence preferences. Additionally, we elicited basic demographics. We discuss the details of our variables in the Estimation Approach in Section 2.6.

Payoff procedures

The financial incentives were structured as follows: participants received 1 USD as flat compensation. After the experiment, we randomly selected only one of the 36 questions to be paid out in real money, re-rolling for each cohort. While this leads to relatively low stakes for the experiment, previous literature indicates that low stakes experiments on MTurk replicate lab experiments well, see Amir et al. (2012). Further Carpenter et al. (2005) find that stakes do not impact distribution decisions in experiments. The average payout is also within the average 1-5 USD hourly wage of experiments on MTurk (see, e.g., Snowberg and Yariv, 2021). All Payments to participants were made through MTurk. The corresponding donation was made to Direct Relief, an international nonprofit, nonpartisan organisation providing essential medical resources to medical staff worldwide. A receipt for the total donations made was made available to each participant. Note that this receipt was not tax deductible for our participants, as this would create significant heterogeneity in the value of the donation. The date of payment and amount of the payout depended on the decision of the respective participant on this allocation decision. Participants had 2.50 USD to allocate for each decision situation. Due to the efficiency rates of the right option, the potential payouts respectively donations varied between 1.50 USD and 4.00 USD. On average participants received 2.56 USD as payout and donated 1.20 USD.

Legal

The experiment was pre-registered on OSF. There were a total of two registrations, one prior to data collection on April 20, 2020, followed up by a registration specifying the analysis made before finishing the data collection, on May 15 2020. The participants were informed about the task being an economic experiment prior to choosing to accept the task on the MTurk platform. Additionally, participants were able to abort the experiment at any point by closing their browser window. The study has been approved to comply with the Terms of Use and Ethical Standards by the IRB of the University of Hamburg. A corresponding statement can be provided upon request.

2.2. Overall experimental decisions

Fig. 2 gives an overview over average behaviour within each decision block. Since we look at the raw decisions, we include all individuals. Table 2 presents corresponding OLS regression models, where the dependent variable is the amount of tokens allocated to the right-hand-side option, that is, the side that is affected by the efficiency parameter R.[7] We cluster standard errors on the individual level to account for the multiple observations for each participant. Model 1 compares overall behaviour for each treatment. There is a tendency to, on average, allocate less tokens to donations, as indicated by the negative values for DonationLate, BothNow and BothLate, where the right-hand-side is the donation and the positive value on SelfLate, where the left-hand-side is the donation.

[6] In contrast, Andreoni and Sprenger (2012) test allocation decisions with exclusively efficiency gains for the postponed option.

[7] We follow Kölle and Wenner (2021) in denoting efficiency as the total multiplier R instead of the $1 + r$ formulation in Andreoni and Sprenger (2012). As R= $1 + r$, this is only a matter of notation and does not impact the results in any way.

Table 2
OLS estimation of amount of tokens allocated to right-hand-side option.

	Model 1	Model 2
(intercept)	4.40***	0.38*
	(0.08)	(0.23)
DonationLate	−0.84***	2.66***
	(0.09)	(0.19)
SelfLate	1.44***	4.88***
	(0.11)	(0.27)
Donation	0.17**	0.64***
	(0.07)	(0.18)
BothNow	−0.87***	2.90***
	(0.09)	(0.19)
BothLate	−0.84***	2.84***
	(0.09)	(0.19)
R		3.65***
		(0.21)
R∗DonationLate		−3.18***
		(0.19)
R∗SelfLate		−3.13***
		(0.20)
R∗Donation		−0.43***
		(0.16)
R∗BothNow		−3.42***
		(0.20)
R∗BothLate		−3.34***
		(0.20)

Notes: Standard errors are clustered on the individual level.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 2 Model 2 is an OLS model that includes the efficiency parameter R and interactions for each block.[8] The overall coefficient for efficiency is highly significant and positive. In fact, within each block individually, there is a positive reaction to efficiency.[9] The positive reaction to efficiency in blocks BothNow and BothLate aligns with the large body of literature (e.g., Andreoni and Miller, 2002; Karlan and List, 2007; Capraro et al., 2024) indicating a negative relationship between the price of giving and charitable donations.[10] However, efficiency matters considerably less for all interpersonal blocks.[11] This is novel evidence towards the efficiency/the price of giving being of relatively less importance in allocation decisions between different individuals. The difference is substantial, with individuals allocating on average 3.43 more tokens for each 1 unit increase in efficiency when the recipients are the same against an increase of only 0.38 tokens allocated when the recipients differ.[12] There is also a significant difference within the intrapersonal blocks as seen in the coefficient for R∗Donation, but the difference is much smaller compared to the interpersonal blocks.

2.3. Structural estimation methodology

The following section will present the approach to estimating individual-level preferences based on the allocation decisions. Our analysis of the different blocks is based on a simplified version of the approach by Kölle and Wenner (2021). This approach is based on two different utility functions for intra- and interpersonal allocation decisions. These can be used to generate structural estimates for each individual. Both utility functions are based on a quasi-hyperbolic discounting function (Strotz, 1973; Laibson, 1997; O'Donoghue and Rabin, 1999; Frederick et al., 2002), but differ with respect to the form of the utility function. The main difference is that the interpersonal decisions accommodate an altruism weight that indicates how an individual evaluates own and others' consumption. Our approach differs from Kölle and Wenner (2021) in that, given that we only allow allocation between now and two weeks in the future, we are not able to estimate a present bias. As a result, any present bias is included in the estimated time discounting factors. In turn, we cannot distinguish if a change in our estimated time preferences is driven by a change in discounting

[8] We also tested for the inclusion or quadratic efficiency terms in the regression. The coefficients remain largely unchanged, with the exception of the coefficient of R∗Donation which is no longer significant. The overall robustness to the inclusion of quadratic terms speaks towards an overall linear effect of efficiency on token allocation.

[9] The test of R + R∗Block$= 0$ is significant at the 5%-level for each block, see Table A1 in the Appendix.

[10] Note that in our setting, due to the notation, the efficiency measure R is the inverse of the price of giving.

[11] The coefficients of the interaction terms for R∗DonationLate, R∗SelfLate, R∗BothNow, R∗BothLate are negative and significant. Further, these coefficients are significantly larger in absolute terms than the coefficient of R∗Donation (at a 5%-level, see Table A1 in the Appendix).

[12] These are calculated by taking the average of R and R+ R∗Donation for intrapersonal decisions and the average of R+ R∗DonationLate, R+ R∗SelfLate, R+ R∗BothNow and R+ R∗BothLate for interpersonal decisions.

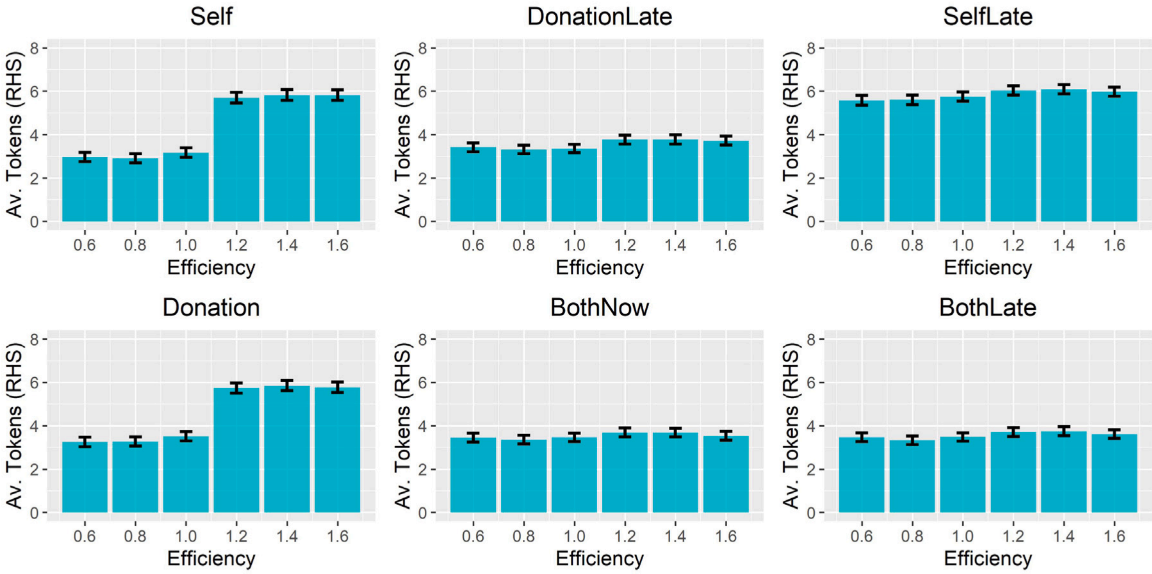

Fig. 2. Average experimental tokens allocations. The amount always corresponds to the option on the right hand side (RHS), see Table 1 for details. Error bars show 95%-confidence intervals. Details on decision block names in Table 1.

or present bias. Additionally, the calculation of the interpersonal parameters is different, as the tasks are formulated slightly different in terms of which recipient is affected by the efficiency, and the payouts being financial payouts and not effort allocations. But, overall, the structural estimation is based on the same underlying utility functions and subsequent solution methods.

Intrapersonal allocation decisions

We will first focus on choices where the recipients on both sides are the same (blocks Self & Donation). We will present the approach on decisions made in block Self, which allocate consumption for the individual itself. This follows Andreoni and Sprenger (2012) both in approach and notation using the following CRRA utility function:

$$U_i(c_{i,0}, c_{i,1}) = (c_{i,0} - \omega)^{\alpha_i} + \delta_{si}^k (c_{i,1} - \omega)^{\alpha_i} \tag{1}$$

such that $c_{i,0}, c_{i,1}$ are experimental payouts to the individual i at $t = 0$ and $t = 1$, δ_{si} is the individual's daily discounting factor (δ_{di} replaces the latter parameter for decisions made in the block Donation),[13] and α_i is the individual preference for consumption smoothing.[14] The budget restriction is $Rc_0 + c_1 = m$, using future budget notation. k indicates the number of days before the future payment. Finally, ω indicates the background consumption.[15] There are two main reasons for including background consumption levels. Firstly, a positive background consumption ensures that the logarithm is well defined for all experimental choices, especially corner solutions. Secondly, the background consumption represents an inter-temporal reference point and is widely used in studies that elicit risk and time preferences (e.g. Andreoni and Sprenger, 2012; Andersen et al., 2008).

We operationalise the utility function by maximising substitute to the budget constraint and log-linearising the resulting first-order-condition, yielding:

$$ln(\frac{c_0 - \omega}{c_1 - \omega}) = \frac{1}{\alpha_i - 1} ln(\delta_{si}^k) + \frac{1}{\alpha_i - 1} ln(R) \tag{2}$$

The same procedure can be applied to the block Donation, where individuals choose over donated amounts. Assuming the same curvature parameter for both decisions (i.e., α_i is constant for own payoffs and donations), the combined optimality condition for blocks Self and Donation is:

$$ln(\frac{c_0 - \omega}{c_1 - \omega}) = \frac{1}{\alpha_i - 1} ln(\delta_{si}^k) + I_d \frac{1}{\alpha_i - 1} ln(\frac{\delta_{di}^k}{\delta_{si}^k}) + \frac{1}{\alpha_i - 1} ln(R) \tag{3}$$

where I_d is a dummy indicating that both options are donations. Based on (3), the parameters α_i and δ_{si} can be estimated using a 2-limit Tobit estimator to account for corner solutions. If Tobit is not applicable, either due to no or exclusively censored data, we estimate OLS. For details on the structural estimation, refer to Appendix C.1.

[13] We abstract from present bias in this study. As the payments were all made the day after the experiment, present bias should not play a significant role in our results.

[14] Or as in Andreoni and Sprenger (2012) the CRRA curvature parameter.

[15] We assume constant background consumption within the time-frame of our experiment. We check the robustness of our results with regards to different background consumption levels by averaging results over an array of values of ω.

Interpersonal allocation decisions

The analysis of interpersonal decisions differs in that an altruism weight has to be included to allow for individual preferences for others' consumption. As before, the framework is closely related to Kölle and Wenner (2021). We represent this by the following utility function:

$$U_i(c_{i,0}, c_{i,1}, c_{j,0}, c_{j,1}) = (1 - a_i)(c_{i,0} - \omega + \delta'^k_{si} c_{i,1})^{\rho_i} + (a_i)(c_{j,0} - \omega + \delta'^k_{di} c_{j,1})^{\rho_i} \tag{4}$$

where $c_{i,0}, c_{i,1}, c_{j,0}, c_{j,1}$ are experimental payouts to the individual i or the donation j at $t = 0$ and $t = 1$, δ'_{si} and δ'_{di} are the individuals discounting factors, and ρ_i is the individuals preference for consumption smoothing between yourself and others. As before, k indicates the number of days to the future payment. Finally, a_i captures the altruism weight, scaled between 0 and 1, where 0 indicates being completely selfish and 1 indicating gaining utility exclusively from others' consumption. As before, this can be maximised and log-linearised into an estimation equation. We detail the approach in Appendix C.2.

Parameters

The interpretation of the estimated parameters is as follows: The discount factors δ_{si}, δ_{di}, δ'_{si}, δ'_{di} are straightforward daily discount rates, with values below 1 indicating that a future consumption is discounted. The curvature parameter, α_i, indicates how strongly an individual reacts to changes in efficiency, with a value of 1 indicating (in the absence of discounting) always choosing the more efficient option, while a value of 0 indicating ignoring efficiency concerns.[16] The altruism weight a is scaled between 0 and 1, with 0 indicating only caring own payouts while 1 indicates caring only for others' payouts. Finally, ρ_i has a similar interpretation as α_i, as it represents a concern for efficiency in allocation decision between yourself and others (abstracting from discounting and the altruism weight).

Since the structural model requires a non-zero background consumption ω for both the intra- and interpersonal decision, we run the structural estimations over a range of values. Both Andreoni and Sprenger (2012) and Kölle and Wenner (2021) focus on a background consumption close to the value of money that is allocated in each decision task. In a similar vein, we focus on a background consumption of 10 (we denote background consumption in experimental tokens). We include an array of background consumption levels both above and below 10 to show the robustness of our results. We include the background consumption levels 2, 4, 6, 8, 10, 12, 14, 16 and 18 in our analysis. We do not include values close to 0, as these represent a substantial transformation that creates extreme outliers.

Note that the structural approach puts a restriction on the values of α_i, ρ_i, as the second derivative of both (1) and (4) have to be negative, which restricts the values to be smaller than 1. We exclude individuals that have estimates ≥ 1 from our analysis. This applies to 12.87% of our sample.[17] Further, it is not possible to estimate any coefficients for individuals that choose only corner-solutions in the blocks used in the corresponding structural estimation. These are predominantly individuals that choose to consume everything in the later time (left-hand option). There is a number of outliers in our data, so we exclude any individual that has a z-score greater than 3 in any of the estimated parameters. After these corrections, we end up with 77% of our initial participants, averaged over all background consumption levels.

2.4. Predictions

In the framework of this study, changes in preferences are directly related to a change in behaviour, and vice versa. We, thus, use preferences and behaviour interchangeably. Further, we assume that experimental choices reveal actual preferences. The traditional view on preferences is static. That is, preferences are assumed to be stable over longer periods (see for instance Stigler and Becker, 1977). Provided that taste parameters remain the same, having less money makes subjects more selfish (for this, Andreoni et al., 2021, provide field evidence). Yet, there is growing evidence that exogenous shocks such as economic crises or natural catastrophes do not only influence monetary endowments, but affect preferences in a systematic way as well (see, e.g., the survey article on risk preferences by Schildberg-Hörisch, 2018). Well documented is the effect of natural disasters such as hurricanes or tsunamis on risk acceptance (e.g., Chuang and Schechter, 2015): the majority of studies report increasing risk aversion after experiencing such events; however, there is also some evidence for decreasing risk aversion.

With respect to the COVID-19 pandemic, the evidence is mixed: some studies find high rates of altruism (e.g, Shachat et al., 2021; Adena and Harke, 2022),[18] while other find no or negative effects (e.g., Schneider et al., 2021; Branas-Garza et al., 2022; Bokern et al., 2023). Overall, it could be that the concern with the pandemic may have different meanings causing different reactions across the studies.[19] Our questions regarding the personal medical and financial affectedness by the pandemic relates to the individual vulnerability. Therefore, we assume that participants who consider themselves as medically and/or financially in need to become less altruistic. That is,

[16] We also find negative values of α_i in our data. These indicate a tendency for choosing a less efficient option.

[17] Averaged over all background consumption levels.

[18] An explicit reminder about the crisis makes respondents more willing to prioritise society's issues over their own problems (Cappelen et al., 2021). The meta analysis of 24 papers by Umer (2024) indicates a significant increase of altruism.

[19] For instance, if participants agree to be "financially affected by the pandemic", they could assume predominantly others to become needy triggering intensified altruism. In turn, they may assume predominantly themselves to be needy, thus lowering their own willingness to give. Following the second line of arguments, the results of Alsharawy et al. (2021) on the fear of COVID-19 and its negative impact on risk tolerance could be interpreted along a stronger personal vulnerability and a greater need for security.

Hypothesis 1a. Being medically vulnerable to COVID-19 decreases the altruism of subjects.

Hypothesis 1b. Being financially affected by the pandemic decreases the altruism of subjects.

In their seminal paper, Haushofer and Fehr (2014) provide evidence that economic pressure and being poor cause stress and negative affective states which in turn lead to short-sighted decision-making. Cassar et al. (2017) confirms the claim by analysing the survey data of tsunami victims: subjects who were more affected by the tsunami are more impatient. However, it seems that the effect of COVID-19 on the inter-temporal discount factors differs from the effect of natural disasters. Earlier experiments on time effects of the pandemic show stable preferences amid geographical variation in virus prevalence (e.g., Lohmann et al., 2020; Drichoutis and Nayga, 2022; Harrison et al., 2022; Bokern et al., 2023).[20] It is important to stress that those papers measure only one time preferences for subjects' own payments. For our data, one may want to distinguish between time preferences for subjects' own payments, for subjects' donations, and for the exchange between own payments and subjects' donations.[21] However, since we do not have previous evidence on the systematical influence of the pandemic or other exogenous shocks on the specific type of time preference, we restrict ourselves to a general prediction for the evolution of inter-temporal discounting:

Hypothesis 2a. Being medically vulnerable to COVID-19 does not influence time preferences of subjects.

Hypothesis 2b. Being financially affected by the pandemic does not influence time preferences of subjects.

Finally, unlike other approaches, our structural CRRA utility estimation following Andreoni and Sprenger (2012) allows us to disentangle time preferences and efficiency considerations. That is, we estimate at the same time an individual discounting factor (δ and δ', respectively) and an individual consumption smoothing parameter (α and ρ, respectively). Lower smoothing parameters indicate higher utility gained from a constant income stream at the level of the background consumption. In turn, high smoothing parameters indicate higher utility gained from peak markups beyond the level of the background consumption. We interpret the latter as a taste for extra efficiency gains, that is, efficiency considerations. We assume a similar rational regarding the importance of efficiency considerations as for the importance of altruism: if participants consider themselves as medically and/or financially in need, they care less about efficiency gains and prefer a constant income stream. That is,

Hypothesis 3a. Being medically vulnerable to COVID-19 decreases efficiency concerns of subjects.

Hypothesis 3b. Being financially affected by the pandemic decreases efficiency concerns of subjects.

2.5. Structural estimation results

Table 3 shows the average estimates for all gathered parameters. The deltas can be interpreted as daily discount-factors, while altruism is the relative weight on others' payouts, following the previous notation. In line with Fig. 2, the mean discount-factors from the intrapersonal blocks δ_s and δ_d are different from one, while the mean interpersonal discount factors, δ'_s and δ'_d are close to one. Overall, average estimates are also stable with respect to different background consumption levels, with the exception of mean α and ρ, which scale with higher background consumption levels. Figs. 3 and 4 show the distributions of the estimated parameters for background consumption level 10. The discount factors for the interpersonal discount factors, δ_{si} and δ_{di} show a similar distribution to Kölle and Wenner (2021), with a slightly wider distribution. The same applies for the interpersonal discount factors, δ'_{si} and δ'_{di}. The comparison of the distribution of α_i is more difficult as other studies often do not include negative efficiencies, which in turn implies different values, or only the average is reported and not the distribution. Still, compared to Andreoni and Sprenger (2012) our estimates show a similar skewness towards the upper end of the distribution, but features a high number of estimates around 0. With regards to the altruism weight, the last panel of Fig. 4 shows the presence of both completely selfish ($a_i = 0$) and fully altruistic ($a_i = 1$) individuals. There is also a significant group of individuals that go for a 50/50 split between yourself and others ($a_i = 0.5$). This distribution, along with an average a of 0.375 corresponds to common findings in experimental literature (see e.g. Engel, 2011).

2.6. Second step estimation

We use the estimates generated by the structural estimation to detect changes and determinants on changes in preferences due to the pandemic. We run two main OLS regressions. Firstly, a regression that includes state level variables and cohort dummies. These are less prone to potential endogeneity, since selection into a state is connected to high transaction costs. In our second model, we include survey measures of our participants, in addition to the previously used variables. The survey measures have the advantage that they can capture heterogeneity in the degree to which individuals are impacted by the pandemic. As our observed variables are potentially correlated, we check if their inclusion into our regressions results in potential collinearity. Table A6 in the Appendix shows the variance inflation factors for both the model with and without the survey variables, showing at most moderate correlation

[20] However, Alsharawy et al. (2021) show that, again, the fear of COVID-19 has negative impact on patience.

[21] This has been done elsewhere (e.g., Kölle and Wenner, 2021).

Table 3
Mean estimated parameters.

BC	Intrapersonal			Interpersonal			
	δ_s	δ_d	α	δ_s'	δ_d'	a	ρ
2	0.94	0.95	−0.19	1.00	1.00	0.37	−3.95
4	0.94	0.94	−0.64	1.00	1.00	0.38	−4.11
6	0.94	0.95	−1.04	1.00	1.00	0.38	−4.75
8	0.94	0.94	−1.43	1.00	1.00	0.38	−6.98
10	0.94	0.94	−1.77	1.00	1.00	0.38	−7.76
12	0.94	0.94	−2.10	1.00	1.00	0.38	−8.76
14	0.94	0.94	−2.49	1.00	1.00	0.38	−7.55
16	0.94	0.94	−2.80	1.00	1.00	0.37	−8.18
18	0.94	0.94	−3.18	1.00	1.00	0.38	−11.34

Note: Mean Estimated parameters from the structural Estimation Approach. Column BC indicates the chosen background consumption level.

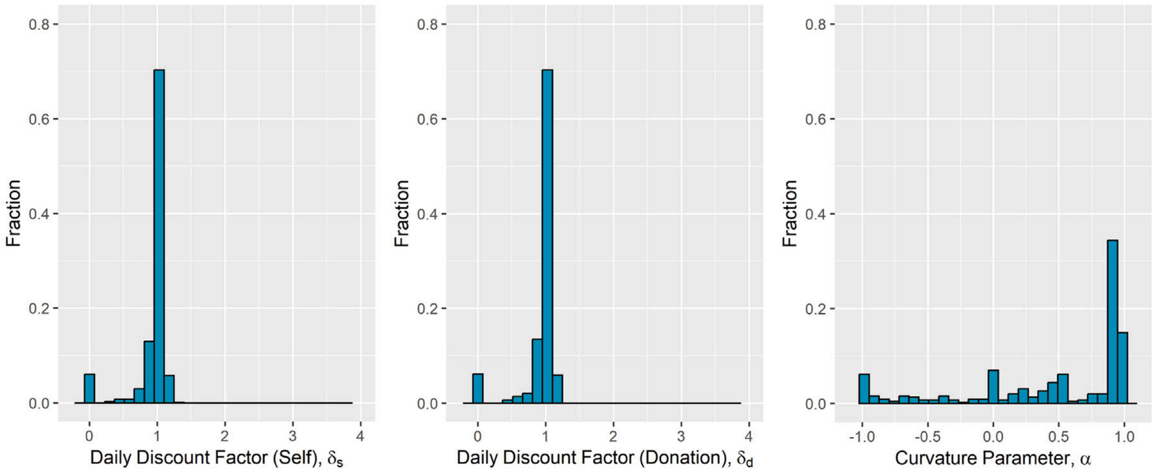

Fig. 3. Histogram of discount factors (δ_{si}, δ_{di}) and curvature parameters from intrapersonal decisions (blocks Self & Donation). Background consumption: 10.

for the cohort dummies, but the variance inflation factors are still within the acceptable 0–10 range. Note that we do not include state level fixed effects as these introduce a high collinearity to the models.

Table 4 gives an overview of participant and state demographics both for our full sample and for each cohort separately. Individual level variables are gathered through our post experiment questionnaire, while state level variables, for instance, for pandemic progression are either based on publicly available data sources, see Appendix B for details. The state level variables capture both larger trends and also exogeneous variation in the impact of the pandemic on individuals. We only use COVID-19 case numbers on the state level as no finer granular data on, for instance, FIPs-code level is available for roughly half our dataset. In addition to case numbers, we capture the severity of state-level lockdown measures via the stringency index. This index is a composite measure based on indicators including school and workplace closures, stay home requirements and travel bans, see Hallas et al. (2020) for details. Unemployment numbers are decreasing in cohort 3, which can be explained by the steep 10%-points rise in US unemployment numbers from March to April, before the start of our data collection. Restrictions to daily life, such as workplace- and school-closing and stay-home requirements all show a decrease in cohort 3, while the case numbers are continuously increasing. Note that for all regression, we standardise the values for the cases per capita, the stringency index, the unemployment rate and age, to allow for better visibility and comparability in the tables and graphs.

In order to identify more individual level variation in the impact of the pandemic, we also include survey measures in our analysis. While the base demographics stay constant over all our cohorts — except for a dummy indicating a one-person household, most variables that capture specific impact of the pandemic show significant variation, with the dummy for loosing your job and having health insurance being the exception. However, we only observe a relatively small amount on participants that are or were infected themselves, with only a total of 57 participants report having been positively tested for COVID-19 at the time of the experiment. Surprisingly, there is a trend towards more participants reporting to have at least one risk-factor for COVID-19, as captured in the *predisposed* variable. This could be due to changes in knowledge about these risk-factors themselves. We also asked participants for their political alignment between liberalism and conservatism, which is indicated by variable *conservatism*. We primarily include this variable to account for general shifts in public sentiment during the pandemic.

Since we are not primarily interested in the aggregated values of structural estimates, for the second step estimations, we aggregate the models to an average model over all background consumption levels. This makes sure that the results are not driven

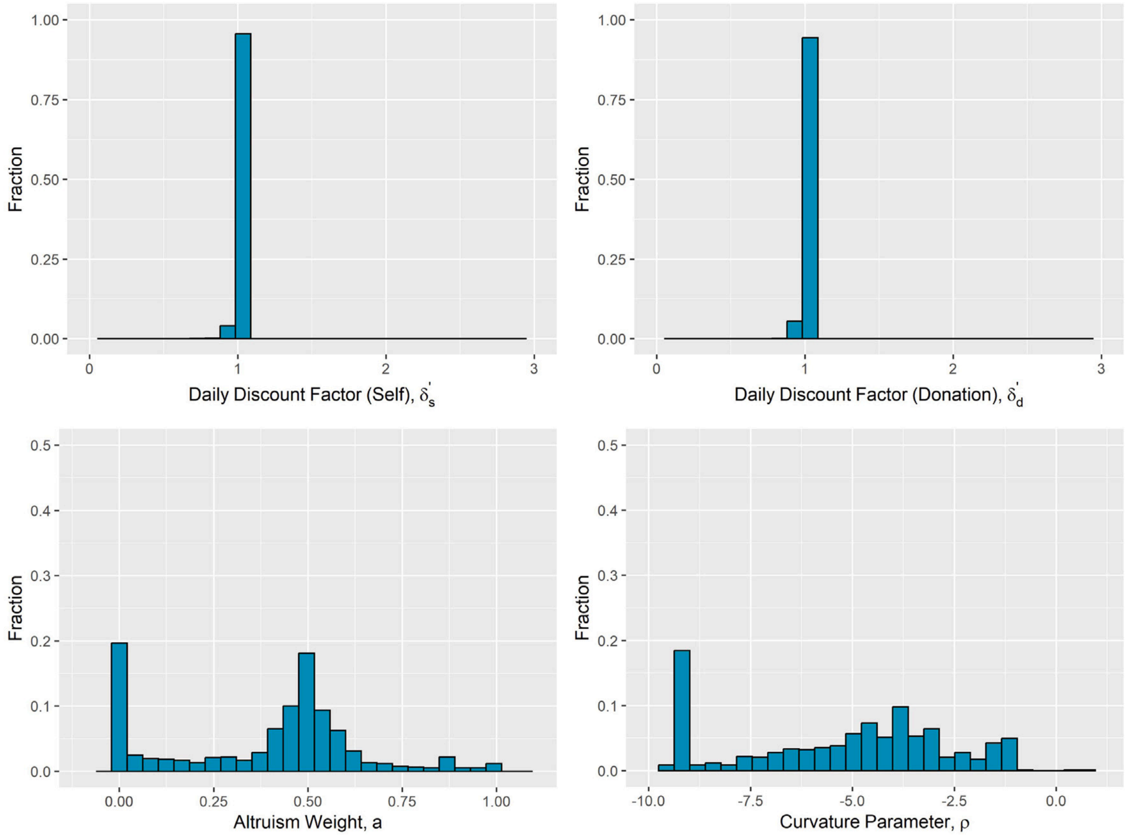

Fig. 4. Histogram discount factors (δ'_{si}, δ'_{di}) and curvature parameters from interpersonal decisions (blocks Self & Donation). Background consumption: 10.

by a single background consumption but rather represent average effect sizes and significance. In addition, we report the results for all background consumption levels in Appendix. For the aggregation, we treat coefficients and their standard error/variance as independent variables, and calculate the averages accordingly.[22]

Second step estimation results

Stability of preferences during the crisis

We start by investigating the variation in the average preference parameters during the pandemic. Figs. 5 and 6 show the coefficients of the regressions that include cohort dummies and demographic controls (we omit income and education in the figures for better visibility). The full regression details are reported in Table 5. The data shows stability in all preferences, except for α_i, the measure that captures the reaction to efficiency in intrapersonal choices. This points to an overall shift towards less care for efficiency during the time of observation, whereas invariance of altruism and time preferences. With regards to the controls, individuals with children and multi-person households show less concern for efficiency but higher altruism.

Heterogeneous effects of the pandemic

Our data also allows us to investigate heterogeneity in the way an individual is affected by the pandemic. Specifically, we can include measures for the state level progress of the pandemic (cases per capita, stringency index), survey items for personal and financial affectedness and items that are potential mediators, such as being predisposed (having at least one COVID-19 risk factor). Figs. 7 and 8 show the coefficients of the corresponding regressions. Since the progress of the pandemic is captured by other variables and we want to evade colinearity issues, we do not include cohort controls. The full regression details are reported in Table 6.

[22] Specifically we calculate the average coefficient as the arithmetic mean and the corresponding standard error based on n standard errors, se, for n base consumption rates, with $\sqrt{\frac{\sum_{i=1}^{n} se_i^2}{n}}$, the p-value can then be calculated in the same way as in the standard OLS model. We then calculate p-values with these aggregated values. Note that this is a more conservative approach, compared to selecting individual background consumption levels. We report the models for each individual background consumption in Appendix Tables A5 to A18.

Table 4
Sample demographics.

Variable	Full Set	Cohort 1	Cohort 2	Cohort 3	p-value
Base demographics					
age	38.51	38.38	39.02	38.13	0.82
gender	0.40	0.40	0.39	0.41	0.92
educ	3.65	3.64	3.65	3.65	0.99
children	1.00	1.03	0.96	1.02	0.29
single HH	0.23	0.27	0.23	0.18	0.04
Income $\leq$ 20K	0.10	0.03	0.02	0.04	0.22
20K $<$ Income $\leq$ 40K	0.21	0.08	0.07	0.06	0.23
40K $<$ Income $\leq$ 60K	0.29	0.08	0.10	0.11	0.10
60K $<$ Income $\leq$ 80K	0.18	0.06	0.06	0.06	0.94
80K $<$ Income $\leq$ 100K	0.10	0.04	0.03	0.03	0.69
100K $<$ Income	0.12	0.04	0.05	0.04	0.44
educationlevel	3.65	3.64	3.65	3.65	0.99
Financial impact					
jobloss	0.16	0.15	0.16	0.18	0.67
financialaffected	6.21	5.99	5.97	6.67	0.00
Medical impact					
infected	0.06	0.04	0.04	0.11	0.00
predisposed	0.21	0.15	0.23	0.26	0.00
knowinfected	0.28	0.22	0.26	0.37	0.00
State-level variables					
casespercap	0.73	0.34	0.64	1.21	0.00
case incidence	0.87	0.87	0.52	1.22	0.00
stringency	7.03	7.78	7.09	6.23	0.00
Other					
insurance	0.82	0.82	0.83	0.81	0.81
conservatism	5.20	4.93	5.11	5.57	0.02
observations	886	296	292	298	NA

Note: Income indicates yearly income notated in USD. Last column shows p-value results from a Kruskal–Wallis test between all cohorts. The pandemic progression variables are defined as follows: casespercap: the number of COVID-19 cases per population/10.000, case incidence: the number of total new cases within the last 7 days, stringency index: indicates the strength of lockdown measures on a 0-100 scale, based on (Hallas et al., 2020). Last column shows p-value results from a Kruskal–Wallis test between all cohorts.

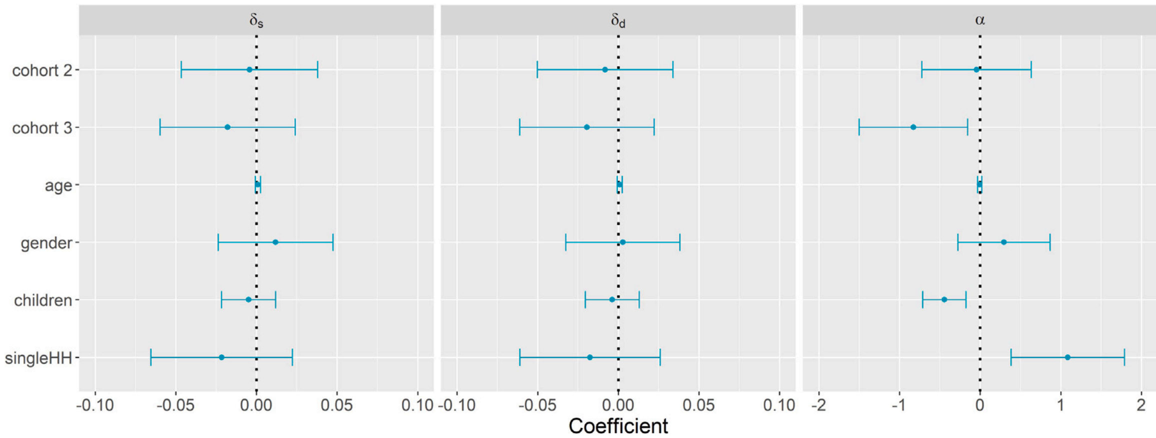

Fig. 5. Average coefficients over all background consumption levels. Intrapersonal choices. Coefficients and 95% confidence interval, controls include: age, gender, children, household type, income, education and health insurance.

We find a borderline significant negative effect of prior COVID-19-infection on efficiency preference. While substantial, the effect is driven by low numbers of individuals, with only 6.5% of participants reporting ever having been positively tested. Further, in line with Hypothesis 3b, being financially affected by COVID-19 is negatively correlated with the care for efficiency, while at the same time being positively correlated with altruism. That is, in line with Hypothesis 3b but contrasting Hypothesis 1b, being negatively financial impacted coincides with less caring for the efficiency in intrapersonal decisions for yourself or for others, while at the same time coinciding with donating more to others, independent of efficiency. Our results help to clarify the effect of being financially affected by the pandemic which has mixed consequences in earlier studies. Unlike other studies, our estimations allow the distinction between efficiency and time preferences. While our results indicate financial distress relating to less care for efficiency (and more

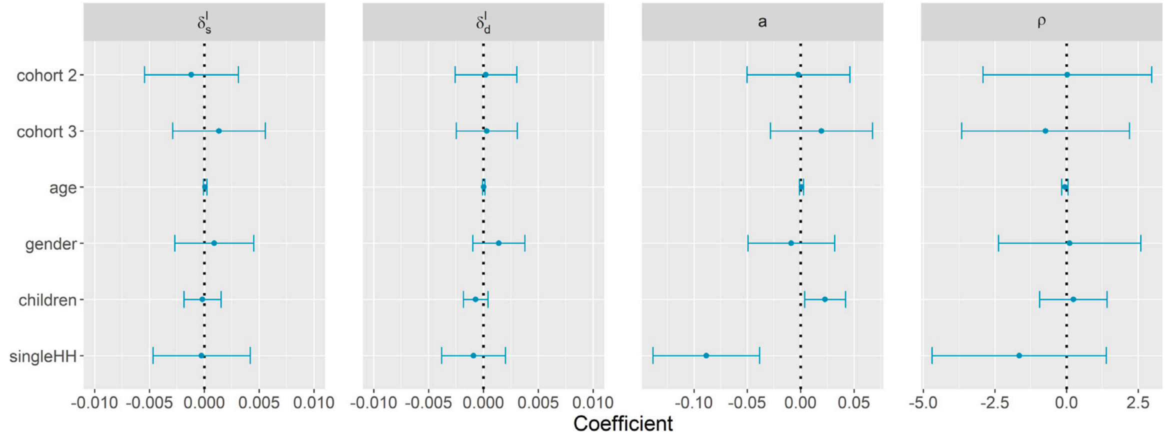

Fig. 6. Average coefficients over all background consumption levels. Interpersonal choices. Coefficients and 95% confidence interval, controls include: age, gender, children, household type, income, education and health insurance.

Table 5
Second step estimation with cohort dummies, averaged over background consumption levels.

	Intrapersonal			Interpersonal			
	δ_s	δ_d	α	$\delta_s^{'}$	$\delta_d^{'}$	a	ρ
(intercept)	0.88***	0.87***	−2.57	0.97***	0.97***	0.42***	−2.30
	(0.11)	(0.11)	(1.74)	(0.01)	(0.01)	(0.12)	(7.60)
cohort 2	−0.00	−0.01	−0.05	−0.00	0.00	−0.00	0.02
	(0.02)	(0.02)	(0.35)	(0.00)	(0.00)	(0.02)	(1.50)
cohort 3	−0.02	−0.02	−0.83**	0.00	0.00	0.02	−0.73
	(0.02)	(0.02)	(0.34)	(0.00)	(0.00)	(0.02)	(1.49)
age	0.00	0.00	−0.01	0.00	0.00	0.00	−0.06
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.06)
gender	0.01	0.00	0.29	0.00	0.00	−0.01	0.11
	(0.02)	(0.02)	(0.29)	(0.00)	(0.00)	(0.02)	(1.27)
children	−0.00	−0.00	−0.45***	−0.00	−0.00	0.02**	0.24
	(0.01)	(0.01)	(0.14)	(0.00)	(0.00)	(0.01)	(0.60)
singleHH	−0.02	−0.02	1.09***	−0.00	−0.00	−0.09***	−1.65
	(0.02)	(0.02)	(0.36)	(0.00)	(0.00)	(0.03)	(1.55)
20K < Income ≤ 40K	0.08**	0.09**	0.34	−0.00	−0.00*	0.03	0.07
	(0.04)	(0.04)	(0.57)	(0.00)	(0.00)	(0.04)	(2.48)
40K < Income ≤ 60K	0.08**	0.08**	0.30	0.00	−0.00	0.02	−1.56
	(0.03)	(0.03)	(0.55)	(0.00)	(0.00)	(0.04)	(2.38)
60K < Income ≤ 80K	0.10***	0.12***	0.08	0.00	−0.00	−0.00	−1.39
	(0.04)	(0.04)	(0.59)	(0.00)	(0.00)	(0.04)	(2.55)
80K < Income ≤ 100K	0.09**	0.10**	1.44**	0.00	−0.00	−0.01	−0.18
	(0.04)	(0.04)	(0.66)	(0.00)	(0.00)	(0.05)	(2.88)
100K < Income	0.11***	0.13***	1.98***	0.00	−0.00	−0.07	−2.45
	(0.04)	(0.04)	(0.64)	(0.00)	(0.00)	(0.05)	(2.78)
educ: lower sec	−0.00	0.03	2.75	0.03**	0.03***	−0.14	0.08
	(0.11)	(0.11)	(1.81)	(0.01)	(0.01)	(0.13)	(7.90)
educ: higher sec	−0.00	0.02	1.37	0.03***	0.03***	−0.12	−3.40
	(0.11)	(0.10)	(1.70)	(0.01)	(0.01)	(0.12)	(7.39)
educ: ter	0.00	0.02	1.23	0.03***	0.04***	−0.12	−1.66
	(0.10)	(0.10)	(1.68)	(0.01)	(0.01)	(0.12)	(7.32)
insurance	−0.05**	−0.07***	−0.52	−0.00	−0.00	0.04	0.94
	(0.02)	(0.02)	(0.39)	(0.00)	(0.00)	(0.03)	(1.69)
R^2	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Notes: Regressions are run for background consumption levels 2, 4, 6, 8, 10, 12, 14, 16, 18; the coefficients are averaged; standard errors are calculated by taking the square-root of the sum of squared standard errors of the individual models; the p-values are then calculated based on the aggregated coefficient and standard error; we report all individual models in the appendix

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

donations), but no systematic on time preferences, former studies may mix the efficiency and time consideration potentially yielding inconclusive findings.

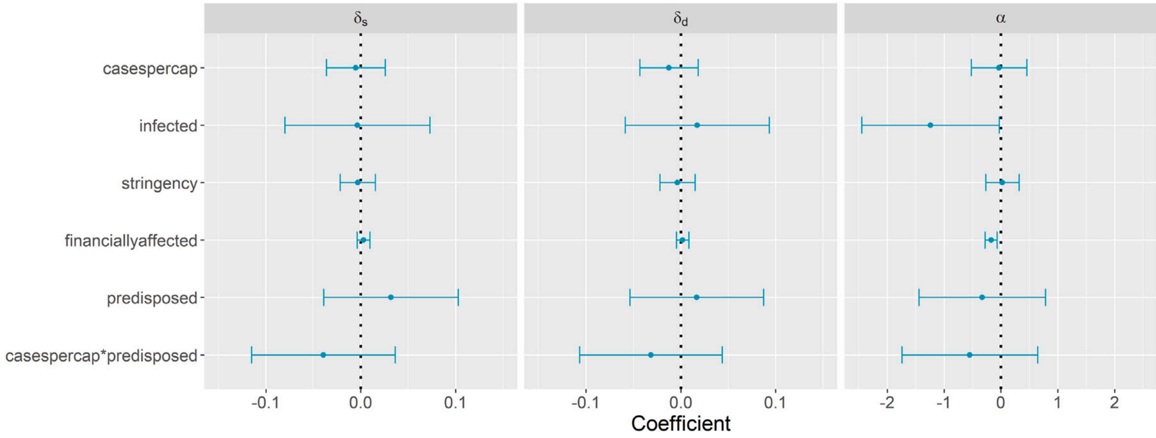

Fig. 7. Average coefficients over all background consumption levels. Intrapersonal choices. Coefficients and 95% confidence interval. We exclude the education coefficients here for better visibility.

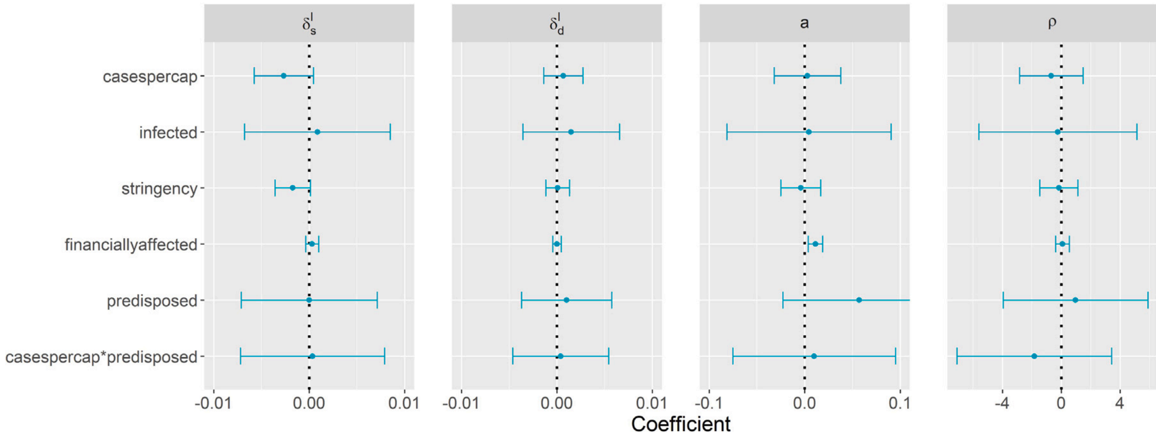

Fig. 8. Average coefficients over all background consumption levels. Interpersonal choices. Coefficients and 95% confidence interval. We exclude the education coefficients here for better visibility.

We do not find any evidence that having at least one COVID-19 risk factor (variable predisposed) has any impact by itself or in combination with the current case numbers. This indicates that the potential individual risk is not related to any changes of preferences driven by the pandemic (rejecting our Hypotheses 1a and 3a). Finally, we do not find contradictions for our Hypotheses 2a and 2b: there is no significant coefficient of being financially affected or medically predisposed in the regressions on discount factors. We also test for the robustness of our results with regard to multiple testing corrections. We apply a model-wise Bonferroni correction, see the corresponding Appendix Table A2.[23] Our results are robust to this correction, with the exception of the negative effect of prior infection on efficiency preference, which is close to being rejected anyhow prior to the correction.

An additional finding is that a dummy for having any kind of health insurance is correlated with lower discount factors for intrapersonal decisions. The direction of the correlation is surprising, as you would expect individuals that discount more strongly to be less likely to insure themselves against future damages, not more likely. In addition there is no significant coefficient for insurance on discounting in the interpersonal domain. We find a similar relationship for income. Having an annual income above 20,000 USD correlates with higher patience in intrapersonal decisions, but not in interpersonal decision. A further finding is that being a high earner (>100,000 USD per year) coincides with a higher concern for efficiency, but, as before, exclusively in the intrapersonal domain.

In addition to being affected by the pandemic in different ways, changes in preferences can also be driven by different beliefs about the progression/severity of the pandemic. We can investigate this in two ways. Firstly, since we ask participants to look up (based on a source we provided) and report the current number of cases in their state, we can investigate the role of over- or

[23] Note that we only consider the variables that capture the impact of Covid-19 (and are thus related to the hypotheses) for the correction. Those are casespercap, infected, stringency, financiallyaffected, predisposed and predicposed∗casespercap.

Table 6
Second step estimation, heterogeneous effect, averaged over background consumption levels.

	Intrapersonal			Interpersonal			
	δ_s	δ_d	α	δ_s'	δ_d'	a	ρ
(intercept)	0.88***	0.88***	−1.88	0.98***	0.97***	0.39***	−1.58
	(0.13)	(0.13)	(2.06)	(0.01)	(0.01)	(0.15)	(9.13)
casespercap	−0.01	−0.01	−0.03	−0.00*	0.00	0.00	−0.68
	(0.02)	(0.02)	(0.25)	(0.00)	(0.00)	(0.02)	(1.10)
infected	−0.00	0.02	−1.24**	0.00	0.00	0.00	−0.24
	(0.04)	(0.04)	(0.62)	(0.00)	(0.00)	(0.04)	(2.74)
stringency	−0.00	−0.00	0.02	−0.00*	0.00	−0.00	−0.17
	(0.01)	(0.01)	(0.15)	(0.00)	(0.00)	(0.01)	(0.66)
financiallyaffected	0.00	0.00	−0.17***	0.00	−0.00	0.01***	0.08
	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.24)
predisposed	0.03	0.02	−0.33	0.00	0.00	0.06	0.97
	(0.04)	(0.04)	(0.57)	(0.00)	(0.00)	(0.04)	(2.51)
casespercap∗predisposed	−0.04	−0.03	−0.55	0.00	0.00	0.01	−1.83
	(0.04)	(0.04)	(0.61)	(0.00)	(0.00)	(0.04)	(2.68)
age	0.00	0.00	−0.00	0.00	0.00	0.00	−0.06
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.06)
gender	0.01	0.00	0.15	0.00	0.00	−0.00	−0.04
	(0.02)	(0.02)	(0.29)	(0.00)	(0.00)	(0.02)	(1.29)
children	−0.01	−0.00	−0.37***	−0.00	−0.00	0.02*	0.25
	(0.01)	(0.01)	(0.14)	(0.00)	(0.00)	(0.01)	(0.61)
singleHH	−0.02	−0.01	0.92***	0.00	−0.00	−0.08***	−1.54
	(0.02)	(0.02)	(0.35)	(0.00)	(0.00)	(0.03)	(1.56)
20K < Income ≤ 40K	0.08**	0.09***	0.26	−0.00	−0.00	0.05	0.19
	(0.04)	(0.04)	(0.56)	(0.00)	(0.00)	(0.04)	(2.49)
40K < Income ≤ 60K	0.09**	0.08**	0.16	0.00	−0.00	0.04	−1.38
	(0.03)	(0.03)	(0.55)	(0.00)	(0.00)	(0.04)	(2.42)
60K < Income ≤ 80K	0.11***	0.12***	−0.15	0.00	−0.00	0.02	−1.17
	(0.04)	(0.04)	(0.58)	(0.00)	(0.00)	(0.04)	(2.59)
80K < Income ≤ 100K	0.10**	0.11***	1.07	0.00	−0.00	0.02	0.21
	(0.04)	(0.04)	(0.66)	(0.00)	(0.00)	(0.05)	(2.94)
100K < Income	0.12***	0.14***	1.35**	0.00	−0.00	−0.02	−2.04
	(0.04)	(0.04)	(0.65)	(0.00)	(0.00)	(0.05)	(2.89)
educ: lower sec	−0.01	0.02	2.78	0.03**	0.03***	−0.15	0.09
	(0.11)	(0.11)	(1.77)	(0.01)	(0.01)	(0.13)	(7.88)
educ: higher sec	−0.01	0.02	1.42	0.03***	0.03***	−0.13	−3.44
	(0.11)	(0.10)	(1.66)	(0.01)	(0.01)	(0.12)	(7.38)
educ: ter	−0.00	0.02	1.29	0.03***	0.04***	−0.13	−1.63
	(0.10)	(0.10)	(1.65)	(0.01)	(0.01)	(0.12)	(7.32)
insurance	−0.05**	−0.06***	−0.33	−0.00	−0.00	0.03	1.13
	(0.02)	(0.02)	(0.39)	(0.00)	(0.00)	(0.03)	(1.72)
R^2	0.05	0.05	0.05	0.05	0.05	0.05	0.05

Notes: Regressions are run for background consumption levels 2, 4, 6, 8, 10, 12, 14, 16, 18; the coefficients are averaged; standard errors are calculated by taking the square-root of the sum of squared standard errors of the individual models; the p-values are then calculated based on the aggregated coefficient and standard error; we report all individual models in the appendix
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

under-reporting of these numbers. Table 7 includes dummies that indicate individuals report being at least 20% above/below the actual number. While we cannot provide insight into the reasons of the misreporting,[24] our data shows an interesting pattern of individuals that misreport in either direction having less concern for efficiency but behave more altruistic. Note that the effect of a prior infection is no longer significant in this regression, but our results for the financial affectedness persist.[25]

Secondly, we can use controls for media usage as well as the type of media used as control variables. While information on media consumption is not a direct measure of beliefs, there is evidence that beliefs about the COVID-19 pandemic are correlated with media consumption behaviour (see, e.g., Romer and Jamieson, 2021). So, in order to further address the possibility that our results are driven by beliefs about the future development of the pandemic, we present a model that includes survey items on the frequency and type of media consumption. The model is reported in Appendix Table A7. While the effect of having been infected is no longer significant, the other findings remain robust to this inclusion.

[24] Giving a wrong number could be driven by prior beliefs about COVID-19 numbers, but also inattention, errors in copy/pasting from the source or general negligence.

[25] We acknowledge that these results are less robust to correction for multiple testing. The coefficient of overreporting on altruism and the effect of financially affected are no longer significant after the correction. This is potentially driven by the large number of explanatory variables considered.

Table 7
Second step estimation, heterogeneous effect, includes dummies for over- and underreporting of actual number of cases, averaged over background consumption levels.

	Intrapersonal			Interpersonal			
	δ_s	δ_d	α	δ_s'	δ_d'	a	ρ
(intercept)	0.88***	0.88***	−1.97	0.98***	0.97***	0.40***	−1.47
	(0.13)	(0.13)	(2.03)	(0.01)	(0.01)	(0.15)	(9.13)
casespercap	−0.00	−0.01	−0.04	−0.00*	0.00	0.00	−0.81
	(0.02)	(0.02)	(0.25)	(0.00)	(0.00)	(0.02)	(1.11)
overreporter	0.02	0.01	−1.80***	0.00	0.00	0.07*	−1.09
	(0.04)	(0.03)	(0.54)	(0.00)	(0.00)	(0.04)	(2.44)
underreporter	0.00	−0.00	−1.46***	0.00	0.00	0.11***	1.18
	(0.03)	(0.03)	(0.43)	(0.00)	(0.00)	(0.03)	(1.94)
infected	−0.01	0.02	−0.82	0.00	0.00	−0.02	−0.52
	(0.04)	(0.04)	(0.62)	(0.00)	(0.00)	(0.04)	(2.79)
stringency	−0.00	−0.00	0.04	−0.00*	0.00	−0.00	−0.12
	(0.01)	(0.01)	(0.15)	(0.00)	(0.00)	(0.01)	(0.66)
financiallyaffected	0.00	0.00	−0.13**	0.00	−0.00	0.01**	0.06
	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.24)
predisposed	0.03	0.02	−0.06	−0.00	0.00	0.04	0.87
	(0.04)	(0.04)	(0.56)	(0.00)	(0.00)	(0.04)	(2.52)
casespercap∗predisposed	−0.04	−0.03	−0.56	0.00	0.00	0.01	−1.87
	(0.04)	(0.04)	(0.60)	(0.00)	(0.00)	(0.04)	(2.68)
age	0.00	0.00	−0.00	0.00	0.00	0.00	−0.06
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.06)
gender	0.01	0.00	0.14	0.00	0.00	−0.00	−0.00
	(0.02)	(0.02)	(0.29)	(0.00)	(0.00)	(0.02)	(1.29)
children	−0.01	−0.00	−0.35***	−0.00	−0.00	0.02*	0.25
	(0.01)	(0.01)	(0.13)	(0.00)	(0.00)	(0.01)	(0.61)
singleHH	−0.02	−0.01	0.79**	0.00	−0.00	−0.07***	−1.46
	(0.02)	(0.02)	(0.35)	(0.00)	(0.00)	(0.03)	(1.57)
20K < Income ≤ 40K	0.08**	0.09***	0.46	−0.00	−0.00	0.04	0.12
	(0.04)	(0.04)	(0.56)	(0.00)	(0.00)	(0.04)	(2.50)
40K < Income ≤ 60K	0.08**	0.08**	0.40	0.00	−0.00	0.03	−1.49
	(0.03)	(0.03)	(0.54)	(0.00)	(0.00)	(0.04)	(2.43)
60K < Income ≤ 80K	0.11***	0.12***	0.06	0.00	−0.00	0.00	−1.33
	(0.04)	(0.04)	(0.58)	(0.00)	(0.00)	(0.04)	(2.60)
80K < Income ≤ 100K	0.10**	0.11***	1.16*	0.00	−0.00	0.02	0.15
	(0.04)	(0.04)	(0.65)	(0.00)	(0.00)	(0.05)	(2.94)
100K < Income	0.12***	0.14***	1.40**	0.00	−0.00	−0.03	−2.07
	(0.04)	(0.04)	(0.64)	(0.00)	(0.00)	(0.05)	(2.89)
educ: lower sec	−0.01	0.02	2.77	0.03**	0.03***	−0.15	−0.04
	(0.11)	(0.11)	(1.74)	(0.01)	(0.01)	(0.13)	(7.87)
educ: higher sec	−0.01	0.02	1.43	0.03***	0.03***	−0.14	−3.76
	(0.11)	(0.11)	(1.64)	(0.01)	(0.01)	(0.12)	(7.39)
educ: ter	−0.00	0.02	1.35	0.03***	0.04***	−0.14	−1.86
	(0.10)	(0.10)	(1.62)	(0.01)	(0.01)	(0.12)	(7.32)
insurance	−0.05**	−0.06***	−0.51	−0.00	−0.00	0.04	1.17
	(0.02)	(0.02)	(0.38)	(0.00)	(0.00)	(0.03)	(1.73)
R^2	0.05	0.05	0.05	0.05	0.05	0.05	0.05

Notes: Regressions are run for background consumption levels 2, 4, 6, 8, 10, 12, 14, 16, 18; the coefficients are averaged; standard errors are calculated by taking the square-root of the sum of squared standard errors of the individual models; the p-values are then calculated based on the aggregated coefficient and standard error; we report all individual models in the appendix

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

3. Discussion

COVID-19 has imposed enormous costs on mankind. The International Monetary Fund expects that the pandemic will cost the global economy 12.5 trillion US dollars through 2024 (Reuters, 2022). In addition to direct effects, the pandemic coincides with systematic changes in preferences of affected individuals. We investigate the impact of the pandemic on two levels of abstraction. On the one hand we follow earlier studies by measuring the change of preferences over the progress of the pandemic. We find evidence of the overall progression of the pandemic decreasing the degree to which individuals seek efficient outcomes. Changes in the preference for efficiency are particularly relevant as they translate to success over a variety of economic outcomes such as health and financial success. On the other hand, we investigate heterogeneous effects of the pandemic through individual indicators as well as regional measures of the COVID-19 pandemic like the number of cases and the stringency of the lockdown (Violato et al., 2021). The decrease in care for efficiency is primarily driven by financial affectedness. In addition, financial impact also increases altruism. Those sizeable, economically relevant effects on preferences ought to be taken into account by policy aiming at alleviating the effects of a crisis.

Our data shows mixed evidence towards the relationship between individual health factors and preferences. The effect of being infected is present, but not particularly pronounced. At the same time, variables that capture the overall risk of infection, and the potential damage, that is having at least one COVID-19 risk factor, do not relate to any change in preferences. This relation represents a difficult problem for policy makers. When faced with a choice between medical relief (masks, additional medical staff, vaccination roll out) and direct individual financial relief (tax breaks, direct financial relief packages) choosing the latter option can reduce detrimental preference changes, although the former provides a direct impact on the pandemic progression.

On its own, the intensified altruism regardless of the exacerbating personal economic pressure of the pandemic indicates that people are willing to bear those additional costs and give more to others as the severity of the crisis intensifies. This finding corresponds with some previous studies on behavioural patterns triggered by the COVID-19 pandemic (Grimalda et al., 2021; Adena and Harke, 2022; Hajek and König, 2022). Yet, the results of our experiment indicate an important, but so far overlooked by-product of the greater solidarity between participants: using the structural estimation approach by Andreoni and Sprenger (2012) allows us to disentangle temporal and efficiency considerations. Separating both taste parameters shows that greater altruism comes at an additional cost of greatly reduced care for efficiency. This indicates that looking at altruism in isolation misses an important footprint of the pandemic on the preference parameters of subjects: the (potentially persistent) shift in efficiency considerations.[26]

Thus, the effect of the pandemic can have tremendous effects in the long run as efficient spending is vital for both wealth and health of a society. For instance, some national governments pushing and outbidding for vaccine deliveries multiply the costs for solving the pandemic considerably. It seems that more coordination and emphasis on the efficient use of funding not only had saved (financial) resources, but also helped to manage the crisis more effectively.

As for our results, it appears important to distinguish between efficiency considerations for intrapersonal decisions (i.e., when participants allocate their donations or their own money between two points in time) and efficiency considerations for interpersonal decisions (i.e., when distributing resources between the two domains). Whereas efficiency seems to be an important criterion for the former decisions with diminishing importance when the pandemic intensifies, individuals tend to show close to no reaction to efficiency in latter decisions. Yet, efficiency concerns matter little for interpersonal decisions anyhow, and perhaps the concerns cannot diminish further for that reason. This claim is a potential subject for subsequent extension of our research.

Another limitation of our study is the preference elicitation in three separate cohorts of different participants, using the variation of COVID-19 as a natural experiment. While participant demographics stay highly stable over all cohorts, reverse causality may be an issue: that is, our results may suffer from endogeneity if, for example, altruistic individuals have a higher probability of being adversely affected by COVID-19. We specifically designed the study to only include experienced MTurk workers (i.e., workers who were already active on MTurk prior to the pandemic) to prevent any time-dependent selection into our sample. Our study also has limitations with regards to external validity, due to the selection of participants based on the state of residence. While this is a relevant design feature, as it ensures that there is enough variation in terms of COVID-10 impact, it also makes the results less comparable to the US population as a whole. On the other hand, it ensures that COVID-19 related shifts in MTurk participation does not lead to over-representation of specific states leading to a potentially biased sample. Further, one may claim that individual beliefs about the future progression of the pandemic can drive our results. As we require subjects to report the current case numbers at the beginning of the experiment, while we find no evidence of media usage or the frequency of media usage to impact the measured preferences in a significant way, we assume that this problem does not influence our estimations crucially.

We also acknowledge that we are limited to the extent with which we can identify precise mechanisms of the change in preference. However, we argue that the synchronous change in altruistic and efficiency preferences we identify is relevant on its own. In general, our results demonstrate the ambivalent response of participants to the severity of the crisis. Medical and financial threats of the pandemic stimulates donations of record highs (USA, 2020). However, altruistic giving may end up as “activism at the cost of efficiency”. The adverse effects of the behavioural change appear of crucial importance. Inefficient spending is particularly problematic in a crisis, when resources become increasingly scarce. Therefore, our results emphasise the relevance of efficiency in a public debate about facing a threatening pandemic and facilitating a wise and thoughtful decision-making in the management of future crises.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Instructions and the complete data of the experiment are available at: https://osf.io/923jb/?view_only=daf44956556640c195ebe0d7ff289b7f.

[26] Since we do not have data from past COVID-19 years, we have to leave the question how persistent the preferential shift is, to future research.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jebo.2024.106763.

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