Gambling on Others' Health: Risky Pro-social Decision-Making in the Era of Covid19

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Abstract

How does cost and uncertainty shape an ordinary person's action towards a stranger's wellbeing? During the Covid19 pandemic, individuals were asked to perform costly actions to reduce harm to strangers, even while the general population, including authorities and experts, grappled with the uncertainty surrounding the novel virus. Many researches have examined health decision-making by experts, but the study of lay, non-expert, individuals decision-making on a stranger's health has been left to the wayside, as ordinary citizens are usually not tasked with such decisions. We sought to capture a snapshot of this specific choice behavior by administering two surveys to the general population in the early days of the Covid-19 pandemic. We presented respondents with hypothetical diseases of variable severity affecting either oneself, a beloved person or a stranger. Participants had to choose between treatments who could either lead to a certain mild improvement (sure option) or cure entirely the effected person at a given probability (risky option). Respondents preferred risky options overall, but their risk-seeking attitude decreased progressively the higher the expected severity of the disease. This pattern was observed regardless of the identity of recipient. Instead,

distinctions between targets emerged when decisions were conditioned on treatment cost, with participants preferring cheaper options for strangers. Overall, these findings provide a descriptive model of individual risky decision-making for others; and inform on the limits of what can be asked of an individual in service to a stranger.

Data Availability Statement:

The data and code relating to the manuscript “Gambling on Others’ Health: Risky Pro-social Decision-Making in the Era of Covid19” can be found at the following links in OSF: https://osf.io/9fjdq/?view_only=09b98e50a02f47e2bb4b912f14aafa7d

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Introduction

In December 2019, an unprecedented outbreak of pneumonia caused by the SARS-CoV-2 virus, emerged in the city of Whuan (China). This disease, known as Covid19, rapidly spread throughout the globe, finding authorities, healthcare providers and lay individuals woefully unprepared, and leading a high degree of uncertainty [1]. To contain the spread, around March 2020, many countries put in place restrictive measures like lockdown, curfew, social distancing, quarantines, etc. These measures had economical and psychological consequences on the people involved [2–6], with some individuals more affected than others [7–9]. Furthermore, the effect of the virus was not uniformly distributed, changing as a function of age and pre-existing medical conditions [10,11]. As such, the pandemic presents a stark dilemma to the individual: shall we incur such cost, given the uncertainty, for other people's health? This problem spilled over into socio-political discourse [12–14] and even prompted acts of violence [15–17], possibly exacerbated by the fact that the same social restrictions implemented to protect the population impacted negatively sensitivity to others' suffering and empathic traits [18,19].

Risk Decisions for Self and Others

Uncertainty has been extensively studied in economic decision-making [20–22] particularly in the form of 'risk', the uncertainty expected from available information. For instance, seminal theoretical accounts within the domain of economic decision-making (expected utility theory, [23–25], and prospect theory [26]) show that risk is known to steer decision-making away from maximizing predicted gains: agents are risk-averse in the gain domain, assigning more value to less risky options, while they are risk-seeking when facing loss. Importantly, this risk-seeking stance decreases linearly with the expected monetary loss, pushing towards risk-neutrality (or even risk-aversion) for high stakes. This phenomenon is robust, and has been replicated across different countries [27,28]. It remains unclear whether such risk preferences are conserved when deciding for others.

Several empirical studies [29–31] as well as human social structure [32], provide evidence that altruism and sacrifice are common forms of motivated choice behavior that violate the *homo economicus* model [33]. Individuals commonly engage in costly actions to cooperate with others [34,35] or to help people in need

[36]. Furthermore, several studies have found that decisions made on behalf of others resemble those made for the self [37–40], thus suggesting individual ability to put oneself in the shoes of unknown others. When looking specifically at risk preferences, a recent meta-analysis reveal strong variability in the effects described from the literature, all converging with an overall trend at behaving in slightly more risk-seeking fashion for others relative to themselves [41].

Risk Decisions for People's Health

The role of risk and uncertainty in decision-making extends also to health choices [42]. In this case, decisions are often made by experts, such authorities or individual physicians, who are specifically trained in assessing risk. For instance, authorities may rely on the Precautionary Principle, by taking a risk-averse stance towards public health [43–45]. Other health evaluations commonly use expected utility [46–50] to investigate and proscribe choice in health settings. For example, the Quality-Adjusted Life-Years (QALY) is a form of expected utility integrating time that guides cost analysis [51] and health policy implementations [52,53]. With both the Precautionary Principle and QALYs, the calculus employed in the service of making a decision is explicit. However, the novelty and virulence of Sars-Cov-2 imposed the burden of decision-making on people's health under uncertainty on lay people, leaving the question open as to what strategy is used in such a context. In this perspective, Tversky & Kahneman [54] speculated that individuals would be risk-seeking for treatment when facing novel infectious disease, mirroring the behavior observed when dealing with potential monetary loss. However, whereas some studies investigating pain-management choices confirm this prediction [55], others show that individuals might be risk-averse for their own treatment options [56] or for choices that could influence their life expectancy [57].

It is unclear how people react to risk during a pandemic, where individual choices may have a profound impact on unknown, distant others. To our knowledge, the closest answer comes from two meta-analyses who showed that decision-making in medical context led to a shift towards more cautions (risk-averse) decisions in others relative to the self, differently from what observed in monetary/managerial scenarios [41,58]. However, the medical contexts included in these meta-analyses involved prevalently physicians (or people acting as

physicians) choosing for patients [41,58], thus still focusing on decision-making processes in professional individuals, rather than in the untrained mind. One recent study from our group found that lay individual decisions about pain management for unknown others was more risk-averse than the same choices made for oneself or one's spouse [55]. To the best of our knowledge no study have tested how lay individuals make risk-decisions about disease treatments for unknown others.

The present research

Here, we investigated uncertainty's role in decision-making for people's health by applying an expected value model of disease severity in a probabilistic task. In particular, we administered two anonymous surveys to the general population between May and July, 2020, in which we presented respondents with fictitious diseases and their associated risks of contraction, along with different treatment options. Critically, participants had to choose between a risky treatment (avoid the disease altogether at the given probability) or certain but less effective one (mitigate some symptoms). Similarly to our previous study about pain management [55], we also manipulated target of the decision, which could be participants themselves (*Self*), their romantic partner (*Beloved*), and a stranger (*Other*). Results associated with the other (relative to self) are of key interest for the present study, as they represent a proxy for understanding individual risk-decisions for the health of unknown people in the context of the Covid19 pandemic. We included the beloved person to further characterize any potential self-other difference, and to investigate effects related to the social proximity with the deciding agent. Following the literature reviewed above, we predict that (1) in the self condition, individuals would choose for disease treatment similarly than what observed for money-losses (as suggested by [54]), that is by displaying an overall risk-seeking stance which progressively declines the more the expected value of the negative event increases. Furthermore, (2) previous meta-analyses suggest differences in risk-decisions between self and others, but with unclear direction: whereas there is an overall tendency at behaving in more risk-seeking fashion for others [41], this appears not to be the case in medical contents [41,58], or in the domain of pain management [55]. Finally, (3) consistently with our prior research [55], we expect social proximity between self and other to influence the results, with the beloved condition eliciting behavior more

similar to that of the self relative to the unknown other.

Survey 1

Methods

Tested population

The survey was made available online to individuals 18 years and older. Respondents were recruited through the Prolific.co platform (<https://www.prolific.co/>). Participation was voluntary and compensated £5/hour. The study was approved by the Ethics Committee of the Faculty of Psychology and Educational Sciences of the University of Geneva.

Survey Items

Survey 1 contained 45 items, each describing a risk of contracting a given disease. For each item, respondents chose one of 3 treatment options. Below is an example:

"Your loved one has a 25% chance of contracting and falling severely ill with disease F. Symptoms include high fever, muscle pain and vomiting of blood. Standard treatment requires a two-week hospital stay in intensive care. The illness leaves minor but lasting cardiac deficits and a slight but permanent hearing impairment.

You can:

- *Do nothing and let your loved one face the initial chance of falling severely ill with disease F*
- *Pay half your monthly salary for additional treatment that will certainly reduce the severity of the illness, such that it leaves only a slight but permanent hearing impairment*
- *Pay one tenth of your monthly salary to halve the risk of contracting the illness altogether with an experimental treatment"*

The scenarios described 5 possible diseases, with different risks of contraction (p_D ; in the example above, 0.25), and levels of severity (S_D ; either death or severe lasting deficits). Diseases were also described according to their symptoms, which were loosely based on real world infectious diseases (C for Chikungunya; D for

Dengue; E for Ebola; F for Flu, etc.), with, however, fictitious morbidity and mortality rates. Each item threatened one of three possible targets (*Self*, *Beloved*, or *Other*), and were followed by 3 possible options:

- Do nothing and let the person face the initial risk of disease;
- Pay an amount of money for a known treatment that partially reduces disease severity (sure option);
- Pay an amount of money for an experimental treatment that reduces the risk of initial contraction (the gamble).

The gamble cost was always set to one tenth of the respondent's monthly income. Sure treatment options for each disease varied in price, between 0.1, 0.5, or 1 unit of the respondent's monthly income. Selecting the sure option treatment for diseases with a mortal risk (C, D and E from Table 1) reduced prognosis to severe lasting deficits. Known treatment reduced prognosis to mild lasting deficits for diseases that carried severe lasting deficits (F and M) (see Table 1). Four attentional catch questions were interspersed across the survey to ensure respondent engagement (e.g. "Is 7 > 3?"). All items were randomized across diseases and targets.

We also collected participants' non-identifying demographic information (country of residence, age and gender, and household monthly income and education, that could impact costly, prosocial decision-making [59–61]. We also asked participants to identify a loved one (*Beloved*) by their role. The survey was designed using LimeWire software, and was fully anonymous; and available in English, French and Italian (English version available at the following link: https://osf.io/9fjdq/?view_only=09b98e50a02f47e2bb4b912f14aafa7d)

Data Analysis

Respondents who did not complete the questionnaire, or provided implausible answers (e.g., listing a non-human as a beloved) were excluded from analysis, as were those who made >1 error in catch trials. Analyses were performed using R 4.1.2 freeware software (<https://cran.r-project.org/>); processing scripts are available

under the Open Science Framework at the following link:
https://osf.io/9fjdq/?view_only=09b98e50a02f47e2bb4b912f14aafa7d.

Expected (dis)utility of Disease and Risk Preferences

We modeled responses to disease vignettes using expected utility theory. Specifically, we computed the expected value of disease and associated treatment options to address the main question of decision-making under risk. Each illness presented an expected disutility of disease severity (EDS), computed as follows:

$$EDS = p_D * S_D$$

where p_D is the probability of contraction and S_D is disease severity. Each disease has a specific p_D (ranging from 0.05 to 0.50, see Tables 1 and 2). S_D is a value on an ordinary scale ranging from 1 to 3, where 3 = death; 2 = severe lasting deficits and 1 = minor lasting deficits (the latter case was never used as starting value, but only as outcome of the sure option treatment).

Linear Models

We analyzed participants' choices using a generalized linear mixed model with binomial distribution and Laplace approximation, to examine factors influencing decisions. First, we assessed the likelihood of making a costly choice (either certain or gamble) as opposed to inaction (Model 1a). Subsequently, we assessed, among costly choices, the likelihood of selecting a gamble over a sure option (Model 1b). In both models, participants' choices were cast as a function of *EDS*, and the sure option's *Price* (0.1, 0.5 and 1 unit of monthly income) as continuous predictors. Furthermore, we modeled disease *Target* (*Self*, *Beloved* and *Other*) as a categorical factor, and the interactions between the variables of interest. We then modeled chosen treatment prices as a function of *EDS*, *Target* and their interactions (Model 1c). In all models, participant identity was specified as a random factor, with random intercept and slope for all within-subject predictors. In modeling the random components, we always chose the most complex random structure (slope of main effects and high order interactions), except in cases of misconvergence, where a simpler structure was adopted (see Supplementary Table 1 for more details). The

analysis was performed using the *lmerTest* package of R [62].

Results

Cohort characteristics are described in Table 2. In all, 381 participants began the survey; 366 completed the questionnaire. We excluded an additional 22 participants for making >1 attentional errors, leaving $n=344$ for analysis. De-identified data are available under the Open Science Framework at the following link: https://osf.io/9fjdq/?view_only=09b98e50a02f47e2bb4b912f14aafa7d

Choice Analysis

Overall, costly actions were significantly more frequent than inactions (76.53% , 26.67 interquartile range [IQR]; test against 50%: $t_{(343)} = 25.47$, $p < 0.001$). This effect was driven by *Self* and *Beloved* conditions, where costly actions were chosen most often (88.06%, IQR: 13.33 and 93.72%, IQR: 6.66) respectively). When choosing for a stranger (*Other* condition), costly options were selected less often ~47.81% (IQR= 87.67; $t_{(343)} = -1.03$, $p = 0.300$; see Figure 1A). Among costly actions, participants preferred gambles (56.04% , IQR: 40.96; $t_{(341)} = 4.25$, $p < 0.001$). This effect was driven by *Self* and *Other* conditions, where gambles occurred 56.00% (IQR: 51.83) and 71.50% (IQR: 45.63) of the time, respectively. For the *Beloved*, gambles were chosen ~48.22% (IQR: 50.26; $t_{(340)} = -1.10$, $p = 0.273$) of the time.

We extended our analysis in a generalized linear mixed model with a binomial distribution to assess factors affecting choice (Model 1a; Model 1b; Table 3). First, we found a positive main effect of *EDS* on costly (Model 1a) and sure choices (Model 1b) (see Figure 1C; Table 3). We also found an effect of *Price*, with preferences for the cheaper option (Inaction in Model 1a; Gambles in Model 1b) as the sure option's price increased; and a main effect of *Target*, with fewer costly (Model 1a) and sure choices (Model 1b) made for the *Other* (see Figure 1A-C). In Model 1b, when participants chose a costly option, they gambled less for the *Beloved*. Finally, the three factors of interest interacted with one another, suggesting *EDS* and *Price* effects were conditioned on the Target. To further explore these interactions we repeated the previous models in each Target separately (Figure 2). Results confirm

both *EDS* and *Price* influence self-regarding decisions in opposite directions. Whereas *EDS* promotes costly (Model 1a) and sure (Model 1b) choice selection, *Price* promotes inaction and gambles (Figure 2, left column). *Price* influences decisions for the *Beloved* less (Figure 2, middle column) while decisions for the *Other* are less influenced by *EDS* and more by *Price* (Figure 2, right column).

Chosen treatment price

In a follow-up model, the cost of the selected option was modeled as a dependent variable. Results (see Table 3) confirmed that participants spent more on the *Beloved*, but less on the *Other*. Furthermore, participants spent more for high *EDS* across targets, but this effect was less pronounced for the *Other*.

Follow-up analyses

Nuisance Variables

We repeated all above analyses by accounting for *Sex*, *Age*, *Monthly Income* and *Covid-19 financial loss* (log-transformed USD) as nuisance variables. Results confirm effects observed in the main analysis (Supplementary Table 2). We also found a significant effect of *Sex*, where males chose gambles less frequently (Model 1b) and accepted higher treatment prices (Model 1c).

Alternative approach to EDS

All the analyses reported insofar were carried out by modeling the predictor *EDS*, an adaptation of expected utility theory to health-based decision-making. In particular, *EDS* is defined as the product of the probability of contraction (p_D) with disease severity (S_D), where the latter is treated as a ratio-value although resulting from an ordinal predictor (e.g., 3 = death; 2 = severe lasting deficits and 1 = minor lasting deficits; Methods). As it could be argued that imposing linearity on S_D biases the analysis, we repeated the main analyses above, this time modeling the severity of disease as $p_D + S_D$, two independent predictors. Here, p_D was specified as a continuous predictor, and S_D as a categorical factor (in all diseases, initial S_D is either 2 or 3). Full results are displayed in Supplementary Table 3, and reveal that the effects originally attributed to *EDS* are now associated with p_D . In some instances (albeit non-systematically) participants' choices were also influenced by

S_D.

Discussion

This survey tested individual risky decision-making on other's health using an expected disutility of disease framework. We found that individuals display risk-seeking behavior in the disease domain, as expressed by overall preference for gambles (Model 1b), similarly to what found in the economic loss domain [54] and pain management [55]. *EDS* heavily influenced participants' choices and treatment price: disease of higher expected severity increased sure option selection and higher treatment cost increased gamble selection. Choices also changed as a function of *Target*, with participants exhibiting less risk-seeking for a *Beloved*. Participants selected costly and sure options less frequently when acting for a *Stranger*. The *Target* also affected the role played by *EDS* and *Price* on the decision, with choices for the *Beloved* more strongly influenced by *EDS*, while those for the *Other* were predominantly price-based (Figure 2).

Finally, although our main analysis was framed on the estimation of a (dis)utility score for the disease (*EDS*), the results were not conditional to this choice. Similar effects could be observed also when modeling the raw probability of disease contraction (p_D).

Survey 2

In Survey 2, we explicitly differentiated risk preferences from cost concerns. For this purpose, we devised a modified version of Survey 1, where participants chose between sure and risky treatment options, and were subsequently asked to bid (in their own currency) on their chosen option. This measure of willingness-to-pay (WTP) has previously been used as to valuate health intervention [63]. Importantly, removing the factor "price" made for a shorter survey of only 15 scenarios (5 diseases * 3 Targets). We further shortened the questionnaire to 12 scenarios (4 diseases * 3 Targets) to a survey that could be filled in ~15 minutes.

Methods

Unless otherwise stated, the set-up and analysis of Survey 2 were identical to those of Survey 1.

Tested Population

In Survey 2, respondents were not remunerated and were recruited through social media (Facebook, Twitter and LinkedIn) and survey swapping platforms (<https://www.surveycircle.com/>).

Survey Items

Survey 2 included 12 scenarios with 4 diseases (Supplementary Table 1) affecting one of 3 possible targets (*Self*, *Beloved* and *Other*). Participants were asked to select between a sure option and a gamble, as in Survey 1. Respondents were not allowed to forgo action. Furthermore, no cost was associated with the options. Following choice, participants were asked to name a price (Willingness to Pay [WTP]), in their own currency for the chosen option. Respondents were explicitly told they could enter a value of 0 if they wished. Given its brevity, Survey 2 did not include any catch trials to assess attention.

Data Analysis

As in Survey 1, we first performed a choice analysis (Model 2a) testing whether *EDS*, *Target* or their interaction affected choice. Then we examined (*WTP*) as a dependent variable (Model 2b), with *EDS*, *Target*, previous *Choice* (Gamble vs. Sure Option) and their interaction as predictors of interest. The WTPs were converted from participants' local currency to USD (based on the official exchange rate on the day of their response), and log-transformed to account for the large range in responses (Supplementary Table 1).

Each model was associated with a power analysis to test whether the current design at a given sample size would be sufficiently powered to replicate findings from Survey 1. Estimates of fixed factors coefficients and random-effect terms for Model 2a were obtained by re-analyzing Models 1b from Survey 1 without the factor "price". As for Model 2b, we took the coefficients/terms obtained from the analysis of treatment price (Model 1c), although this model provides only partial information as no factor "choice" was specified in Survey 1. For each model, and each

main/interaction effect, we ran 1000 Monte-Carlo simulations aimed at replicating the same fixed factors coefficients and random-effect terms observed in Survey 1 on the design from Survey 2 for a given sample size. Power was then estimated from the frequency of significant effects from the simulated data, as implemented in the *simr* package of R [64]

Results

In Survey 2, a total of 175 participants (out of 273) completed the questionnaire. Five participants were excluded from analysis for omitting to list a human loved one, leaving a sample of $n = 170$ for analysis. The two cohorts were comparable for age (of both respondents and chosen beloved), education and number of countries represented (Table 4). However, the cohorts differed on sex ratio and income (Survey 2 included more females and respondents earned more).

Choice Analysis

Power analysis reveals that this design and sample are sufficiently sensitive to replicate the main effects of *EDS* and *Target* observed in Model 1b from Survey 1 with a probability of at least 0.88.

As in Survey 1, participants preferred gambles over sure options (62.72%, IQR: 25.00; test against 50%: $t_{(169)} = 6.18$, $p < 0.001$), an effect observed in all three targets with comparable percentages. We further inspected choice preferences through a generalized linear mixed model, under binomial distribution (Model 2a). Results confirmed the same main effect of *EDS* observed in Survey 1 (Table 4), where gambles decreased with increasing *EDS* (Figure 1D). We found no effect of *Target*. Overall, the analysis of Survey 2 revealed that when risk preferences are dissociated from cost *Target* effects disappear.

Willingness-to-pay

The design and sample of Survey 2 were also sufficiently sensitive to replicate main effects of *EDS* and *Target* from Model 1c with a probability of at least 0.96. In contrast to risk preferences, *Target* influences *WTP*, with participants bidding less

on a stranger (Table 4, Figure 3B). Additionally, we found an effect of previous *Choice*, with participants bidding more on sure options than gambles (Figure 3C).

Follow-up analyses

Nuisance Variables

We repeated analyses including Sex, Age, Monthly Income and Covid-19 financial loss as nuisance variables. Results confirmed all effects observed in the main analysis (Supplementary Table 4), with the exception of the Choice main effect from Model 2c ($\beta = -0.31$, $t_{(627.62)} = -1.70$, $p = 0.090$). When analyzing the effect of the nuisance variables, we found a significant positive effect of Covid-19 financial loss on WTP (Supplementary Figure S1), suggesting that participants who sustained a higher financial loss due to the pandemic were willing to pay more for others. This was observed by specifying both monthly income and financial loss in the same model, indicating this effect was not confounded with personal wealth.

Alternative approach to EDS

As for the case of Survey 1, we re-run the main models by replacing EDS with $p_D + S_D$, as two independent predictors. Full results are displayed in Supplementary Table 5, and reveal that all effects originally attributed to EDS are now associated with p_D . No effect was associated with S_D .

Discussion

Survey 2 confirms the first result from Survey 1 that, overall, individuals displaying risk-seeking behavior in the disease domain, as highlighted by the preference towards gambles vs. sure options (Figure 1D). However, WTP served to differentiate targets, with participants bidding less to treat the *Other* (Figure 3B). This result disambiguates an open issue from Survey 1, suggesting target differences in health-based decisions are conditioned on cost considerations, and not risk preferences. Finally, while respondents preferred gambles on overall, WTP analyses reveal a higher monetary valuation placed on sure options (Figure 3C).

General Discussion

The goal of this study was to probe risky decision-making on health interventions in

self and others in the context of the Covid19 pandemic's early days. The study was specifically aimed at gaining a cross-sectional description of how a lay individual views costly, risky action on behalf of an unknown person's health. As authorities have called on the public to act for others' sake during the pandemic, the burden of uncertain decision-making was thrust onto individual shoulders. Across two surveys we provide stringent evidence that individuals act similarly than what observed for money-losses, that is by displaying an overall risk-seeking stance which progressively declines the more the expected value of the negative event increases. This effect was independent for the target of the decision (at least when cost considerations were put aside). Instead, distinctions between targets emerged when decisions were conditioned on treatment cost, with participants preferring cheaper options for strangers, but not for a beloved person. Overall, these findings inform about individual risky decision-making for others' health in the context of a global pandemic.

Individuals are risk-seeking, but less for high expected severity

Across two surveys, we provide converging confirmation to the first hypothesis of this study, according to which individuals behave in risk-seeking fashion in the context of disease prevention. This effect is in line with studies on different kinds of negative rewards, ranging from monetary loss [54], to pain prevention [55]. It is possible, that framing of decision outcomes in the present study as negative (getting sick) could have influenced the results towards a pattern similar to that of monetary losses [54]. In this perspective, an alternative framing with a positive outcome (being healed) should in principle lead to opposite results. However, this survey was targeted to general population who, while in good health, were confronted with the risk of contracting Covid19 (positive cases to SARS-Cov-2 virus were negligible, Table 1). Casting the retention of improved health as positive outcome in this population may have stretched responders' credulity. This may differ in patient populations, where treatments for different disease scenarios could be realistically framed as a positive shift from their present condition.

Critically, however, although participants display an overall preference for gambles, they become progressively more risk-neutral (and even risk-averse) the more the *EDS* is high (Figure 1C-D). This is consistent with previous research in the

domain of economic decision-making [54] and pain management [55], but also in a study on professional healthcare providers who show how risk-averse stance in decisions about patients increases linearly with the prospective benefit for the patient [65]. In addition to confirming our predictions, these results put forward the effectiveness of expected utility model in explaining health decision making [66]. Although several studies criticize such approach for health decisions [47,67], we argue that expected utility is a useful tool for modeling individual behavior, in line with what is known on life quality [68], pain management [55], as well as brain activity [69–71]. Importantly, however, we would like to stress that our results are not idiosyncratic to the theoretical framework adopted in our study, as similar effects could be obtained when replacing *EDS* with the raw probability of disease contraction (p_D). This suggests that, absent any explicit requests to compute probabilistic outcomes, individuals in our study appear to choose according to those quantities nonetheless.

Finally, although individuals selected gambles more often (a tendency that decreased linearly with increasing disease severity), they simultaneously assigned a higher monetary value to sure treatment options (Figure 3C). This effect is well-known as *preference reversal* [72,73], prevalent in economic frameworks but observed also in the domain of pain management [55]. Although the cause of preference reversals is still debated, scholars attributed it (among other things) to the sequential nature of many paradigms that distort pricing estimates, or to a general tendency to overprice options with high probability and low benefit at the expense of options with low probability and high benefit (see [72] for a review). Both these explanations fit the case of Survey 2, further stressing how choices in the context disease prevention nicely dovetail the predictions from economic decision-making.

Target Differences are prevalently explained by cost considerations

In both surveys, participants' behavior differed as a function of disease target, especially for strangers. In Survey 1, respondents selected gambles more often for strangers than for themselves or their loved ones (Figure 1C). *Prima facie*, these results may support the recent meta-analysis from Polman and Wu [41] suggesting a stronger risk-seeking stance for other-regarding decisions. However, Survey 1

results may also reflect the fact that the price associated with gambles in the survey was 1) stable across trials, and 2) cheaper or equal to that of sure options. Participants' behavior towards strangers was also characterized by a high amount of inactions (Figure 1A) where participants refrained from choosing to avoid incurring personal cost. In Survey 2, where choices were embedded in a cost-free context, individuals did not differentiate between themselves and others along risk dimensions, but only in terms of willingness-to-pay. We therefore propose that, when cost is not a factor in decision-making, risk influences choices similarly for self and others. This might spawn from self-referential strategy of risk preference, which could represent a less taxing process that minimizes cognitive demand [74]. However, when cost is a factor, decisions differ between targets by pushing agents towards a value-based heuristic, where cheaper options are preferred for strangers.

However, although benefiting less than the self and beloved ones, strangers still received treatments that were systematically more costly than the cheapest option: in Survey 1, costly choices were ~48%, whereas in Survey 2 participants allocated reliable amount of money although they could give nothing. This could be explained in terms of pro-social (altruistic) decisions in service of strangers, replicating previous findings from behavioral economics [34,75]. Alternatively, it could be argued that these donations are the result of a so-called *experimenter effect*, according to which participants are concerned about exhibiting selfish behavior towards the experimenters [76]. Indeed, the experimenter effect was observed in tasks such as the dictator game, by showing how full anonymity between the participant and the experimenters decreased systematically the amount of free donations [76]. As also our study guarantees full anonymity, we believe that the risk of such confounds are negligible. Furthermore, participants' WTP in survey 2 was positively influenced by confinement-related financial loss (while controlling for personal wealth). This hints towards a genuine altruistic, societal due held by respondents to provide for others' health, including strangers. These results are in line with previous environmental research measuring willingness-to-pay for options that benefit members of a future generation. Even in those scenarios, where delay-discounting can dampen pro-social motivations, people exhibit a positive attitude towards others' wellbeing [77].

It is unclear why the present study did not document any self-other differences except those associated with cost considerations, whereas previous

research and meta-analyses found positive effects at the level of risk attitudes [41,58]. One possibility is that treatment decisions in the context of a pandemic differ drastically with respect to behavior from previous research, including those testing medical or pain management decisions. However, it should be mentioned that, although previous meta-analyses converge in describing overall tendencies, they are also characterized by an extreme variability between studies, pointing to a wide range of moderators that influence participants choices [41,58]. Among these there are the framing of the context, involving positive vs. negative outcomes, or financial vs. safety & medical decisions. Furthermore, there is the presence of reciprocity (where the target of the decision can, in turn, decide for the agent). Finally, and most critically there is the identity of the target (adult, child, patient), including his/her personal relationship with the deciding agent (family member, colleague, stranger) [41,58]. It is possible that any of these moderating factors (or the combination thereof) might have influenced our results with respect to prior literature.

Choices for the Beloved person are more similar to those for the Self

Finally, both our surveys converge in confirming our third hypothesis, according to which participants choices are influenced by the social proximity with the target. In particular, choices for beloved people were on overall more similar (albeit not identical) to those observed for the self and the unknown other. Indeed, whereas participants choose a cheaper option for the stranger, the cost for treating a romantic partner was either higher (Survey 1) or comparable (Survey 2) to that of the self. This effect is reminiscent of that observed in the literature on pain decisions, whereby individuals' behavior and susceptibility to risk differs strongly between other and beloved, with the latter eliciting responses highly similar to those of the self [55]. Furthermore, social neuroscience literature repeatedly put forward an empathy model, according to which individuals treat the suffering of others like one's own, by triggering those same neural processes that mediate direct pain experience [40,78,79]. This model acknowledges a strong role played by social proximity, with less pronounced empathic responses for those people deemed distant from the self [80–82].

Although more similar to one another, the responses associated with self and beloved conditions were not identical. In particular, Survey 1 highlights that choices

for the beloved differed in several aspects from the self-condition: they were more risk averse; less influenced by price and more by *EDS* (or p_D , depending on the analysis); on overall associated with greater costs. These results further highlight the effect of social proximity which shifts one's behaviour toward other people from disease-oriented (for close others) to price-oriented (for strangers; see Figure 2b). Unfortunately, these effects were not observed in Survey 2, despite power analysis established that the sample collected was adequate to reproducing *Target* differences from Survey 1. It is possible that these effects could manifest themselves only in complex settings where price and *EDS* were integrated together. However, it should also be mentioned that the power analysis tested effects of *Target* as a whole: i.e., across all the three levels. It is therefore possible that the results were influenced by the strong modulations of the other, whereas a more sensitive cohort would have been necessary to replicate more subtle self vs. beloved differences.

Concluding remarks

The recent pandemic imposed the burden of costly decision making for people's health on lay people. Most of the restrictive measures implemented in many countries had negative economical, but also psychological consequences on the people involved [2–6]. Most worryingly, these restrictions impacted negatively also sensitivity to others' suffering, and empathy traits [18,19], thus raising the question about the costs that lay individuals would be ready to incur to prevent strangers from getting sick under uncertainty. Furthermore, as global society faces looming events such as climate change [83] or migration [84] that demand individual participation for their mitigation, it is crucial to gain an understanding of factors influencing other-regarding decision-making under uncertainty. While the hypothetical scenarios presented were fictional, they were captured during a real pandemic when most individuals were forced to consider such decisions [13]. Overall, our findings provide a descriptive model of individual risky decision-making for others; and inform on the limits of what can be asked of an individual in service to a stranger. As respondents showed a readiness to incur cost for the sake of strangers, authorities can assume a general goodwill and willingness to help others (albeit reliably lower to that observed for the self and beloved people), underscoring our tendency towards pro-sociality.

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Tables

Table 1

Disease Items and Treatment Options

	Disease	Prognosis (S_D)	Contraction Risk (p_D)	Sure Prognosis	Option	Gamble Success
Survey 1	C	Death	5%	Minor, lingering cardiac deficits and slight, but permanent hearing impairment		75%
	D	Death	25%	Minor, lingering respiratory deficits and slight, but permanent visual impairment		75%
	E	Death	5%	Minor, lingering respiratory deficits and slight, but permanent visual impairment		50%
	F	Minor but lasting cardiac deficits, and a slight but permanent hearing impairment	25%	Slight but permanent hearing impairment		50%
	M	Minor but lasting respiratory deficits and a slight but permanent visual impairment	10%	Slight but permanent visual impairment		75%
Survey 2	C	Death	5%	Minor, lingering cardiac deficits and slight, but permanent hearing impairment		75%
	D	Death	25%	Minor, lingering respiratory deficits		75%

				and slight, but permanent visual impairment
P	Minor but lasting 50% cardiac deficits and a slight but permanent hearing impairment			Slight but 50% permanent hearing impairment
M	Minor but lasting 10% respiratory deficits and a slight but permanent visual impairment			Slight but 75% permanent visual impairment

Table 2

Surveys 1 and 2 cohort details. Continuous variables are described in terms of median and inter-quartile range (iqr). Group differences are estimated in terms of χ^2 test (for proportions) or independent sample t-test (for continuous variables). Significant effects are highlighted in bold, with *** corresponding to $p < 0.001$.

	SURVEY 1	SURVEY 2	COMPARISON
GENDER	43% Females	64% Females	$\chi^2 = \mathbf{20.45^{***}}$
PARTICIPANT'S AGE	25 (iqr = 10)	26(iqr =10)	t = -1.29
BELOVED'S AGE	30 (iqr = 29)	32 (iqr = 28)	t = -0.49
# COUNTRIES REPRESENTED	42	44	$\chi^2 = 0.06$
MONTHLY INCOME	\$2499 (iqr = \$3250)	\$3499 (iqr = \$6500)	t = -4.25***
PANDEMIC-RELATED MONETARY LOSS	\$200 (iqr= \$1000)	\$3.5 (iqr= \$2000)	t = 0.99
PERCEIVED ADEQUACY OF CONFINEMENT MEASURES (MOST FREQUENT RESPONSE)	Adequate (69.60%)	Adequate (63.75%)	$\chi^2 = 1.67$
JOB-LOSS DUE TO COVID-19	27	16	$\chi^2 = 0.44$
POSITIVE COVID-19 TO	4	2	$\chi^2 = 0$

Table 3

Results of Survey 1. For each model, each fixed factor is described in terms of β coefficient and a statistical test (Z for binomial models, t for linear models) testing potential deviations from 0. Significant effects are highlighted in bold, with *** corresponding to $p < 0.001$, ** to $p < 0.01$, and * to $p < 0.05$

<i>Predictor</i>	<i>Model 1a</i> (<i>Act. vs. Inact.</i>)		<i>Model 1b</i> (<i>Gamble vs. Sure</i>)		<i>Model 1c</i> (<i>Treatment Cost</i>)	
	β	Z	β	Z	β	t
Intercept	9.07	10.30***	0.38	2.59**	0.26	-33.61***
EDS	12.97	6.94***	-2.29	-12.44***	0.13	14.83***
Price	-0.73	-2.35*	0.32	2.31*	--	--
Target <i>Beloved</i>	-0.89	-0.80	-0.71	-8.23***	0.06	10.52***
Target <i>Other</i>	-8.94	-9.99***	1.64	9.16***	-0.15	-19.98***
EDS*Price	-2.06	-3.13**	0.25	0.75	--	--
EDS*Target <i>Beloved</i>	-3.90	-1.61	-0.22	-1.16	~0	-0.07
EDS*Target <i>Other</i>	-10.50	-5.63***	1.43	5.53***	-0.09	-7.60***
Price*Target <i>Beloved</i>	1.07	2.34*	-0.84	-4.06***	--	--
Price*Target <i>Other</i>	0.39	1.16	1.69	4.54***	--	--
EDS*Price*Target <i>Bel.</i>	3.21	3.15**	-1.47	-2.84***	--	--
EDS*Price*Target <i>Oth.</i>	1.58	2.19*	1.04	1.63	--	--

Table 4

Results of Survey 2. For each model, each fixed effect is described in terms of β coefficient and a statistical test testing potential deviations from 0. Significant effects are highlighted in bold, with *** corresponding to $p < 0.001$, ** to $p < 0.01$, * to $p < 0.05$ and ^ to $0.05 < p < 0.1$.

<i>Predictor</i>	<i>Model 2a</i> (<i>Gamble vs. Sure</i>)		<i>Model 2b</i> (<i>Willingness to Pay</i>)	
	β	<i>Z</i>	β	<i>t</i>
Intercept	0.71	4.57***	7.99	25.67***
EDS	-1.57	-4.75***	0.40	1.51
Choice	--	--	-0.36	-2.63**
Target <i>Beloved</i>	0.09	0.51	0.11	0.81
Target <i>Other</i>	0.08	0.50	-2.00	-7.40***
EDS*Choice	--	--	0.33	0.91
EDS*Target <i>Beloved</i>	-0.69	-1.48	0.18	0.50
EDS*Target <i>Other</i>	-0.48	-1.11	-0.67	-1.67
Choice*Target <i>Beloved</i>	--	--	0.15	0.85
Choice*Target <i>Other</i>	--	--	0.31	1.52
EDS*Choice*Target <i>Bel.</i>	--	--	-0.27	-0.57
EDS*Choice*Target <i>Oth.</i>	--	--	0.04	0.08

Figure Legends

Figure 1. (A-B) Boxplots describing the percentage of each kind of choice across decision targets. For each boxplot, the horizontal line represents the median value of the distribution, the star represents the average, the box edges refer to the inter-quartile range, and the whiskers to the data range within 1.5 of the inter-quartile range. Individual data-points are also displayed as dots. *(C-D)* Line-graphs describing the relative percentage of Gambles vs. Sure Options across EDS and Target. Each condition is represented by the overall mean with bootstrap-based 95% confidence intervals. The horizontal dashed grey line shows the indifference point.

Figure 2. Results from simplified versions of *(A)* Model 1a and *(B)* Model 1b for *Self* (left), *Beloved* (middle) and *Other* (right) conditions. Significant effects are highlighted as full arrows associated with the corresponding β coefficient from a generalized linear mixed model with binomial distribution. Non-significant effects are displayed as dotted lines.

Figure 3: Treatment Cost and Willingness to Pay. (A) Survey 1: Line-graphs describing the average cost (and bootstrap-based 95% confidence intervals) of the chosen treatment across EDS (horizontal axis) and Target (different color-coded lines). Costs are described as proportions of participants' monthly salary. *(B)* Survey 2: Line-graphs describing the average willingness to pay of the chosen treatment described as log-transformed USD units. *(C)* Survey 2: Boxplots describing the willingness to pay across Target and previous choice. Values (in log-transformed USD) are displayed in different colors (to discriminate Targets) and luminance (to discriminate Choice).

Figures

Figure 1

Figure 2

A Model 1a

B Model 1b

Figure 3

Supplementary Results

Supplementary Table 1

Details of each linear model implemented in the Study.

Model	Dependent Variable	Distribution	Main Predictors	Random Structure [†]
1a	Choice (<i>Costly Action</i> vs. <i>Inaction</i>)	Binomial	EDS*Target*Price	(EDS*Target+Price Subjects)
1b	Choice (<i>Gamble</i> vs. <i>Sure option</i>)	Binomial	EDS*Target*Price	(EDS*Target*Price Subjects)
1c	Treat. Cost (<i>Chosen Price</i>)	Linear	EDS*Target	(EDS*Target Subjects)
2a	Choice (<i>Gamble</i> vs. <i>Sure option</i>)	Binomial	EDS*Target	(EDS*Target Subjects)
2b	Willingness to Pay (WTP)	Linear	EDS*Target*Choice	(EDS*Target + EDS*Choice Subjects)

[†]Among the converging models, we privileged those with the most complex random structure

Supplementary Table 2

Follow-up analysis of Survey 1: control for nuisance variables. Results from the same models described in Table 7 with the inclusion of four nuisance variables.

<i>Predictor</i>	<i>Model 1a</i> (<i>Act. vs. Inact.</i>)		<i>Model 1b</i> (<i>Gamble vs. Sure</i>)		<i>Model 1c</i> (<i>Treatment Cost</i>)	
	β	<i>Z</i>	β	<i>Z</i>	β	<i>t</i>
Intercept	5.66	12.30***	0.82	3.86**	0.23	-21.46***
EDS	5.33	11.60***	-2.09	-13.56***	0.14	13.65***
Price	-1.08	-3.08**	0.24	1.76	--	--
Target <i>Beloved</i>	0.60	1.36	-0.66	-7.59***	0.05	8.81***
Target <i>Other</i>	-5.82	-13.83***	1.35	7.91***	-0.16	-17.58***
EDS*Price	-2.57	-3.43***	0.18	0.63	--	--
EDS*Target <i>Beloved</i>	0.25	0.44	-0.13	-0.87	0.01	0.57
EDS*Target <i>Other</i>	-2.69	-6.39***	1.07	5.59***	-0.09	-7.11***
Price*Target <i>Beloved</i>	1.45	2.87**	-0.45	-2.52*	--	--
Price*Target <i>Other</i>	0.73	1.94	0.82	3.43***	--	--
EDS*Price*Target <i>Bel.</i>	4.46	3.67***	-0.47	-1.20	--	--
EDS*Price*Target <i>Oth.</i>	2.03	2.48*	1.02	2.21*	--	--
Gender	0.29	0.66	-0.60	-2.29*	0.04	3.31**
Age	-0.01	-0.64	-0.02	-1.26	~0	1.17
Monthly Income	0.36	1.25	-0.11	-0.61	0.01	1.69
Covid-19 Loss	0.05	0.94	0.01	0.43	~0	0.41

Supplementary Table 3

Follow-up analysis of Survey 1: alternative approach to *EDS*. For Models 1a, 1b and 1d, *EDS* is replaced by two separate orthogonal predictors: disease probability (p_D) and severity (S_D) as continuous and categorical factors respectively.

<i>Predictor</i>	<i>Model 1a</i> (<i>Act. vs. Inact.</i>)		<i>Model 1b</i> (<i>Gamble vs. Sure</i>)		<i>Model 1d</i> (<i>Treatment Cost</i>)	
	β	Z	β	Z	β	t
Intercept	6.21	13.43^{***}	0.84	6.03^{***}	0.24	27.02^{***}
p_D	0.18	10.62^{***}	-0.08	-10.91^{***}	0.01	11.51^{***}
S_D	-0.80	-3.55^{***}	0.37	3.25^{**}	-0.15	-1.85
Price	-0.41	-1.30	0.23	1.39	--	--
Target <i>Beloved</i>	-0.13	0.28	-0.64	-6.36^{***}	0.05	6.84^{***}
Target <i>Other</i>	-7.02	-14.30^{***}	1.13	6.55^{***}	-0.15	-16.11^{***}
p_D *Price	-0.05	-1.88	0.08	0.32	--	--
S_D *Price	0.37	0.88	0.06	0.22	--	--
p_D *Target <i>Beloved</i>	-0.04	-2.25^{***}	~0	0.19	~0	-0.57
p_D *Target <i>Other</i>	-0.08	-4.60^{***}	0.01	1.11	-0.003	-5.19^{***}
S_D *Target <i>Beloved</i>	0.42	1.56	-0.15	-1.15	~0	0.04
S_D *Target <i>Other</i>	1.24	5.11^{***}	-0.17	-1.00	0.03	2.38[*]
Price*Target <i>Beloved</i>	0.40	0.82	-0.56	-2.46[*]	--	--
Price*Target <i>Other</i>	0.14	0.37	0.73	2.28[*]	--	--
p_D *Price*Target <i>Bel.</i>	0.06	1.55	0.02	0.77	--	--
p_D *Price*Target <i>Oth.</i>	0.01	0.48	~0	-0.06	--	--
S_D *Price*Target <i>Bel.</i>	-0.55	-0.85	0.15	0.45	--	--
S_D *Price*Target <i>Oth.</i>	-0.34	-0.64	-0.07	-0.15	--	--

Supplementary Table 4

Follow-up analysis of Survey 2: control for nuisance variables. Results from the same models described in Table 7 with the inclusion of four nuisance variables.

<i>Predictor</i>	<i>Model 2a</i> (<i>Gamble vs. Sure</i>)		<i>Model 2b</i> (<i>Willingness to Pay</i>)	
	β	<i>Z</i>	β	<i>t</i>
Intercept	0.61	2.84^{***}	8.35	17.81^{***}
EDS	-1.76	-4.09^{***}	0.60	1.73
Choice	--	--	-0.31	-1.70
Target <i>Beloved</i>	-0.03	-0.14	0.19	1.06
Target <i>Other</i>	0.03	0.14	-1.95	-5.32^{***}
EDS*Choice	--	--	0.22	0.43
EDS*Target <i>Beloved</i>	-0.52	-0.88	0.14	0.31
EDS*Target <i>Other</i>	-0.61	-1.11	-0.96	-1.77
Choice*Target <i>Beloved</i>	--	--	0.20	0.86
Choice*Target <i>Other</i>	--	--	0.19	0.72
EDS*Choice*Target <i>Bel.</i>	--	--	-0.02	-0.03
EDS*Choice*Target <i>Oth.</i>	--	--	0.17	0.25
Gender	0.44	1.52	-1.01	-1.56
Age	~0	0.05	-0.01	-0.21
Monthly Income	0.06	0.41	0.63	1.76
Covid-19 Loss	-0.01	-0.16	0.24	3.06^{**}

Supplementary Table 5

Follow-up analysis of Survey 2: alternative approach to *EDS*. Models 2a and 2c, *EDS* is replaced by two separate orthogonal predictors: disease probability (p_D) and severity (S_D) as continuous and categorical factors respectively.

<i>Predictor</i>	<i>Model 2a</i> (<i>Gamble vs. Sure</i>)		<i>Model 2c</i> (<i>Willingness to Pay</i>)	
	β	<i>Z</i>	β	<i>t</i>
Intercept	0.57	3.02**	7.88	24.15***
p_D	-0.03	-4.14***	0.01	1.51
S_D	0.38	1.49	0.27	1.24
Choice	--	--	-0.23	-1.21
Target <i>Beloved</i>	-0.24	-1.08	0.09	0.47
Target <i>Other</i>	-0.01	-0.06	-1.99	-6.50***
p_D *Choice	--	--	~0	0.89
S_D *Choice	--	--	0.26	-0.94
p_D *Target <i>Beloved</i>	~0	-0.95	~0	0.44
p_D *Target <i>Other</i>	~0	-0.86	-0.10	-1.17
S_D *Target <i>Beloved</i>	0.47	1.43	0.08	0.28
S_D *Target <i>Other</i>	0.16	0.51	-0.02	-0.08
Choice*Target <i>Beloved</i>	--	--	0.11	0.42
Choice*Target <i>Other</i>	--	--	0.12	0.44
p_D *Choice*Target <i>Bel.</i>	--	--	~0	-0.39
p_D *Choice*Target <i>Oth.</i>	--	--	~0	-0.16
S_D *Choice*Target <i>Bel.</i>	--	--	0.03	0.08
S_D *Choice*Target <i>Oth.</i>	--	--	~0	0.08

Supplementary Figure S1

Survey 2: Scatter Plot with linear regression lines (and 95% confidence interval area) describing the relationship between Willingness to Pay against Covid-19 Financial Loss (both in log-transformed USD units). The Spearman's correlation coefficient are also displayed with significance highlighted as follows: “***” $p < 0.001$.