How do citizens weigh societal impacts of a pandemic when it transitions into an endemic? The results of a discrete choice experiment in the Netherlands

Authors: Niek Mouter, Tom Geijsen, Aylin Munyasya, Jose Ignacio Hernandez, Ellen Uiters, Marijn Stok, Marijn de Bruin

Abstract

Objectives: This is the first study which empirically investigates how citizens weigh key societal impacts of pandemic policies when the COVID-19 pandemic transitions into an endemic.

Methods: We performed a discrete choice experiment among 2,181 Dutch adults which included six attributes: COVID-19 deaths, physical health problems, mental health problems, financial problems, delay of surgeries and degree to which individual liberties are restricted.

Results: From the observed choices, we were able to infer the trade-offs made by Dutch citizens between societal impacts of pandemic policies. We find that participants are willing to accept 1 COVID-19 death to avoid 36 – 110 citizens with physical complaints longer than 3 months, 62 - 153 citizens with mental health issues longer than 3 months or 50 - 79 citizens who have difficulty making ends meet. The average respondent has a strong negative preference for closing restaurants and bars, but is indifferent concerning less restrictive measures such as an obligation to wear mouth masks. When participants are provided with information about the stringency of COVID-19 measures, they assign relatively less value to preventing COVID-19 deaths and surgeries and relatively more value to preventing physical and mental problems.

Discussion: After having gone through a 3-year pandemic, Dutch citizens clearly prefer that pandemic policies consider citizens' financial situation, physical problems, mental health problems, and individual liberties alongside effects on excess mortality and pressure on healthcare. The current study provides an empirical basis for appraisal models including these attributes and policy makers facing such complex decisions.

1. Introduction

The outbreak of COVID-19 early 2020 was followed by an unprecedented package of measures to protect public health and prevent overburdening the health care system. These measures also had considerable impacts on economic, social and cultural life. The policy decision-making process regarding which COVID-19 measures to implement required trade-offs about their presumed effects on COVID-19 morbidity and mortality, and societal impacts such as poverty and mental health issues – many of which may not have been evident to policy makers at the start of the pandemic.

Aligning decisions on COVID-19 measures with the preferences of citizens can increase public support and adherence (Betsch, 2020; Mühlbacher et al., 2022). Hence, during the pandemic preference elicitation studies such as discrete choice experiments (DCEs) were conducted, in which citizens were asked to choose between policy scenarios specified in terms of societal impacts (Haghani et al., 2022). Unlike regular surveys, DCEs provide information on the relative weights citizens attach to different impacts of measures (Reed et al., 2020). Such quantification of the public's acceptance of these trade-offs could provide information to government and public health officials (Reed et al., 2020). For instance, it can provide quantitative evidence regarding how much decline in mental and financial health people are willing to accept in order to avoid a given number of COVID-19 hospitalisations and deaths; and identify subgroups in society with distinctive preferences and characteristics (Reed et al., 2020).

The literature shows that the stage of the pandemic significantly affects people's preferences for (the societal impacts of) COVID-19 policies (e.g. Loría-Rebolledo et al., 2022; Mouter et al., 2022; Ozedemir et al., 2021). In the first wave, three DCEs investigated how citizens trade-off societal impacts of COVID-19 policies (Chorus et al., 2020; Krauth et al., 2021; Reed et al., 2020). People's willingness to make individual/societal financial sacrifices in favour of saving lives, as a dominant preference, was a repeated observation in these studies. In the study of Reed et al. (2020) most respondents were reluctant to accept increases in COVID-19 risks and only 13% of the respondents strongly preferred reopening nonessential businesses in the short run. A DCE conducted in Germany in the first wave (Krauth et al., 2021) established that citizens found avoiding a mandatory tracing device and a provision of sufficient ICU capacities equally important. These two attributes dominated all other attributes included in their study. Krauth et al. (2021) conclude that for respondents the health outcome was more important than the economic outcome. Respondents would rather accept a 20% unemployment rate for the next two years than an overload of ICU capacities at times.

The DCEs regarding the trade-offs of societal impacts that were carried out in the second wave of the pandemic revealed that citizens wanted their government to strongly focus in their policies on other societal impacts than the prevention of COVID-19 deaths. For instance, Mühlbacher et al. (2022) show that economic effects of COVID-19 measures such as individual income decreases had a large impact on preferences of German citizens for and against lockdown scenarios. Prevention of excess mortality and decrease in GDP were also important factors influencing citizens' preferences.

The analysis showed that consequences of pandemic measures, such as excess mortality, risk of infection, decrease in income, and decrease in GDP had the most significant impact on respondents' choice decisions. Mühlbacher et al. (2022) establish that respondents did not prefer any closures of sectors. At the same time they conclude that curfews, contact restrictions, personal data transmissions, and mandatory masking in public had a lesser impact on people's preferences. The study of Sicsic et al. (2022) shows that a targeted lockdown for sectors with high COVID-19 incidence, medically prescribed self-isolation, and restrictions in nursing homes are likely to be accepted by French citizens when these measures would avoid an overload of intensive care units. Hence, both the study of Mühlbacher et al. (2022) and Sicsic et al. (2022) reveal that in this stage of the pandemic German and French citizens have a high willingness to accept stringent measures if excess mortality can be prevented and to avoid an overload of intensive care units. In contrast, a study conducted in the United Kingdom in this stage of the pandemic (Loría-Rebolledo et al., 2022) concluded that 80% of the respondents were willing to accept an increase in excess deaths for relaxations in lockdown restrictions. The average UK citizen was willing to accept around 14,000 excess death to avoid a very strict (red) lockdown.

Given that preferences are evolving in the course of a pandemic, the literature recommends to closely monitor the dynamics of trade-offs between societal impacts of pandemic policies (Chorus et al., 2020; Loría-Rebolledo et al., 2022). We contribute to the DCEs conducted in early stages in the pandemic by conducting a DCE in which we investigate how citizens weigh societal impacts of pandemic policies in November 2022 - a period in time in which the COVID-19 pandemic was in a transition phase (from pandemic to endemic). At this timepoint many citizens had experienced or observed a wide range of societal impacts of COVID-19 prevention measures. Therefore this DCE could be an anchor point to inform policy making in the endemic phase of pandemics in general and the COVID-19 pandemic in particular. The primary aim of this study is to determine how citizens weigh the different societal impacts of pandemic policies in the transition phase of the COVID-19 pandemic.

Methods

Setup of the experiment

In a DCE respondents are asked to make a series of choices between two or more policy options specified by a number of dimensions (called: 'attributes') that differ in their settings (called: 'levels') between the options. By observing a large number of choices, researchers can infer how attributes and levels implicitly determine the value of the competing options for respondents (De Bekker-Grob et al., 2012; Lancsar and Louviere, 2008). This information can then be used to learn about the relative importance individuals attach to various policies and their impacts, and predict levels of support for specific policies (Salloum et al., 2017).

For selecting the attributes we used the Chorus et al. (2020) study that was also conducted in the Netherlands as point of departure. This study included seven attributes (COVID-19 deaths, physical injuries, mental health problems, pressure on the health care system, decline in income, educational disadvantages and a one-time COVID-19 tax). We first discussed the relevance of the seven attributes of the Chorus et al. (2020) with members of the research team. Some of the members of the research team had much experience with advising the government on COVID-19 policies and based on their input the selection of attributes and operationalisation was modified to better align the design of the DCE with the information needs of policy makers. Moreover, two members from the Societal Impact Team (SIT), an official committee which advices the Dutch Cabinet on COVID-19 decision-making provided feedback on our research design. Based on these two iterations three decisions were made. First, it was determined that two attributes of the Chorus et al. (2020) study (i.e., 'educational disadvantages' and 'the one-time COVID-19 tax', see Chorus et al., 2020) were not relevant in this stage of the pandemic and excluded in the design. Second, the operationalisation of some of the attributes was rephrased to better align them with the COVID-19 situation late 2022. For instance, because 'the extent to which surgeries are delayed' was deemed to be a more relevant operationalization of the pressure to the health care system than 'working pressure experienced by health care workers' in the Chorus et al. (2020) study we decided the use the former operationalization. Third, members of the SIT advised us to include 'stringency of COVID-19 measures' as a sixth attribute in our DCE as they wanted to know more about the trade-offs citizens make between the impacts of the COVID-19 measures on the daily lives of citizens and societal impacts such as mental health problems and the prevention of COVID-19 deaths. We decided to provide half of our sample with a DCE in which this attribute was included and half of our sample a DCE in which this attribute was excluded. The main reason to exclude this DCE for half of our sample was the strong correlation between the stringency of COVID-19 measures and the other attributes. That is, the we were worried that realism of the DCE would be impaired if we would present choice tasks to respondents in which one option would be characterized by a higher stringency of COVID-19 measures and a lower number of citizens with mental health issues. Choosing for this split-sample design also allows us to investigate the extent to which citizens' trade-offs between societal impacts are affected by providing information about the stringency of the measures from which these impacts accrue. From now on we refer to the DCE with five attributes as 'DCE 1' and the DCE which includes the sixth attribute as 'DCE 2'.

The attribute levels were selected through a desk research and expert consultation (see Appendix A). Next, we tested in a pilot survey whether the levels that we constructed were relevant enough to participants. Based on the results of the pilot survey we decided to increase the difference between the levels of 'mental health issues' as this attribute was insignificant in the pilot studies and decreased the difference between the levels of 'to which extent should surgeries be delayed?' as several respondents in the pilot study non-traded on this attribute.

Table 1: Overview of the attributes and their levels as included in the discrete choice experiment.

	Level 1	**Level 2**	**Level 3**	**Level 4**	**Level 5**
Additional deaths in 2023 due to the COVID-19 pandemic	4,000	5,500	7,000	8,500	10,000
Additional number of citizens with physical complaints longer than 3	150,000	250,000	350,000	450,000	550,000

months in 2023 due to the COVID-19 pandemic					
Additional number of citizens with mental health issues longer than 3 months in 2023 due to the COVID-19 pandemic	150,000	300,000	450,000	600,000	750,000
Additional number of citizens who have difficulty making ends meet in 2023 due the COVID-19 pandemic	0	150,000	300,000	450,000	600,000
Will surgeries have to be postponed in 2023 because there are many COVID-19 patients in hospital?	There is no need to postpone surgeries	Hospitals have to postpone some surgeries for about 1 month. This happens only for surgeries that are not so urgent, such as knee surgeries and cataract surgeries.	Hospitals have to postpone some surgeries for about 3 month. This happens only for surgeries that are not so urgent, such as knee surgeries and cataract surgeries.	Hospitals have to postpone some surgeries for about 5 month. This happens only for surgeries that are not so urgent, such as knee surgeries and cataract surgeries.	Hospitals postpone surgeries that are not as urgent (such as knee surgery and cataract surgery) by about 5 months. Some surgeries that are urgent but not life-threatening, such as some heart surgeries, are also postponed by about 1 month.
Are there any COVID-19 measures taken that will affect the daily lives of citizens in 2023? **(only in DCE 2)**	There are no measures that affect our daily lives	The measures have minor effects on our daily lives. For example, compulsory wearing a mouth mask in the supermarket and Public Transport	The measures affect our daily lives. For example compulsory wearing a mouth mask. And taking a COVID-19 test to go to concerts and sports events	The measures have big implications for our daily lives. For example, fewer people are allowed in a restaurant or café	The measures have very big impacts on our daily lives. Nightclubs, restaurants and cafes have to close, for example

Figure 1 provides a screenshot of one of the choice tasks.

Figure 1: Example of a choice task of DCE 2

	Approach 1	Approach 2
Additional number of people dying in 2023	7.000	4.000
Additional number of people that suffers from physical health issues for longer than 3 months in 2023	350.000	350.000
Additional number of people that suffers from mental health issues for longer than 3 months in 2023	150.000	750.000
Additional number of people who don't have enough money to live on in 2023	150.000	450.000
Do hospitals have to postpone surgeries in 2023?	Hospitals have to postpone some surgeries for about 3 month. This happens only if surgeries aren't urgent, for instance, with knee surgeries and cataract surgeries.	Hospitals have to postpone some surgeries for about 3 month. This happens only if surgeries aren't urgent, for instance, with knee surgeries and cataract surgeries.
Does the government take measures in 2023 that have consequences for our daily lives?	The measures have small consequences for our daily lives. For instance, wearing a face mask in the supermarket and in public transport.	The measures have consequences for our daily lives. For instance, wearing a face mask and needing a corona test before being allowed to go a concert or an athletic competition.
	Choose this approach	Choose this approach

An important criterion for avoiding hypothetical bias in a preference elicitation study is that 'consequentiality' is ensured which entails that respondents must feel that their choices might potentially have consequences in real life (e.g. Carson and Groves, 2007). We secured consequentiality, by (truthfully) informing respondents that the outcomes of this study would be shared with policy makers at relevant Ministries.

Experimental design

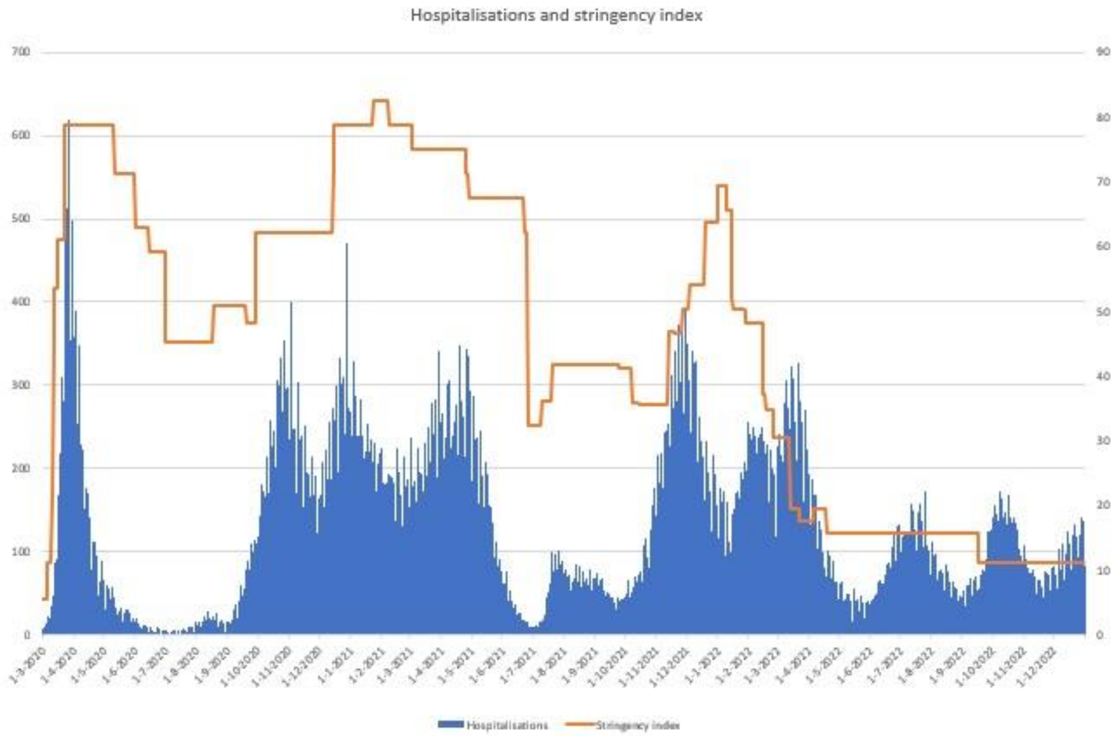
The attributes and levels presented in Table 1 were used to construct 20 binary choice situations for each DCE. These choice situations were constructed with a D-efficient experimental design, following standard practices for discrete choice experiments in healthcare (Johnson et al., 2013). In a D-efficient design, the attribute levels of each choice situation are chosen such that the variance of the estimates of a choice model is minimised. A D-efficient design aims to find the set of choice situations that minimises the D-error, which is the determinant of the variance-covariance matrix of a specific choice model (e.g., a multinomial logit (MNL) model), given a fixed number of choice situations and so-called prior parameters defined by the analyst. By doing so, D-efficient designs aim to maximise the statistical efficiency of the final model and minimise the required sample sizes during the data collection process.

The D-efficient design of our experiment was conducted in two stages. In the first stage, we constructed 20 choice situations for each DCE to be used in the pilot survey using small prior values for each attribute, whose signs were fixed based on previous studies on COVID-19 preferences. The D-efficient design aimed to minimise the D-error of a MNL model with linear utility functions. In addition, we restricted the experimental design to rule out dominant and dominated alternatives in a choice situation since such alternatives may provide no relevant information about respondents' trade-offs for attributes, jeopardising the statistical efficiency of the final model. In the second stage, we used the responses to the pilot survey to estimate a MNL model, and we used the resulting estimates as priors to construct the final set of 20 choice situations for each DCE with the attribute levels presented in Table 1 and keeping the same restrictions to avoid dominant or dominated alternatives. All experimental designs were constructed using Ngene, a software to construct experimental designs for discrete choice experiments.

Data Collection

The participants in the DCE were sampled from an internet panel of Dynata between November 24 and December 12, with a view to be representative for the Dutch adult population with regard to age, gender and education. We also asked Dynata to ensure that we have at least 30 respondents in all combinations of gender (2 groups), age (3 groups) and education (3 groups). The Human Research Ethics Committee of TU Delft approved our study protocol (Nr. 2583). The full list of questions can be found in the supplementary material. At the time that we conducted our study, around 15 citizens were hospitalised per day and no COVID-19 measures were in place except for the advice to take a self-test in case of having COVID-19 symptoms, to isolate in case of a COVID-19 infection, and obtain a booster vaccination.

Figure 1: The 'DCE situation' indicates the context of the COVID-19 pandemic in which our study took place. The stringency index indicates the strictness of COVID-19 measures.



To gain insight into preference heterogeneity regarding (impacts of) the COVID-19 measures, we amongst other things collected information about socio-demographic characteristics (e.g., age, sex, education), intention to take the COVID-19 vaccine and perceived risk of being hospitalized or dying after infection with COVID-19.

Statistical analysis

The statistical analyses of this paper were conducted using two discrete choice models, namely a MNL model, and a latent class (LC) choice model. We also estimated Mixed Logit Models, but as these models did not provide substantial additional insights we decided to report them in Appendix B. The MNL model is based on the notion that decision-makers aim to maximise their utility when faced with a set of discrete alternatives. The utility of each alternative is modelled as a linear-in-parameters function that depends on the attributes and a set of associated parameters that account for the preferences for increases of such attributes. Formally, for a given decision-maker n, the utility of choosing alternative j is given by:

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \alpha_j + \beta' X_{nj} + \varepsilon_{nj},$$

where X_{nj} is the vector of attributes of alternative j, α_j is an alternative-specific constant included when a labelled DCE is analysed, β is a vector of taste parameters that account for the positive (negative) preferences for increases on each attribute, and ε_{nj} is a stochastic error term with Extreme Value (Gumbel) distribution that accounts for unobserved factors and measurement errors. Following Train (2009), in the MNL model, the probability of choosing alternative i by decision-maker n is given by:

$$p_{ni,MNL} = P(U_{ni} \geq U_{nk}, \forall i \neq k) = \frac{\exp(V_{ni})}{\sum_j \exp(V_{nj})}$$

The MNL model is estimated using maximum likelihood estimation (MLE). Given a sample of decision-makers N, the log-likelihood function of the MNL model is given by:

$$LL(\beta) = \sum_n \sum_j y_{nj} \cdot \ln(p_{nj})$$

The second model is a latent class (LC) choice model. The LC model extends the MNL model by allowing (discrete) heterogeneity of preferences across decision-makers. This heterogeneity is modelled by estimating a mixture of MNL models with separate preference parameters. By doing so, the analyst identifies different population groups that vary in terms of their preferences for attribute increases and their size. Formally, for a given number of classes C defined by the analyst, the choice probabilities of the LC model are defined by:

$$p_{ni,LC}(\beta) = \sum_c \pi_{nc} \cdot p_{ni,MNL}(\beta_c),$$

Where π_{nc} is the probability of belonging to class c by decision-maker n, with $\sum_c \pi_{nc} = 1$, and β_c is a vector of estimated parameters specific to class c. The class probability of decision-maker n for a given class i is given by:

$$\pi_{ni} = \frac{\exp(\delta_i)}{\sum_c \exp(\delta_c)}$$

As the reader may notice, the choice probabilities of a LC choice model are a weighted sum of separate MNL choice probabilities per latent class. Each class is interpreted as a population segment characterised by their own set of preference parameters β_c.

To find the optimal number of classes, subsequent models were estimated with 1 to 6 latent classes. Then, we contrasted all models in terms of the Bayesian Information Criterion (BIC):

$$BIC = -2 \cdot LL + \ln(N) \cdot k,$$

Where LL is the log-likelihood of the model at the optimum and k is the number of estimated parameters of the LC model. The BIC weighs both model fit and parsimony of the model (i.e. the number of estimated parameters). The optimal number of latent classes is identified through the estimated LC model with the lowest BIC. Nevertheless, a model with slightly higher BIC but a lower number of latent classes can be chosen if the analyst can provide a more meaningful interpretation of results from such model.

We also added the adjusted ρ^2 measures for the various models as an additional goodness-of-fit statistic, besides the BIC. The adjusted ρ^2 is calculated as follows:

$$\bar{\rho}^2 = 1 - \frac{LL(\hat{\theta}) - k}{LL(0)}$$

Where $LL(\hat{\theta})$ is the log-likelihood of the estimated model, $LL(0)$ is the log-likelihood of the nul-model and k is the number of estimated parameters. The adjusted ρ^2 gives a value between 0 and 1. The closer this value is to 1, the better the model fit.

The BIC index indicates that the 3 class and the 4 class models are optimal for respectively DCE 1 and DCE 2. However, as the BIC index of the 3 class and the 4 class model for DCE 2 are almost equal and the 3 class model performs better in terms of interpretability, we decided to report the 3 class model for both DCEs.

Table 2 Performance of the Latent Class models

DCE 1				
Number of classes	LL	BIC	Adjusted R^2	Number of parameters
1-Class	-4074	8192	0.0833	5
2-Class	-3984	8072	0.1021	12
3-Class	-3899	7956	0.1197	18
4-Class	-3885	7980	0.1215	24
5-Class	-3868	7998	0.1241	30
6-Class	-3861	8037	0.1243	36

DCE 2				
Number of classes	LL	BIC	Adjusted R^2	Number of parameters
1-Class	-3584	7220	0.0633	6
2-Class	-3433	6987	0.1007	14
3-Class	-3393	6967	0.1094	21
4-Class	-3362	6966	0.1155	28
5-Class	-3343	6987	0.1187	35
6-Class	-3335	7032	0.1189	42

3. Results

3.1 Data collection

A total of 2,187 participants completed the study (81.5% of the respondents who started completed the study). Furthermore, we excluded 11 respondents from the final dataset because they filled out the survey too quickly, i.e. in less than a third of the median time to complete the survey for the entire sample (so-called respondent speeding) and provided the same answer to each choice question (so-called respondent straightlining). As a result, we based our analyses on survey results from 1,070 respondents of DCE 1 and 1,106 respondents in DCE 2. All relevant segments of the Dutch population in terms of age, gender and educational level were included in our sample (Table 2 reports the socio-demographic characteristics of our sample).

Table 3: Socio-demographic characteristics of the sample and adult population

	DCE 1	DCE 2	Percentage of the Dutch adult population (CBS, 2020)	Chi-square test (2-sided)
Total	1070	1106		
Gender				
Male	49,1% (523)	48,8% (536)	49,3%	1, p = .75
Female	50,9% (543)	51,2% (562)	50,3%	.22, p = .64
Age				
34 years or younger	29,0% (310)	31,9% (352)	26,7%	3.17, p = .20
35 – 64 years	48,5% (518)	46,9% (517)	49,5%	16.1, p = .00
65 years or older	22,5% (240)	21,1% (233)	23,8%	
Education Level				
Low	20,1% (214)	18,7% (205)	28,5%	
Medium	40,6% (431)	43,5% (477)	36,8%	37.02, p = .0 53.55, p = .0
High	39,3% (418)	37,8% (414)	34,6%	
Vaccination Status				
Vaccinated	84,7% (906)	83,6% (925)	82,3%	4.14, p = .04 1.35, p = .24

3.2 Multinomial logit models

Table 2 shows the estimation results of the MNL model of each DCE. Before estimation, we ensured to scale the attributes associated with deaths, injuries and income issues to avoid numerical overflow and ease of interpretation. All estimates are statistically significant at a 95% confidence level and they have a negative sign, as expected. Therefore, the average participant of both DCEs dislikes additional deaths, increases of physical and mental injuries, and additional households with difficulties to making ends meet (i.e., income issues). In addition, the average participant of DCE 2 dislikes more stringent COVID-19 measures which lead to higher restrictions of individual liberties.

Table 4: Results from the estimation of the MNL model

	DCE 1 (5 attributes)			DCE 2 (6 attributes)		
Estimates	**Estimate**	**Std. Err.**	**T-statistic**	**Estimate**	**Std. Err.**	**T-statistic**
Death (per 1,000)	-0.143	0.010	-14.484	-0.073	0.020	-3.586
Physical problems (per 100,000)	-0.130	0.015	-8.897	-0.201	0.024	-8.384
Mental problems (per 100,000)	-0.093	0.007	-14.144	-0.117	0.009	-12.334
Financial problems (per 100,000)	-0.182	0.009	-20.755	-0.145	0.009	-15.752
Delay surgeries	-0.265	0.018	-14.627	-0.089	0.015	-5.781
Stringency measures	-	-	-	-0.063	0.024	-2.565

Marginal rates of substitution:		
Death/Physical problems	1.103	0.363
Death/Mental problems	1.537	0.625
Death/Income problems	0.788	0.501
Death/Delay surgeries	0.542	0.817
Death/Stringency measures		1.160
Model outputs:		
Number of observations	6,420	5,530
Log-likelihood (null)	-4,450.00	-3,833.10
Log-likelihood (final)	-4,074.20	-3,584.34
AIC	8,158.41	7,180.68
BIC	8,192.24	7,220.39
Rho-squared	0.08	0.06

The estimated parameters are used to compute the marginal rates of substitution (MRS) between additional deaths and the other effects. These MRS provide an estimate of the implied average willingness to accept in the Dutch society to avoid one COVID-19 death. For DCE 1, our estimates suggest that, on average, Dutch citizens are willing to accept one COVID-19 death to avoid:

- 110 additional cases of physical problems;
- 153 additional cases of mental health problems;
- 79 more citizens who have difficulties making ends meet.

Whereas for DCE 2, on average, Dutch citizens are willing to accept one COVID-19 death to avoid:

- 36 additional cases of physical problems;
- 62 additional cases of mental health problems;
- 50 more citizens who have difficulty making ends meet.

In terms of the relative importance of preventing surgery delays, we find that a one-step increase in the delay of surgeries (in terms of disutility to Dutch society) corresponds to 1,846 additional COVID-19 deaths in DCE 1, whereas for DCE 2, we find that the same increase in the delay of surgeries corresponds to 1,219 additional COVID-19 deaths. Additionally, a one-step increase in the stringency of COVID-19 measures corresponds to 863 additional deaths in DCE 2. When comparing the marginal rates of substitution of DCE 1 and DCE 2 presented in Table 4 we can conclude that when participants are provided with information about the stringency of COVID-19 measures, they assign relatively less value to preventing deaths and surgeries and relatively more value to preventing physical and mental problems.

We further explored potential nonlinear effects on people's preferences for avoiding surgery delays and stringency of measures, by estimating the same MNL model, through specifying such attributes as categorical (dummy) variables. Table 5 shows that respondents in DCE 2 particularly assign value to avoiding the highest level of delaying surgeries (hospitals postpone surgeries that are not as urgent by about 5 months and urgent surgeries that are not life-threatening are also postponed by about 1 month) and the highest level of stringency of measures (the measures have very big impacts on our daily lives. Nightclubs, restaurants and cafes have to close, for example). Moreover, respondents did not assign significant value to the other attribute levels of stringency measures. Hence, it can be derived that respondents are willing to accept COVID-19 deaths or other societal effects such as households having difficulty making ends meet to avoid closure of restaurants and cafes, but that they are not willing to make such sacrifices to avoid measures that have a lower impact on people's daily lives such as the obligation to wear mouth masks.

Table 5: Results from the estimation of the MNL model with categorical variables

	DCE 1 (5 attributes)			DCE 2 (6 attributes)		
Estimates	**Estimate**	**Std. Err.**	**T-statistic**	**Estimate**	**Std. Err.**	**T-statistic**
Death (per 1,000)	-0.145	0.010	-14.191	-0.088	0.024	-3.638
Physical problems (per 100,000)	-0.129	0.015	-8.633	-0.181	0.031	-5.780
Mental problems (per 100,000)	-0.095	0.007	-14.248	-0.106	0.014	-7.618
Financial problems (per 100,000)	-0.182	0.009	-19.903	-0.145	0.011	-13.495
Delay surgeries 1	-0.318	0.063	-5.057	-0.138	0.093	-1.476
Delay surgeries 2	-0.470	0.066	-7.156	-0.292	0.095	-3.086
Delay surgeries 3	-0.844	0.069	-12.194	-0.165	0.103	-1.606
Delay surgeries 4	-1.070	0.081	-13.277	-0.428	0.095	-4.487
Stringency measures 1	-	-	-	0.028	0.104	0.266
Stringency measures 2	-	-	-	0.011	0.064	0.167
Stringency measures 3	-	-	-	-0.107	0.098	-1.095
Stringency measures 4	-	-	-	-0.442	0.121	-3.651
Marginal rates of substitution						
Death/Physical injuries	1.124			0.484		
Death/Mental injuries	1.534			0.826		
Death/Income issues	0.797			0.604		
Death/Delay surgeries 1	0.456			0.635		
Death/Delay surgeries 2	0.309			0.300		
Death/Delay surgeries 3	0.172			0.531		
Death/Delay surgeries 4	0.136			0.205		
Death/Stringency measures 1	-			-3.174		
Death/Stringency measures 2	-			-8.264		
Death/Stringency measures 3	-			0.819		
Death/Stringency measures 4	-			0.198		
Model outputs:						
Number of observations	6,420			5,530		
Log-likelihood (null)	-4,450.01			-3,833.10		
Log-likelihood (final)	-4,071.67			-3,576.14		
AIC	8,159.35			7,176.27		
BIC	8,213.49			7,255.69		
Rho-squared	0.09			0.07		

3.3 Latent class analysis

Table 6 summarizes the estimates of the 3-class LC choice model for DCE 1. This model outperforms the MNL model regarding goodness-of-fit and information criteria, i.e., AIC and BIC. We also estimated LC choice models in which we added co-variates for socio-demographic characteristics and answers of respondents to the question of how they experienced the COVID-19 pandemic to characterize the classes. However, these models provided unstable results. For this reason we present the model with the best goodness-of-fit in

Appendix C and in the main text we present LC choice models in which covariates are excluded. Regarding class sizes, the first class represents 29.1% of population, the second class represents 37.1% of the population, and the third class represents the remaining 33.8% of the population. All the attribute-specific estimates of class 2 and 3 are statistically significant at the 95% confidence level and they have a negative sign, which means that, on average, participants of these classes dislike increases of all attributes. For class 1, only the estimates associated with additional delay of surgeries is statistically significant at 95%. Furthermore, we observe that participants of this class prefer a longer delay of surgeries. However, the magnitude of this estimate (0.101) is comparatively smaller than the same parameter at the other two classes in absolute value (-0.543 and -0.265 for class 2 and class 3, respectively), which suggests that the impact of this attribute for participants of class 1, albeit significant, is rather low.

The magnitude of the attribute-specific parameters allows us to characterize each latent class. Class 1 encompasses participants who are rather indifferent to societal impacts of COVID-19 policies. Class 2 (30.3%) is characterized by participants who assign a relatively high value to avoiding financial problems for citizens and delay of surgeries. Class 3 encompasses participants who assign a relatively high value to avoiding financial problems for citizens and avoiding COVID-19 deaths.

Table 6 Results Latent Class analysis DCE 1

	Class 1			**Class 2**			**Class 3**		
Class size	**29.1%**			**37.1%**			**33.8%**		
Estimates	**Est.**	**S.E.**	**T-stat.**	**Est.**	**S.E.**	**T-stat.**	**Est.**	**S.E.**	**T-stat.**
Death (per 1,000)	0.054	0.030	1.790	-0.127	0.031	-4.133	-0.531	0.081	-6.516
Physical problems (per 100,000)	-0.002	0.037	-0.053	-0.279	0.052	-5.384	-0.244	0.058	-4.240
Mental problems (per 100,000)	-0.001	0.021	-0.056	-0.128	0.021	-5.982	-0.279	0.038	-7.342
Financial problems (per 100,000)	-0.049	0.045	-1.074	-0.370	0.046	-8.034	-0.548	0.099	-5.531
Delay surgeries	0.101	0.036	2.774	-0.543	0.060	-9.115	-0.265	0.039	-6.707
Class membership parameters									
Intercept	-0.243	0.232	-1.047	0 (fixed)	-	-	-0.094	0.266	-0.352
Model outputs									
Number of observations	6,330								
Log-likelihood (null)	-4,387.62								
Log-likelihood (final)	-3,837.64								
AIC	7,711.27								
BIC	7,832.83								
Rho-squared	0.13								

The estimation results of the 3-class LC model for DCE 2 are presented in Table 7. We find considerable model fit improvements of this model in terms of log-likelihood values and information criteria, compared with the MNL model. The first class represents 37.9% of population, the second class represents 46.7% and the third class represents the remaining 15.3% of the population. Almost all attribute-specific estimates of class 1 are statistically significant and have a negative sign, except for additional COVID-19 deaths. For class 2, all estimates are statistically significant and have a negative sign, expect citizens with mental problems and the stringency of COVID-19 measures. In class 3, the attribute-specific estimates have mixed signs. On the one hand, the parameters associated with additional deaths, surgery delays and stringency of measures are positive, whereas the parameters associated with physical and mental injuries have a negative sign.

Table 7 Results Latent Class analysis DCE 2

	Class 1			Class 2			Class 3		
Class size	**37.9%**			**46.7%**			**15.3%**		
Estimates	**Est.**	**S.E.**	**T-stat.**	**Est.**	**S.E.**	**T-stat.**	**Est.**	**S.E.**	**T-stat.**
Death (per 1,000)	-0.163	0.095	-1.710	-0.103	0.037	-2.802	0.494	0.203	2.438
Physical problems (per 100,000)	-0.337	0.099	-3.393	-0.087	0.047	-1.863	-2.163	0.956	-2.263
Mental problems (per 100,000)	-0.330	0.049	-6.701	-0.013	0.022	-0.585	-0.463	0.230	-2.015
Financial problems (per 100,000)	-0.255	0.057	-4.499	-0.170	0.030	-5.576	2.429	0.760	3.199
Delay surgeries	-0.518	0.073	-7.060	-0.064	0.021	-2.980	0.171	0.294	0.580
Stringency measures	-0.457	0.140	-3.272	-0.063	0.055	-1.143	3.127	0.910	3.438
Class membership parameters									
Intercept	-0.208	0.205	-1.015	0 (fixed)	-	-	-1.115	0.148	-7.516
Model outputs									
Number of observations	5,435								
Log-likelihood (null)	-3,767.25								
Log-likelihood (final)	-3,328.97								
AIC	6,699.93								
BIC	6,838.55								
Rho-squared	0.12								

As in DCE 1, the attribute-specific parameters allow us to characterize each latent class. Class 1 are participants with a relatively high and negative perception of increases of the impacts of alternatives. Class 2 is characterized by participants with low sensitivity to attribute increases. Class 3 (15.4%) is characterized by participants who assign a negative value to physical problems and mental problems and they do not perceive additional deaths and surgery delays as negative impacts, and they prefer stringency of measures.

Discussion

Our study provides policy makers with a range of insights towards how Dutch citizens weigh various societal impacts of pandemic policies when a pandemic is in a transition phase (from pandemic to endemic). Firstly, our results enable policy makers to determine whether the net valuation in society is positive or negative for particular combinations of societal effects. For example, take the situation in which a certain policy package leads to an expected reduction in deaths, but also to an increase in the number of people who have difficulty making ends meet. Our study, for instance, suggests that if the number of households who have difficulty making ends meet as a result of the policy package is fewer than about 50 per avoided death, the measure is assessed positively by the average Dutch person (see Table 4, DCE 2). However, if the number is higher than 79 per avoided death (see Table 4, DCE 1), the net valuation is negative.

Secondly, our results enable policy makers to identify levels of support and opposition among Dutch citizens for different policy packages. For example, the binary logit model, fed by the estimated parameters, can be used to determine the percentage of Dutch people who support a certain policy package. For this, the effects of the policy package must of course be within the scope of those presented in Table 1.

Thirdly, our study provides various specific empirical insights. An empirical finding of this study is that when participants in a DCE are provided with information on the stringency of COVID-19 measures (DCE 2) they assign relatively less value to preventing deaths and preventing the delay of surgeries and relatively more value on the prevention of physical and mental problems when compared to a choice situation in which no such information is provided (DCE 1). Hence, policy makers should keep in mind that citizens might perceive the importance of various societal impacts differently when they are considered in the context of decisions on specific COVID-19 measures.

Particularly participants in DCE 2 are willing to accept COVID-19 deaths to avoid that citizens experience physical complaints, mental health issues and financial problems. Specifically, we can infer that citizens are willing to accept 1 COVID-19 death to avoid 36 citizens with physical complaints longer than 3 months, 62 citizens with mental health issues longer than 3 months or 50 citizens who have difficulty making ends meet. Contrasting these empirical results with the results of DCEs carried out in earlier stages of the pandemic suggests that the prevention of deaths develops from a key priority according to citizens in the early stage of the pandemic (Chorus et al., 2020; Reed et al., 2020) to an important goal alongside other goals in a later stage of the pandemic (e.g., Mühlbacher et al., 2022; Loría-Rebolledo et al., 2022) and to a low priority goal when a pandemic transitions into an endemic. A more in-depth investigation of the relation between the stage of a pandemic and people's preferences regarding government focus on the prevention of deaths caused by a pandemic may be an important topic for further research.

We also find that the average respondent in our study has a strong negative preference for closing restaurants and bars, but does not assign a significant value to less restrictive measures such as an obligation to wear mouth masks or a restriction to the number of people that are allowed in restaurants and bars. Hence, it can be derived that respondents are willing to accept COVID-19 deaths or other societal effects such as households having difficulty making ends meet to avoid closure of restaurants and cafes, but that they are not willing to make such sacrifices to avoid measures that have a lower impact on people's daily lives such as the obligation to wear mouth masks. This contrast with a study conducted in the second wave of the pandemic (Mühlbacher et al., 2022) who found that people had a significant negative preference for avoiding mandatory masking in public.

Another empirical finding is that in DCE 1 a latent class of respondents was observed that did not assign a significant value to most of the societal impacts included in this study. This suggests that at the stage that a pandemic transforms into an endemic a group of citizens will not seriously consider preference elicitation experiments in which they are asked to trade-off societal impacts of pandemic policies. It is plausible that this class of citizens does not believe that it is likely that these societal impacts will materialize.

Referenties

Betsch C. Behavioural science data can help mitigate the COVID-19 crisis. Nat Hum Behav (2020) 4:438. doi:10.1038/s41562-020-0866-1 10.

Blayac T, Dubois D, Duchêne S, Nguyen-Van P, Ventelou B, Willinger M. Population preferences for inclusive COVID-19 policy responses. Lancet Public Health 2020;6: e9.

Carson, R.T., Groves, T., 2007. Incentive and informational properties of preference questions. Environmental and Resource Economics 37, 181 - 200.

Chorus C, Sandorf ED, Mouter N. Diabolical dilemmas of COVID-19: An empirical study into Dutch society's trade-offs between health impacts and other effects of the lockdown. PLoS One. 2020;15(9):e0238683.

De Bekker-Grob EW, Ryan M, Gerard K. Discrete choice experiments in health economics: A review of the literature. Health Econ 2012;21(2):145–172.

Habersaat K, Betsch C, Danchin M, Sunstein S, Böhm R, Falk A, et al. Ten considerations for effectively managing the COVID-19 transition. Nat Hum Behav (2020) 4:677–87. doi:10.1038/s41562-020-0906-x.

Haghani, M., Bliemer, M.C.J., de Bekker-Grob, E.W. 2022. Applications of discrete choice experiments in COVID-19 research: Disparity in survey qualities between health and transport fields. Journal of Choice Modelling 44. 100371.

Hensher DA, Rose JM, Greene WH. Applied Choice Analysis: A Primer. Cambridge: Cambridge University Press; 2005.

Johnson, F. R., Lancsar, E., Marshall, D., Kilambi, V., Mühlbacher, A., Regier, D. A., ... & Bridges, J. F. (2013). Constructing experimental designs for discrete-choice experiments: report of the ISPOR conjoint analysis experimental design good research practices task force. Value in health, 16(1), 3-13.

Krauth, C., Oedingen, C., Bartling, T., Dreier, M., Spura, A., De Bock, F., Von Rueden, U., Betsch, C., Korn, L., Robra, B.-P.: Public preferences for exit strategies from COVID-19 lockdown in Germany—a discrete choice experiment. Int. J. Public. Health. 66, 591027 (2021). https://doi.org/10.3389/ijph.2021.591027

Mouter, N., Jara, K. T., Hernandez, J. I., Kroesen, M., de Vries, M., Geijsen, T., Kroese, F., Uiters, E. & de Bruin, M. (2022). Stepping into the shoes of the policy maker: Results of a Participatory Value Evaluation for the Dutch long term COVID-19 strategy. Social Science and Medicine. 314, 115430.

Mühlbacher, A.C., Sadler, A., Jorda, Y. 2022. Population preferences for non-pharmaceutical interventions to control the SARS-CoV-2 pandemic: trade-ofs among public health, individual rights, and economics. The European Journal of Health Economics.

Lancsar E, Louviere J. Conducting Discrete Choice Experiments to Inform Healthcare Decision Making. Pharmacoeconomics 2008;26(8):661–677.

Loría-Rebolledo LE, Ryan M, Watson V, et al. Public acceptability of nonpharmaceutical interventions to control a pandemic in the UK: a discrete choice experiment. BMJ Open 2022;12:e054155. doi:10.1136/ bmjopen-2021-054155

Ozdemir S, Tan SNG, Chaudhry I, et al. Public preferences for government response policies on outbreak control. Patient. 2021. https://doi.org/10.1007/s40271-020-00494-9. 2.

Reed, S., Gonzalez, J.M., Johnson, R., 2020. Willingness to Accept Trade-Offs Among COVID-19 Cases, Social-Distancing Restrictions, and Economic Impact: A Nationwide US Study. Value in Health 23 (11), 1438-1443.

Salloum RG, Shenkman EA, Louviere JJ, Chambers, DA. Application of discrete choice experiments to enhance stakeholder engagement as a strategy for advancing implementation: a systematic review. Implement Sci 2017;12:140.

Sicsic J, Blondel S, Chyderiotis S., Langot F, Mueller, J.E. 2022. Preferences for COVID-19 epidemic control measures among French adults: a discrete choice experiment. The European Journal of Health Economics.

Train, K., 2009. Discrete choice methods with simulation. Cambridge University Press, 2nd Edition, New York.

Appendix

Appendix A: Selection of attribute levels

After selecting the attributes, we looked for information to substantiate the levels of the different attributes. We decided that the levels should reflect the differences between 2023 and a situation without COVID-19. To illustrate, the additional deaths in 2023 due to the COVID-19 pandemic reflect the excess mortality due to COVID-19. To ensure that the results of the DCE are applicable to multiple possible scenarios of the 2023 COVID-19 situation and policy packages that could be considered in these scenarios, we chose to select five levels for each attribute, allowing for reasonably large variation. Below, we present for each of the attributes the rationale for the selection of attribute levels.

1) Additional deaths in 2023 due to the COVID-19 pandemic

At the time that we designed our study the excess mortality in 2022 was not yet known, but based on the data of Statistics Netherlands (Research and Statistics Netherlands, 2022), it could be estimated that the excess mortality in 2022 would be around 7,000 citizens. As we did not saw a clear pattern in the CBS data to suggest that excess mortality has been declining rapidly in the period January 2022 – October 2022 we decided to include an excess mortality of 7,000 Dutch citizens per year as the middle attribute (level 3) and to vary the other levels around this.

2) Additional number of citizens with physical complaints for longer than 3 months by 2023, such as extreme fatigue or shortness of breath due to the COVID-19 pandemic

We know from research that about 1 in 8 people who become infected with COVID-19 experience long-term symptoms (Ballering et al., 2022). The RIVM estimated that in 2021 around 5 million citizens were infected with COVID-19 which would result in 625,000 people with long-term symptoms. Because the Omicron strain of the coronavirus in the winter of 2021/2022 caused less severe illness compared to previous variants such as Alfa and Delta, we have chosen to include attribute levels that are lower or a lot lower than the 625,000 people in the DCE.

3) Additional number of citizens who feel gloomy, depressed or anxious for longer than 3 months by 2023 due to the COVID-19 pandemic

Research of Statistics Netherlands (2021) shows that the percentage of Dutch people who are mentally unhealthy increased in 2021. Between 2014 and 2020, the percentage was 12% and in 2021 this increased to 15%. If we assume a 3% increase among the 15 million Dutch citizens aged over 12, we arrive at an increase of 450,000 people who are mentally unhealthy. We decided to take this number as the middle attribute (level 3). Because there is an upward trend in the number of people with mental complaints during the pandemic, it may be that this number goes up in a scenario with new measures (levels 4 and 5), but the number may also decrease sharply in the absence of new measures (levels 1 and 2).

4) Additional number of citizens who have difficulty making ends meet due to the COVID-19 pandemic

In the decade before the COVID-19 pandemic the number of citizens struggling to make ends meet has fluctuated around 1 million residents for years (Bureau for Economic Policy Analysis & Netherlands Institute for Social Research, 2020). Sometimes there is an increase towards the 1.2 million citizens and sometimes there is a drop to 900,000 residents. Early 2022 the Dutch government decided that no support will be provided to businesses in case of a new outbreak of COVID-19 in 2022. As business had always been supported during the first waves of COVID-19 there is high certainty towards the levels of this attribute. Hence, we chose to work with a wide range. Since the difference in the number of people struggling to make ends meet hovers around 300,000 inhabitants in the last decade, we chose to choose 300,000 as level 3 of the attributes. Around this, we took wide bandwidths (600,000 for level 5, at most 2 times the fluctuation in the number of people struggling to make ends meet from the last 10 years and 0 for level 1).

5) Will surgeries have to be postponed in 2023 due to high numbers of corona patients in hospital?

It was indicated within the RIVM that end of October 2022 delayed operations are still not caught up and waiting times remain unabated making it plausible to assume 1 months and 5 months of delay as levels for non-urgent operations. 5 months in a situation where it gets a lot busier in hospitals due to corona. Also we included attribute level 5 in which non-urgent surgeries are delayed with 5 months and urgent surgeries are delayed with 1 month as this resembled the situation of during peaks of the COVID-19 pandemic.

Are there any COVID-19 measures taken that will affect the daily lives of citizens in 2023? (only in DCE 2)

Level 1 concerned a situation without COVID-19 measures. Level 2 a situation with measures that have a minor impact on people's daily lives such as wearing a mouth mask in the supermarket and in public transport. In level 3 additional measures were added such as taking a COVID-19 test to attend concerts and sports event. In level 4 also the number of people allowed in a restaurant or café was restricted and in level 5 nightclubs, restaurants and cafes were closed.

References

Ballering, A.V., Sander K R van Zon, Tim C olde Hartman, Judith G M Rosmalen, (2022). Persistence of somatic symptoms after COVID-19 in the Netherlands: an observational cohort study. The Lancet, DI: https://doi.org/10.1016/S0140-6736(22)01214-4

Bureau for Economic Policy Analysis and Netherlands Institute for Social Research, 2020. Kansrijk armoedebeleid. https://www.scp.nl/publicaties/publicaties/2020/06/18/kansrijk-armoedebeleid

Research of Statistics Netherlands (2021). Ervaren impact corona op mentale gezondheid en leefstijl. https://www.cbs.nl/nl-nl/longread/statistische-trends/2021/ervaren-impact-corona-op-mentale-gezondheid-en-leefstijl?onepage=true

Research of Statistics Netherlands (2022). 3480 mensen overleden aan COVID-19 in eerste kwartaal. https://www.cbs.nl/nl-nl/nieuws/2022/30/3480-mensen-overleden-aan-covid-19-in-eerste-kwartaal

Appendix B: Results of Mixed Logit Model

In addition to MNL and LC choice models, we estimate a mixed logit (MXL) model for each experiment. MXL models are a special class of discrete choice models that incorporate random parameters to account for heterogeneity across respondents. Furthermore, MXL models circumvent the assumption of independence of irrelevant alternatives of conventional MNL models, allowing for more realistic substitution patterns across alternatives. These strengths give mixed logit models a relevant role in explaining individuals' trade-offs for the impacts of COVID-19 measures in a broader way.

MXL models incorporate the notion of random parameters into the RUM model. To do so, the utility of a decision-maker n for alternative j is described as a function of individual-specific parameters:

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \alpha_{nj} + \beta_n' X_{nj} + \varepsilon_{nj},$$

where α_{nj} and β_n are parameters that vary across respondents. However, estimating individual-specific parameters is not computationally feasible, thus the analyst assumes that α_{nj} and β_n are vectors of random parameters with a known distribution, such that:

$$U_{nj}^{MXL} = V_{nj} + \varepsilon_{nj} = \alpha_j^r + \beta^{r\prime} X_{nj} + \varepsilon_{nj},$$

where α^r and β^r are vectors of random parameters. The analyst imposes a specific distribution for the parameters (e.g., normal, log-normal) and estimates the parameters that describe such distribution (e.g., mean, variance). By doing so, the analyst can account for heterogeneity across respondents by reconstructing the random parameters in terms of the estimates of the MXL logit.

For our results of the MXL model, we assumed random parameters for all attributes except for physical injuries, as this attribute was not statistically significant on the MNL model. The random parameters were assumed to distribute log-normal, as the MNL and LC choice models constantly reported that the estimates of such attributes have a negative sign. Furthermore, we found no model fit improvements from estimating an alternative MXL model with normal-distributed random parameters.

Table B1 summarises the estimation results of the mixed logit models. All estimates are statistically significant at the 95% of confidence level. All the estimated means of the random parameters and the fixed parameter for physical injuries have a negative sign, which supports the hypothesis that decision-makers are negative towards increases of the impacts of COVID-19 measures. Furthermore, we found heterogeneity of preferences across respondents, as evidenced by the statistically significant standard deviations of the random parameters (i.e., the SD parameters).

Table B1: Estimation results, mixed logit models

	DCE 1 (5 attributes)			DCE 2 (6 attributes)		
	Estimate	**Std. Err.**	**T-statistic**	**Estimate**	**Std. Err.**	**T-statistic**
Estimates:						
Death (per 1,000)	-2.187	0.157	-13.962	-3.169	0.474	-6.685
SD Death (per 1,000)	1.418	0.170	8.358	2.067	0.340	6.083
Physical injuries (per 100,000)	-0.152	0.018	-8.356	-0.265	0.031	-8.670
Mental Injuries (per 100,000)	-2.346	0.122	-19.225	-2.638	0.235	-11.206
SD Mental Injuries (per 100,000)	0.831	0.139	5.983	1.673	0.269	6.210
Income issues (per 100,000)	-1.694	0.086	-19.766	-2.008	0.131	-15.292
SD Income issues (per 100,000)	0.938	0.093	10.047	1.219	0.144	8.447
Delay surgeries	-1.746	0.170	-10.262	-2.311	0.276	-8.376
SD Delay surgeries	1.215	0.149	8.145	1.079	0.224	4.812
Stringency measures				-5.229	1.127	-4.639
SD Stringency measures				3.675	0.685	5.368
Marginal rates of substitution:						
Death/Physical injuries	14.436			11.964		
Death/Mental injuries	0.932			1.202		
Death/Income issues	1.291			1.579		
Death/Delay surgeries	1.253			1.371		
Death/Stringency measures				0.606		
Model outputs:						
Number of observations	6,420			5,530		
Log-likelihood (null)	-4450.00			-3833.10		
Log-likelihood (final)	-3942.27			-3411.09		
AIC	7902.53			6844.18		
Rho-squared	0.11			0.11		

Appendix C: Results of Latent Class analysis with covariates

Table C1 Results Latent Class analysis DCE 1

	Class 1			Class 2			Class 3		
Class size	37.4%			30.3%			32.4%		
Estimates	**Est.**	**S.E.**	**T-stat.**	**Est.**	**S.E.**	**T-stat.**	**Est.**	**S.E.**	**T-stat.**
Death (per 1,000)	-0.481	0.063	-7.656	-0.123	0.038	-3.273	0.037	0.027	1.372
Physical problems (per 100,000)	-0.261	0.053	-4.898	-0.339	0.072	-4.715	-0.001	0.032	-0.036
Mental problems (per 100,000)	-0.272	0.033	-8.159	-0.140	0.027	-5.182	-0.001	0.017	-0.033
Financial problems (per 100,000)	-0.279	0.035	-7.916	-0.646	0.086	-7.525	0.072	0.031	2.350
Delay surgeries	-0.526	0.087	-6.028	-0.398	0.057	-6.945	-0.053	0.043	-1.241
Class membership parameters									
Intercept	-0.787	0.676	-1.163	0 (fixed)	-	-	0.954	0.674	1.414
Gender	-0.097	0.218	-0.447	0 (fixed)	-	-	-0.105	0.224	-0.468
Education level	0.138	0.155	0.886	0 (fixed)	-	-	-0.065	0.163	-0.400
Age	0.403	0.163	2.479	0 (fixed)	-	-	-0.415	0.173	-2.394
Income Issues	0.000	0.123	0.004	0 (fixed)	-	-	-0.064	0.129	-0.499
Chronic Disease	0.219	0.231	0.951	0 (fixed)	-	-	0.453	0.256	1.768
Roommate with Chronic Disease	-0.266	0.292	-0.910	0 (fixed)	-	-	-0.585	0.303	-1.931
Vaccination	0.098	0.291	0.338	0 (fixed)	-	-	0.298	0.291	1.023
Can't live desired life due to COVID-19	0.041	0.103	0.400	0 (fixed)	-	-	-0.047	0.105	-0.444
Social life deteriorated due to COVID-19	0.113	0.115	0.986	0 (fixed)	-	-	0.307	0.114	2.681
Feeling worse due to COVID-19	-0.021	0.106	-0.196	0 (fixed)	-	-	-0.172	0.109	-1.573
COVID-19 would make me very ill	0.124	0.146	0.849	0 (fixed)	-	-	0.523	0.154	3.405
I would be hospitalised due to COVID-19	-0.207	0.201	-1.033	0 (fixed)	-	-	-0.257	0.209	-1.229
I would die of a COVID-19 infection	0.191	0.185	1.034	0 (fixed)	-	-	-0.313	0.183	-1.711
Model outputs									
Number of observations	6,330								
Log-likelihood (null)	-4,387.62								
Log-likelihood (final)	-3,803.11								
AIC	7,991.36								
BIC	7,694.22								
Rho-squared	0.13								
Model profile (only significant variables)									
Age									
Younger than 35 year	18.8%			29.0%			40.8%		
35 - 64 year	50.9%			47.0%			46.0%		
65 years and older	30.1%			23.9%			12.9%		
Social life deteriorated due to COVID-19									
Totally agree	22.9%			28.0%			13.0%		
Agree	15.7%			16.1%			21.5%		
Neutral	18.4%			18.4%			26.6%		
Disagree	37.3%			31.4%			27.4%		
Totally disagree	5.7%			6.1%			11.4%		
COVID-19 would make me very ill									
Extremely high risk	2.2%			3.6%			2.6%		
High risk	8.4%			9.5%			8.6%		
Average risk	41.2%			42.8%			37.4%		
Low risk	41.2%			37.7%			38.4%		
No risk	7.0%			6.4%			12.9%		

Most class membership parameters are not statistically significant, with the only exceptions of the parameters associated with age in classes 1 and 3, the perception that social life deteriorated due to COVID-19 and that the perception of the respondent that COVID-19 would make him/her very ill in class 3. The model profiles for such covariates suggest that class 1 is associated with middle- and older-aged participants, while class 3 is associated with respondents of younger and middle age, who are neutral-to-disagree that their social life deteriorated due to COVID-19 and have an average-to-low risk perception that the disease would make them very ill.

The estimation results of the 3-class LC model for DCE 2 are presented in Table 7. We find considerable model fit improvements of this model in terms of log-likelihood values and information criteria, compared with the MNL model. The first class represents 46.1% of population, the second class represents 38.6% and the third class represents the remaining 15.4% of the population. Almost all attribute-specific estimates of class 1 are statistically significant and have a negative sign, except for additional mental problems and stringency of measures. For class 2, all estimates are statistically significant and have a negative sign. In class 3, almost all estimates are statistically significant, except for additional households that struggle to make ends meet. In this class, the attribute-specific estimates have mixed signs. On the one hand, the parameters associated with additional deaths, surgery delays and stringency of measures are positive, whereas the parameters associated with physical and mental injuries have a negative sign.

Table C2 Results Latent Class analysis DCE 2

Class size	**46.1%**			**38.6%**			**15.4%**		
Estimates	**Est.**	**S.E.**	**T-stat.**	**Est.**	**S.E.**	**T-stat.**	**Est.**	**S.E.**	**T-stat.**
Death (per 1,000)	-0.082	0.038	-2.162	-0.212	0.097	-2.198	0.374	0.165	2.270
Physical problems (per 100,000)	-0.095	0.046	-2.063	-0.288	0.092	-3.131	-1.713	0.543	-3.157
Mental problems (per 100,000)	-0.016	0.021	-0.729	-0.308	0.044	-7.051	-0.457	0.214	-2.137
Income problems (per 100,000)	-0.072	0.020	-3.571	-0.489	0.069	-7.082	0.229	0.237	0.965
Delay surgeries	-0.168	0.030	-5.542	-0.244	0.053	-4.566	2.048	0.571	3.585
Stringency measures	-0.019	0.055	-0.347	-0.530	0.134	-3.960	2.675	0.794	3.370
Class membership parameters									
Intercept	2.498	0.651	3.835	0 (fixed)	-	-	0.40201	0.7267	0.553
Gender	-0.083	0.200	-0.416	0 (fixed)	-	-	-0.253	0.227	-1.116
Education level	-0.101	0.151	-0.667	0 (fixed)	-	-	0.016	0.164	0.096
Age	-0.625	0.164	-3.802	0 (fixed)	-	-	-0.106	0.173	-0.612
Income Issues	-0.136	0.124	-1.092	0 (fixed)	-	-	-0.143	0.128	-1.118
Chronic Disease	-0.058	0.231	-0.253	0 (fixed)	-	-	0.594	0.266	2.233
Roommate with Chronic Disease	-0.481	0.276	-1.741	0 (fixed)	-	-	-0.278	0.341	-0.818
Vaccination	0.019	0.238	0.079	0 (fixed)	-	-	-0.214	0.292	-0.730
Can't live desired life due to COVID-19	0.121	0.106	1.144	0 (fixed)	-	-	0.165	0.116	1.421
Social life deteriorated due to COVID-19	0.046	0.113	0.412	0 (fixed)	-	-	-0.154	0.132	-1.163
Feeling worse due to COVID-19	-0.100	0.098	-1.012	0 (fixed)	-	-	-0.005	0.120	-0.039
COVID-19 would make me very ill	0.068	0.137	0.492	0 (fixed)	-	-	-0.027	0.164	-0.167
I would be hospitalised due to COVID-19	-0.216	0.185	-1.168	0 (fixed)	-	-	-0.283	0.213	-1.325
I would die of a COVID-19 infection	-0.189	0.172	-1.098	0 (fixed)	-	-	-0.051	0.189	-0.271
Model outputs									
Number of observations	5,530								
Log-likelihood (null)	-3,767.25								
Log-likelihood (final)	-3,303.39								
AIC	7,011.01								
BIC	6,700.78								
Rho-squared	0.12								
Model profile (only significant vars.)									

Age			
Younger than 35 year	40.9%	23.3%	26.1%
35 - 64 year	42.9%	48.6%	51.2%
65 years and older	16.0%	27.7%	22.1%
Chronic Disease			
Yes	34.4%	29.0%	22.8%
No	63.6%	67.5%	71.0%

As in DCE 1, the attribute-specific parameters allow us to characterize each latent class. Class 1 (46.1%) is characterized by participants with low sensitivity to attribute increases. Class 2 (38.6%) are participants with a relatively high and negative perception of increases of the impacts of alternatives. Class 3 (15.4%) is characterized by participants who do not perceive additional deaths and surgery delays as negative impacts, and they prefer stringency of measures. In terms of class membership parameters, only the parameters associated with age in class 1 and with chronic disease in class 3 are statistically significant. The model profiles of these variables suggest that class 1 is associated with participants of younger-to-middle age, while class 3 is associated with respondents without a chronic disease.