The path towards herd immunity: predicting COVID-19 vaccination uptake through results from a stated choice study across six continents
Online supplementary material

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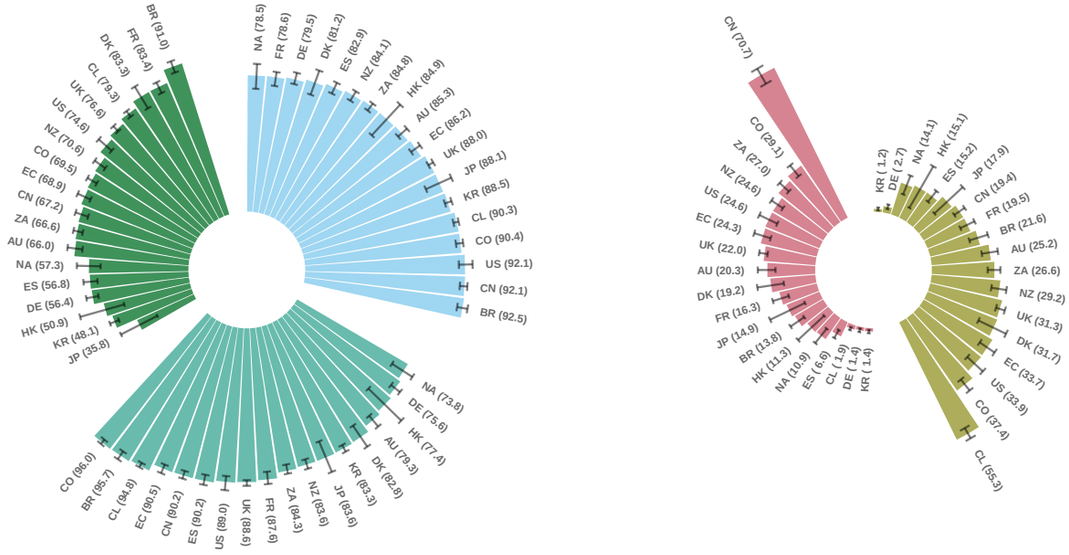
A Supplementary Material

A.1 Initial data analysis

While the core of the analysis was concerned with modelling the choices from the SC component of the survey using discrete choice models, we also analysed reasons for vaccination. Excluding those respondents who were identified as vaccine-resistant individuals (who were not asked this questions), Figure A.1 looks at the reasons for vaccination, where respondents could select multiple options. There are substantial differences across study areas in terms of the share of respondents indicating that they would choose to be vaccinated to protect themselves, their family, or the public. In addition, the results show that a non-negligible share of respondents indicate they would use contact with an infected person or the appearance of symptoms (chosen by a majority in China) as a reason for vaccination, suggesting that further education is needed about the time it takes for vaccines to offer protection (i.e. that vaccinating after exposure or appearance of symptoms is too late).



	units	AU	BR	CL	CN	CO	DE	DK	EC	ES	FR	HK	JP	KR	NA	NZ	UK	US	ZA
To protect myself	%	85.30	92.51	90.35	92.11	90.37	79.55	81.24	86.18	82.87	78.60	84.91	88.06	88.48	78.45	84.10	88.03	92.07	84.81
To protect my family	%	79.30	95.71	94.81	90.22	96.04	75.58	82.84	90.49	90.20	87.58	77.36	83.58	83.29	73.75	83.59	88.57	89.00	84.34
To protect the public	%	65.97	91.02	79.29	67.16	69.50	56.42	83.34	68.89	56.80	83.41	50.94	35.82	48.14	57.29	70.61	76.65	74.56	66.55
	units	**AU**	**BR**	**CL**	**CN**	**CO**	**DE**	**DK**	**EC**	**ES**	**FR**	**HK**	**JP**	**KR**	**NA**	**NZ**	**UK**	**US**	**ZA**
Due to contact with an infected person	%	25.16	21.61	55.33	19.38	37.41	2.69	31.75	33.69	15.18	19.48	15.09	17.91	1.17	14.07	29.21	31.30	33.87	26.57
Due to appearance of symptoms	%	20.29	13.85	1.87	70.68	29.07	1.45	19.16	24.34	6.63	16.26	11.32	14.93	1.38	10.92	24.63	21.99	24.61	27.04

Figure A.1: Reasons for COVID-19 vaccination, multiple answers possible (95% confidence intervals by bootstrapping from data)

A.2 Ordered logit analysis

A.2.1 Ordered logit analysis: additional theory

The likelihood for an OL model estimated on the entire data is given by:

$$L\left(\Omega_{OL}\right) = \prod_{c=1}^{C}\prod_{n=1}^{N_c}\sum_{s=0}^{S} I\left(Y_{n,c} = \frac{s}{6}\right)\left[\frac{e^{\tau_{s+1}-V_{n,c}}}{1+e^{\tau_{s+1}-V_{n,c}}} - \frac{e^{\tau_s-V_{n,c}}}{1+e^{\tau_s-V_{n,c}}}\right], \tag{1}$$

where $c = 1, 2, \ldots, C$ is an index for study areas (with $C = 18$), and $s = 0, \ldots, S$ is an index for the possible rates of choosing a vaccine across the six tasks, with $S = 6$, and where $I\left(...\right) = 1$ if the argument inside the bracket is true. For normalisation, we set $\tau_0 = -\infty$ and $\tau_7 = +\infty$, such that the probability of $Y_{n,c} = 0$ is given by $\frac{e^{\tau_1-V_{n,c}}}{1+e^{\tau_1-V_{n,c}}}$ while the probability of $Y_{n,c} = 1$ is given by $1 - \frac{e^{\tau_6-V_{n,c}}}{1+e^{\tau_6-V_{n,c}}}$. The likelihood in Equation 1 depends on the vector of parameters Ω_{OL}, which groups together those thresholds that are not normalised, $\tau = \langle\tau_1, \tau_2, \ldots, \tau_6\rangle$, as well as the δ, κ and γ parameters from Equation **??**.

The OL model was estimated using maximum likelihood routines in Apollo v0.2.5 (Hess and Palma, 2019). No weighting was used in estimation as the OL analysis was carried out in order to determine the presence of differences across socio-demographic groups which would then inform any reweighting in the later analysis.

While the model uses an ordered structure, the dependent variable itself relates to a continuous scale (probability of uptake), and, in application, we can thus look at the predicted vaccine uptake for a given individual n in study area c, which, conditional on the estimated parameters $\widehat{\Omega}_{OL}$ and the study area characteristics $q_{n,c}$ and person characteristics $z_{n,c}$, is calculated as:

$$Y_{n,c}\left(\widehat{\Omega}_{OL}, q_{n,c}, z_{n,c}\right) = \sum_{s=0}^{S}\frac{s}{6}\left[\frac{e^{\widehat{\tau}_{s+1}-\widehat{V}_{n,c}}}{1+e^{\widehat{\tau}_{s+1}-\widehat{V}_{n,c}}} - \frac{e^{\widehat{\tau}_s-\widehat{V}_{n,c}}}{1+e^{\widehat{\tau}_s-\widehat{V}_{n,c}}}\right], \tag{2}$$

The predicted vaccine uptake in a given study area, conditional on study area and person characteristics, is then calculated as:

$$Y_c\left(\widehat{\Omega}_{OL}, q_c, Z_c\right) = \frac{\sum_{n=1}^{N_c} Y_{n,c}\left(\widehat{\Omega}_{OL}, q_{n,c}, z_{n,c}\right)}{N_c}, \tag{3}$$

where $Q_c = \langle q_{1,c}, \ldots, q_{N_c,c}\rangle$ and $Z_c = \langle z_{1,c}, \ldots, z_{N_c,c}\rangle$.

A.2.2 Ordered logit analysis: results

The OL model results are shown in Table A.1.

The final model includes study area-specific constants, alongside two measures of the status of the pandemic in the study area at the point of data collection, obtained from Ritchie et al. (2021). The first of these is the reproduction number (R), calculated for the week during which a specific respondent completed the survey. After testing for non-linearity, a linear specification was used for the impact of R, which was found to be positive, and where, using a one-sided test, we could easily reject the H_0 at the 5% significance level. The second attribute relates to the cumulative number of COVID-19 related deaths per 100K inhabitants at the time of data collection, in the study area in question. For this variable, careful specification testing led us to a piece-wise non-linear specification, where there was no impact below 5 cases per 100K inhabitants, with a logarithmic transform applied to increases above 5, up to a level of 50 per 100K. The impact of this variable on vaccine uptake was found to be

Table A.1: Results for ordered logit (OL) model of vaccine uptake in SC survey

Number of individuals	13,128
LL(final)	-12,691.38
AIC	25,590.76
BIC	26,368.94

	est.	rob.t(0)	p (2 sided)
τ_1	-2.0029	-1.62	0.11
τ_2	-1.8904	-1.53	0.13
τ_3	-1.7388	-1.41	0.16
τ_4	-1.4484	-1.17	0.24
τ_5	-1.0278	-0.83	0.41
τ_6	-0.2317	-0.19	0.85
δ_{AU}	2.1208	1.4	0.16
δ_{BR}	-2.1035	-1.33	0.18
δ_{CL}	0.2161	0.39	0.7
δ_{CN}	4.0387	2.52	0.01
δ_{CO}	-0.1203	-0.13	0.9
δ_{DE}	-0.4547	-0.5	0.62
δ_{DK}	1.8413	2.01	0.04
δ_{EC}	-0.4364	-0.44	0.66
δ_{ES}	-1.5281	-1.45	0.15
δ_{FR}	-0.556	-0.77	0.44
δ_{HK}	2.7509	1.58	0.11
δ_{JP}	3.4197	1.34	0.18
δ_{KR}	-0.3386	-0.24	0.81
δ_{NA}	-1.1844	-1	0.32
δ_{NZ}	1.0871	0.77	0.44
δ_{UK}	0	-	-
δ_{US}	1.8962	1.8	0.07
δ_{ZA}	-1.1899	-1.46	0.14
$\kappa_{domestic\,R}$	0.3201	2.59	<0.01
$\kappa_{log\,domestic\,cumulative\,deaths\,over\,5\,per\,100K}$	0.3485	1.22	0.22
$\gamma_{lives\,alone}$	0	-	-
$\gamma_{other\,adults\,in\,hh}$	0.1237	2.04	0.04
$\gamma_{children\,in\,hh}$	0.0628	1.35	0.18
$\gamma_{no\,chronic\,health\,condition}$	0	-	-
$\gamma_{chronic\,health\,condition}$	0.2528	5.35	<0.01
$\gamma_{no\,public\,transport\,use}$	0	-	-
$\gamma_{public\,transport\,use\,less\,than\,4\,days\,pw}$	0.1105	2.11	0.03
$\gamma_{public\,transport\,5\,days\,or\,more\,pw}$	0.1849	3.52	<0.01
$\gamma_{no\,air\,travel}$	0	-	-
$\gamma_{air\,travel\,once\,or\,twice\,py}$	0	-	-
$\gamma_{air\,travel\,three\,or\,more\,py}$	0.2139	4.77	<0.01

	est.	rob.t(0)	p (2 sided)
γ_{male}	0	-	-
$\gamma_{female,AU}$	-0.0766	-0.36	0.72
$\gamma_{female,BR}$	0.5621	1.4	0.16
$\gamma_{female,CL}$	-0.3579	-3.37	<0.01
$\gamma_{female,CN}$	-0.053	-0.25	0.8
$\gamma_{female,CO}$	-0.1508	-1.05	0.29
$\gamma_{female,DE}$	-0.2389	-1.68	0.09
$\gamma_{female,DK}$	0.3671	1.2	0.23
$\gamma_{female,EC}$	-0.5297	-2.59	<0.01
$\gamma_{female,ES}$	-0.0699	-0.4	0.69
$\gamma_{female,FR}$	0.2214	1.36	0.17
$\gamma_{female,HK}$	-0.3455	-0.69	0.49
$\gamma_{female,JP}$	-0.0856	-0.12	0.9
$\gamma_{female,KR}$	0	0	1
$\gamma_{female,NA}$	0.2585	0.98	0.33
$\gamma_{female,NZ}$	-0.0148	-0.08	0.94
$\gamma_{female,UK}$	-0.105	-1.07	0.28
$\gamma_{female,US}$	-1.1517	-4.97	<0.01
$\gamma_{female,ZA}$	0.01	0.08	0.94
$\gamma_{no\,univ.\,degree}$	0	-	-
$\gamma_{univ.\,degree,AU}$	0.3432	1.48	0.14
$\gamma_{univ.\,degree,BR}$	-0.1621	-0.35	0.73
$\gamma_{univ.\,degree,CL}$	-0.1565	-0.74	0.46
$\gamma_{univ.\,degree,CN}$	-0.0434	-0.15	0.88
$\gamma_{univ.\,degree,CO}$	0.3505	2.16	0.03
$\gamma_{univ.\,degree,DE}$	0.2628	1.69	0.09
$\gamma_{univ.\,degree,DK}$	0.4223	1.08	0.28
$\gamma_{univ.\,degree,EC}$	-0.1354	-0.61	0.54
$\gamma_{univ.\,degree,ES}$	0.1069	0.6	0.55
$\gamma_{univ.\,degree,FR}$	0.4985	1.72	0.09
$\gamma_{univ.\,degree,HK}$	-0.4543	-0.87	0.38
$\gamma_{univ.\,degree,JP}$	-0.1862	-0.26	0.79
$\gamma_{univ.\,degree,KR}$	0.1094	0.63	0.53
$\gamma_{univ.\,degree,NA}$	-0.6647	-2.24	0.03
$\gamma_{univ.\,degree,NZ}$	0.3787	2.21	0.03
$\gamma_{univ.\,degree,UK}$	0.1711	1.77	0.08
$\gamma_{univ.\,degree,US}$	0.3728	1.74	0.08

	est.	rob.t(0)	p (2 sided)
$\gamma_{age,missing}$	-3.2033	-6.08	<0.01
$\gamma_{age,AU}$	-0.0781	-2.09	0.04
$\gamma_{age,BR}$	0.1111	1.49	0.14
$\gamma_{age,CL}$	-0.0511	-2.59	<0.01
$\gamma_{age,CN}$	-0.2082	-3.03	<0.01
$\gamma_{age,CO}$	-0.0624	-1.19	0.23
$\gamma_{age,DE}$	-0.0386	-1.31	0.19
$\gamma_{age,DK}$	-0.1923	-5.43	<0.01
$\gamma_{age,EC}$	-0.0114	-0.21	0.83
$\gamma_{age,ES}$	0.004	0.09	0.93
$\gamma_{age,FR}$	-0.097	-3.27	<0.01
$\gamma_{age,HK}$	-0.1403	-2.06	0.04
$\gamma_{age,JP}$	-0.2183	-1.53	0.13
$\gamma_{age,KR}$	0.0628	1.53	0.13
$\gamma_{age,NA}$	0.0066	0.15	0.88
$\gamma_{age,NZ}$	-0.0469	-1.43	0.15
$\gamma_{age,UK}$	-0.0727	-3.9	<0.01
$\gamma_{age,US}$	-0.1265	-2.98	<0.01
$\gamma_{age,ZA}$	-0.034	-0.83	0.41
$\gamma_{age\,squared,AU}$	0.0007	1.93	0.05
$\gamma_{age\,squared,BR}$	-0.0012	-1.42	0.16
$\gamma_{age\,squared,CL}$	0.0005	2.23	0.03
$\gamma_{age\,squared,CN}$	0.0027	2.8	<0.01
$\gamma_{age\,squared,CO}$	0.0008	1.21	0.23
$\gamma_{age\,squared,DE}$	0.0004	1.22	0.22
$\gamma_{age\,squared,DK}$	0.0022	4.85	<0.01
$\gamma_{age\,squared,EC}$	0.0002	0.26	0.79
$\gamma_{age\,squared,ES}$	0	-0.08	0.94
$\gamma_{age\,squared,FR}$	0.001	3.06	<0.01
$\gamma_{age\,squared,HK}$	0.0015	1.55	0.12
$\gamma_{age\,squared,JP}$	0.003	1.6	0.11
$\gamma_{age\,squared,KR}$	-0.0008	-1.65	0.1
$\gamma_{age\,squared,NA}$	0.0001	0.2	0.84
$\gamma_{age\,squared,NZ}$	0.0005	1.33	0.18
$\gamma_{age\,squared,UK}$	0.0008	4.17	<0.01
$\gamma_{age\,squared,US}$	0.0011	2.35	0.02
$\gamma_{age\,squared,ZA}$	0.0006	1.07	0.28

positive, and although, using a one-sided test, we could not reject the H_0 of no impact at the 5% significance level, the variable was retained in the model given its importance for the analysis and behavioural reasonableness of the finding. These two variables thus show that a more active state of the pandemic or a higher cumulative number of COVID-19 related deaths lead to increased vaccine uptake.

Three parameters, again generic across study areas, were estimated to capture the impact of household composition and whether a respondent was suffering from a chronic health condition, while a further three parameters were used to capture exposure risk in terms of travel patterns by public transport (PT) and air. We see positive shifts in the utility (and hence the likelihood of higher levels of vaccine uptake) for respondents who live in multi-person households, respondents suffering from a chronic health condition, respondents who travel by public transport, especially if doing so every day, and respondents making three or more air journeys per year. Study area-specific parameters were estimated for gender, education (university degree *vs* less) and age, where a second order polynomial specification was used to capture the non-linear effects of age. For these study area-specific terms, the directionality and size of impacts vary, and parameters were retained for all study areas for comparison purposes, even if the the null hypothesis of no effect could not be rejected everywhere.

A.3 Latent class analysis

A.3.1 Latent class analysis: additional theory

Equation **??** shows how the LC likelihood function depends on the class allocation weights $\pi_{n,c,s}$. These are in turn given by a logit probability, with:

$$\pi_{n,c,s} = \frac{e^{\alpha_{c,s}}}{\sum_{k=1}^{S_c} e^{\alpha_{c,k}}}, \tag{4}$$

where, for normalisation, we set $\alpha_{c,1} = 0$. The class allocation probabilities in our model are constant, i.e., they do not vary as a function of characteristics of the individual. The model thus captures only random as opposed to deterministic heterogeneity, a decision that was taken for the sake of a consistent model specification across study areas.

The LC model was estimated using maximum likelihood routines in Apollo v0.2.5 (Hess and Palma, 2019). No weighting was used in estimation, and the results were instead reweighted after estimation, as we now discuss.

After model estimation, we can calculate the posterior class allocation probabilities, which take into account the sample level model estimates and the individual-level choices. In particular, we have that:

$$\widetilde{\pi}_{n,c,s} = \frac{\widehat{\pi}_{n,c,s} \prod_{t=1}^{6} \widehat{P}_{n,c,t,s}}{\sum_{k=1}^{S_c} \widehat{\pi}_{n,c,k} \prod_{t=1}^{6} \widehat{P}_{n,c,t,k}}, \tag{5}$$

where $\widehat{P}_{n,c,t,s}$ and $\widehat{\pi}_{n,c,s}$ are the within class probabilities from Equation **??** and class allocation probabilities from Equation 4, respectively, both conditional on the final maximum likelihood estimates for the model parameters. The posterior probabilities $\widetilde{\pi}_{n,c,s}$ give the most likely value for the class allocation probabilities for person n in study area c given the choices observed for that individual (cf. Hess, 2014).

We use the posterior class allocation probabilities together with person-specific weights to produce reweighted sample level results for the model. In particular, let $w_{n,c}$ again be the weight for person n in study area c, where $\sum_{n=1}^{N_c} w_{n,c} = N_c$. Let us then consider a situation where we wish to predict the uptake of a vaccine with given characteristics. With $\widehat{P}_{n,c,s,i}$ giving the prediction from the model for the probability of individual n in study

area c choosing vaccine i, conditional on class s and the maximum likelihood estimates for the parameters, the reweighted uptake prediction for a given vaccine i would be calculated as:

$$\widetilde{P}_{c,i} = \frac{\sum_{n=1}^{N_c} w_{n,c}\,(1 - vr_{n,c}) \sum_{s=1}^{S_c} \widetilde{\pi}_{n,c,s} \widehat{P}_{n,c,s,i}}{\sum_{n=1}^{N_c} w_{n,c}}. \tag{6}$$

It should be noted that the term $(1 - vr_{n,c})$ is used in the numerator, ensuring that for any vaccine-resistant individuals, the probability of uptake is set to zero. These individuals are still included in the denominator to calculate the overall average uptake.

Predictions from the LC model rely on the estimated model parameters as well as the study area specific share of vaccine resistant individuals, i.e. $\sum_{n=1}^{N} w_{n,c} vr_{n,c}$, and both are potentially affected by the differences in timing of data collection (and thus status of the pandemic) across study areas. A recalibration process was used to address this, employing the results from the OL model in relation to the impact of the R reproduction number and the cumulative COVID-19 related deaths, using the following five steps, where, to recall, $vr_{n,c} = 1$ if this individual is classed as vaccine resistant.

Step 1: Two predictions of vaccine uptake were made from the OL model for each study area, one using the reproduction number and cumulative COVID-19 related deaths at the time of data collection, and one for a reproduction number of $R = 1$ and at the cumulative COVID-19 related deaths for the country at the time of writing this paper (27 September 2021). These two predictions were labelled as $P_{OL-uptake,c,base}$ and $P_{OL-uptake,c,current}$. A correction factor for the probability of not choosing to be vaccinated was then calculated for each country as $CF_c = \frac{1-P_{OL-uptake,c,current}}{1-P_{OL-uptake,c,base}}$.

Step 2: The rate of choosing the no vaccine option in study area c for the sample excluding the vaccine resistant group was calculated as $NV_c = \frac{\sum_{n=1}^{N_c} w_{n,c}(1-vr_{n,c}) \sum_{t=1}^{6} \frac{1-Y_{n,c,t}}{6}}{\sum_{n=1}^{N_c} w_{n,c}(1-vr_{n,c})}$ (using the earlier notation), and this was then adjusted using the output from step 1 as $NV_{c,adjusted} = CF_c \cdot NV_c$

Step 3: For each study area, a baseline prediction from the LC model was made for the data used in estimation, excluding the vaccine resistant segment, with the probability of no vaccine (nv) choice predicted as:

$$P_{LC-nv,c,base} = \frac{\sum_{n=1}^{N_c} w_{n,c}\,(1 - vr_{n,c}) \sum_{s=1}^{S_c} \widetilde{\pi}_{n,c,s} \sum_{t=1}^{6} \widehat{P}_{n,c,t,s,5}}{\sum_{n=1}^{N_c} w_{n,c}\,(1 - vr_{n,c})}, \tag{7}$$

where $\widehat{P}_{n,c,t,s,5}$ is the predicted probability of respondent n in country c choosing option 5 (i.e. the no vaccine option) in task t.

Step 4: The prediction $P_{LC-nv,c,base}$ was then compared to $NV_{c,adjusted}$. A correction to the alternative specific constant (ASC) for the no vaccine option was calculated as

$$\delta_{c,5,adjusted} = \delta_{c,5,base} + \ln\left(\frac{NV_c}{P_{LC-nv,c,base}}\right), \tag{8}$$

i.e., using the standard recalibration approach discussed for example by Train (2009, Section 2.8). A new prediction using the calibrated ASC was made, and the remaining bias was calculated as $P_{LC-nv,c,adjusted} - NV_{c,adjusted}$. As long as this bias remained above 10^{-4}, the process repeated steps 3 and 4, gradually updating the ASC. It should be noted that although the ASC for the no vaccine option had been normalised to zero in estimation, the choice of which ASC to adjust is arbitrary, and a generic adjustment across classes to the no-vaccine ASC was the most logical approach.

Step 5: An adjustment to one subsegment of the vaccine resistant group was made, namely those individuals who stated that *"Vaccines for COVID-19 will need to undergo more testing before I would trust the vaccine"*, where the size of this group was scaled by CF_c, consequently also leading to a change in the size of the vaccine resistant group for that study area.

After this recalibration process, Equation 6 can be used to make predictions for scenarios with a given set of vaccines, using the adjusted ASCs and share of vaccine resistant individuals. The calibration process is based on the assumption that the findings from the OL model in terms of the relationship between vaccine uptake, national reproduction number and cumulative numbers of COVID-19 related deaths can be extrapolated to the LC models. This assumption is justified by the fact that both models rely on the same data, and the estimation of a pooled LC model (i.e. combining data from all study areas) was not practical due to sample sizes and not advisable given the anticipated (and empirically confirmed) heterogeneity in preferences across countries. The recalibration approach used in Step 4 is standard practice in choice modelling, and ensures that market shares can be adjusted while still retaining the model insights in relation to marginal effects. The inclusion of a partial adjustment of the vaccine resistant group is a subjective judgement call, as is any calibration, but this part of the vaccine resistant group was small overall, and the size of the vaccine resistant group only changed by on average 0.3% across study areas, with the largest changes (between 1.1% and 1.9%) observed for Denmark, Germany and Namibia.

A.3.2 Latent class analysis: results

The LC estimation results are presented in Tables A.2 and A.3. For most study areas, the final model made use of three classes ($S_c = 3$), with the exception of Brazil, where a two-class structure was preferred, and Hong Kong and Japan, where a single class structure was used, which is a direct result of the smaller sample size for these two study areas. Overall, we found that:

- Risk of infection and risk of illness have negative impacts on utility in all study areas, meaning that vaccines with a higher efficacy (i.e. greater reduction in risk) obtain a greater utility. Overall, the (per percentage point) impact of changes in the risk of infection is larger than the impact of changes in the risk of illness.
- Increases in the length of time that a vaccine protects from infection/illness have a positive impact on the utility of vaccination in all study areas, where there is an additional disutility if the protection duration is unknown.
- Increases in mild and severe side effects have negative impacts on utility in all study areas, where the impact of a change in the risk of severe side effects is on average several hundred times larger than a corresponding increase in the risk of mild side effects.
- Increases in waiting time reduce the utility of vaccines, as do increases in the cost for paid vaccine options.
- Increases in the share of the population already vaccinated have a positive impact on the utility of vaccination in most study areas, but the impact is negative in both classes for Brazil, while for some study areas, the effect is negative in some classes or no different from zero (e.g. China, Colombia, Germany).
- If vaccination implies an exemption from travel restrictions, then this has a positive impact on the utility of vaccination in some countries (though not in all classes within those countries), while no effect is observed for other countries (Australia, Colombia, Ecuador, Japan, South Africa, Spain).

In addition to the above description of the overall effects, it should be noted that, for all attributes, the models uncovered substantial heterogeneity in preferences across individuals, with different sensitivities obtained in the different classes of the LC structures. In some cases, selected parameters were merged across classes in the absence of differences, while some parameters were also constrained to 0 if the effect in a class was not meaningful or did

not reject the H_0 of no effect at reasonable levels of significance. The same applied for the nesting parameters λ_s, which were in many cases constrained to 1, i.e. collapsing to Multinomial Logit (MNL) models inside the respective classes.

As an illustration of the differences within and across study areas, we use the estimated model to make predictions on the estimation data, and combine the predictions for the two free vaccine options into one, with the same process for the two paid vaccine options. The weight for class s is calculated as $\frac{\sum_{n=1}^{N_c} w_{n,c}(1-vr_{n,c})\widetilde{\pi}_{n,c,s}}{\sum_{n=1}^{N_c} w_{n,c}}$, where we include the vaccine-resistant (vr) share of the population as a separate class (always choosing no vaccine), with a weight of $\sum_{n=1}^{N_c} w_{n,c} \cdot vr_{n,c}$. Figure A.2 shows the outputs of this process, where the results omit Hong Kong and Japan, where a single class model was used. Note that these results relate to the reweighted estimation data, but without any adjustment made on the basis of the impact of the current pandemic status. In all study areas except Chile and South Africa, the largest class has the highest probability of choosing the free vaccine options, while in Chile and South Africa, it is for the paid vaccine options. It should be noted that a high WTP for COVID-19 vaccines for Chile was previously found by Cerda and Garcia (2021). The second largest class is dominated by the paid options (except for Chile and South Africa), while the third class is dominated by choosing the no vaccine option (in those study areas with three class models). The relative sizes of the classes varies extensively across study areas, with a much more even split between the first two classes in some study areas (Australia, Chile, South Africa, the United States) than in others. Similarly, the size of the additional vr class varies in line with the results in Figure 4 in the main body of the paper, with it only clearly exceeding the size of the smallest non-vr class in Namibia.

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Table A.2: Results for latent class (LC) model (part 1)

Country	AU		BR		CL		CN		CO		DE		DK		EC		ES	
Number of individuals	490		346		1,635		618		924		758		183		511		631	
Number of modelled outcomes	2,940		2,076		9,810		3,708		5,544		4,548		1,098		3,066		3,786	
Classes	3		2		3		3		3		3		3		3		3	
Estimated parameters	37		25		42		42		39		43		39		34		39	
LL(final)	-3,531.76		-1,975.27		-11,623.23		-4,638.55		-6,853.23		-5,029.00		-1,272.25		-3,725.93		-4,583.59	
Adj.Rho-square (0)	0.2458		0.4013		0.2612		0.2157		0.2276		0.3071		0.2580		0.2380		0.2414	
AIC	7,137.52		4,000.55		23,330.46		9,361.09		13,784.46		10,143.99		2,622.50		7,519.86		9,245.18	
BIC	7,359.01		4,141.50		23,330.46		9,622.26		14,042.66		10,420.16		2,817.55		7,724.82		9,488.50	
	est.	rob.t(0)	est.	rob.t(0)	est.	rob.t(0)	est.	rob.t(0)	est.	rob.t(0)	est.	rob.t(0)	est.	rob.t(0)	est.	rob.t(0)	est.	rob.t(0)
$\delta_{position,s_1}$	0.0939	2.14	0.1416	2.47	0.0071	0.52	0.0332	0.90	0.0201	0.74	0.0643	1.09	-0.0003	-0.02	0.1025	1.76	0.0287	0.84
$\delta_{position,s_2}$	-0.0369	-0.92	0.0233	0.42	0.0192	0.94	0.0111	0.51	-0.0139	-0.50	0.0802	1.37	0.0178	0.29	0.0151	1.05	-0.0336	-1.26
$\delta_{position,s_3}$	0.1171	1.24			0.0104	0.33	-0.0125	-0.18	0.0053	0.38	0.0009	0.03	0.0119	0.34	0.2137	1.59	-0.0314	-0.59
$\delta_{free\ vaccine,s_1}$	0.6264	1.53	3.9824	5.83	1.0828	4.64	1.0716	2.22	1.3274	2.15	0.1019	0.08	-2.0215	-1.46	1.5084	2.26	1.2608	3.35
$\delta_{free\ vaccine,s_2}$	1.3726	2.94	4.3576	7.59	1.4559	3.60	1.9126	5.25	1.8717	5.28	-2.0153	-3.23	0.7300	1.15	1.9498	6.47	1.6165	4.28
$\delta_{free\ vaccine,s_3}$	-1.7423	-1.89			-2.9175	-3.55	-1.8897	-1.37	-1.9684	-3.91	0.4809	1.47	1.7678	2.60	-1.6017	-1.73	-3.0812	-2.39
$\delta_{paid\ vaccine,s_1}$	-0.2427	-0.44	4.7445	6.77	1.7187	6.41	1.9247	4.68	1.8578	4.35	0.7545	0.91	-2.2304	-1.58	4.1414	6.43	1.5002	4.19
$\delta_{paid\ vaccine,s_2}$	2.0396	4.32	3.3299	5.36	1.4232	3.80	1.2252	2.19	1.4945	3.88	-2.4145	-3.00	-0.1575	-0.15	1.8776	6.28	1.1195	3.00
$\delta_{paid\ vaccine,s_3}$	-2.6341	-2.68			-3.0731	-3.67	-2.0338	-1.50	-2.1014	-4.21	0.2748	0.91	2.0242	3.94	-2.0137	-2.13	-3.7199	-2.90
$\delta_{no\ vaccine}$	0	-	0	-	0	-	0	-	0	-	0	-	0	-	0	-	0	-
$\beta_{risk\ infection,s_1}$	-0.1145	-3.24	-0.2083	-4.42	-0.1841	-6.29	-0.1381	-3.15	-0.1354	-3.08	-0.0585	-1.55	-0.1187	-2.65	-0.2270	-5.92	-0.0715	-2.59
$\beta_{risk\ infection,s_2}$	-0.1868	-4.49	-0.0904	-2.30	-0.0905	-3.37	-0.0991	-2.07	-0.1713	-5.77	-0.0957	-1.91	0.0107	0.14	-0.0653	-3.33	-0.0478	-2.12
$\beta_{risk\ infection,s_3}$	0	-			-0.2096	-4.11	-0.1904	-1.35	-0.1328	-3.16	-0.0822	-3.18	-0.0240	-0.88	-0.1240	-1.20	-0.2749	-3.09
$\beta_{risk\ illness,s_1}$	-0.0958	-5.26	-0.0239*	-1.55*	-0.1076	-6.38	-0.0378	-2.74	-0.0609	-3.20	-0.0871	-1.48	-0.0523	-2.40	-0.0199	-0.85	-0.0478	-2.94
$\beta_{risk\ illness,s_2}$	-0.0676	-3.87	-0.0239*	-1.55*	-0.0935	-4.50	-0.0357	-2.06	-0.0545	-4.75	-0.0540	-2.38	-0.1334	-4.63	-0.0119	-1.54	-0.0702	-4.09
$\beta_{risk\ illness,s_3}$	-0.0371	-0.96			-0.1220	-4.07	-0.0550	-1.52	-0.0365	-2.98	-0.1633	-13.34	-0.0316	-1.10	0	-	-0.1168	-1.62
$\beta_{protection\ unknown,s_1}$	-0.2074	-1.62	-1.1617	-4.41	-0.7443	-5.92	-0.2977	-2.33	-0.3823	-3.12	-0.1425	-0.87	-0.6828	-2.01	-1.0692	-5.03	-0.1158	-0.91
$\beta_{protection\ unknown,s_2}$	-0.0762	-0.52	-1.0022	-4.88	-0.5754	-4.27	-0.0386	-0.49	-0.5743	-5.18	-0.3484	-1.13	0	-	-0.5052	-4.19	-0.1798	-1.82
$\beta_{protection\ unknown,s_3}$	0	-			-0.6849	-2.47	-0.1315	-0.35	-0.2676	-2.44	-0.2839	-2.53	-0.0414	-0.40	-0.2100	-0.42	0	-
$\beta_{protection,s_1}$ †	0.0176	5.80	0.0298	7.63	0.0166	6.12	0.0135	3.32	0.0158	3.02	0.0088	1.63	0.0054	2.20	0.0242	6.94	0.0108	2.95
$\beta_{protection,s_2}$ †	0.0179	5.99	0.0240	7.77	0.0188	3.90	0.0103	2.22	0.0227	10.61	0.0162	3.87	0.0241	5.18	0.0081	4.02	0.0111	3.72
$\beta_{protection,s_3}$ †	0.0146	1.66			0.0142	3.83	0.0026	0.50	0.0059	2.31	0.0151	7.41	0.0084	1.31	0.0113	1.42	0.0128	3.11
$\beta_{mild\ side\ effects,s_1}$	-0.0189	-1.28	-0.0635	-3.20	-0.0693	-6.56	-0.0479	-2.99	-0.0092	-0.93	-0.0218	-1.54	-0.0105	-1.49	-0.0309	-1.78	-0.0502	-2.49
$\beta_{mild\ side\ effects,s_2}$	-0.0442	-3.05	-0.0201	-1.17	-0.0441	-3.76	-0.0384	-1.91	0	-	-0.0259	-1.41	-0.0413	-1.72	-0.0100	-1.43	-0.0456	-3.13
$\beta_{mild\ side\ effects,s_3}$	-0.0384	-1.00			-0.0835	-4.61	-0.0969	-1.60	-0.0399	-3.30	-0.0481	-4.49	-0.0146	-1.09	-0.0268	-0.65	-0.1427	-2.55
$\beta_{severe\ side\ effects,s_1}$	-20.8550	-2.41	-47.4843	-3.01	-22.2399	-4.84	-14.2646	-2.13	-9.9390	-1.50	-18.2135	-1.58	-16.3284	-1.70	-41.2052	-3.18	0	-
$\beta_{severe\ side\ effects,s_2}$	-26.1127	-2.99	-21.9986	-2.11	-30.5389	-3.59	-8.0677	-1.46	-35.0751	-4.07	-35.4579	-3.62	-42.4553	-2.91	-26.4116	-3.88	-15.8972	-2.35
$\beta_{severe\ side\ effects,s_3}$	-40.8858	-1.60			-30.9384	-3.01	-5.8041	-0.29	-18.3384	-2.19	-21.5006	-3.25	-17.6955	-1.12	-75.2086	-3.42	-29.4673	-1.38
$\beta_{waiting\ time,s_1}$ ‡	-0.0177	-2.44	-0.1182*	-10.74*	-0.0550	-6.60	-0.0508	-2.81	-0.0516	-2.76	-0.0490	-1.21	-0.0155*	-2.86*	-0.0129*	-2.83*	-0.0470	-2.05
$\beta_{waiting\ time,s_2}$ ‡	-0.0522	-5.68	-0.1182*	-10.74*	-0.0316	-3.97	-0.0193	-1.87	-0.0423	-3.68	-0.0102	-0.82	-0.0155*	-2.86*	-0.0129*	-2.83*	-0.0176	-2.78
$\beta_{waiting\ time,s_3}$ ‡	-0.0361	-1.32			-0.0519	-4.97	-0.0129	-1.04	-0.0159	-2.51	-0.0374	-6.41	-0.0155*	-2.86*	-0.0129*	-2.83*	-0.0244	-1.06
β_{fee,s_1} §	-0.0299	-4.75	-0.0146	-9.28	-0.0121	-6.28	-0.0060	-2.70	-0.0064	-2.92	-0.0038	-1.16	-0.0006	-1.97	-0.0079*	-6.62*	-0.0048	-2.09
β_{fee,s_2} §	-0.0049	-7.33	-0.0982	-2.83	-0.0508	-2.45	-0.0065	-1.98	-0.0290	-2.40	-0.0285	-1.93	-0.0264	-1.37	-0.0079*	-6.62*	-0.0363	-2.91
β_{fee,s_3} §	-0.0002	-0.20			0.0000	-4.61	-0.0046	-1.18	-0.0030	-2.12	-0.0365	-7.79	-0.0011	-1.69	-0.0079*	-6.62*	-0.0025	-0.88
$\beta_{population\ coverage,s_1}$	0.0139	1.46	-0.0289	-1.42	0.0114	1.27	0.0278	2.25	0.0164	1.48	0.0127	1.14	0.0110	1.29	-0.0237	-2.41	0.0064	0.90
$\beta_{population\ coverage,s_2}$	-0.0031	-0.31	-0.0211	-2.52	0.0190	1.54	0.0245	1.83	-0.0074	-1.40	-0.0007	-0.15	0.0163	1.40	0.0297	3.14	0.0142	1.56
$\beta_{population\ coverage,s_3}$	0.0110	1.39			0.0103	2.24	-0.0121	-1.35	0.0318	4.54	-0.0069	-1.20	0.0011	0.10	-0.0007	-0.11	-0.0096	-0.91
$\beta_{travel\ exemption,s_1}$	0	-	1.4912	0.92	0	-	0	-	0	-	0.3932	0.60	1.0209	1.66	0	-	0	-
$\beta_{travel\ exemption,s_2}$	0	-	1.1473	1.90	0	-	0	-	0	-	-0.0111	-0.04	0	-	0	-	0	-
$\beta_{travel\ exemption,s_3}$	0	-			0.7155	3.58	0.9170	1.88	0	-	0.6751	1.87	1.1044	1.63	0	-	0	-
$\lambda_{vaccine,s_1}$	1	-	1	-	0.6072	6.17	0.7271	3.47	0.5349	3.01	0.7912	1.47	0.0953	1.92	1	-	0.8113	2.41
$\lambda_{vaccine,s_2}$	1	-	1	-	0.7041	3.97	0.5690	2.20	1	-	0.5384	3.27	1	-	0.4212	4.64	0.6819	4.00
$\lambda_{vaccine,s_3}$	0.2660	1.34			0.3807	3.87	0.2394	1.35	0.1529	1.75	1	-	0.3189	1.31	1	-	0.2751	2.77
ω_{s_1}	0	-	0	-	0	-	0	-	0	-	0	-	0	-	0	-	0	-
ω_{s_2}	-0.1052	-0.89	0.6044	3.64	-0.2495	-1.74	0.4101	2.05	0.4734	1.59	-0.3867	-1.98	1.1246	2.91	0.7339	3.78	0.1693	1.03
ω_{s_3}	-2.4087	-9.85			-1.4840	-7.35	-1.9087	-7.54	-0.9974	-4.23	1.2224	8.54	0.6768	1.77	-1.0848	-4.61	-1.7853	-5.62
Class allocation probabilities (π)																		
s_1	50.25%		35.33%		49.85%		37.66%		33.62%		19.71%		16.54%		29.23%		42.51%	
s_2	45.23%		64.67%		38.84%		56.75%		53.98%		13.39%		50.92%		60.89%		50.36%	
s_3	4.52%		0%		11.31%		5.59%		12.40%		66.90%		32.54%		9.88%		7.13%	

*: parameter constrained to be equal across some classes

†: Protection duration expressed in months

‡: Waiting time expressed in weeks

§: All cost coefficients are expressed in GBP. The exchange used at the time of the study design was 1GBP=(1.8AUD, 6.64BRL, 980.86CLP, 8.93CNY, 4,670COP, 8.33DKK, 1.1EUR, 9.87HKD, 135.43JPY, 1,532KPW, 21.06NAD, 1.92NZD, 1.27USD, 21.37ZAR)

Table A.3: Results for latent class (LC) model (part 2)

	FR		HK		JP		KR		NA		NZ		UK		US		ZA	
Number of individuals	479		53		67		1,107		269		664		2,147		387		1,122	
Number of modelled outcomes	2,874		318		402		6,642		1,614		3,984		12,882		2,322		6,732	
Classes	3		1		1		3		3		3		3		3		3	
Estimated parameters	41		14		13		38		31		41		41		37		31	
LL(final)	-3,107.35		-406.09		-504.35		-7,871.62		-2,072.28		-4,636.04		-14,698.79		-2,968.88		-9,315.34	
Adj.Rho-square (0)	0.3194		0.1792		0.2004		0.2601		0.1903		0.2706		0.2891		0.1957		0.1374	
AIC	6,298.69		840.17		1,034.69		15,819.24		4,206.55		9,354.09		29,479.58		6,011.75		18,692.67	
BIC	6,549.16		892.84		1,086.65		16,077.69		4,373.53		9,611.98		29,785.59		6,224.51		18,903.92	
	est.	rob.t(0)	est.	rob.t(0)	est.	rob.t(0)	est.	rob.t(0)	est.	rob.t(0)	est.	rob.t(0)	est.	rob.t(0)	est.	rob.t(0)	est.	rob.t(0)
$\delta_{position,s_1}$	-0.0191	-0.85	0.0100	0.39	-0.0235	-0.69	-0.0084	-0.24	-0.0062	-0.10	0.0207	1.02	0.0351	2.77	0.0983	1.63	0.0675	2.01
$\delta_{position,s_2}$	0.0495	1.24					-0.2487	-8.94	-0.0561	-1.18	0.0166	0.91	0.0126	0.90	0.0087	0.32	0.0610	0.64
$\delta_{position,s_3}$	0.0727	1.59					-0.1937	-1.34	-0.0319	-0.12	0.0677	1.18	0.0501	1.26	-0.005	-0.09	0.0434	2.18
$\delta_{free\,vaccine,s_1}$	0.2949	0.87	0.6040	1.40	0.1926	0.41	2.3347	4.16	1.6034	3.21	2.0325	3.36	1.4658	7.69	1.1984	1.19	1.5112	4.76
$\delta_{free\,vaccine,s_2}$	0.6676	1.09					2.0687	5.73	1.5853	3.13	1.4340	5.35	1.0600	4.86	-1.1461	-2.59	-1.9699	-3.49
$\delta_{free\,vaccine,s_3}$	-2.2380	-2.31					-1.6197	-1.90	-9.0273	-4.30	-0.6231	-0.95	-2.8894	-5.31	1.1769	1.48	2.0668	4.88
$\delta_{paid\,vaccine,s_1}$	0.0809	0.24	0.3498	0.79	0.0963	0.20	3.3514	5.81	2.2972	4.80	2.1638	3.80	1.7338	8.86	2.3271	2.43	-0.6757	-1.56
$\delta_{paid\,vaccine,s_2}$	0.8957	1.45					0.2411	0.60	-0.9267	-1.91	1.1590	4.11	0.6273	2.69	-1.5719	-2.65	-2.9207	-4.24
$\delta_{paid\,vaccine,s_3}$	-2.7846	-2.62					-1.5868	-1.86	-8.3582	-3.19	-1.0103	-1.28	-3.7888	-5.79	-0.834	-0.99	2.2276	5.51
$\delta_{no\,vaccine}$	0	-	0	-	0	-	0	-	0	-	0	-	0	-	0	-	0	-
$\beta_{risk\,infection,s_1}$	-0.1622	-4.63	-0.0416	-1.48	-0.1363	-3.24	0	-	-0.0052	-0.12	-0.0490	-1.34	-0.1545	-7.69	-0.0388	-0.78	-0.0663	-2.65
$\beta_{risk\,infection,s_2}$	-0.2274	-2.58					-0.0963	-4.60	-0.0228	-0.61	-0.0485	-2.41	-0.1272	-6.42	-0.0195	-0.69	0	-
$\beta_{risk\,infection,s_3}$	-0.1180	-1.98					-0.0938	-2.00	0	-	-0.0240	-0.25	-0.1399	-3.82	-0.2082	-3.68	0	-
$\beta_{risk\,illness,s_1}$	-0.1286	-5.48	-0.0378	-2.84	-0.0695	-3.07	-0.0264	-2.19	0	-	-0.0246	-1.31	-0.0837	-8.02	-0.0757	-3.19	-0.0508	-4.09
$\beta_{risk\,illness,s_2}$	-0.1292	-2.76					-0.0740	-7.17	-0.0433	-3.05	-0.0649	-3.82	-0.1281	-7.75	-0.0403	-1.8	0	-
$\beta_{risk\,illness,s_3}$	-0.1010	-3.00					-0.0801	-2.60	-0.3550	-2.85	-0.0350	-0.86	-0.0932	-3.99	-0.0665	-2.56	-0.0141	-2.20
$\beta_{protection\,unknown,s_1}$	-0.3793	-3.26	-0.2387	-1.48	-0.4410	-2.67	-0.2140	-2.10	0	-	-0.0249	-0.46	-0.3962	-5.53	0	-	0	-
$\beta_{protection\,unknown,s_2}$	-0.2012	-1.05					-0.2310	-2.73	0	-	-0.1906	-2.25	-0.2959	-4.31	0	-	0	-
$\beta_{protection\,unknown,s_3}$	0	-					-0.0877	-0.24	-0.3968	-0.27	-0.1918	-0.75	0	-	-0.3485	-1.47	-0.0676	-1.30
$\beta_{protection,s_1}$ †	0.0096	4.21	0.0093	2.59	0.0060	2.33	0.0121	6.13	0.0025	0.65	0.0085	1.41	0.0136	7.60	0.0153	2.95	0.0113	3.98
$\beta_{protection,s_2}$ †	0.0153	2.69					0.0119	6.25	0.0030	0.88	0.0107	4.07	0.0179	6.84	0.0018	0.74	0.0063	1.23
$\beta_{protection,s_3}$ †	0.0127	3.44					0	-	0	-	0	-	0.0184	5.58	0.0205	4.11	0.0053	2.62
$\beta_{mild\,side\,effects,s_1}$	-0.0410	-3.79	-0.0396	-2.80	-0.0367	-2.50	-0.0262	-2.64	-0.0225	-1.01	-0.0184	-1.29	-0.0527	-7.20	0	-	-0.0346	-3.09
$\beta_{mild\,side\,effects,s_2}$	-0.0858	-2.55					-0.0350	-3.50	-0.0257	-1.44	-0.0387	-3.37	-0.0421	-5.74	-0.0132	-0.85	-0.0223	-0.71
$\beta_{mild\,side\,effects,s_3}$	-0.0555	-3.32					-0.0530	-2.21	0	-	-0.0471	-0.96	-0.0500	-3.66	-0.0438	-2.01	-0.0043	-0.93
$\beta_{severe\,side\,effects,s_1}$	-28.0157	-4.53	-12.6245	-1.60	-14.9522	-2.01	-12.4227	-1.97	-40.0652	-4.43	-8.7330	-1.33	-16.9558	-5.04	-12.9824	-1.3	-1.9109	-0.33
$\beta_{severe\,side\,effects,s_2}$	-20.4744	-1.93					-14.2423	-2.71	0	-	-21.4429	-3.54	-22.0941	-5.38	-14.0445	-1.02	0	-
$\beta_{severe\,side\,effects,s_3}$	-35.4840	-2.78					-4.0686	-0.25	0	-	-25.0972	-1.73	-33.3987	-3.37	-37.6677	-3.08	-4.8202	-1.76
$\beta_{waiting\,time,s_1}$ ‡	-0.0295	-4.62	-0.0163	-2.24	-0.0225	-2.89	-0.0256	-3.01	-0.0559	-4.17	-0.0182	-1.31	-0.0539	-7.52	-0.0112	-0.84	-0.0105*	-2.62*
$\beta_{waiting\,time,s_2}$ ‡	-0.0752	-2.87					-0.0171	-3.19	-0.0075	-0.89	-0.0163	-3.19	-0.0316	-6.66	-0.0104	-0.82	-0.0105*	-2.62*
$\beta_{waiting\,time,s_3}$ ‡	-0.0326	-4.25					-0.0361	-1.89	-0.0103	-0.28	-0.0323	-1.72	-0.0177	-1.93	-0.0212	-2.36	-0.0105*	-2.62*
β_{fee,s_1} §	-0.0205	-5.17	-0.0013	-2.45	-0.0028	-3.31	-0.0036	-8.89	-0.0079	-4.25	-0.0015	-1.37	-0.0033	-7.27	-0.0042	-4.07	-0.0023*	-2.71*
β_{fee,s_2} §	-0.0045	-2.89					-0.0084	-2.25	-0.0036	-1.17	-0.0168	-3.51	-0.0254	-6.78	-0.0007	-0.65	-0.0023*	-2.71*
β_{fee,s_3} §	-0.0026	-3.45					-0.0115	-1.65	-0.0075	-0.84	-0.0025	-1.61	-0.0022	-2.37	-0.0052	-1.29	-0.0023*	-2.71*
$\beta_{population\,coverage,s_1}$	0.0133	1.18	0.0120	1.64	0.0287	2.02	0.0011	0.15	0.0005	0.04	0.0165	0.96	0.0090	1.47	-5.00E-04	-0.04	0.0087	0.92
$\beta_{population\,coverage,s_2}$	0.0148	0.43					0.0169	1.50	0.0099	1.08	0.0317	1.99	0.0188	2.17	0.0097	1.91	0.0115	2.96
$\beta_{population\,coverage,s_3}$	0	-					-0.0017	-0.33	0.0061	0.51	-0.0027	-0.42	0.0106	3.09	-0.002	-0.07	0.0025	0.60
$\beta_{travel\,exemption,s_1}$	0	-	1.2445	2.48	0	-	0	-	0.4283	0.86	0	-	0	-	0	-	0	-
$\beta_{travel\,exemption,s_2}$	6.9013	2.94					0	-	0	-	0	-	0	-	0	-	0	-
$\beta_{travel\,exemption,s_3}$	0.5210	1.62					0.3738	1.15	0	-	0.6146	1.98	0.1748	0.72	1.4894	0.52	0	-
$\lambda_{vaccine,s_1}$	0.5921	5.55	0.3328	3.01	0.4404	3.61	1	-	1	-	0.3061	1.43	0.5636	7.66	1	-	1	-
$\lambda_{vaccine,s_2}$	0.4913	3.02					1	-	1	-	0.5314	4.19	0.7617	7.33	0.3187	1.33	1	-
$\lambda_{vaccine,s_3}$	0.3103	2.72					0.7642	1.93	1	-	0.3073	1.95	0.6009	5.25	1	-	0.4383	2.71
ω_{s_1}	0	-					0	-	0	-	0	-	0	-	0	-	0	-
ω_{s_2}	-1.1786	-6.84					0.4255	3.50	0.2393	1.44	0.5599	4.23	0.3249	5.19	-0.8214	-3.7	-1.4389	-4.10
ω_{s_3}	-1.3097	-5.68					-1.6807	-5.33	-1.5754	-6.25	-1.5844	-4.75	-1.4676	-10.57	0.1805	0.82	0.1033	0.38
Class allocation probabilities (π)																		
s_1	63.39%		100%		100%		36.81%		40.37%		33.83%		38.25%		37.91%		42.63%	
s_2	19.50%		0%		0%		56.33%		51.28%		59.23%		52.93%		16.67%		10.11%	
s_3	17.11%		0%		0%		6.86%		8.35%		6.94%		8.82%		45.42%		47.26%	

*: parameter constrained to be equal across some classes

†: Protection duration expressed in months

‡: Waiting time expressed in weeks

§: All cost coefficients are expressed in GBP. The exchange used at the time of the study design was 1GBP=(1.8AUD, 6.64BRL, 980.86CLP, 8.93CNY, 4,670COP, 8.33DKK, 1.1EUR, 9.87HKD, 135.43JPY, 1,532KPW, 21.06NAD, 1.92NZD, 1.27USD, 21.37ZAR)

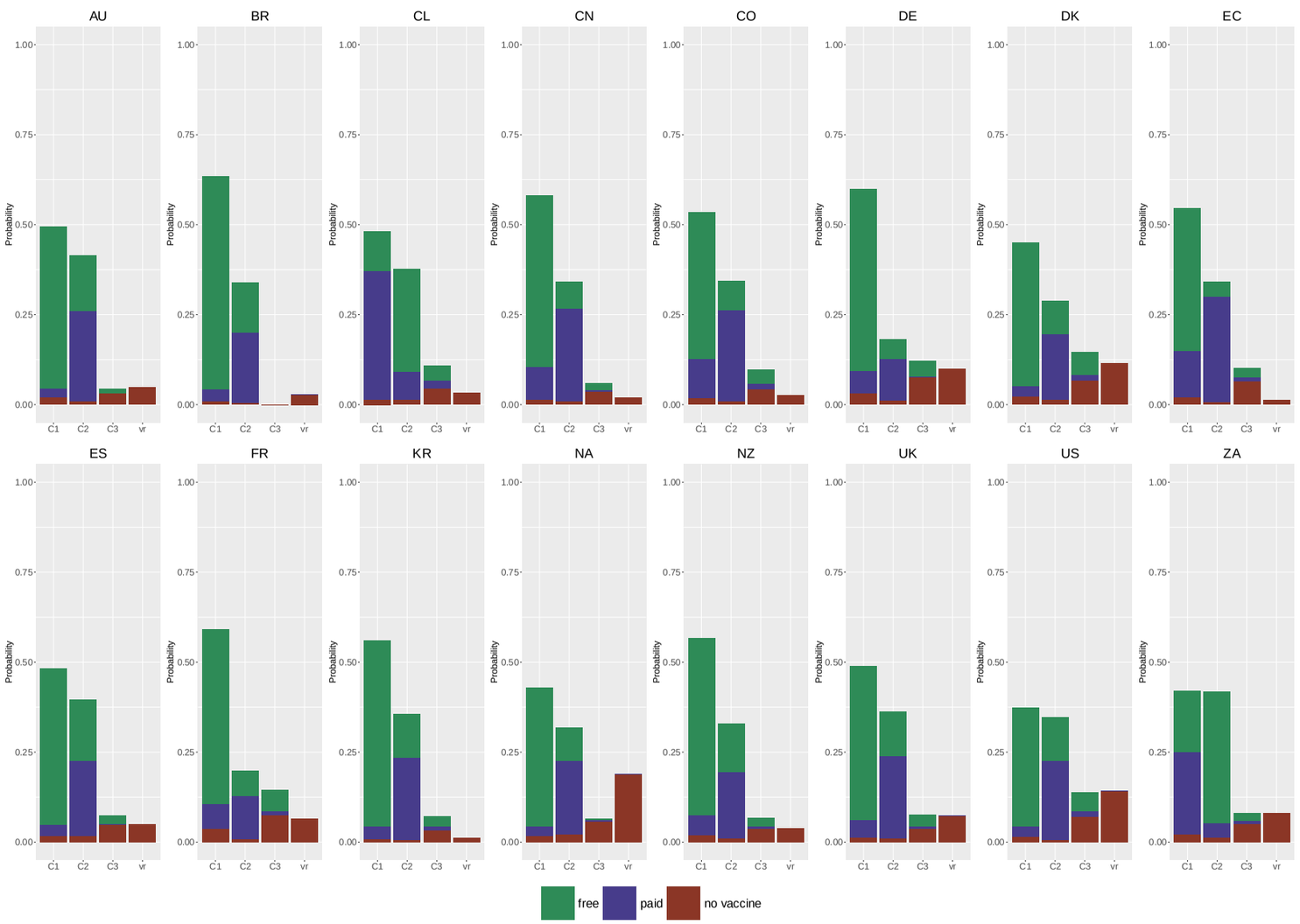

Figure A.2: Class sizes and predicted choices within classes in overall data (height shows class weight)